Cureus Journal of Business and Economics

Open Access Original Article

Competitiveness of Artificial Intelligence's (AI) Technology-Adoption in the Healthcare Sector in China: An Expert Analysis

Received 06/27/2025
Review began 08/10/2025
Review ended 10/03/2025
Published 11/27/2025

DOI:
https://doi.org/10.7759/s44404-025-08306-9

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Abstract

This research examined China's three-tier national hospital system to understand how Artificial Intelligence (AI) technology influences unit-level competitiveness in both clerical and clinical functions. Through content analysis, the study found that the sector currently operates at the level of *artificial narrow intelligence*. Experts largely agreed that its adoption has been driven by the need to meet hospitals' unitary requirements.

Fragmentation emerged as the dominant paradigm in experts' perspectives, with four distinct clusters of opinion reflecting stakeholder-specific, compartmentalized views of AI's utility. While sentiment was divided, it remained broadly positive, shaped by two key rupture factors: (i) the varying cultural and technical readiness across hospitals, and (ii) the paradoxical allocation of financial resources within the current national public funding framework-perceived as disproportionate to each unit's specialization and thereby constraining further investment in AI initiatives.

Categories: Strategic Operation management, Organisational Development, Digital business
Keywords: artificial intelligence (ai), china, competitiveness, dynamic capabilities (dc), healthcare, "project caita", vrio

Introduction

Background and objectives

Within the sphere of the Philosophy of Management, it is inevitable to avow that both neoclassical and contemporary doctrines of Strategic Management (SM) described, are anchored on the seminal idea that competitiveness is an essential characteristic any enterprise ought to possess. Placed at the epicenter of different streams of thought, the understanding of the assumptions held upon this concept is paramount to grasp the corporate thinking behind the pursuing of organizational efficiency, success, and wealth of any enterprise (Hitt et al., 2019). Unsurprisingly, this topic has been scrutinized for decades through different scholarly lenses.

The field of SM is though accustomed to dichotomic thinking (with a focus on either effectiveness or efficiency), influencing the decision-making competitiveness avenues: (i) the exploring of inner resource-bundles; and (ii) exploring the knowledge about the competitive landscape of the inherent industry characteristics for one's potential growth. Herein, the former idea (i.e. one ought to prioritize the exploring of one's own resource-bundles!) historically antagonizes the second idea (i.e. one ought to focus on the competitive landscape!). The first reasoning, advocated by the so-called Resource-based View (RBV), asserts that the competitiveness of an organization resides on its assets and skills, while the latter reasoning belonging to the Industrial Organization (I/O) dominant (structuralist) economic view, is pillared on the (senior managers and executive boards) beliefs about competitiveness-gains centred upon the dissimilar features of the markets dictating their attractiveness to industry practitioners. In confrontation are, consequently, two models (I/O versus the RBV), somehow assumed to be incommensurable and whose theoretical evolutionary path and virtues we have refrained to elaborate on, furthermore, due to the objectives we have established for this study and the expected contribution, which are independent of these two diametric perspectives of the most effective competitiveness for the firm's growth.

Hence, regardless of the epistemological assumptions held by this research team about the competitiveness conundrum of a medical institution, our study depicts the "Competitiveness of Artificial Intelligence´s technology-adoption" (CAITA), right in the middle of the continuum of both paradigms (I/O and RBV), blending an inside-out approach to competitiveness dynamics (RBV) to the outside-in approach

How to cite this article
Abrantes B F, Miao X, Trigo V, et al. (November 27, 2025) Competitiveness of Artificial Intelligence's (AI) Technology-Adoption in the Healthcare Sector in China: An Expert Analysis. Cureus J Bus Econ 2 : es44404-025-08306-9. DOI https://doi.org/10.7759/s44404-025-08306-9

(I/O), encompassing the examination of one (intangible) resource, i.e. artificial intelligence (AI) to perform an assessment of the potential inherent to such resource. Yet, we go beyond the mere establishment of a roadmap of possession (resource-ownership), as this study entails a general appraisal of AI resource-utilization in the medical sector in China, due to the significant allocation of financial resources in such technology, and the clear distributive funding model shared across medical units. Moreover, the importance of this study is emphasized by previous RBV literature which associate resource-utilization with the premises of superiority and uniqueness among other capabilities, fitting this construct within the category of a dynamic capability (DC) and linking it to the formation of sustainable competitive advantages (SCA), as further explored in the literature review (Abrantes et al., 2022). Consequently, we analyzed in this CAITA-analysis project, both the explicit ability to use AI and the latent organizational capabilities underlying to AI resource-utilization and tested furthermore the experts mapping of AI-like capabilities by the experts through the sieve of a resource appraisal model, i.e. the VRIO framework.

Hence, this research avoided the likely easier path of measurement of the performance implications for the AI resource-adopter, which we conjecture to be a scholarly exercise yielding shorter-term results and with a limited contribution for opening new horizons of investigation at this stage. Instead, we explore, from the lens of the AI experts in the fields of Computer and Medical Sciences, the virtues of this typology of resource and its competitive potential to the Chinese medical institutions, such as hospitals, clinics, and other healthcare unit providers.

The following objects were fashioned for the project CAITA:

Objective 1 (O1): Understand the current status of AI adoption in Chinese hospitals.

Objective 2: (O2): Map the benefits, drawbacks, and limitations of AI adoption.

Objective 3 (O3): Garner the AI-related resources and capabilities (R&C) associated with hospital/unit-level competitiveness.

These objectives were established with the reasoning described in the introduction section, and with an exploratory purpose of scaffolding the perception and sentiment of experts on such technology and/or sector regarding its adoption and the window of opportunity for seizing it. Furthermore, considering these objectives and the empirical findings of this study, this research team is optimistic, that the spillovers of this study will not be left to chance by other scholars nor by the industry practitioners, as AI is a theme of seminal interest across regions of the globe and still in its infancy, and societies and organizations possess nowadays a very limited knowledge about it-as we are still at an early-stage of tech-adoption, known as Artificial Narrow Intelligence (ANI), further explored in the literature review.

Resource-based management: neoclassic competitiveness

For the antagonists of the Industrial Organization theory-i.e. the Resource-Based Theory(ists) (RBT)-competitive advantage gains fall under the control of the firm behavior, not being fatefully determined by the market conditions as assumed by the former (Abrantes et al., 2022) (Adomako and Tran, 2022). The notion of firm-level competitiveness is defined as a status intrinsically dependent on the inner conditions of an organization to create economic value, which is not easily imitated by others.

According to such J. Barney's RBV, both the acquiring and the sustaining of a firm-specific advantage are premised on the relationship between the ownership of heterogeneous bundles of resources and the subsequent performance one is able to attain from their use (Barney and Clark, 2011). Likewise, the formation of organizational capabilities (OCs) resulting from the resource utilization, appropriately becoming an organizational asset, ought to possess two minimum attributes in order to yield any kind of specific advantage: value (V) and rarity (R) (Abrantes et al., 2022), (Cardeal et al., 2014), and (Barney and Clark, 2011). The strategic value of a resource or capability is dependent on whether it supports the seizing of new opportunities, the tackling of threats or the “pushing of boundaries” further-not merely the productivity frontier but also the effectiveness of goal attainment and/or the efficiency of processes (Barney and Clark, 2011). Hence, economic value is generated through an increase in economic rents, or from the reduction of costs, or both. The rarity of a R&C derives from the number of competing firms controlling it. Rarity occurs whenever the number of firms owning a certain (valuable) resource is less than the total number of firms in the industry in perfect competition. A given R&C, if not scarce, is owned by many firms in the same industry, which consequently affects transversally the marginal value to all the resource holders.

The ownership of valuable and rare R&Cs, and their utilization, however, only reach a status of sustainable competitive advantage (SCA) with two additional attributes met: inimitability (I) and organization (O). The former refers to the resources that one cannot easily copy in another enterprise through direct replication or substitution. The organization entails a non-replicability attribute. Hence, the utility of adopting a VRIO framework lies in the analyzability of the linkage between resource ownership and the inherent competitive implications (peer disadvantages; parities or advantages) and performance implications (below, average, or above-average economic returns).

These four attributes (V; R; I; O) in Figure *1* constitute a seminal framework for the appraisal of resource competitiveness. Beyond the simplistic expression of these four parameters, the VRIO framework analyzes as a series of questions concerning those parameters. For instance, do a firm's resources and capabilities enable the firm to respond to environmental opportunities or threats (OT)? Is a resource currently controlled by only a small number of competing firms? Do firms without a resource face a cost-disadvantage in obtaining or developing it? Are a firm's policies and procedures organized to support the exploitation of its valuable, rare, and costly-to-imitate resources? Competitively, such exercise allows the categorization of the resources' utility into four typologies (Figure *1*): Competitive Disadvantage, Competitive Parity, Temporary Competitive Advantage, and Sustained Competitive Advantage.

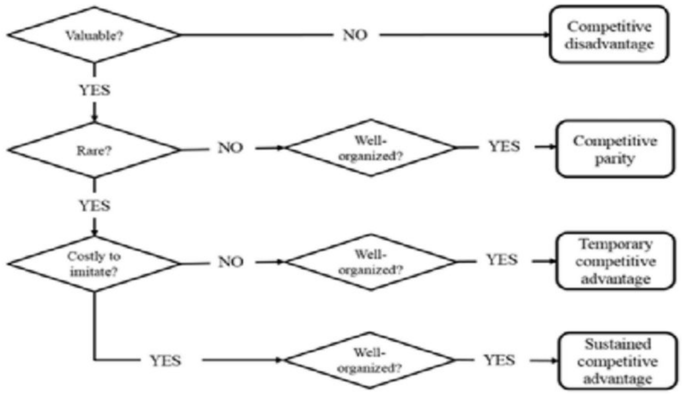

FIGURE 1: VRIO analysis framework

Source: (Barney and Clark, 2011)

The labeling as a competitive disadvantage symbolizes that a focal resource has below-average implications for the overall value-added and value-appropriated by the firm. Competitive parity stands for its alignment with others competing resources at an average level within the same industry. Temporary competitive advantage is a classification of higher competitive utility, in which, the resource is associated with an equivalent high-performance implication, i.e. above-average returns (AAR) (Hitt et al., 2019). The SCA resulting from the "O" (VRI + O) is explained by the intertwining of three separate aspects. Firstly, the uniqueness of time and space of resource-ownership, conferring a unique pioneering position and some lead time ahead. Secondly, the lack of understanding by other firms of the cause and effect of these resources, regarding the formation of the resource or regarding the source of its intrinsic value. Thirdly, the existence of historical links, causal ambiguity, or social complexity hindering the capacity of a competitor to copy or substitute the value associated with the characteristics of those resources to another, in which the substitutability might occur by one of two forms: the substitution of similar resources or the substitution of similar functions (Barney and Clark, 2011).

Dynamic Capabilities Theory (DCT): The contemporary competitiveness

In the last three decades, the RBT has transformed itself into a "new resource theory" of the firm through the search for continuous competitive-advantage forms (Huang and Xie, 2021) (Du and Feng, 2020). Far removed from the original Penrosian conceptions from the 1950s, prominently developed specially in the 1980s by scholars such as Birger Wernerfelt or Richard. Rumelt, and by "resource-picking" theories (as exemplified above with the VRIO analysis framework), the RBT stretched horizons to domains such as the Resource Patchwork Theory, Resource Arrangement Theory, or the Network Arrangement Theory. Furthermore, these evolutionary versions of the resource-based logic became rather centered on capability-building theorizations and widened into new perspectives (such as, the Attention-Based View; the Dynamic Capabilities View; the Knowledge-Based View; or the Technology-Based View) (Mackay et al., 2020), (Makadok, 2001), and (Barney, 2001).

In this context, DCT emerged as an influential subfield and new hotspot of the RBT with five major streams of research. Firstly, it focused on the delimitation of resource-based and capabilities theories (Diao and Li, 2014), (Cardeal et al., 2014), (Su and Sun, 2012), (McKelvie and Davidsson, 2009), (Døving and Gooderham, 2008), (Pil and Cohen, 2006), (Blyler and Coff, 2003), (King and Tucci, 2002), and (Helfat, 1997). Secondly, it expanded the research into strategic adaptability to rapid changing external environments (Su and Sun, 2012), (Eisenhardt and Martin, 2000), and (Teece et al., 1997). Thirdly, linked capabilities' possession with long-lasting firm-level competitiveness (Weerawardena and Mavondo, 2011), (Helfat and Peteraf, 2009), (Bowman and Ambrosini, 2003), (Eisenhardt and Martin, 2000), and (Teece et al., 1997). Fourthly, it explored dynamic capabilities as a promoter of organizational change and enterprise evolution encapsulated into the following domains: digital-view, humanistic-view, strategic-view; team-view; learning-view, and virtualization view (Bojesson and Fundin, 2021), (Sune and Gibb, 2015), (Kexing and Xie, 2013), and (Ding and Ji, 2004). Fifthly, depicted organizations as learning entities (Eisenhardt and Martin, 2000).

Inevitably, a large number of scholars have endeavored to define dynamic capabilities providing a plethora of definitions, most of them extensively discussed in recent literature (Teece et al., 1997), (Helfat, 1997), (Eisenhardt and Martin, 2000), (Griffith and Harvey, 2001), (Winter, 2003), (Helfat et al., 2007), (Wang and Ahmed, 2007), (McKelvie and Davidson, 2009), and (Barreto, 2010). In short, a dynamic capability (DC) is regarded as a superior type of organizational capability capable of modifying the current resource-base and/or seize new opportunities. Hence, these high-level capabilities are here termed as a “competitive golden pill” prescribed by several scholars.

Although, the Dynamic Capabilities View (DCV) has kept evolving with time, from the early stages focused on deployment and learning issues and mostly circumscribed to developed countries, it later extended the array of influence toward other functional and geographical areas beyond the five streams of research above, embracing other cognitive and managerial capabilities, such as, related to cultural-integration, collaborative network, design, entrepreneurship, knowledge, innovation, product-design and patching, among others (Abrantes and Ström, 2023), (Abrantes et al., 2022), (Bari et al., 2022), (Bayu et al., 2022), (Abrantes, 2020), and (Diao and Li, 2014).

However, the conceptual heterogeneity surrounding the definition of dynamic capabilities, aggravated by the emergence of a vast theoretical framework, adds a layer of difficulty to the measurement of what a DC actually is.

Nowadays, there are two approaches to this problem. One is to measure dynamic capabilities as a single-dimensional concept. For example, Griffith and Harvey (Griffith and Harvey, 2001) used single dimensions such as the number of new-product developments, the decision-making power attributes, or the reconfiguration of knowledge bundles. Another approach assumes a multi-dimensional concept. Here, scholars instrumentalize two or more constructs to measure a given DC. Abrantes et al. (Abrantes et al., 2022) measured a DC (intra-organizational knowledge-sharing) by using various morphological aspects of such capability as their variables of measurement: DC-mobility; DC-transferability; DC-reciprocity and assuming the international corporate governance model as one mediating variable.

AI technology

The rapid development of AI technology is leading societies to the next technological revolution and is believed to have a significant and far-reaching impact on human life. Firstly, one ought to separate AI technology, from other spheres of technology-as internet; information and communication; or automation-whose close relatedness often leads to them being mistakenly taken for the first. Then, one ought to assert the utility of this technology as an intangible resource, the endowment to clerical and clinical processes which might yield VRIO competitive and performance implications, as discussed in the previous section. This context is instrumentalized as a starting point or leapway toward the study of its competitive impact, according to the research design briefly pointed in the introduction and subsequently outlined in "Research Method".

Although there does not seem to be a clear and accepted definition of AI that sets its boundaries, the ultimate threshold has seemed until now to be passing the Turing test as the ultimate tier of human resistance for the acceptance of machine intelligence, since the method implies as machine interacting with a human being who is unaware of the nature of the former. Scholars have established four criteria for machine processing to become recognized as “intelligent”. Firstly, the ability to perceive, as the basic approach to obtain external information. Secondly, the ability to memorize and think, which is the fundamental reason that humans can have intelligence. Memory is used to store knowledge and thinking is used to process information, including the use of knowledge to analyze, calculate, compare, judge, reason, associate, and decide upon alternatives. Thirdly, there is the ability to learn, and fourth, the ability to act or express itself. Such a definition considers AI as a system with a set of abilities that the system ought to hold in theory and practice.

However, Li and Wang (Li and Wang, 2019) propose an alternative and straightforward definition. They consider AI to be a computer program that makes reasonable actions autonomously to obtain the maximum benefits from it. In essence, the processing is a manifestation of the AI's learning ability, a common denominator across various definitions, and one of the key features of the intelligence subject that distinguishes it from an automated program that requires manual intervention and adjustment.

AI differs from human intelligence, as the latter is, originally, rooted in mechanical thinking that starts from causality and seeks definite solutions. Yet, facing complex problems with limited information poses a scenario of uncertainty, which is harsh to the human understanding and consequently reduces chances to attain rational judgements. Conversely, AI technology and big data inputs have the power to replace the original causal thinking with correlation thinking, and solve problems by seeking coherence from strong patterns in information. As a result, AI can overcome the limitations of mechanical thinking, while ensuring the quality of decision-making. The number and efficiency of problem-solving have been greatly improved based on three critical types of capabilities (i.e. deep learning, large-scale computing, and big data) (Li and Wang, 2019).

The micro-foundations of deep learning can be traced back to the predecessor of deep learning, i.e. artificial neural network. This hypothetical model of human neural processing of information proposed by neuroscientists in 1943, was used in early research on neural perception and machine learning, such as the Hebbian theory and, naturally, the multi-layer neural network, nowadays known as deep learning (Cooper, 2005).

With the increase in computing power and the sheer data volume that machines are able to handle, deep learning technology emerged leveraged by major theoretical breakthroughs in algorithms, with the field entering a stage of heyday of development. The principle of deep learning, in simple terms, concerns the needs of computer learning, as a large amount of data to be absorbed and thrown into a complex, multi-level, pre-set parameter data processing network, afterwards checked its processing and determined whether the results requirements are aligned with the requirements per layer representation. Otherwise, one ought to adjust the network parameters repeatedly until the output meets expectations (Li and Wang, 2017). In a nutshell, deep learning is a pragmatic, semi-theoretical, and semi-experiential modeling method. It uses human mathematical knowledge and computer algorithms to build an overall architecture and then combines it with big data (and inevitably large-scale computing power) to adjust the internal parameters to approach the pre-set target. It is argued that these new learning algorithms and multi-layer architectures, currently under development for deep neural networks, will surely accelerate the AI's diffusion among industry practitioners (Li and Wang, 2017).

Nonetheless, Bernard Marr emphasized once, the success of AI-diffusion as a business goal, the importance of incorporating data strategies for improving decision-making, enhancing operations, and generating data benefits (Marr, 2018). He considered data, not only a part of the organization's business processes that require specific capability development but also the source of a firm's sustained competitive advantage. He asserts that IT management capabilities require data acumen pillared on big data technology and their materialization into a big data strategy, which, in turn, yields competitive gains for the whole organization.

A big data strategy comprises a multi-layer strategy to be followed in a step-wise manner through these five phases: collection, analysis, building of a technical architecture, (re)organize data, and develop governance capabilities. Firstly, collection as a process, ought to include internal data (used), external data (accessed), other external data (purchased), and other data inputs obtained through sensors or other methods. The ability to obtain data is key. The collection process ought to be swift, diverse, authentic and valuable; as well as, suitable to the strategy and efficient operationalization of its automation.

Secondly, the data analysis ought to generate insights that can help firms to improve their operating methods by using algorithms and analysis tools to extract the necessary information that might answer key business questions, leverage operational performance, and cash-in on data (monetization). The data analysis technology has evolved from the earliest SQL statement analysis, to search engine optimization, biometric data interpretation, text analysis, sentiment analysis, image analysis, video analysis, voice analysis, and other forms of data mining using tools and apparatus as, BirdEye; Podium; TrustPilot; Yotpo; or Google Play including core big data analytics ones, as Apache Spark; Collibra; Hadoop; HPCC; MSFT Azure; Sisense, among others (Abrantes and Ostergaard, 2022). Hence, (super) large-scale datasets are used to test the effectiveness of objects, study relations between variables, scenario-building, time series analysis, and explore trends and make predictions (even using data-fumes).

The third phase entails the building of a technical architecture to transform data into insights; the corresponding software and hardware are needed. These tools include four types of infrastructure: data collection, data storage, data analysis and processing, and data access and communication. Small businesses or firms that do not aim to commercialize data can consider directly purchasing Big Data as a Service (BDaaS) because it provides a series of services so that those who lack data, have a tight budget, or have difficulty can also easily enjoy the value of data. For firms to improve decision-making or data commercialization, they should build a full range of facilities for collection, storage, analysis, and access. Common collection tools include sensors, Apps, CCTV, website cookies, and social media; common storage tools are mainly distributed storage systems such as Hadoop. The analysis procedure includes three steps: data preparation, analysis and modelling, and extraction of insights. Companies such as Amazon, IBM, and Microsoft also have corresponding analysis products; in terms of data access, more and more firms are using self-service business intelligence (BI) systems that allow users to independently query data, rather than relying on highly standardized BI reports.

The fourth step is to develop the organization's ability to organize data. In addition to developing appropriate data technologies and capabilities, organizational capabilities that link data to business needs are also crucial. Methods include recruiting talent and outsourcing business. A qualified talent in a data organization should be equipped with the following five skills: business ability, analytical ability, computer science knowledge, knowledge in mathematical statistics, and creativity; if the firm lacks such professional talents, then a data crowdsourcing competition platform like Kaggle is also an option to consider. Firms on Kaggle bring their problems, data, and prizes, while a large number of data scientists on the platform compete to offer the best solutions. This crowdsourcing method has advantages in identifying invisible talents and improving corporate data organization capabilities; another aspect of organizational capability is the organization's data culture and continuous optimization of data strategy. In terms of data culture, data should be regarded as a key asset for firms, and data should be used to improve all levels of the firm and should be regarded as the foundation of the operation of the firm.

The fifth step concerns data governance capabilities. Inherent in the convenience of AI and big data are concerns about data privacy and security. Data governance refers to the overall management and daily management of data, including data availability, integrity, and security. This means that firms should recognize the ethics and legal requirements faced in each step of data operations, take practical measures, and roll out effective policies and procedures to manage each step.

However, the acquisition of IT systems, exploring big data and analytics, is postulated to carry drawbacks, especially through supplier-specific investment, which is not per se a source of competitive advantage, since it traps the firm in a holdup, because the appropriation comprises a disproportionate share of the value through a "create-capture-keep" paradigm (Barney and Clark, 2011). Paradoxically, these scholars sustain that IT systems (as a resource), and inherently the capabilities surrounding them are hard-to-build and/or costly-to-acquire/develop. Moreover, firms might incur a high risk of technological and market uncertainty, concerning aspects surrounding hasty technological advancements, such as secrecy, legal protection (of proprietary technology), pre-emption of resources and deterrence, or causal ambiguity. Some firms are summoned to obtain a large amount of venture capital in order to reinforce IT systems and consequently build on competitive advantages.

For decades, the outlook of (information) technology-as-a-resource was particularly regarded as a source of competitive advantage. Nowadays, the paradigm has shifted toward technology-as-a-capability, particularly managerial IT capabilities, such as, IT-enabled knowledge management capabilities, deemed as a core competence for the overall ability to innovate and relaunch performance gains, encompassing the cumulative management of a triad of knowledge pools: IT infrastructure resource, IT human resource, and IT relationship resource.

AI technology's adoption in medical practice in China

Within the medical/healthcare sector, AI is reckoned to be especially applicable to medical imaging and believed to be one of the most crucial technological tools in clinical and differential diagnosis in modern medicine.

The appropriateness of AI technology to medical imaging is foremost due to its necessity, since nearly 70% of clinical diagnoses require medical imaging. Moreover, it is asserted that AI-assisted imaging yields results with a higher degree of efficiency, subsequently, affecting most directly the effectiveness of clinical diagnosis (plus the further treatment) and also the patient's experience. Unsurprisingly, the data from Global Market Insights corroborates the thesis above. Medical imaging diagnosis technology became the fastest growing industry in smart medicine from 2017 to 2022. It is estimated that by 2024, the industry scale will reach 25 billion US dollars, with a growth rate of over 40% (Global Market Insights, 2023).

However, the current medical imaging diagnosis has several prominent problems. Firstly, the number of radiologists cannot catch up with the increasing demand for medical imaging; thus, AI might function as an attenuating factor for the lack of medical personnel (Xiao and Liu, 2019). Secondly, it is noticed in China, that the current annual growth rate of AI in medical imaging data is about 30% while the annual growth rate of radiologists is only 4.1%. Moreover, it takes, on average, more than eight years to train a new radiologist. Therefore, there is a huge gap to fill between the demand and supply (Xiao and Liu, 2019).

Thirdly, the distribution of medical imaging services per institution's category is uneven, similar to the distribution of other medical resources. Looking at the China Health Statistical Yearbook, from 2019

(Table 1), the country holds a three-tier system (Table 1), both applicable to public and private medical units: primary institutions (or I class - township hospitals); secondary institutions (II class - medium-sized city hospitals); and tertiary institutions (III class - general hospitals) with the categorization corresponding to an ascending number of outpatients and corresponding number personnel (China Health Statistical Yearbook, 2019).

Institution	N*	Outpatients **	Personnel ***	Beds		Year Patients/Type	
				Range ****	Utilization	Aggregate	%
Primary	10831	30K	0,7	20-99	55%	324.93M	0,04
Secondary	9017	120K	0,88	100-499	80%	1.082.04M	0,18
Tertiary	2548	520K	1,03	≥ 500	100%	1.324.96M	0,78

TABLE 1: General figures: resources and patients per institution´s type

* N – number of medical units per institution type.

**Average number of outpatients per year (expressed in “K” or “M”– thousands or millions unit scale).

*** Doctors/bed; **** Installed capacity of beds (total number of beds).

Source: Own elaboration.

Despite the distribution of medical services per institution-type, the medical imaging services are provided in an unbalanced manner. Primary hospitals hold 17% of imaging services, secondary institutions 46%, and tertiary institutions the remaining 37%.

Fourthly, the diagnostic skills (and the diagnosis accuracy) vary among medical doctors and per institution´s type. Doctors in tertiary hospitals are relatively more skilled and more likely to commit mistakes due to heavy workloads pressuring their cognitive abilities (Xiao and Liu, 2019). Although the doctor workload in primary and secondary hospitals is lighter, they are identically prone to error due to lower experience. A study on imaging diagnosis with a sample size of 8,850 cases in a provincial tertiary hospital (the highest-level hospitals in China), confirmed that the comprehensive detection rate of doctors at different levels of hospitals is only 80.1%; and, on imaging diagnosis the detection rate of lung cancer is as low as 65%. Conversely, the accuracy rate of AI imaging diagnosis is very high, the comprehensive detection rate of AI imaging diagnosis in provincial tertiary hospitals is as high as 94.2%, which is 18% better than the performance of human doctors. In the case of lung cancer screening study of county-level hospitals, the detection rate of AI is as high as 98%, which is 51% better than that of human doctors.

Fifthly, the time of diagnosis is another concern. Conversely, one of the advantages of AI imaging is the rapid diagnosis. For instance, AI imaging products for lung nodules will first select the suspected nodules in the image, and then perform quantitative analysis, and generate a structured report. The medical doctor only needs to check the diagnosis results, eliminate false positives and then confirm the final results. This process greatly shortens the time required for doctors to screen the images and edit the report, and thus improves work efficiency. The whole procedure can be finished in just 20 seconds.

Since 90% of medical data comes from medical imaging and the processing of images is naturally better organized and the diagnostic process is more standardized, medical imaging has become the first field in clinical medicine to benefit from AI technology (Xiao and Liu, 2019) (Li, 2020). Public data show that medical imaging attracts the most capital in terms of AI medicine. Medical imaging received the highest financing in 2013-2017, accounting for 31% of the total financing of AI medicine. Industry insiders generally believe that AI medical imaging is most likely to achieve commercialization as a specific field in AI medicine.

The use of AI imaging products in primary hospitals has also improved medical care at the grassroots level to a certain extent, because AI imaging products have undergone training based on excessive data, and the training data are selected based on stringent standards proposed by senior experts and checked at various levels. It is like the AI is receiving training from a senior doctor. Therefore, doctors from primary hospitals can use AI products and at the same time learn from AI and thus improve themselves (Xiao and Liu, 2019). In terms of how AI imaging works, the first step is image generation, which aims to automatically generate more effective pseudo-A images from A images, such as using single section tomographic CT images to generate multi-section MRI images or using low radiant.

MRI images to generate high-resolution CT images. The algorithms involved include noise reduction and artifact processing; the second step is object segmentation, which means segmenting the organs and substructures in the image for further analysis. U-NET and FCN are both commonly used segmentation models based on convolutional neural networks (CNN); the third step is image classification, such as the recognition of nodules and other lesions. The model automatically assigns category labels on the images. The core algorithm extracts image features and constructs classifiers.

Traditional image classification methods are mainly based on artificially designed features, which are complicated but might not be accurate, while CNN can mine the hidden statistical patterns in massive data, automatically learn the most distinguishing image features for classification tasks, and the classification accuracy will increase as the network goes deeper. As a result, efficiency will be greatly improved. When some annotated data are small in amount, AI can still improve its classification efficiency through transfer learning (weights are initialized mainly through a pre-training model); the fourth step is target detection, which aims to locate and identify specific lesions in the image. AI should not only identify the category of the target but also give the location and scope of the target in the image. The algorithms used are mainly one-phase methods with faster speed and two-phase methods with higher accuracy. In an AI-assisted diagnosis and treatment of COVID-19, the U-Net or variant image semantic model is also used to cut out the area of the lung from the original image; then in the CT classification diagnosis, a matrix algorithm is used to extract features, and then support vector machine is used for classification. The final accuracy rate is as high as 99.68% (Meng and Li, 2020).

Research Method

Considering the earlier objectives (O1-3) established for this project, we have deduced the following testable propositions (Pr1-3): Proposition 1 (Pr1): Grasp the outlook of AI-adoption in Chinese hospitals; Proposition 2.1 (Pr2.1): Map the current set of opportunities and threats (OTs); Proposition 2.2 (Pr2.1): Appraise the perceived utility of AI-tech (VRIO); Proposition 3 (O3): Unravel the AI-related R&C yielding (hospital-level) competitive-advantage gains (TCAs or SCAs). The testable propositions set the empirical procedure toward a research framework (Figure 2) with a particular research design here represented.

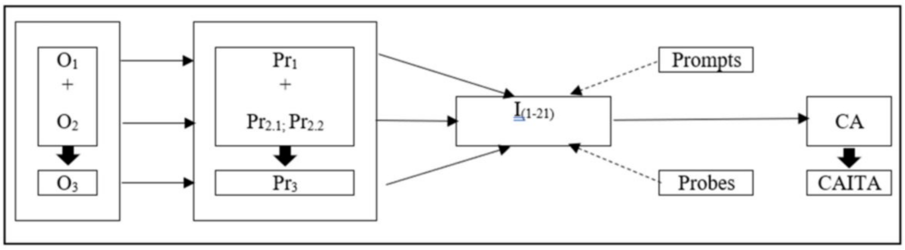

FIGURE 2: Project CAITA's research framework

(Notes: O(n) - Objectives; Pr(n) – Propositions; I(n) – Interviews; CA – Content Analysis, CAITA – Competitiveness of AI-tech adoption).

Source: Own elaboration.

The project held a general objective (O3) which was dependent on two precursory specific objectives (O1 and O2), cumulatively, exposing the outlook of CAITA and the underlying rationale through the lens of the experts participating in this study. With a linear linkage between objectives and propositions, the formulation of Prn aimed to achieve the respective objective (O1 ~ Pr1; O2 ~ Pr2.1 + Pr 2.2; O3 ~ Pr3). Nonetheless, O3 being a general objective, depended on results achieved for the specific objectives (O1; O2).

A set of 21 semi-structured research interviews (Table 2), internet-mediated and blending two techniques (prompting and probing), were conducted in the first quarter of 2022 and recorded with the participants' consent for further transcription and translation into English for further analysis.

A BRU Scientific Committee (BRU-ISCTE Scientific Council) approved the ethics of this research project, including the involvement of human participants in strict respect for confidentiality, anonymity, non-harm, and protection of individual data. The adherence of all experts in this study was voluntary, and consent forms were signed by all participants before the collection of data.

The sample of experts allowed us to reach a point of saturation of data for the premises set for this study (objectives and propositions), covering four stakeholder-groups: (i) Biomedical tech companies; (ii)

Hospitals; (iii) Universities; (iv) Other institutions (i.e. Municipalities and Professional Associations), with the sample holding the following configuration:

Factor	Biomed co.	Hospitals	Universities	Other Org	Aggregate
Count	5	7	5	4	21
Frequency	0,24	0,33	0,24	0,19	1

TABLE 2: Demographics per stakeholder group

Source: Own elaboration.

The interviews had an aggregate time of exposure of 1.011 minutes, with an average of 48.14 minutes/participant, ranging from 30 minutes (min) to 75 minutes (max). The sample covered the major healthcare sector's stakeholder groups in China with expertise in AI, with a rather equivalent distribution of representatives per group. A detailed profile description of the experts per organization category is presented in the appendix. The data analysis focused on a particular subset of qualitative data (manifest data), which we instrumentalized as the signifiers of the study, as experts verbalized their ideas and we interpreted them as information (i.e. signifieds).

We used the method of Content Analysis (CA) due to its suitability to this typology of investigation and followed two seminal theoretical frameworks as a referential for our empirical work, i.e. the Weber´s Protocol and Miles and Huberman´s analytical procedure (Milles et al., 1994) (Weber, 1990). Data were coded using Atlas.Ti, a computer-assisted qual data analysis software.

The transcription and translation stages occurred along the 2nd quarter of 2022 while the data manipulation and analysis went on the rest of the year and 1st quarter of 2023, with the majority of work surrounding the tasks of coding; validation of quotations; establishing relations across phenomena; detextualization of outputs; and interpretation of results. Axial and open coding approaches were combined for a dual sense-making/sense-giving purpose. The first (open coding) aimed to establish patterns across signifiers while the second (axial coding) corresponded to an amalgamation of codes into code groups.

In total, 53 codes were identified and gathered into 6 code groups: Advantages and Opportunities (A&O); Application in Medicine (AiM); Disadvantages and Threats (D&T); Expert Analysis (EA); State-of-the-art (SoA) in Medicine; and VRIO. This allowed us to generate 244 expert notes divided across 6 memo groups (upon our quotations), and build 24 networks of semantic representations, regarding the association of the construct. An outline of the data analysis procedure is presented in the next section.

Results And Discussion

Data and findings

Table *3* and Table *4* present a general outlook of the data outputs extracted from the coding procedure and the distribution of quotations per code group, stakeholder group, and participant.

Factor	P(n)	I(n)		Codes	Quotations	Cooc	Networks	Memos
		N	Time (min)					
Sum	21	21	1011	53	577	424	24	243
AVG	-	-	48,14	-	34,14	20,19	-	11,57

TABLE 3: Outlook of coding

(Note: Cooc – the co-occurrence between quotations; AVG – average per participant).

Source: Own elaboration.

Code Groups	Groundedness			
	Biomed *	Hospitals **	Other Org. ***	Universities ****
Advantages and Opportunities (A&O)	32	45	9	32
Application in Medicine (AiM)	24	38	4	29
Disadvantages and Threats (D&T)	19	38	20	14
Expert Analysis (EA)	16	18	15	21
State-of-the-art (SoA)	30	36	12	37
Value, Rare, Inimitable, Organized (VRIO)	17	28	15	28
Total	138	203	75	161

TABLE 4: Quotations per code-group and stakeholder-group

* Biomedical tech/engineering companies (Participants: P1; P2; P6; P13; P16).

** Hospitals (Participants: P3; P5; P9; P10; P12; P14; P17).

*** Other public/private organizations (Participants: P4; P7; P20; P21).

**** Universities (Participants: P8; P11; P15; P18; P19).

Source: Own elaboration.

The groundedness (G) of quotations (in Figure 3; and Figure 6, Figure 7, Figure 8, Figure 9, and Figure 10) allowed us to identify the dominant areas in the experts' speech; and, moreover, to grasp the differences from one participant to the others. Furthermore, the G figures contained hints of experts' thinking and sentiment upon AI-adoption, transferred into the semantic and Sankey diagrams below, demonstrating diagrammatically the individual meaning and utility (G figures refers to the results of "groundedness", shown in Figure 3, Figure 6, Figure 7, and Figure 8).

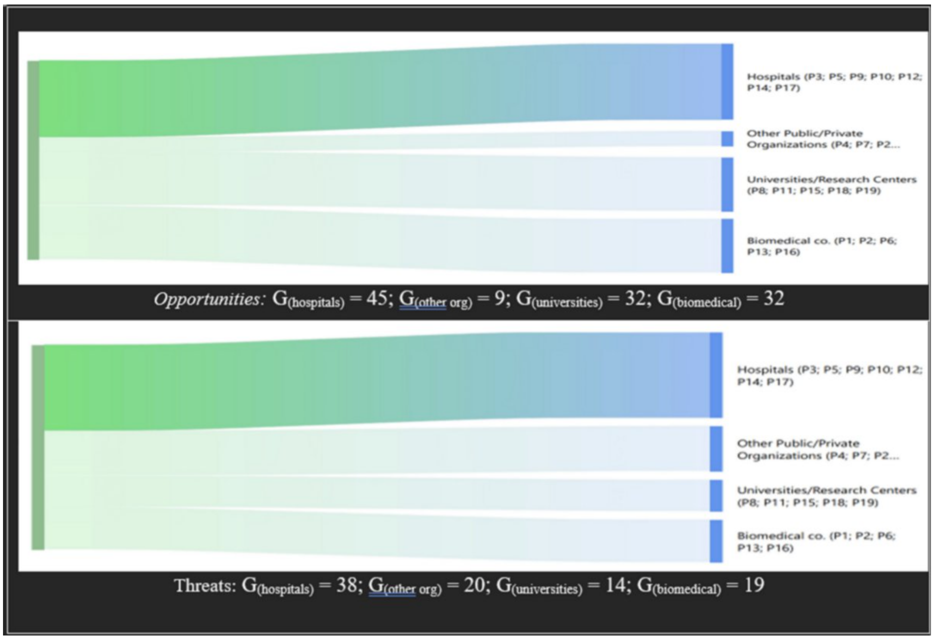

FIGURE 3: Opportunities & Threats (OT) analysis

Note: upper part is Opportunities (Os) and lower (Threats)

Opportunities: G(hospitals) = 45; G(other org) = 9; G(universities) = 32; G(biomedical) = 32.

Threats: G(hospitals) = 38; G(other org) = 20; G(universities) = 14; G(biomedical) = 19.

Source: Own elaboration.

The diagrams swiftly revealed that hospital representatives were more vocal on the pros and cons of AI and were the main contributors to the mapping of advantages/disadvantages and opportunities/threats.

For the profiling of the experts' viewpoint, and to grasping the overall sentiment regarding AI-tech adoption, we have also combined the G figures of two code groups (A&O; D&T) to obtain the OT ratios (Table 5), indicative of the individual opinion of these experts and by organization type.

	Sum $P_{(n)}$			Biomed			Hospitals			O. Org.			Universities	
	N = 21	f		N = 5	f		N = 7	f		N = 4	f		N =5	f
A&O	118	-		32	.27		45	.38		9	.07		32	.27
D&T	91	-		19	.21		38	.42		20	.22		14	.15
O+	10	.48		2	.4		3	.43		1	.25		4	.8
T+	6	.29		1	.2		3	.43		2	.5		-	-
O/T null	5	.23		2	.4		1	.14		1	.25		1	.2

TABLE 5: OT ratios

Source: Own elaboration.

Despite the non-consensual rhetoric of the experts, the OT ratios above disclosed an overall positiveness upon AI. A marked positive sentiment is noticed on the side of the universities, particularly with participant P19, who had the second-highest opinion index (OI = 4) (Table 6). Hospitals hold the highest contribution to groundedness with both higher number of quotations on A&O and D&T and denote an overall positive attitude (O+), though less accentuated than the former stakeholder-group (universities). The latter also hold the highest OI in P12 (OI = 7). The average OI per participant is 2.1, with only other public/private organizations scoring below the average (0.88).

Factor	AVG	Biomed	Hospitals	O. Org.	Universities
OI $_{(P; S)}$	2,1	2,67	2,17	0,88	2,7
∆ OT ratio*	-	.27+	.03+	.6-	.29+

TABLE 6: Opinion Index (OI) - Participants (P) and Stakeholder-groups (S)

* Variation of the OT ratio per stakeholder-group to the average opinion index (OI = 2.1).

Source: Own elaboration.

The opinion index ranked the participants (P) and stakeholder groups (S), considering the quotation's differences between code groups.

$$OIgroundedness(Pn) = \frac{A \cup O}{D \cup T}; OIgroundedness(Sn) = \frac{A1 \cup O1}{D1 \cup T1} + \frac{A2 \cup O2}{D2 \cup T2} + \frac{A3 \cup O3}{D3 \cup T3} + \frac{A4 \cup O4}{D4 \cup T4}$$

Noteworthy, the gauging of the tendency of positivity (O+), negativity (T+) and mixed (O/T-null) attitude toward AI-tech adoption took into account, firstly, this arithmetic differential of groundedness between code groups: O+ (f); or T+; or OT null = (GA&O - GD&T). The semantic diagrams of A&O and D&T below additionally illustrate the scope of the unraveled data (expressed in the degree of relations) and their themes.

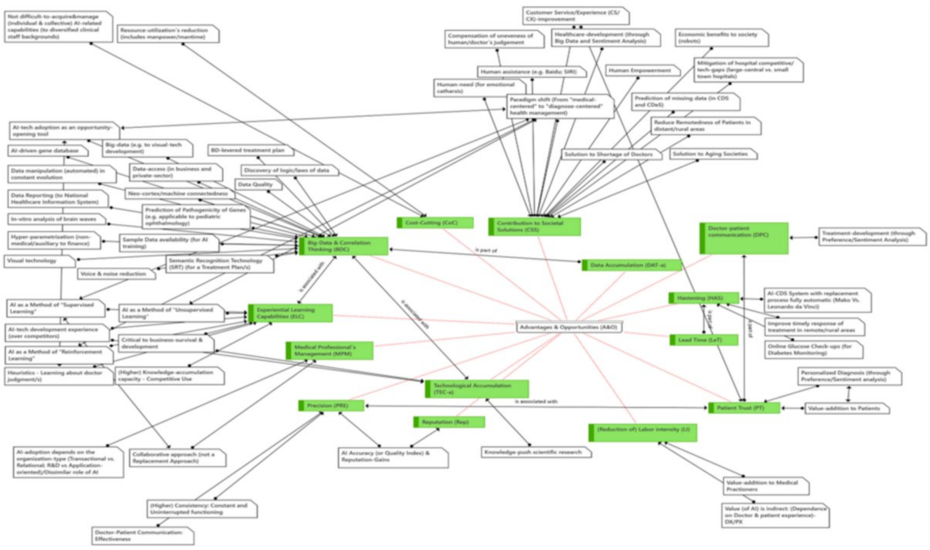

FIGURE 4: Network of Advantages and Opportunities (A&Os)

A&Os, Advantages and Opportunities

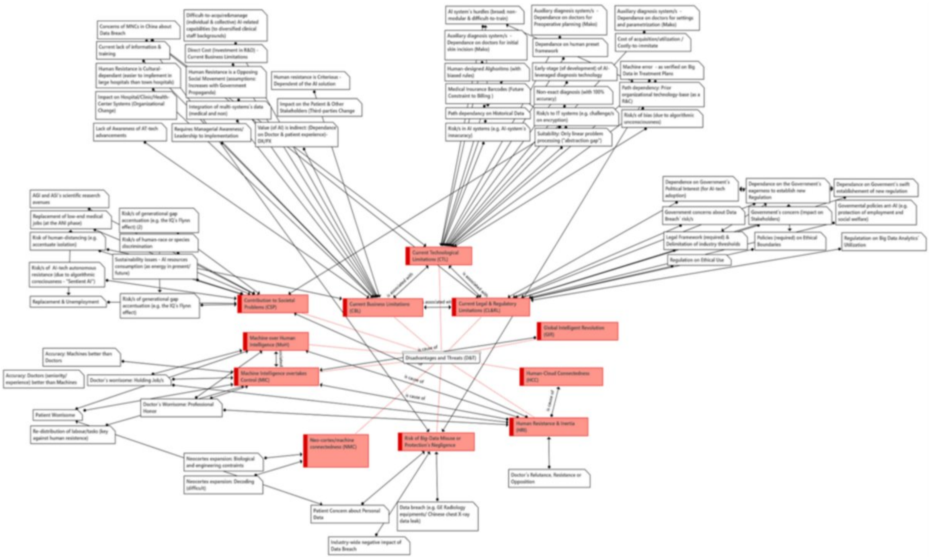

FIGURE 5: Network of Disadvantages & Threats (D&Ts)

Source: Own elaboration.

The OT analysis corresponds to the highest extent of relations. With regard to the VRIO analysis and competitiveness, based on the groundedness of the codes (CoU; V; R; I; and, O), the diagrams below (Figure 6 and Figure 7) focused on the *strategic importance* (V + R), while Figure 7 and Figure 8 focused on *relative strength* (I + O) providing an overview of the soundness and direction of opinions and scope of data.

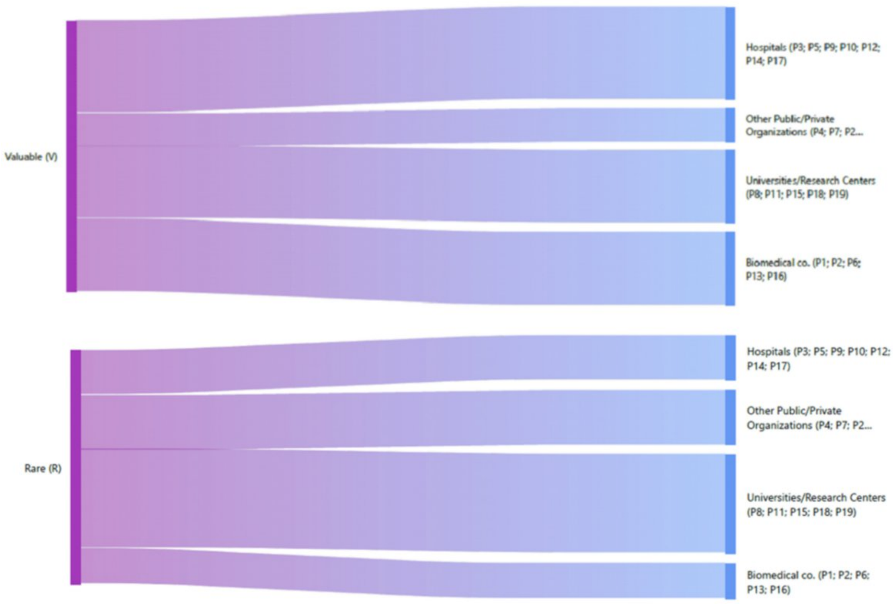

FIGURE 6: Expert's assessment of VRIO's utility in AI-tech adoption (SI = V + R)

Note: the upper diagram corresponds to the Valuable (V) dimension and the lower to the Rareness (R)

V: G(hospitals) = 14; G(other org) = 5; G(universities) = 11; G(biomedical) = 11

R: G(hospitals) = 5; G(other org) = 6; G(universities) = 23; G(biomedical) = 4

Source: Own elaboration.

FIGURE 7: Experts' assessment of VRIO's utility in AI-tech adoption (relative importance: I + O)

Notes: the upper stands for the I and the lower for the O

I-assesment: G(hospitals) = 9; G(other org) = 5; G(universities) = 10; G(biomedical) = 6

O-assessment: G(hospitals) = 4; G(other org) = 3; G(universities) = 6; G(biomedical) = 9

Source: Own elaboration.

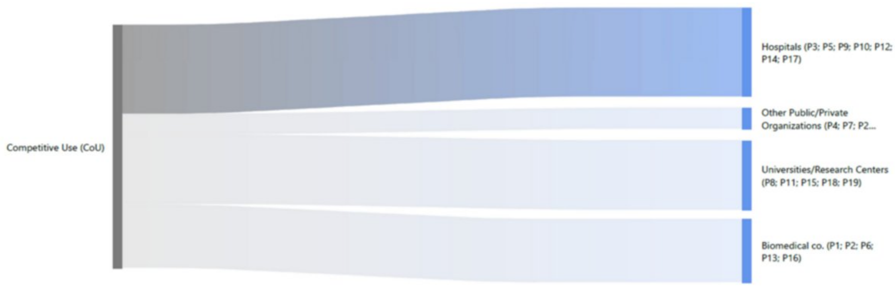

FIGURE 8: Competitiveness of Use (CoU)

G(hospitals) = 29; G(other org) = 7; G(universities) = 23; G(biomedical) = 21

Source: Own elaboration.

The highest contributor's position for VRIO coding is though shared among stakeholders: hospitals in V; universities in R and I; and, biomedical companies in O, demonstrating again a particular orientation of each organization-type.

Below, the networks (Figure *8* and Figure *9*) exhibit distinctive pieces of information with regard to competitiveness and overall utility (VRIO), even though the performance on the two dimensions of strategic importance (V + R) and relative strength (I + O) are inseparable from CoU, since they carry competitive implications to the adopting organization. Nonetheless, the experts separated those properties (of VRIO) from their competitive implications. Their perception of utility focused on the bundle of R&C, while the competitiveness factors referred to the overall set of 13 activities associated with gains of competitive intensity. Hence, these two separate viewpoints are disclosed in the following networks.

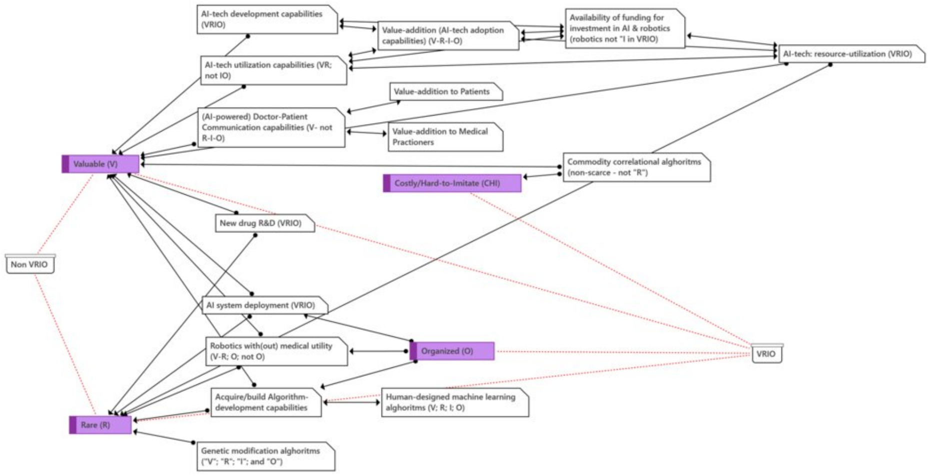

FIGURE 9: Network of VRIO

Source: Own elaboration.

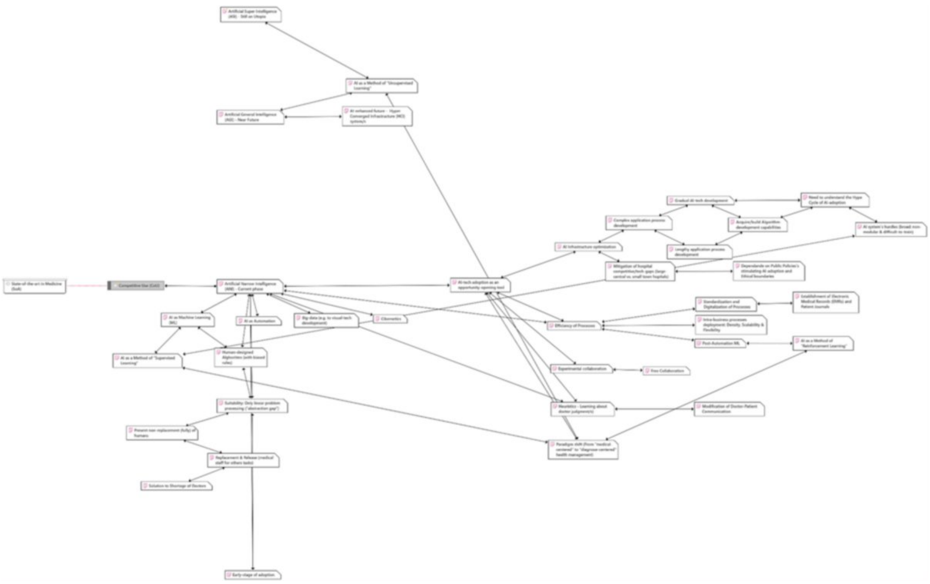

FIGURE 10: Network of Competitiveness of use (CoU)

Source: Own elaboration.

A Cooc-matrix holding the cross-groundedness of the 14 codes in A&O was intertwined with the CoU codes through the analysis of the levels of co-occurrence across these code-groups. Two codes reveal a weak linkage to competitiveness (i.e. exploring of reputation-gains and lead-time gains), since they hold a single co-occurrence status. Conversely, the highest benefits are perceived to derive from: (i) cost-cutting; (ii) contribution to societal solutions (beyond the organization's interest); and, (iii) use of big data, especially at the current early-stage of AI-adoption - ANI (Table *8*). In addition, a sum of stats from the networks aforementioned (Figure *4*, Figure *5*, Figure *9*, and Figure *10*) is presented in the appendix section, a tabulation designated as "Networks: Overview of degrees and complexity". Furthermore, the analytical generalizations reached with such a sample, allowing us to establish the exploratory threshold of data collection in this study (thus, the point of saturation of data), is furthermore justified in the appendix by the (N quotations) in this project, plus the intersection of the figures regarding the degree (D) that represents the number of links for any one “node” in a network; and, the complexity ratio (C) of the network considering the function: C(f) = (D × Q)/1000.

The overall positive attitude toward AI, scrutinized on the OT analysis, is confirmed in the gauging of competitiveness. Despite the 5 hazards to society, experts verbalized, on the other hand, they noted 12 societal benefits, 9 of which are associated with medical services. These large societal contributions of AI technology to the improvement of the medical field are complemented by a set of other five more specific advantages recognized in the healthcare sector (i.e. improvement of clinical decisions; improvement of clinical diagnosis, improvement of the patient´s medical journal; use of nursing and surgery robotics; and path planning and motion).

The VRIO furthermore provides insights about the direction of opinion and divergence of thought across experts. From one side, it is asserted, in unison, the relevance of AI, largely agreeing on the current meager use (rareness) in this sector in China. The consensus is broken on the capabilities held by hospitals. Some experts emphasized that commodity correlational algorithms are already in use and are not scarce anymore. Nonetheless, all other capabilities in the category of algorithm-development, such as genetic modification, are remained understood as being a VRIO and so a competitive source of SCA.

A major fundamental rupture of thought is found in the dimension “imitability”. An opposing view within the category of AI-tech development capabilities is noticed. Some experts claim that AI-tech utilization; AI-powered doctor-patient communication and robotics with(out) medical utility are easy-to-imitate while others consider them hard-to-imitate, or costly-to-imitate, or both. In addition, a hybrid view is unraveled on algorithm development and new drug R&D with some attributes being hard-to-imitate while others not.

Findings

Nowadays, AI-technology is recognized in the Chinese medical practice across 11 different specialties (cardiology; gastroenterology; genetics; hepatology; nephrology; neurology; oncology; orthodontics; ophthalmology; and pulmonology) being utilized across 7 types of activities: clinical diagnosis; clinical decision-making; medical imaging; nursing robotics; path planning and motion; patient medical journals; and robotic surgeries.

Experts pinpointed a vast array of virtues and drawbacks with regard to AI-technology, and a naturally, some division of opinions was acknowledged among them, with the predominance of a general favorable opinion (O+). The four stakeholder-groups in analysis revealed four unique clusters of opinion. Universities are clearly more optimistic (O+ > T+), hospitals hold a mixture (of positive and negative) sentiment (O+ = T+), similar to biomedical companies divided between optimism and neutrality (O+ = OT null).

A consensus as the competitive benefits of AI, is broken, especially, among hospital representatives, where the opinions are not solely compartmentalized-as in case of the biomedical companies (between O+ and OT null)-but are also polarized between optimism (O+) and skepticism (T+), and the harmony is mostly broken on the appraisal of imitability.

The results from the manipulation of the data-outputs deriving from the coding procedure allowed us to understand such fragmentation of viewpoints, here denominated as the “hybrid view of CAITA”, in which, the exercise of data triangulation was crucial to delve into those clusters; for instance, the cross-check of the Coocs with the networks of Competitive of Use (CoU) and VRIO's quotations.

Right from its inception, once we started working on the transcriptions, we held an initial epistemological assumption, due to our awareness about the qual data procedure, that study might well encounter quotation gaps across stakeholders groups which origin could be participant bias or error beyond our span of control, or even, the various narrative styles hindering the sense-making process.

Yet, the results demonstrated the existence of two major streams of thought, demarked by the understanding of, on one side, “VR” benefits at a temporary-level (TCA) and, on the other side, the assertion of “VRIO” long-lasting benefits at a SCA-level. Indeed, we have encountered dissimilar perceptions manifested in the heterogeneity of coding as to the AI´s ability to yield firm-level competitiveness. In multiple cases, one could not match in coding the perceptions of competitiveness with the perceptions of utility, as a mutual confirmatory ground of VRIO validation and vice-versa. In addition, a cross-validation of the quotations against Barney & Clark's (Barney and Clark, 2011) theoretical foundations of the VRIO analysis framework did not allow us to a straightforward judgement of where TCAs and SCAs reside.

Conversely, the overlapping of codes, with opposing perspectives, simultaneously acknowledged as VRIO by one participant and non-VRIO for another, led us to dissimilar interpretation from these scholars above as to the importance of AI-tech adoption and establishment of a rationale explanatory of the conundrum (VRIO/Non-VRIO thinking). The interpretation of the expert´s opinion of one given AI-resource, as begin either a VR or VRIO (with respective TCA or SCA), did not solely depend on the proactiveness of the hospital´s board to acquire and utilize it AI-tech resources and the subsequent develop in capabilities developed from AI-utilization. The competitive outlook surrounding the AI results from the current industry´s structuring ´model, which grouping into class (I, II, and III) yields profound differences of skills between large central hospitals (tertiary - or III class) against township hospitals (primary - I class), revealed mostly in the speech of the participants P9, P10, and P14 against P5; and P12. These results confirm the assertion of Xiao and Liu (Xiao and Liu, 2019) that the primary hospitals in the three-tier system in China are less equipped with preparatory skills to cushion AI-technology.

In addition to such technological gap (leveraged by a capability-gap per hospital typology) is also acknowledged a financial gap, accentuating these differences above. For instance, participant P14, a reputed medical practitioner in orthopedics, revealed that a large financial investment is required in the hospital to acquire an AI-assisted medical tool (MAKO) capable of fully replacing a surgeon for hip and knee replacement surgeries. This constitutes, in the expert´s opinion a great advancement, beyond the DA VINCI tool where a human doctor is required to manipulate a robotic arm, yet, financial constraints limit their adoption. These type of anecdotes shared by P14 together with the remaining participants were essential for understanding those gaps. Furthermore it allowed us to map the networks of CoU and VRIO (as displayed in the semantic diagrams here exposed), and so depict the full range of R&Cs associated with competitive advantages (CAITA). In summary, the "VR" conditions which hold more harmony of opinion refers to capabilities on AI-utilization; AI-tech-development; new drug R&D; and auxiliary robotics. This constitutes certainly an avenue for further research for someone willing to pursue an identical research line or even an iteration of this study.

Conclusions

This research project, entitled "CAITA", is devoted to the understanding of the competitiveness of AI-technology to the Chinese healthcare sector. Our team counted with the inestimable contribution of renowned experts in the country within this field to accomplish three separate objectives (O1; O2; O3 - as shown in Introduction section) in a study fashioned with an exploratory purpose. These objectives were fully accomplished in compliance with the research framework encompassing an Expert Analysis with a qualitative nature, supported by the content analysis method. The reaching of the threshold (i.e. saturation of qual data) led us to adapt a Delphi methodology to an Expert analysis, though with some difficulty felt, as typical in equivalent studies, in quantification of some paradigms (e.g. units of use per AI-powered equipment per hospital; length of medical assessment; or, time per patient). This context, intertwinned with the available official data, and our inaccessibility of data at each healthcare unit constituted a great limitation to this study.

The healthcare sector in China, is organized in a three-tier hierarchical system, covering the spectrum of medical care from basic primary services (preventative, minimal healthcare and rehabilitation) to more complex high-end medical services, with the majority of hospitals fitting into the first tier of primary care. Those primary institutions correspond to township hospitals and are also the ones with fewer resources and capabilities preparatory for AI-tech investments and so less capable of seizing the opportunities of AI-tech adoption. Tertiary hospitals are large general hospitals placed in the most populated urban areas, covering a broader range of comprehensive medical services in multiple specialties, and include medical education and research, being inexorably also the most skillful ones.

For some years, AI-technology has grown in the country foremost due to its necessity, and concentrated itself especially in medical imaging, since the growing demand for imaging services did not secure enough radiologists in an equivalent number to fulfill the rise of the demand-side; thus, such phenomenon pushed newer investments inn AI to compensate for the shortage of medical professionals (Objective 1). Despite the concentration of resources in tertiary institutions, the secondary institutions are, though, the ones that absorb almost half the demand in imaging services, from the nearly 70% of clinical diagnosis in the country that are in need of some sort of imaging services. These secondary institutions are medium-sized (city, county, or district) hospitals.

According to these experts, the adoption of AI-technology in the country is at an early stage of adoption, denominated as ANI; however, it is beginning a transition to another stage of adoption, i.e. Artificial General Intelligence; nonetheless, they are oblivious to a prediction exercise about the future stage of Artificial Super Intelligence, believed to be the "true AI" paradigm, fully machine-led and machine-controlled.

In this ANI phase, AI-tech has though started to spread to other medical fields beyond medical imaging, both in clinical practice and experimental research, anchored on the hospital efforts and their free collaboration with third parties and stakeholder-groups, here represented in this study by the representatives of biomedical companies; municipalities; professional associations; and, universities/research centers.

Currently, hospital's investments in AI-tech are supported by available funding, and AI is already present in 11 medical specialties within 7 major clinical activities with spillovers to other 3 hospital-administration areas: facility's maintenance, logistics, and finance.

The viewpoints about the net utility of AI-technology to the Chinese society and to this industry vary across stakeholder-groups. Four clusters of opinion were identified. Universities are the most optimistic type of entities, and conversely, hospitals are the least optimistic; the latter with opinions markedly divided between a positive and negative competitive implications. Across the subset of hospital representatives participating in this study, a hybrid view of AI-tech utility is markedly accentuated between a clear positiveness (O+) and clear negativeness (T+), uncovering both a phenomenon of compartmentalization and a polarization of opinions.

Nonetheless, the general opinion about AI-tech adoption is a positive one (O+) (Objective 2). Such opinion may be summarized into the accounting of five hazardous factors of societal concern (i.e. (replacement of low-end medical jobs; risk of human distancing; risk of AI-autonomous resistance; risk of generational gap accentuation; risk of human-race or other specifies discrimination) contrasting with 12 societal factors of perceived benefits. Herein, the virtue of the AI to healthcare sector may be grouped into 9 general and 5 specific types of benefits. The general ones mapped from the expert´s insight were the knowledge push of scientific research; healthcare development through Big data and Sentiment analysis; paradigm shift from “medical professional-centered” to “diagnose-centered” health management; mitigation of competitive/technical gaps between large and township hospitals; compensation of unevenness in human/doctor´s judgements; patient service and experience improvement; solution to shortage of medical doctors; reduction of remoteness to patients in distant/rural areas; and, improvement of timely response to patients in remote areas. The specific benefits are the improvement of clinical decisions; improvement of clinical diagnosis, improvement of the patient´s medical journal; use of nursing and surgery robotics; and path planning and motion.

The gauging of the perception of competitiveness yielded four categories of resources and capabilities classified, as to their competitive implications, as being TCA enablers; and, two categories classified as long-term/SCA enablers. Moreover, this study uncovered two opposing streams of thought, concerning the appraisal of whether AI-related resources and capabilities in the sector yield temporary or long-lasting competitive-gains (Objective 3). In some cases, an individual resources is classified by a participant as being valuable, rare, costly/hard-to-imitate and organized, while for other participants these same resources are easy-to-imitate. This is the case of four categories of R&Cs (i.e. AI-tech utilization; AI-powered doctor-patient communication; algorithmic-development, and, auxiliary robotics), that we have classified as TCA-enablers on the basis of the divergence of opinion upon their competitive implications. Such classification constitutes the common ground across experts. Moreover, we have mapped two categories of resources and capabilities as SCA-enablers: AI-system deployment and new drug R&D capabilities, considered to hold, cumulatively, and uncontestably, the four VRIO attributes.

Within, the stakeholder-group of hospitals, the results demonstrated that the higher utility to generate SCAs is perceived as to the side of primary and secondary institutions. Tertiary institutions perceive a rather moderate utility of AI - of TCAs and in some cases, as simple necessity (or competitive imperative) to generate competitive parity status, against others public and private medical units (e.g. in the case of algorithmic-development as to the subgroup of commodity correlational algorithms) (Objective 3).

As a general reflection upon these conclusions above, we argue, AI-tech adoption ought not to be considered a one-size-fits all solution. Higher degree of competitiveness, also directly associated with higher degree of performance outputs (e.g. AAR), requires some degree of consciousness, as to the technological adaptation to the unique setup of the organizational environment, and even to the external environment faced in the country and within the healthcare sector. The extraction of competitive and performance benefits from AI-tech broad range of opportunities, is believed to exceed its potential risks. Hence, we summon the incumbents in hospital boards to a wise utilization of AI technology, suited to the organization´s specificities (of structure, systems and capabilities), and considerate of its impact in society.

In addition, we assert, that large investments in AI-technology per hospital unit ought not to be left to the chance of each hospital´s administration and their ability to execute national funding to the implementation of AI and robotics tools, but leveraged by larger sector policies to approximate the medical practice to the resources each unit and department requires. Looking at the larger picture, AI ought to reduce the inefficiencies, plus the asymmetries between general and township hospitals and urban/rural areas and their underlying dystopic risks (as the one exemplified in Introduction section, with the majority of medical imaging services being not concentrated in tertiary hospitals).

Upcoming investments in AI are believed to be more fruitful when orchestrated as a national collaborative effort of healthcare development, in which, a collaborative approach implies a cross-organizational collaborative approach, plus an intra-organizational and internal collaborative approach which opposes to a more radical view of AI-tech as replacement approach toward low-end or high-end medical jobs. In such model, AI-tech investments are suggested not to be dictated by the hospital´s resources, size or typology, nor per geographical positioning to access funding and acquire external resources. Instead, an equitable distribution of investments is here proposed (coordinated by regulatory authorities) on the grounds of: (i) the historical track of medical practice, accounting the inherent fluctuations in service ratios to be (timely) statistically monitored as a whole; (ii) the solving of current resource-necessities per each hospital unit; and, (iii) the seizing of medical unit specific opportunities, whether linked or not the former point. Altogether, this might constitute a more truthful way to redistribute investments in Chinese hospitals to reach higher degrees of competitiveness at the industry level. Moreover, such revision of the AI-funding model has clear implications on patient waiting time, and subsequently on possible deterioration of health, and other clinical complications, such as the development of new pathologies, most specially in vulnerable groups, as elderly or with chronic diseases.

Appendices

Appendixes

Table *8* to Table *11* provide a comprehensive overview of the metadata codebook, code group frequencies and groundedness, network complexity metrics, expert profiles by organization type, and summarized excerpts from interviewees, offering detailed insights into the study's qualitative data analysis.

Code	Code Group
(Patient) Medical Journal (MJ)	2 - Application in Medicine (AiM)
(Reduction of) Labor intensity (LI)	1 - Advantages & Opportunities (A&O)
Big-Data & Correlation Thinking (BDC)	1 - Advantages & Opportunities (A&O)
Cardiology (Cardio)	2 - Application in Medicine (AiM)
Clinical Decision Support (CDeS)	2 - Application in Medicine (AiM)
Clinical Diagnosis Support (CDS)	2 - Application in Medicine (AiM)
Competitive Use (CoU)	5 - State-of-the-art in Medicine (SoA)
Contribution to Societal Problems (CSP)	3 - Disadvantages and Threats (D&T)
Contribution to Societal Solutions (CSS)	1 - Advantages & Opportunities (A&O)
Cost-Cutting (CoC)	1 - Advantages & Opportunities (A&O)
Costly/Hard-to-Imitate (CHI)	6 - VRIO
Current Business Limitations (CBL)	3 - Disadvantages and Threats (D&T)
Current Legal & Regulatory Limitations (CL&RL)	3 - Disadvantages and Threats (D&T)
Current Technological Limitations (CTL)	3 - Disadvantages and Threats (D&T)
Data Accumulation (DAT-a)	1 - Advantages & Opportunities (A&O)
Doctor-patient communication (DPC)	1 - Advantages & Opportunities (A&O)
Experiential Learning Capabilities (ELC)	1 - Advantages & Opportunities (A&O)
Expert Review Notes (ERN)	4 - Experts Analysis (EA)
Gastroenterology & Hepatology (G&H)	2 - Application in Medicine (AiM)
Genetics (GEN)	2 - Application in Medicine (AiM)
Global Intelligent Revolution (GIR)	3 - Disadvantages and Threats (D&T)
Hastening (HAS)	1 - Advantages & Opportunities (A&O)
Human Resistance & Inertia (HRI)	3 - Disadvantages and Threats (D&T)
Human-Cloud Connectedness (HCC)	3 - Disadvantages and Threats (D&T)
Lead Time (LeT)	1 - Advantages & Opportunities (A&O)
Machine Intelligence overtakes Control (MIC)	3 - Disadvantages and Threats (D&T)
Machine over Human Intelligence (MoH)	3 - Disadvantages and Threats (D&T)
Medical Imaging (MI)	2 - Application in Medicine (AiM)
Medical Professional´s Management (MPM)	1 - Advantages & Opportunities (A&O)

Neo-cortex/machine connectedness (NMC)	3 - Disadvantages and Threats (D&T)
Nephrology (Neph)	2 - Application in Medicine (AiM)
Neurology (Neu)	2 - Application in Medicine (AiM)
New Drug Research and Development (NDR&D)	2 - Application in Medicine (AiM)
Nursing Robots (NR)	2 - Application in Medicine (AiM)
Oncology (Onc)	2 - Application in Medicine (AiM)
Ophthalmology (Opht)	2 - Application in Medicine (AiM)
Organized (O)	6 - VRIO
Orthodontics (Orth)	2 - Application in Medicine (AiM)
Paradigms & Phases (P&P)	5 - State-of-the-art in Medicine (SoA)
Path planning & motion (PPM)	2 - Application in Medicine (AiM)
Patient Trust (PT)	1 - Advantages & Opportunities (A&O)
Precision (PRE)	1 - Advantages & Opportunities (A&O)
Principles & Attributes (P&A)	5 - State-of-the-art in Medicine (SoA)
Pulmonology (Pulm)	2 - Application in Medicine (AiM)
Rare (R)	6 - VRIO
Reputation (Rep)	1 - Advantages & Opportunities (A&O)
Risk of Big-Data Misuse or Protection´s Negligence	3 - Disadvantages and Threats (D&T)
Robotic surgeries (RoS)	2 - Application in Medicine (AiM)
Stomatology (Stom)	2 - Application in Medicine (AiM)
Summary of Element (SoE)	4 - Experts Analysis (EA)
Technological Accumulation (TEC-a)	1 - Advantages & Opportunities (A&O)
Technological Accumulation (TEC-a) (2)	1 - Advantages & Opportunities (A&O)
Valuable (V)	6 - VRIO

TABLE 7: Metadata codebook

Source: Own elaboration.

Code Group				Count (n)		Frequencies (f)		Groundedness
No.	Ref.	Description	List of Codes per Group	Codes (N = 54)	Quot. (N = 577)	Codes	Quotations	
			---					-
			(Reduction of) Labor intensity (LI)					9
			Big-Data & Correlation Thinking (BDC)					25
			Contribution to Societal Solutions (CSS)					28
			Cost-Cutting (CoC)					17
			Data Accumulation (DAT-a)					14

1	A&O	Advantages & Opportunities	Doctor-patient communication (DPC)	15	159	0,28	0,2045061	3
			Experiential Learning Capabilities (ELC)					5
			Hastening (HAS)					10
			Lead Time (LeT)					2
			Medical Professional´s Management (MPM)					10
			Patient Trust (PT)					3
			Precision (PRE)					21
			Reputation (Rep)					5
			Technological Accumulation (TEC-a)					7
2	AiM	Application in Medicine	---	18	127	0,34	0,1646447	-
			(Patient) Medical Journal (MJ)					3
			Cardiology (Cardio)					2
			Clinical Decision Support (CDeS)					19
			Clinical Diagnosis Support (CDS)					37
			Gastroenterology & Hepatology (G&H)					1
			Genetics (GEN)					8
			Medical Imaging (MI)					17
			Nephrology (Neph)					3
			Neurology (Neu)					4
			New Drug Research and Development (NDR&D)					1
			Nursing Robots (NR)					4
			Oncology (Onc)					3
			Ophthalmology (Opht)					5
			Orthodontics (Orth)					3
			Path planning & motion (PPM)					4
			Pulmonology (Pulm)					2
			Robotic surgeries (RoS)					9
			Stomatology (Stom)					2
			---					-
			Contribution to Societal Problems (CSP)					1
			Current Business Limitations (CBL)					32
			Current Legal & Regulatory Limitations (CL&RL)					11
			Current Technological Limitations (CTL)					23

			Global Intelligent Revolution (GIR)					0
3	D&T	Disadvantages and Threats	Human Resistance & Inertia (HRI)	11	105	0,21	0,1577123	25
			Human-Cloud Connectedness (HCC)					0
			Machine Intelligence overtakes Control (MIC)					2
			Machine over Human Intelligence (MoH)					7
			Neo-cortex/machine connectedness (NMC)					1
			Risk of Big-Data Misuse or Protection´s Negligence					3
			---					-
4	EA	Experts Analysis	Expert Review Notes (ERN)	2	70	0,04	0,1213172	62
			Summary of Element (SoE)					26
			---					-
5	SoA	State-of-the-art in Medicine	Competitive Use (CoU)	3	119	0,06	0,1993068	80
			Paradigms & Phases (P&P)					31
			Principles & Attributes (P&A)					8
			---					-
			Costly/Hard-to-Imitate (CHI)					30
6	VRIO	Valuable, Rare, Inmitable, Organization	Organized (O)	4	119	0,08	0,152513	22
			Rare (R)					26
			Valuable (V)					41
Total	-	-	-	53	577	1	1	-

TABLE 8: Codes per group: count, frequencies, and groundedness

* Groundedness (Gr) corresponds to the code frequency per unit of analysis (UA) or participant. Thus, it shows how many quotations are linked to a code; **Density (d) refers to the number of linkages to other codes; *** Total exhibits the sum of quotations per code id (cid) and the average density per participant.

Source: Own elaboration.

ID/Description	D*	PS**		C***
		N Quot.	N Codes	
Advantages and Opportunities (A&O)	15	159	17	2,385
Advantages and Opportunities (A&O) - detailed	68	159	17	10,812
Application in Medicine (AiM)	19	129	18	2,451
Application in Medicine (AiM) - detailed	69	129	18	8,901
Competitive Use (CoU)	39	80	1	3,12
Contribution to Societal Problems (CSP)	6	1	1	0,006
Contribution to Societal Solutions (CSS)	15	28	1	0,42
Current Business Limitations (CBL)	11	32	1	0,352
Current Legal & Regulatory Limitations (CL&RL)	12	11	1	0,132
Current Technological Limitations (CTL)	11	23	1	0,253
Disadvantages and Threats (D&T)	12	105	11	1,26
Disadvantages and Threats (D&T) - detailed	73	105	11	7,665
Expert Analysis (EA) - detailed	38	88	2	3,344
OT analysis	27	264	38	7,128
Paradigms and Phases (P&P)	37	31	1	1,147
Principles and Assumptions (P&A)	24	8	1	0,192
Rare (R)	16	26	1	0,416
State-of-the-art (SoA) in Medicine	4	119	1	0,476
State of the art (SoA) in Medicine_detailed	43	119	3	5,117
Valuable (V)	16	41	1	0,656
VRIO	21	119	4	2,499

TABLE 9: Networks: overview of degrees and complexity

(Note: * the degree (D) represents the number of links for any one "node" in a network; ** the point of saturation (N quotations) in this project; *** is the complexity ratio (C) of the network considering the function: $C(f) = (D \times Q)/1000$).

Source: Own elaboration.

Profiles per Interviewee (I):	Biomed co.	Hospitals	Universities	Other Org
I1	-	Hospital Director	-	-
I2	-	General Secretary (academic Committee)	-	-
I3	-	Director (Party Committee Office)	-	-
I4	-	-	-	Researcher (Science and Education Division - Municipality)
I5	-	-	-	Deputy Director (Medical department)
I6	Deputy General Manager	-	-	-
I7	-	-	-	Party branch secretary (of a Medical Industry Association)
I8	-	-	Vice president (Affiliated Ophthalmology and Optometry)	-
I9	-	Vice-president	-	-
I10	-	President	-	-
I11	-	-	Director of the AI Center (at a Research Institute and University)	-
I12	-	President & Secretary of Party Committee	-	-
I13	Chairman and President	-	-	-
I14	-	President	-	-
I15			Teaching Assistant (School of Financial Technology, University)	
I16	Senior Engineer	-	-	-
I17	-	-	-	Deputy Chief Physician
I18	-	-	Researcher (School of Biomedical Engineering and Instrument Science)	-
I19	-	-	Senior Engineering Expert (Lab for Intelligent Education Research)	-
I20	Senior Excutive	-	-	-
I21	Head of Department (Assets Management)	-	-	-

TABLE 10: Experts' profile and distribution per organization's typology

Source: Own elaboration.

Interviewee:	Question (prompt or probe)	Answer
I14	What´s the current application of AI to clinicians and non?	“ … MAKO is currently being used experimentally in our hospital. This system is very expensive, costing 20 million sets. It also depends on the doctor to do detailed preoperative planning and parameter setting first, and the doctor also needs to do the initial skin incision. … This system cooperated with Beijing Donghua Company and found some bugs when testing it , many of which were caused by the deviation of software engineers' understanding of our medical process and management model… …. This also makes me begin to believe that whether it is medical or other industries, intelligence is a big trend.”
I11	What is opinion about the worthiness of AI tech in the health sector?	“…Another interesting case, I once participated in the support mission of Zhongshan Third Hospital to the Kashgar Hospital in Xinjiang, and found that artificial intelligence technology is also applied in such remote areas. For example, Zhongshan Ophthalmology Department has conducted AI screening for cataracts locally. Therefore, we can also think that in some areas where human resources are relatively poor , artificial intelligence may be more useful, because it can make up for the shortage of human doctors in quantity and level.”
I10	What are the benefits of AI-technology for any medical unit in the country?	“…The acceptance of all parties in the organization process can be divided into two situations: one is large public hospitals, which have many patients and tight manpower, so the service pressure is relatively high. In this case, artificial intelligence can play a great role. Patients have a place to ask questions. Another situation is private, high-end hospitals. They are known for their services, and the service recipients may not be willing to operate many IT things in person , and some even need one-on-one, personalization. In such a scenario, artificial intelligence may not be very useful. Another issue to pay attention to is the protection of customer privacy, including blood sample data. It seems that some media have reported the backdoor incident of GE radiology equipment. During the Wuhan epidemic, a large number of Chinese patients' chest X-ray data were leaked. Such a case will actually cause people to worry about data security, their own privacy and foreign manufacturers, and further affect the development of the entire industry. I still believe that these problems can be solved…”

TABLE 11: Sample of interviews (exemplified summaries)

Source: Own elaboration.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Bruno F. Abrantes, Xiang Miao, Virginia Trigo, Nelson António

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Disclosures

Human subjects: Consent was obtained or waived by all participants in this study. BRU Scientific Committee issued approval (BRU-ISCTE Scientific Council). BRU-ISCTE Scientific Council approved the ethics of this research project, including the involvement of human participants in strict respect for confidentiality, anonymity, non-harm, and protection of individual data. The adherence of all experts in this study was voluntary, and consent forms were signed by all participants before the collection of data. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Acknowledgements

The data provided in this manuscript has been in compliance with the ethical guidelines from ISCTE University Institute of Lisbon and Southern Medical University (SMU). The adherence to this study by a pool of experts is totally voluntary, and approved by an informed consent document signed by each one, and the use of the collected data was agreed to be handled solely for the purpose of this study and held securely stored in compliance with the personal data regulation (GDPR) of the EU. The data supporting the findings of this study is not publicly available due to privacy and ethical restrictions. Data access may be granted upon reasonable request and subject to approval by the relevant ethics committees and institutions.

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