Heliyon 8 (2022) e10312

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Impact of big data resources on clinicians' activation of prior medical knowledge

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ARTICLE INFO

Keywords:
Big data resources
Activation of prior medical knowledge
Shared big data resources
Private big data resources

ABSTRACT

Background: Activating prior medical knowledge in diagnosis and treatment is an important basis for clinicians to improve their care ability. However, it has not been systematically explained whether and how various big data resources affect the activation of prior knowledge in the big data environment faced by clinicians.

Objective: The aim of this study is to contribute to a better understanding on how the activation of prior knowledge of clinicians is affected by a wide range of shared and private big data resources, to reveal the impact of big data resources on clinical competence and professional development of clinicians.

Method: Through the comprehensive analysis of extant research results, big data resources are classified as big data itself, big data technology and big data services at the public and institutional levels. A survey was conducted on clinicians and IT personnel in Chinese hospitals. A total of 616 surveys are completed, involving 308 medical institutions. Each medical institution includes a clinician and an IT personnel. SmartPLS version 2.0 software package was used to test the direct impact of big data resources on the activation of prior knowledge. We further analyze their indirect impact of those big data resources without direct impact.

Results: (1) Big data quality environment at the institutional level and the big data sharing environment at the public level directly affect activation of prior medical knowledge; (2) Big data service environment at the institutional level directly affects activation of prior medical knowledge; (3) Big data deployment environment at the institutional level and big data service environment at the public level have no direct impact on activation of prior knowledge of clinicians, but they have an indirect impact through big data quality environment and service environment at the institutional level and the big data sharing environment at the public level.

Conclusions: Big data technology, big data itself and big data service at the public level and institutional level interact and influence each other to activate prior medical knowledge. This study highlights the implications of big data resources on improvement of clinicians' diagnosis and treatment ability.

1. Introduction

As we all know, the clinical skills of clinicians are very important to improve the quality of treatment and relieve patients' pain. However, high-quality diagnosis and treatment is often a complex situation, and clinicians often face various challenges in their career. Whether the appropriate prior knowledge can be activated in time is an important premise to ensure the clinicians to give full play to their clinical and nursing ability. Baenninger et al. (2021) evaluated the possible impact of whether general ophthalmologists in Switzerland have the minimum keratoconus knowledge expected by corneal experts. Their study has shown that the low recall rate of symptoms and risk factors can explain why there are relatively few cases of keratoconus diagnosed by ophthalmologists, resulting in low nursing efficiency and delayed intervention.

Meanwhile, information technology and various big data resources have changed the diagnosis and treatment environment of clinicians (Petrie et al., 2019; Pirracchio et al., 2019) and the learning environment for clinicians to improve clinical ability (Cheung et al., 2019; Akoka et al., 2017; Oravec et al., 2019). With the development and application of big data technology, medical big data has been formed.

Medical big data includes clinical data, such as electronic medical records and ancillary data from hospitals and clinics, diagnostic data from laboratories and radiology departments, biomarkers data from

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https://doi.org/10.1016/j.heliyon.2022.e10312
Received 28 January 2022; Received in revised form 10 July 2022; Accepted 11 August 2022

diagnostic companies, and claims data (such as medical claims and prescription claims) (Szlezak et al., 2014); various medical imaging big data (Yaffe, 2019); patient-generated data, such as from social media (Szlezak et al., 2014); big data from various sensors in the Internet of Things (Saheb and Izadi, 2019); various research data, such as the clinical trials in clinical research, design parameters (compound, size, end points) (Szlezak et al., 2014), biomolecular database (Al-Harazi et al., 2019), big data in system vaccine development (Raeven et al., 2019), and big data in pharmacogenomics (Barrot et al., 2019).

These medical big data include internal data and external public data of medical institutions. However, how these medical big data play their value and how they affect clinicians to activate prior knowledge have not been well explained so far. The goal of this paper is to explore how various big data resources affect clinicians to activate a prior knowledge.

2. Theory

2.1. Big data resources

The value of big data has been illustrated from the wide range of industries. E-commerce, e-government, science and technology, smart health, security and public safety are several important application areas of big data (Chen et al., 2012), and health and government are two important areas (Akoka et al., 2017). Big data in healthcare has impact on medical research, such as on research in pediatric neurosurgery (Oravec et al., 2019) and gastrointestinal research (Cheung et al., 2019). It also changes the way and capability of diagnosis and treatment, such as big data should affect the early detection of melanoma (Petrie et al., 2019a) and contribute to various medical treatments in ICU (Intensive Care Unit) decision-making (Pirracchio et al., 2019).

“Big data” has been regarded as an important breakthrough technology development in the past decade, and experienced the crazy operation of the concept in 2012 (Akoka et al., 2017). The concept of big data often involves two streams. The first stream concentrates on big data itself. One line of research aims to identify various characteristics of the generated data (Cuzzocrea et al., 2011), such as Volume, Velocity, Variety, Value, and Veracity (Kuo et al., 2014; Laney, 2001; Manyika et al., 2011). Another line concerns data quality. For example, the specific big data quality problems, such as inauthentic data collection, incomplete information, representativeness, are discussed (Liu et al., 2016). The second stream mainly considers what big data is from the perspective of technology and methods. They believe that big data is a collection of related technologies (Gantz and Reinsel, 2011), such as storage and management of big data (Zhang et al., 2015), cloud computing and cloud service (Hashem et al., 2015), security technologies and big data standards (Terzi et al., 2015), etc.

However, the deficiency of a value-oriented big data concept will hinder researchers to understand how the organization transforms the potential value of big data into actual value (Günther et al., 2017). Technology, method, information and influence, as the four elements of big data value, must be integrated (De Mauro et al., 2015). The value realization of big data involves talent issues (Fang et al., 2015), data policy, technology, organizational changes, data access, and industry structure (Wamba et al., 2015). The value realization of big data should be analyzed from the work-practice level, the organizational level, and the supra-organizational level (Günther et al., 2017).

Through the comprehensive analysis of extant research results, big data resources involve medical big data itself, big data technology and big data service elements at the public and institutional levels. At the level of medical institutions, healthcare big data itself constitutes big data quality environment (BDIL), big data technology forms big data deployment environment (BDDE), and organizational elements such as big data talents constitute medical big data service environment (BDSI). At the public level, big data resources involve big data sharing environment (BDPL) and big data public service environment (BDSP).

2.1.1. Big data quality environment at the level of medical institutions (BDIL)

Big data in healthcare contains a large amount of highly diverse biological, clinical, environmental and lifestyle information collected from individual to large patient cohorts at one or more time points, which is related to their health and wellness status (Wang and Hajli, 2017). Dinov (2016) believes that big healthcare data refers to complex data sets with some unique characteristics, which exceed their large size, and can also extract actionable knowledge about an observable phenomenon.

The quality of medical big data is very important (Samadbeik et al., 2020), and will affect hospital financing/reimburse men and the reuse in epidemiological or health service research (Khalifa, 2017; Ring and Tierney, 2017). It will also have an important impact on improving the quality of care provided to patients, reducing access gap, improving patients' physical condition, and better allocating resources (Wasserman, 2011).

The big data quality environment refers to the completeness, credibility, integration and visualization of data in medical institutions, which integrates some data characteristics in the definition of big data (Kuo et al., 2014; Laney, 2001; Manyika et al., 2011) and some concepts of data quality (Ge et al., 2018), and reflects the level of high quality of healthcare big data as assets.

Completeness of healthcare data (DP) is a multi-dimensional characteristic index of healthcare big data, focusing on the characteristics of variety (different types of data from several sources) (Cuzzocrea et al., 2011; Laney, 2001) and variability (context of data) (Ge et al., 2018; Sivarajah et al., 2017). Credibility of healthcare data (DC) refers to authenticity or veracity of healthcare data. An important factor affecting the quality of big data is inauthentic data collection (Liu et al., 2016). Integration of healthcare data (DI), as relevance index, refers the connectivity of healthcare data from the various information systems and is the valence feature of big data (Khan et al., 2014; Sivarajah et al., 2017). Visualization of healthcare data (DV) refers to interpreting data and identifying the most relevant information for users (Khan et al., 2014; McComb et al., 2017).

2.1.2. Big data deployment environment at the level of medical institutions (BDDE)

The big data deployment environment involves big data technologies used by medical institutions to collect, store and apply various big data. During the generation and application of big data, mobile technology and wireless networks are important means (Akoka et al., 2017; Gil et al., 2019) which constitutes the big data deployment environment. Coverage of mobile applications (MC) determines the efficiency and scale of the production of big data by medical institutions (Akoka et al., 2017; Chen, Mao and Liu, 2014). Accessing quality of wireless networks (WA) will affect the effectiveness of wireless network use and bring different experience to clinicians (Chen, Mao and Liu, 2014; Saravanan et al., 2015).

2.1.3. Big data service environment at the level of medical institutions (BDSI)

To transform the potential value of big data into actual value, an organization needs big data thinking in addition to big data itself and technology. Big data thinking is reflected in whether the organization has big data talents and other organizational elements (Fang et al., 2015; Jimenez et al., 2020; Machleid et al., 2020). Organizations with big data thinking can use big data technology and big data to build a successful business model, and to realize the value of big data. So, organizations with big data thinking have a good big data service environment.

To improve medical service management and medical service capabilities by using healthcare big data (Hulsen et al., 2019), all kinds of medical staff need to have a certain consciousness of big data. However, the big data consciousness and ability of medical staff require certain training mechanisms and the help of big data professionals (Moore et al., 2019). In addition, applications of healthcare big data often face the leakage of patient privacy (Price and Cohen, 2019) and require specific authorization mechanisms (Hashem et al., 2015; Price and Cohen, 2019). Therefore, big data professionals (BP), big data consciousness (BC), personnel training mechanism (TM) and authorization management mechanism (AM) constitute big data service environment (BDSI).

Big data professionals (BP) refer to talents with big data awareness (BC) and the ability to use technology, reflecting the human assets of medical institutions. The big data professionals in medical institutions are compound talents who need to keep abreast of the latest big data technology trends, have basic computer knowledge, communication skills, and professional competences (Fang et al., 2015). Big data consciousness (BC) is a kind of information consciousness, which refers to people's sensitivity, judgment and insight of value contained in big data (Melville et al., 2004). For example, although digital health provides opportunities to improve the quality, efficiency and safety of primary health care, in order to improve the adoption of digital tools and technologies, there must be a capable and digitally literate workforce. The slow adoption of digital tools and technologies in primary health care is partly due to low digital health literacy (Jimenez et al., 2020). Digital health literacy and digital skills should become the necessary abilities of health professionals to promote the implementation of digital technology and use its potential to improve health (Machleid et al., 2020).

To improve the ability of medical staff to use medical big data, a certain personnel training mechanism is needed. Personnel training mechanism (TM) refers to the standardization and seriousness of medical institutions' training plans, requirements and implementation of medical big data in the form of rules and regulations. Medical institutions shall regularly provide big data professionals with lectures on new technologies, and timely train medical staff to use the new system (Guinez-Molinos et al., 2018). Price and Cohen (2019) reviewed several knowledge areas necessary for the next generation of scientists to fully realize the potential of biomedical big data, including big data and its storage and management, statistics and data science, followed by artificial intelligence, machines learning and natural language processing, and put forward some specific training suggestions. Butler Henderson et al. (2020) reviewed the competency and threshold criteria of allied health professionals to determine whether digital medical capabilities are included, and showed that digital health is a major gap in the ability statement of all joint health disciplines. The cultivation of high-quality digital health ability needs a good training system.

Healthcare big data has become the source of healthcare innovation, but it also brings huge risks and challenges, especially patients' privacy issues (Price and Cohen, 2019). Authorization management mechanism (AM) is a management method that balances patient privacy protection and full utilization of the value of healthcare big data (Bardram and Houben, 2018). According to the business management requirements of medical institutions, the authorization management mechanism establishes rules for allocating big data resources, realizes the whole process management of electronic authorization of healthcare data, controls and traces the leakage of patients' privacy, so that the use of big data is legal, reasonable, safe and easy. Whether a medical institution has an authorization management mechanism is an important indicator for judging the maturity of big data usage.

2.1.4. Big data sharing environment at the public level (BDPL)

An important challenge of implementing precision medicine based on big data is to share data (Hulsen et al., 2019). In the big data sharing environment at the public level (BDPL), there are the sharing of diagnosis and treatment data (TS) (Bardram and Houben, 2018; Lefaivre et al., 2019) and the sharing of medical research data (RS). High quality medical service involves a series of information processing, such as collecting information about patients, analyzing and understanding the information, and eventually making decisions. due to the complexities of care and the challenge of information overload in the healthcare sector, finding high-quality evidence will provides a good opportunity to improve patient treatment. Daei et al. (2020) analyzed clinicians' clinical information-seeking behavior and found that the most commonly used source was consulting colleagues and viewing journal articles, Internet websites, textbooks and Medline/PubMed.

2.1.5. Big data public service environment at the public level (BDSP)

Big data value realization also needs an enabler at the public level (Baesens et al., 2016), that is, the public service environment of big data. BDSP is a soft environment serving medical institutions in the public area, which promotes and restricts the development of medical collaboration practice. Policies and regulations related to big data (PR) will affect the development of the medical big data industry and medical collaboration practice (Khan et al., 2014; Melville et al., 2004). In China, the National Health and Family Planning Commission has issued a series of planning and policy support for regional healthcare service system (such as the three-level referrals and medical consortia). Public funding environment (FE) will affect the coverage (such as the number of participating medical institutions) of the medical service platform in the region (Kantar Consulting, 2019).

2.2. The activation of prior knowledge

According to information processing theory, learning is an information processing process through which information or experience can be accumulated (Chen, Chen and Sun, 2014; Tang et al., 2011; Wang et al., 2018). Whenever new knowledge is input, learners need to be able to activate prior knowledge related to a given task and promote the successful integration of the new knowledge with the existing structure in a meaningful way (Ausubel, 2000; Dochy et al., 2002; Mayer, 2010; Wang et al., 2018; Weinert and Helmke, 1998). Before completing a learning task, the knowledge suitable for completing the task will be brought into working memory from learners' long-term memory, so that the connection between new information and existing knowledge can be carried out there (Mayer, 1979; Erkens and Bodemer, 2019). Therefore, activating prior knowledge is one of the basic conditions for learning (Erkens and Bodemer, 2019). Prior knowledge is a strong determinant in information problem solving process (Chen and Macredie, 2010; Minetou et al., 2008). Tabatabai and Shore (2005) found that people with higher level of prior knowledge participate in more information problem-solving strategies in the process of web searches because they often change strategies and navigate more frequently.

The activation of prior medical knowledge (APMK) refers to the degree to which clinicians recall relevant prior medical knowledge when learning new professional skills or applying learned medical knowledge. During their study and internship in school, medical staff have learned written and categorical clinical medical knowledge. When they start to work in diagnosis and treatment, they need to first take out professional subordinate skills, such as pharmacology, diagnostics and other related contents, so as to recode the subordinate skills and be able to apply these learned medical knowledge. Although the recall of relevant knowledge is very important for diagnosis and treatment, clinicians cannot always recall the previous learning completely and clearly. For example, high quality patient care is a complex phenomenon, which requires the use of interdisciplinary knowledge, and the preparation of medical and health science students for interdisciplinary knowledge is closely related to the actual perceived nursing effect (Sulaiman et al., 2021). Different levels of prior knowledge affect the cognitive load of medical students in the use of whole case and series clue case format, thus affecting students' knowledge acquisition or diagnostic accuracy (Kiesewetter et al., 2020). Baenninger et al. (2021) showed that the low recall rate of symptoms and risk factors by Swiss general ophthalmologists leads to relatively few cases diagnosed with keratoconus, which makes patients unable to receive effective and timely care.

Due to the importance of activating prior knowledge, the influence of various technologies on activating prior knowledge has been concerned by many scholars. Text mining methods can automatically convert unstructured knowledge text into structured format (Miner et al., 2012), which is convenient for learners to identify the content of previous knowledge (Erkens and Bodemer, 2019). In the educational situation based on virtual reality, games with implicit structure will increase students' recall of spatial information (Ferguson et al., 2020). And Arents et al. (2021) investigated whether adding 360° virtual reality video to the internship course for medical students would improve the long-term memory of mild caesarean section and general obstetric knowledge. The study showed that watching 360° virtual reality video did not lead to differences in specific or general knowledge retention between the intervention group and the conventional study group.

2.3. The study aims and questions

Existing studies, on the one hand, show the importance of stimulating prior knowledge, but do not systematically explain whether and how various big data resources affect the stimulation of prior knowledge in the big data environment faced by clinicians. This study aims to explore and understand the influencing mechanism of a wide range of shared and private big data resources (BDRs) on the activation of prior knowledge of clinicians, so as to reveal the impact of BDRs on clinical competence and professional development of clinicians. The research questions are as follows:

(i) What BDRs at the public level directly affect the activation of prior knowledge of clinicians?
(i) What BDRs at the level of medical institutions directly affect the activation of prior knowledge of clinicians?
(iii) What are the indirect influence paths for those big data resources that have no direct impact on the activation of prior knowledge of clinicians?

This paper constructs a big data resource framework at the public and private levels, including big data itself, big data services and big data technology, and explores (1) the impact of big data resources at the public and private levels on the activation of prior knowledge, including direct and indirect impacts; (2) the interactive impact of big data itself, big data services and big data technology on the activation of prior knowledge. Finally, the questionnaire data from 308 hospitals are used to demonstrate these relationships.

3. Methods

3.1. Sample and data collection

Data were collected using a matched-pair field survey of clinicians and information personnel in public hospitals, as well as some private hospitals in the China. Public hospitals are the main body that provides patient diagnosis and treatment services in China. Accordingly, the study mainly chooses clinicians and information personnel in public hospitals, as well as some private hospitals.

The process of data collection is as follows: (1) Identify a contact in each target medical institution who will be responsible for issuing the questionnaire and recycling it. (2) Confirm whether the institution participated in this study through the contact. (3) Determine two respondents in each target hospital by the contact, one for business executive and the other for IS executive. (4) Issue the survey package to the relevant contact via mail or WeChat (if the journey is far away). (5) The contact distributed Part A (relating to BDIL, BDDE, BDSI, and BDPL) to the business executive, and Part B (relating to BDSP) to IS executive.

In the end, 360 medical institutions participated in the survey, and 308 medical institutions provided valid questionnaires, including 308 questionnaires from clinicians, and 308 questionnaires from information personnel.

The hospital survey spans 21 provinces and cities in China, among which, tertiary general hospitals account for 25%, tertiary special hospitals account for 12.7%, second-class general hospitals account for 49%, second-class special hospitals account for 6.8%, and community hospitals account for 6.2; Public hospitals accounted for 91.9% and private hospitals for 8.1%. Among the 616 respondents, male accounted for 66.9%, and women accounted for 33.1%. Among the 308 medical personnel who participated in the survey, internal medicine accounted for 25.8%, surgical department 14.3%, Department of surgery 5.2%, pediatrics 1.6%, emergency department 1.1%, medical technology 1.1% and general practice 0.9%.

3.2. Ethics approval

The study protocol was reviewed and approved by the ethics review committee at the Shanghai Chest Hospital (IS [P]22001). Before conducting the research, all participants were informed in writing of the purpose and procedure of this study. Participants can voluntarily choose not to participate in this study. The confidentiality and anonymity of all participants' collected information were ensured.

3.3. Measurement scales

The development measurement scales for constructs involve two procedures: 1) to create pool of items for each construct; 2) to check potential respondents' response to the questionnaire and refine items by a pilot test.

To ensure content validity, the items for most constructs are employed, expanded and modified from previous research (BaiLey and Pearson, 1983; DeLone and McLean, 2003; Goodhue, 1998; Taylor and Todd, 1995), and measurement scales for big data public service environment (BDSP) are self-developed. The measures were then refined so that we can investigate the variables that reflect the contextual significance of health information use (see Supplementary Material: Questionnaire).

The stage of item design is completed through field interviews and group discussion. Five members participated in the pre-interview, one director of the information center (20 years in the field of hospital informatization, senior engineer), one information center staff (10 years in the field of hospital informatization, engineers), one director of the medical department (18 years of clinical medical work, 8 years of medical management work, in charge of remote diagnosis and treatment services, chief physician), one director of the outpatient office (15 years in clinical medical work, 5 years in outpatient management work, deputy chief physician), and one clinician (8 years in clinical medical work, attending physician). The working group discussed and revised items, especially for some items of which the description was vague and might lead to ambiguity in understanding. The 62 items used in the pilot test are finally formed (Supplementary). All items are expressed in declarative sentences, and measured by 7 levels of Likert scale.

Big data quality environment at the level of medical institutions (BDIL) was assessed regarding four aspects: completeness, credibility, integration and visualization. First, the completeness of healthcare data (DP) was measured using 3 items about the diversity of content and the scope of information (Cronbach's $\alpha = .93$; $M = 5.41$, $SD = 1.27$). Second, the credibility of healthcare data (DC) was measured using 4 items about authenticity, correctness, no contradiction, and consistency of information (Cronbach's $\alpha = .96$; $M = 5.22$, $SD = 1.248$). Third, the integration of healthcare data (DI) was assessed with 4 items asking the degree to which the connectivity of healthcare data from the various information systems is convenient (Cronbach's $\alpha = .96$; $M = 5.14$, $SD = 1.38$). Lastly, the visualization of healthcare data (DV) was assessed using 4 items about the degree to which the content and format of information is easily understandable (Cronbach's $\alpha = .90$; $M = 5.23$, $SD = 1.16$).

Big data deployment environment at the level of medical institutions (BDDE) was assessed regarding two aspects: coverage of mobile applications (MC) and accessing quality of wireless networks (WA). The coverage of mobile applications (MC) was measured using 5 items about the scope, function, and ease of use of mobile application (Cronbach's $\alpha =$ .98; $M = 3.91$, $SD = 1.89$). To measure the accessing quality of wireless networks (AW), we asked respondents 4 items about the coverage, stability of operation, speed and security of wireless network (Cronbach's α = .93; $M = 4.27$, $SD = 1.72$).

Big data service environment at the level of medical institutions (BDSI) was assessed regarding four aspects: Big data professionals (BP), Big data consciousness (BC), Authorization management mechanism (AM), and Personnel training mechanism (TM). First, the big data professionals (BP) was measured by asking participants to answer 4 items about the sufficiency and ability of IT professionals owned by medical institutions (Cronbach's α = .93; M = 5.26, SD = 1.25). Second, the big data consciousness (BC) was measured in terms of the initiative, frequency and coverage of use of healthcare big data using 3 items (Cronbach's α = .94; M = 4.88, SD = 1.46). Third, the authorization management mechanism (AM) was measured using 4 items about the existence, convenience, rapidness, and effects of information authorization procedures (Cronbach's α = .98; M = 5.28, SD = 1.24). Lastly, the personnel training mechanism (TM) was assessed using 4 items about the degree to which the education and train of health information system are provided by medical institutions (Cronbach's α = .92; M = 5.15, SD = 1.20).

Big data sharing environment at the public level (BDPL) was assessed regarding two aspects: the sharing of diagnosis and treatment data (TS) and the sharing of medical research data (RS). The sharing of diagnosis and treatment data (TS) was assessed using 7 items about the degree to which diagnosis and treatment data of other medical institution can be obtained through government public platforms or the third-party platforms (Cronbach's α = .99; M = 4.07, SD = 1.64). To measure the sharing of medical research data (RS), we asked respondents 3 items about the degree to which research data from other medical institutions (such as CNKI, PubMed, etc.) can be obtained (Cronbach's α = .98; M = 4.35, SD = 1.60).

Big data public service environment at the public level (BDSP) was assessed regarding two aspects: Policies and regulations related to big data (PR) and Public funding environment (FE). Items are self-developed. The Policies and regulations related to big data (PR) was assessed using 3 items about the degree of the extent of rationality, existence and functional completeness of relevant policies, laws and regulations about regional medical service platform (Cronbach's α = .96; M = 5.06, SD = 1.33). To measure the Public funding environment (FE), we asked respondents 5 items about the support, coverage, effect, the ease of use, and diversity of public funds (Cronbach's α = .98; M = 4.58, SD = 1.45).

The activation of prior knowledge was measured using 5 items about the degree to which the prior knowledge of drug indications, drug contraindications, pharmacokinetics, and the diagnostics are activated (Cronbach's α = .97; M = 4.69, SD = 1.38).

3.4. Data analysis and procedure

To confirm the dimensions of big data resources (such as BDIL, BDSI, BDDE, BDPL, BDSP), we conducted a confirmatory factor analysis (CFA).

Table 1. Reliability and convergence validity test.

Constructs	Dimensions & Items	Load Value	CR	AVE
BDIL	DP (3 items)	0.881	0.925	0.755
	DC (4 items)	0.867		
	DI (4 items)	0.828		
	DV (4 items)	0.899		
BDSI	BP (4 items)	0.840	0.880	0.647
	BC (3 items)	0.811		
	AM (4 items)	0.797		
	TM (4 items)	0.767		
BDDE	MC (5 items)	0.932	0.934	0.877
	AW (4 items)	0.940		
BDPL	TS (7 items)	0.916	0.918	0.850
	RS (3 items)	0.927		
BDSP	PR (3 items)	0.911	0.901	0.819
	FE (5 items)	0.899		
APMK	5 items	0.931–0.954	0.975	0.886

Each dimension of big data resources consisted of multiple subfactors, which were assessed with 3–7 items and then averaged. This average score was included as an indicator in the CFA. For example, with BDIL being a latent variable, there were four indicators: completeness, credibility, integration and visualization.

SmartPLS version 2.0 software package (Ringle and Wende, 2005) are applied. First, we evaluated the measurement model. Next, we examined the direct impact of big data resources on the activation of prior knowledge. To that end, for those big data resources that have no direct impact on the activation of prior knowledge, we further analyzed their indirect impact.

4. Results

4.1. Measurement model

In Table 1, factor loading values of all items are all higher than 0.80 and significant, above the normal value 0.7 (Hair et al., 2010); composite reliability CR value are around 0.9, above the cut off value 0.7 (Urbach and Ahlemann, 2010). All values meet the minimum requirement for indicator reliability and internal consistency reliability. Also, the average variance extracted AVE employed to assess the convergent validity was ≥0.77 for all constructs, above the normal value 0.50 (Fornell and Larcker, 1981), so the model has good convergence validity.

The test results of discriminant validity are seen in Table 2. The Fornell-Larcker criterion (Fornell and Larcker, 1981) are conformed. The square root of the AVE values of each construct are greater than the correlation coefficient between constructs, the measurement model has good discriminant validity.

4.2. Influence path

Figure 1 shows the results of the analysis for the relationships. 49.1% of the variance in APMK, 41.5% of the variance in BDPL are moderately explained, the cut off value of moderate R^2 is o.333. 32.7% of the variance in BDSI and 28.4% of the variance in BDIL is weakly explained, but meets the cut off level which is 0.190.

The model's Goodness-of-Fit for the current study as calculated is 0.553, which is deemed large (Wetzels et al., 2009).

4.2.1. Direct influence path

From Figure 1 and Table 3, we can see:

(1) The direct effects of big data quality environment (BDIL), big data service environment (BDSI) at the level of medical institutions, and big data sharing environment (BDPL) at the public level on APMK are significant at the level of 0.01. (2) The direct effects of big data deployment environment (BDDE) at the level of medical institutions and big data public service environment (BDSP) at the public level on APMK are not significant.

4.2.2. Mediating effect analysis

Since BDDE and BDSP have no direct impact on APMK, the indirect effect of these two variables on APMK is further analyzed. The results of the mediation test are presented in Table 4 and Figure 1. To assess the magnitude of the indirect effects (Helm et al., 2010), the VAF (variance accounted for) value was calculated, which represented the ration of the indirect effect to the total effect.

From Table 4 we can see:

(a) The indirect impact of BDDE. Although BDDE have no direct impact on APMK, there are three completely mediated path: BDDE- > BDIL- > APMK ($p < 0.05$), BDDE- > BDSI- > APMK ($p < 0.05$), and BDDE- > BDPL- > APMK ($p < 0.01$). In these paths, BDIL, BDSI and BDPL play mediating roles in the effect of BDDE on APMK (VAF is 0.711). The total effect of BDDE on APMK was 0.32, and it was

Table 2. Discriminant validity test.

	BDIL	BDSI	BDDE	BDPL	BDSP	APMK
BDIL	0.8690219					
BDSI	0.773837	0.8042015				
BDDE	0.424342	0.446333	0.936352			
BDPL	0.48585	0.540717	0.611328	0.9214451		
BDSP	0.490506	0.532197	0.496088	0.479758	0.9050851	
APMK	0.599322	0.617777	0.473192	0.563165	0.466829	0.9414951

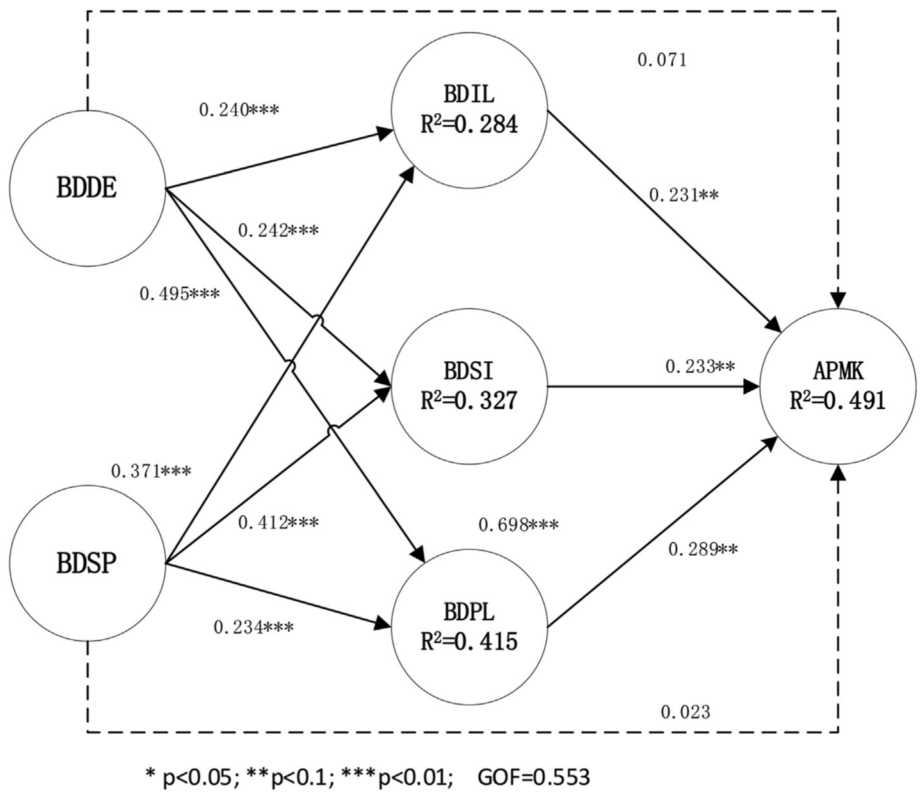

Figure 1. Structural model PLS results including direct and indirect effects.

Table 3. Direct effects.

PATH	Path Coefficient	T Statistics
BDIL - > APMK	0.231**	3.012
BDSI - > APMK	0.233**	2.77
BDDE - > APMK	0.092	1.329
BDPL - > APMK	0.234**	3.054
BDSP - > APMK	0.071	1.045

*p < 0.05; **p < 0.1; ***p < 0.01 Mediating effect analysis.

significant in P < 0.01. However, 71% of the total effects are indirect effects based on BDIL, BDSI and BDPL. It indicates that the accessibility of wireless networks and the coverage of mobile applications in medical institutions not only promotes the generation of medical big data, and the sharing of medical big data (Akoka et al., 2017; Gil et al., 2019) but also improves the big data service environment of medical institutions, such as facilitating the use of big data by medical staff, strengthening the awareness of big data use, triggering more training on relevant contents (Kiesewetter et al., 2020), and finally promoting medical staff to better recall relevant medical knowledge in clinical practice.

(b) The indirect impact of BDSP. Although BDSP have no direct impact on APMK, there are three completely mediated path: BDSP- > BDIL- > APMK (p < 0.01), BDSP - > BDSI- > APMK (p < 0.05), BDSP - > BDPL- > APMK (p < 0.05). In these paths, BDIL, BDDE and BDPL play mediating roles in the effect of BDSP on APMK (VAF is 0.769). The total effect of BDSP on APMK was 0.31, and it was significant in P < 0.01. However, 76.9% of the total effects are indirect effects based on BDIL, BDSI and BDPL. It indicates that the big data service environment at the public level, such as the guidance of policies and the introduction of funds, has strengthened the development of medical big data at both the medical institution level and the public level (Braun and Cusick, 2016), promoted the construction of big data service environment within medical institutions (Rui, 2019), and provided a big data use environment for medical staff. Thus, it is more convenient for medical staff to review relevant medical knowledge in clinical practice.

5. Discussion and conclusions

5.1. Academic implications

This study contributes several important findings to the current body of knowledge. First, whether at the level of medical institutions or at the

Table 4. Mediating effect test.

Indirect effect	Direct path	Path Coefficient P-Value	Mediated Paths	Sobel Test			VAF	Cumulative VAF
				Sobel Statistic	Std Error	Sobel Z P-Value		
BDDE- > BDIL- > APMK	BDDE - > APMK	NS	BDDE - - > APMK; BDDE → BDIL → APMK	2.359	0.023	0.018	0.173	0.711
	BDDE - > BDIL	0.015						
	BDIL- > APMK	0.027						
BDDE- > BDSI- > APMK	BDDE - > APMK	NS	BDDE - - > APMK; BDDE → BDSI → APMK	2.218	0.026	0.027	0.176	
	BDDE - > BDSI	***						
	BDSI- > APMK	**						
BDDE- > BDPL- > APMK	BDDE - > APMK	NS	BDDE - - > APMK; BDDE → BDPL → APMK	2.889	0.041	0.004	0.362	
	BDDE - > BDPL	***						
	BDPL- > APMK	**						
BDSP- > BDIL- > APMK	BDSP- > APMK	NS	BDSP - - > APMK; BDSP → BDIL → APMK	2.665	0.032	0.008	0.278	0.769
	BDSP - > BDIL	***						
	BDIL- > APMK	**						
BDSP- > BDSI- > APMK	BDSP - > APMK	NS	BDSP - - > APMK; BDSP → BDSI → APMK	2.56	0.038	0.01	0.313	
	BDSP - > BDSI	***						
	BDSI - > APMK	**						
BDSP- > BDPL- > APMK	BDSP - > APMK	NS	BDSP - - > APMK; BDSP → BDPL → APMK	2.458	0.022	0.014	0.178	
	BDSP - > BDPL	***						
	BDPL- > APMK	**						

NS: not significant; *$p < 0.05$; **$p < 0.1$; ***$p < 0.01$.

public level, medical big data itself directly affects clinicians' activation of medical knowledge. The quality of medical big data in medical institutions is high, that is, the information contained in medical big data is relatively complete and accurate, the relevance of diagnosis and treatment process is strong, and the data is highly understandable, which can enable clinicians to better activate the previously learned drug knowledge, diagnostic knowledge and laboratory knowledge according to the current patient situation, and better carry out diagnosis and treatment services. The sharing of diagnosis and treatment data and research data at the public level can help clinicians understand the relevant scientific research achievements and diagnosis and treatment level of diseases, help clinicians extract more appropriate relevant diagnosis and treatment knowledge, and improve their diagnosis and treatment ability. This finding corresponds to previous studies that showed the significance of medical data quality at the medical institution level and medical big data shared at the public level (Samadbeik et al., 2020). Samadbeik et al. (2020) emphasized the importance of medical data quality, which will affect the financing/reimbursement of hospitals and its reuse in epidemiological or health service research (Ring and Tierney, 2017; Ayers et al., 2009; Khalifa, 2017). It will also enhance the quality of care provided to patients, reduce access differences and improve patient outcomes, and better allocation of resources (Wasserman, 2011). Daei et al. (2020) believe that clinicians will encounter many problems in the process of patient care. Timely and convenient discovery of high-quality evidence provides a good opportunity to improve patient care. Their research shows that the most common source for clinicians to seek clinical information is to consult their peers, and view journal articles, Internet websites, textbooks and MEDLINE/PubMed at the same time.

Second, the big data service environment at the level of medical institutions directly affects clinicians' activation of medical knowledge. At the level of medical institutions, all kinds of medical staff have a better and certain consciousness of big data, and they are more willing to use medical big data in diagnosis and treatment services. Having sufficient and excellent big data professionals (BP) in medical institutions can provide clinicians with better technical assistance and relevant training. Perfect authorization and good training methods make clinicians have a clear concept of the scope of data acquisition, make it easier for clinicians to activate relevant knowledge in the process of diagnosis and treatment, and finally improve the ability of diagnosis and treatment service. This finding corresponds to previous studies that showed the significance of internal and external big data service environment (Jimenez et al., 2020; Machleid et al., 2020). Jimenez et al. (2020) believed that in order to make full use of medical data in the primary health care system, there must be a workforce with ability and understanding of digital technology. Their research also shows that the adoption of digital tools and technologies is slow, partly due to the low digital health literacy of primary healthcare workers. Butler Henderson et al. (2020) believe that cultivating high-quality specific digital health ability requires a good training system. The difference from these studies is that this study focuses more on the impact of the big data service environment of medical institutions on clinicians' activation of prior knowledge, so as to reflect its importance.

Third, the interaction of the three elements of big data value realization (big data itself, technology and services) affects clinicians' review of relevant medical knowledge. Compared with previous studies (De Mauro et al., 2015; Erkens and Bodemer, 2019; Miner et al., 2012), this study reveals more diversified combination patterns between big data itself, big data technology and big data service that affect AK. Although the deployment environment of big data technology (BDDE) at the medical institution level cannot directly affect the review of medical knowledge, there are three intermediary influence paths to realize the indirect impact on the review of medical knowledge. Two of them are about the indirect impact path of “Technology - > Data - > APMK”, that is, BDDE indirectly affects clinicians' activation of medical knowledge by directly affecting the data quality environment of medical institutions and the shared medical big data environment at the public level; The other is the indirect influence path of “Technology - > Service - > APMK”, that is, BDDE indirectly affects clinicians' activation of relevant medical knowledge by affecting the big data service environment of medical institutions.

Although the public big data service environment (BDPL) cannot directly affect the activation of medical knowledge, there are also three intermediary influence paths. Two of them are “External Service - > Data - > APMK”, that is, the public service environment of medical big data indirectly affects clinicians' activation of medical knowledge by directly affecting the data quality environment of medical institutions and the shared medical big data environment at the public level; the other is the indirect influence path of “External Service - > Internal Service - > APMK ″, that is, it indirectly affects clinicians' activation of relevant medical knowledge by affecting the big data service environment of medical institutions.

Fourth, the interaction of big data resources at different levels affects clinicians' review of relevant medical knowledge. Compared with previous studies (Erkens and Bodemer, 2019; Günther et al., 2017), this study reveals that the diversified combination mode of big data resources at different levels that affect APMK Although the public service environment of medical big data and the technology deployment environment at the medical institution level have no direct impact on APMK, there are also six intermediary influence paths through other big data resources at the public level and institution level. Among them, there are two indirect paths of “Public - > Institution - > APMK”, that is, the public service environment indirectly affects APMK by affecting the big data quality environment and the service environment at the institutional level; there is an indirect path of “Public - > Public - > APMK”, that is, the public service environment indirectly affects APMK by affecting the big data sharing environment at the public level; there are two indirect paths of “Institution - > Institution - > APMK”, that is, the technical environment at the institution level indirectly affects APMK by affecting the big data quality environment at the institution level and the service environment at the institution level; there is also an indirect path of “Institution - > Public - > APMK”, that is, the technical environment at the institutional level indirectly affects APMK by affecting the big data sharing environment at the public level.

5.2. Managerial implications

Several practical applications can be recommended to clinicians, medical institutions, and relevant government departments or companies. Firstly, the findings can help clinicians make better use of various big data resources at the institutional level and public level, improve their ability to activate prior knowledge, and heighten their service ability of diagnosis and treatment.

Secondly, this study provides a framework for medical institutions to better deploy their internal big data environment and make use of big data sharing and service environment at the public level to facilitate clinicians in the institution to activate prior medical knowledge more conveniently, so as to improve their service ability of diagnosis and treatment and improve patients' satisfaction with medical services. For example, medical institutions can heighten the collection and use of medical big data and raise the quality of medical big data (including integrity, high relevance, high accuracy and visualization) by improving the coverage of wireless and the diversification of mobile software; medical institutions can strengthen all kinds of training for medical staff, improve their awareness of big data, and enable medical staff to quickly review relevant medical knowledge (including drug use, diagnosis and treatment process and inspection methods) when they encounter problems.

Thirdly, this study provides a basis for the appropriate policies and funding direction of government departments. For example, designing various collaborative medical networks by specifying policies and sharing diagnosis and treatment data in the collaborative medical network; Investing funds to establish public research database and share research results; by establishing a public big data sharing environment, we can directly improve the ability of medical staff to activate relevant medical knowledge in clinical practice.

5.3. Limitations and future research

First, from the perspective of cognitive information processing theory, in addition to activating prior knowledge, there are other conditions for the improvement of clinicians’ diagnosis and treatment ability through learning, such as concentration, effective organization of knowledge, reflection on self-experience, and acquisition of others' experience. These are important conditions for learning to occur. This study mainly focuses on the impact of big data at the institutional level and the public level on the learning condition (to activate prior knowledge), future research also needs to further explore the impact of various big data resources on other conditions of learning, so as to better understand how to make use of big data resources to improve the diagnosis and treatment ability of medical staff.

Secondly, the occurrence of learning needs various conditions. These conditions not only directly affect the occurrence of learning, but also often promote the occurrence of learning in coordination with other learning conditions. In addition to focusing on the impact of various big data resources on specific learning conditions, future research should further explore the synergistic impact of various big data resources on coordination of various learning conditions, so as to better understand how to use big data resources to improve the diagnosis and treatment ability of medical staff.

Thirdly, this study still adopts the method of convenient sampling, and the research results need to use more samples to test the results of this study. In addition, the conclusion of this study is derived from data collected from questionnaires issued to doctors. For this reason, the main conclusion of this paper mainly reflects the doctors' perception of how big data resources impact their practice rather than direct evidences derived from objective measurements, e.g., through clinical studies.

Finally, this study didn't analyze how the background of physicians affects their view on big data resources. Future research can explore the effects of the background of physicians (eg, their age group, level, educational background, or the level of hospitals they belong to).

6. Conclusion

Activating prior medical knowledge in diagnosis and treatment is an important basis for clinicians to improve their diagnosis and treatment ability. This study explored the impact of various big data resources on clinicians' recall of medical knowledge. This study shows that the quality medical big data environment at the institutional level and the sharing environment of medical big data at the public level directly affect the APMK of medical staff; the service environment of medical big data at the institutional level directly affects clinicians' activation of medical knowledge (APMK). The medical big data deployment environment at the institutional level and the service environment at the public level have no direct impact on APMK, but they have an indirect impact on clinicians’ activation of medical knowledge through the medical data quality environment and service environment at the institutional level and the big data sharing environment at the public level. The research also shows that medical big data itself, big data technology and big data service factors will interact to affect the APMK of medical staff. At the same time, various big data resources at the institutional level and various big data resources at the public level will also interact to affect the APMK of medical staff.

Declarations

Author contribution statement

Sufen Wang: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Junyi Yuan: Conceived and designed the experiments; Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Changqing Pan: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data.

Funding statement

Doctor Changqing Pan was supported by the Information Development Project of Shanghai Economic and Information Commission [202002009].

Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

Supplementary content related to this article has been published online at https://doi.org/10.1016/j.heliyon.2022.e10312.

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