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RESEARCH ARTICLE

Emerging Value-Based Radiology in the Era of Artificial Intelligence

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ABSTRACT

Radiology has a long history of adopting state-of-the-art digital technology to provide better diagnostic services and facilitate advances in image-based therapeutics throughout the healthcare system. The radiology community has been developing diagnostic artificial intelligence (AI) tools over the past 20 years, long before AI became fashionable in the public press. Currently, there are approximately four hundred Food and Drug Administration approved imaging AI products. However, the clinical adoption of these products in radiology has been relatively dismal, indicating that the current technology-push model needs to evolve into the demand-pull model. We will review the current state of AI use in radiology from the perspective of clinical adoption and explore the ways in which AI products will become an ensemble of critically important tools to help radiology transition from volume-based service to value-based healthcare. This transition will create new demands for AI technologies. We contrast the current "technology-push" model with a "demand-pull" model that will aligns technology with user priorities.

We summarize the lessons learned from AI experience over the past twenty years, mainly working with computer-aided detection for breast cancers and lung cancers. The radiology community calls for AI tools that can do more than detection with increasing attention toward higher workflow efficiency and higher productivity of radiologists. Major radiological societies of North America and Europe promulgated the emerging concept of value-based radiology service, an integral part of overall value-based healthcare. The transition to value-based radiology will happen and that higher value will come from the effective use of AI throughout the radiology workflow.

The value-based radiology will need to work with a full range of machine learning tools, including supervised, unsupervised, and reinforcement learning, as well as natural language processing and large language models (e.g., chatbots). The engineering community is rapidly developing many concepts and sophisticated software tools for data orchestration, AI orchestration, and automation orchestration. Current radiology operation has been supported by PACS, a monolithic IT infrastructure of past generations. This system will need to migrate to an intelligence management system to support the new workflow needed for high value radiology.

1.0 Introduction

This research aims to explore the pathways to greater clinical adoption of AI products and tools in radiology practice.

Our research has several objectives:
1. Discuss the emerging evolution of radiology practice from volume-based to value-based healthcare.
2. Discuss that the radiology transition will require a new workflow to improve overall efficiency and individual productivity to allow doing more with less to achieve a service of integrated diagnosis.
3. This value-based transition will demand a wide array of AI tools and products, beyond current computer-aided diagnosis products, integrated into a new platform of the intelligence management system.
4. Discuss the demand-pull technology adoption model builds on the 20 years of experience working with the computer-aided diagnosis products developed in the current technology-push adoption model that has stalled.

We have designed this study as an editorial in a narrative voice with key publications dealing with the future radiology service, lessons from computer-aided diagnosis, and new artificial intelligence tools. This represents the collective personal voices of the authors who have been active participants in all aspects of digital radiology over the past 30 years.

It is hoped that we are offering a possible sustainable AI adoption model that will serve a meaningful partnership as radiology becomes a high-value service.

2.0 Current State of Artificial Intelligence in Radiology

Artificial intelligence (AI) and machine learning are intricately connected and often used interchangeably, but they differ. Machine learning is considered a subset of artificial intelligence. AI refers to the capability of a computer system to mimic human cognitive functions. ML refers to the algorithms that learn from examples rather than being explicitly programmed.

Radiology adopted digital technology in several steps, beginning with (1) radiology information system in the '60s,[1] then (2) the digital imaging technology, such as CT and MRI, beginning in the '70s and (3) image management systems (a.k.a. PACS) for filmless digital operations beginning in the '90s.[2-3] A global teleradiology project spurred the development of teleradiology services.[4] The adoption of AI technology can be seen as the third transitional step. The interest in using pattern recognition technology (an earlier name for AI in imaging) for radiology diagnosis began in the 80s. The use of convolutional neural networks (CNN) for computer-aided diagnosis (CAD) was introduced in the 1990s.[5-7]

The computer-aided diagnosis (CAD) research in medical imaging has evolved into multiple types based on intended clinical uses, according to the FDA.
1. Computer-aided detection (CADe) is to aid in localizing/marking regions of interest that may reveal specific abnormalities, as in the case of cancer screening.
2. Computer-aided diagnosis (CADx) aids in characterizing/assessing disease, disease type, severity, state, and progression.
3. Computer-aided detection/diagnosis (CADe/x) is to aid in localizing and characterizing conditions.
4. Computer-aided triage (CADt) aids in prioritizing/triaging time-sensitive patient detection and diagnosis.
5. Recently computer-aided acquisition/optimization (CADa/o) was added to the list.

The FDA approved CADe for breast cancer in 1998 then for lung cancer in 2004.[8] Its adoption rate for the breast cancer screening was initially less than 5% until the Center for Medicare and Medicaid Services (CMS) allowed reimbursement for using CADe tools in screening mammography in the US. However, this reimbursement model is not universal. With the financial incentive, by 2016, 92% of all breast cancer screenings were done using CADe in the US.[9]

Several large trials in the US and Europe concluded that the use of CADe has not delivered significant benefits and produced false positives resulting in higher recall and biopsy rates.[9,10-12]

CADe for lung cancer screening has been used without any financial incentives.[13] CADe can improve sensitivity, and at the same time, the radiologist's reading speed can be improved by 30%, showing potential for productivity improvement.[14] Its clinical adoption has been slow as well.[15]

Today there are approximately four hundred FDA-approved CAD products. However, the clinical adoption of these AI tools in radiology is relatively dismal, disappointing the developers and investors. Some wonder if radiology is facing an "AI winter".[16]

Most radiologists with many years of experience expect AI to eventually be very useful if AI can remove frustrating inefficiencies in radiology workflow and help with automating many routine mundane manual activities. If the efficiencies can be improved, it would allow radiologists to get more directly involved in collective decision-making and interaction with patients.

There have been discussions that AI will replace radiologists. Dr. Langlotz, a long timer user of CADe for mammography, stated that "AI won't replace radiologists, but radiologists who use AI will replace radiologists who don't".[9]

We believe AI has great potential for remaking radiology. Then how should we take advantage of the potential by integrating of AI tools into radiology service?

This paper is developed following the guidelines for editorial based on selected literature and the authors' long history of active pioneering roles in all phases of the digital transformation of radiology.

3.0 Technology Adoption Model: Technology-Push vs. Demand-Pull

Technology adoption is a complex, multi-faceted process. Julia Adler-Milstein and her team of collaborators addressed the barriers and discussed the clinical adoption of an extensive list of AI tools.[17] They proposed 4 domains of adoption: reason to use, means to use, method to use and desire to use. Here we will focus on a simpler compatible model; the technology-push and demand-pull models that are relevant to the current radiology environment.[18]

Technology-push and demand-pull can be seen as two layers of innovation adoption and they can interact with each other in various ways. Technology-push is to develop new technologies or products mainly driven by the capabilities of the technology itself. In the case of technology- pull, developers and investors are focused primarily on innovating for perceived needs. The development efforts of radiology AI products over the past twenty years have followed the technology-push aiming to help diagnosis by radiologists. That approach has not been successful as noted previously.

On the other hand, the demand-pull models are to develop new technologies or products to meet the needs and want of users. In demand-pull, developers and investors focus on identifying and meeting the real needs of customers. The demand-pull adoption model consists of three levels of interactions; (1) demand as a source of innovation (2) competence to match technology with demand, and (3) distinction between external and internal sources of innovation.[19]

Figure 1 below highlights how the TP and DP models interact to provide sustainable and continuous innovation.[20]

Successful and sustainable innovation requires interaction between these two approaches and an intimate understanding of customer needs on the demand side. Then when and how the demand for AI technology would emerge? The next section will describe the important transformation of radiology practice that will demand AI solutions.

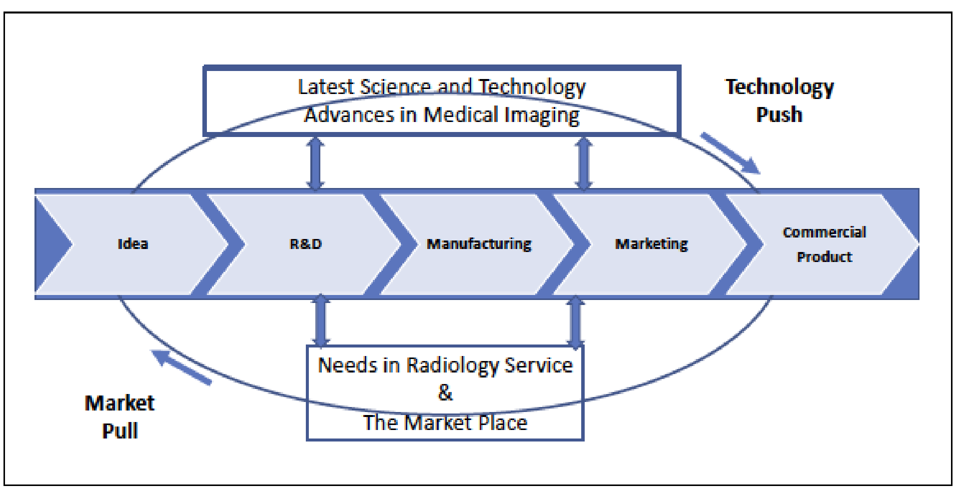

Figure 1: Interactive Model of Innovation: adapted from Reindustrialization and technology, by Rothwell R., Zegveld W. (1985), Longman Group Limited, London. Sourced from Romanowski et al.

4.0 Evolution of Radiology as a Value-Based Service

Radiology leaders representing multiple professional societies in the US and Europe issued a joint statement,[21-23] on Value-Base Healthcare (VBH) as the future of radiology. VBH is an emerging framework for improving individual health outcomes per unit expenditures. Simply put, the essence of value-based systems is doing more with less and at the same time, moving away from measuring volume of work to measuring outcomes. Though there are differences between business models of US and European health systems, these joint statement shows significant commonalities for common clinical goals.

A recent US Interagency Working Group on Medical Imaging identified strategic direction medical imaging. It has identified "advance high-value imaging as an overarching theme to achieve better health outcomes and smarter health care spending through medical imaging."[24]

The American College of Radiology (ACR) recognized that the transition from volume to value in radiology practice is a key component of their 3.0 Imaging initiative.[25] Integration of AI into clinical practice will improve radiologists' clinical performance but can also help the department become more efficient and reduce the cost of operation by automating time-consuming and mundane tasks. A recent publication on Radiology 2040,[22] offers an extensive list of action items needed to ensure radiology thrives in 2040. Of those, the following are relevant to AI in radiology.

1) Radiologists must add value to the healthcare continuum.
2) Radiologists who are limited to image interpretation may eventually become obsolete.
3) Radiologists must recognize that AI will enable them to function at a higher level.
4) Radiology will be responsible for phenotyping and imaging markers.
5) Imaging technology will become increasingly multiscale, multimodal, and multi-omics.

Often when one talks about the work of radiologists, especially during the era of AI, one focuses narrowly on diagnosing and detecting disease, but radiologists do far more. Their work includes prevention, such as screening, delivery, and monitoring of therapy, prognosis, confirmation of disease resolution, and technology consultant to other specialties relying on imaging technology. The following diagram shows where values of radiology are generated and delivered within the current radiology workflow.

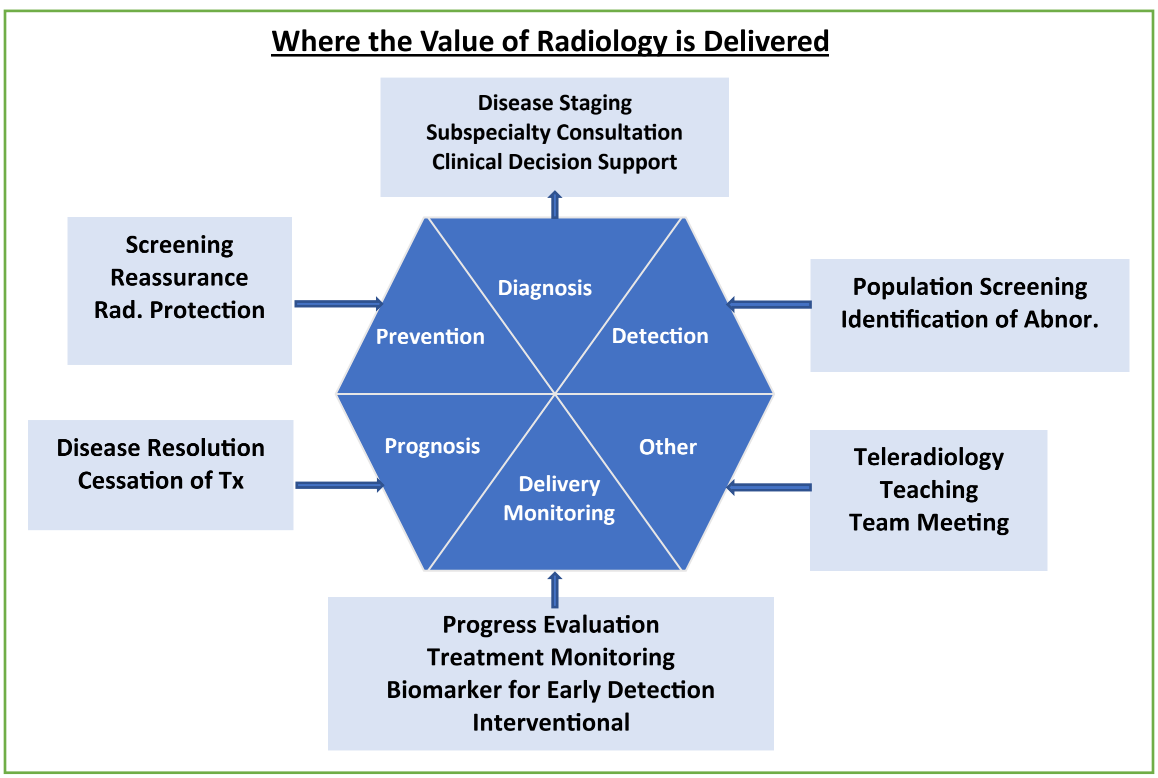

Figure 2: Value of Radiology Service Delivery Based on, Radiology 2040.[22]

Radiology will continue to face challenges dealing with explosive growth in the number of radiology studies undertaken around the clock. 24-hour coverage of radiology services is becoming a norm while we are seeing physician burnout. One of the support tools could include providing support for when not to request imaging, where imaging is unlikely to contribute usefully or answer the question being asked. This type of capability will likely exceed what is achievable by humans alone while reducing physician burnout.[26]

5.0 Technology Demand for Value-Based Radiology

The innovations necessary to support the transition to value-based radiology can be grouped into two types of AI tools.

1. AI tools for radiology workflow optimization to improve efficiency and productivity via
2. AI tools for integrated diagnosis of multiscale, multimodal imaging and multi-omics

5.1 Radiology Workflow Optimization for Value Creation

Radiology has been a leader in digital transformation, but the fundamental workflow of making diagnoses has not changed from the film days. Many experienced users of CAD systems have identified workflow optimization as the top priority of maximizing and documenting the value of radiology services. Key components of AI-enabled workflow include (a) image delivery, (b) image quality control, (c) results storage and management, (d) results processing, (e) results presentation and delivery (f) results in error correction, and (g) performance monitoring.[27]

Potential applications of machine learning in radiology workflow can be organized into 5 groups as shown below.[26]

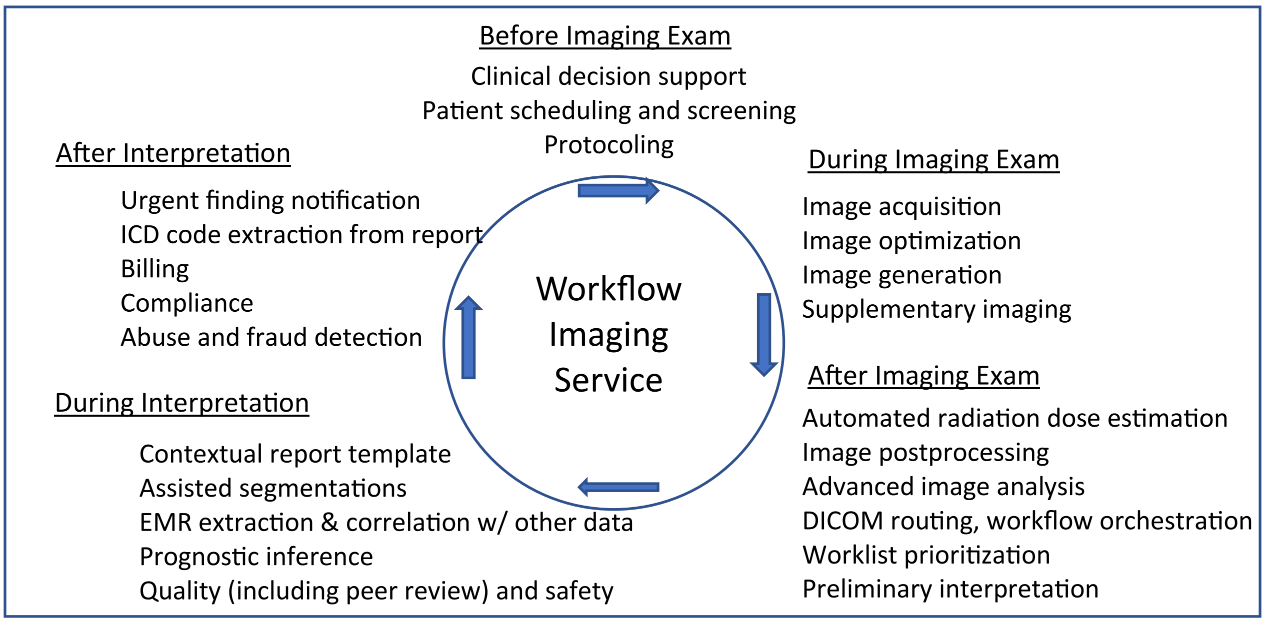

Figure 3: Radiology Workflow Imaging Service.[28-30]

More details of each are described in a recent publication by Pierre, et. al.[29] Within each of the five steps, many manual operations can be automated with AI. For example, the administrative aspect of radiology service should be an integral part of workflow management. Claims and payment administration can be improved using probabilistic matching of data across different databases. Incorrect claims can cause significant difficulties for all parties concerned and sap the productivity of a department.

5.2 Integrated diagnosis with multiscale, multimodal imaging and multi-omics

Open-source CNN packages have been widely used for CAD development; however, current CNN packages were designed for orientation-dependent alphanumeric characters and nature images, while medical images are orientation-independent. Many developers are working to improve the shortcoming of CNN to minimize systematic errors in their output.[30]

In most CADe development with supervised machine learning, the AI system is trained and validated with a large corpus of labeled data. As discussed earlier, current CADe systems tend to produce a high false positive rate.[10] A clinical dataset typically includes normal cases and cases containing clinically actionable or non-actionable abnormalities with a very small number of challenging cases. Instead of training the AI model with random cases, the training set should have about 30% of clinically challenging cases. A CAD trained on very few clinically challenging cases will fail to identify difficult cases making the system clinically irrelevant.

Phenotyping and working with multiple imaging markers will be important strategic goals of enhancing the values of radiology service.[31] The emergence of new integrated diagnostic services will demand the analysis of data from radiology, pathology, genomics, and clinical information.

Quantitative imaging, also known as radiomics, uses engineered features, i.e., quantitative measurements of features radiologists use. Current research efforts have shown the possibility of providing better diagnosis and perhaps the possibility of differential diagnosis without additional studies. The variability of extracted biomarkers and biomarker standardization remain the main challenges in achieving clinical utility.[32]

In the earlier session, we listed 5 types of CAD products. As we integrate multi-modal imaging and multi-omics these AT tools will have complimentary roles that value based radiology service would need.

6.0 New Tools and New Intelligence Management System for High-Value Radiology

In this section, we highlight emerging new tools and concepts for developing, deploying and managing ever-increasing CAD tools, such as CADe, CADx, CADt, and operational efficiency tools to ease the adoption of demand-pull technology. These tools will be managed alongside those that focus on operational efficiency.

1. The potential use of large language models (chatbots) as a means to integrate Imaging AI and language AI
2. Orchestration of massive amounts of diverse types of data from multiple origins
3. Orchestration of real-time automation and AI refresh
4. Intelligence management system as an operational platform

New concepts and new tools to develop AI-based products are becoming available rapidly. Machine learning orchestration tools are used to automate and manage ML development process and ML pipeline infrastructure. These tools help developers track and monitor models for further analysis. Orchestration tools make the ML process easier, and more efficient to help ML teams focus on what's necessary.

6.1 The Use of large language models (chatbots) as a means to integrate Imaging and language AI

Historically the development of AI tools for graphics and language has been on two parallel tracks. Pattern recognition in graphics and images predominantly uses convolutional neural networks (CNN) with supervised and/or reinforcement learning on given imaging datasets representing real-life situations or medical images that may contain the disease. Integration of text data with image analysis will be an important capability for values-based radiology.

The application of NLP aims to provide AI tools with the ability to process and understand unstructured and structured text data. NLP AI tools have been shown to be useful in dealing with the aggregation and summarization of patient notes, treatment analysis, discharge summaries, semantic understanding of patient queries,[33] and assisting medical decision-making.[34]

The ChatGPT is getting much attention these days, but its role in radiology is currently under careful evaluation. The latest ChatGPT-4 has a large multimodal capable of accepting images and text within a combined architecture and producing contextual text outputs. The transformer processor of GPT-4 can analyze the contents of an image and connect that information with the text output. The *Toolformer*, was introduced recently and it can decide which application programming interfaces (APIs) to call, when to call them, what arguments to pass, and how to incorporate the results into the final analysis best.[35] This can be done in a self-supervised way.[36] This tool can make it easier to orchestrate multiple AI's and AI pipelines of multiple AI applications. More research is needed to allow the use of *Toolformer* with proper training.

6.2 Data Orchestration

Orchestration, in engineering, is coordinating and managing multiple computer systems, applications, and services to execute a larger workflow or process. The goal of orchestration is to optimize the execution of frequent and repeatable processes to manage complex workflows. There are many software tools for the orchestration of data and automation and AI development.[37-38]

Data orchestration is an engineering process to gather, clean, organize and analyze data for decision-making. The goal of data orchestration is to make data usable for ML. The data orchestration concept has emerged to bring the right data for the right purpose. The essence of data orchestration is moving data from one application to another by combing, verifying, and storing the data to make it more useful.

So far, the data orchestration for CAD in radiology is based on individual disease types, for example, lung cancer or breast cancer. As AI applications expand, we must apply various ML tools for data orchestration at a larger scale using multiple data sets beyond images, such as EHR, proteomics, and pathology data.

6.3 Machine Learning Orchestration and Automation for Efficiency

In a similar vein, machine learning orchestration (MLO) tools are used to automate and manage ML development process and ML pipeline infrastructure. These tools also help developers track and monitor models for further analysis. The MLO development cycle starts with creating features, setting up the training process, evaluating the model, and monitoring the model.
One of the challenges that the CAD community faces is refreshing the CAD system after the initial clinical deployment. The FDA began to look at its role in product management and optimization of AI performance at users' sites.[39] The orchestration process can be used for continuous performance improvement of imaging AI in radiology. [40]

6.4 Intelligence Management System for Integrated AI Diagnosis

Integrating multiple AI tools into radiology workflow will remain a major challenge in meeting new technology demands emerging from radiology as it evolves to VBS.[41] The radiology workflow has not fundamentally changed over the past 30 years. To achieve VBS the workflow will change with AI integration, AI cannot continue to be a "peripheral" system to existing legacy IT systems. Existing systems must support AI life cycle requirements, like continuous learning and drift mitigation strategies. Image management and PACS must be re-defined as an Intelligence Management System (IMS) for the demand-pull AI adoption model.

There are some embryonic efforts led by multiple professional organizations in North America and Europe to develop acceptable platforms and associated standards, as was the case when PACS was developed with the DICOM standard in open settings. This will require close collaboration involving the entire radiology community following the open engagement model.

7.0 Conclusion

Radiology has led digital transformation in healthcare with digital imaging systems, PACS, teleradiology, and image-guided procedures. Artificial Intelligence (AI) has the potential to revolutionize the practice of radiology, but many tools have been developed in isolation, and the adoption is slow. Moving from the current technology-push model to demand-pull, combined with collective, team-science approaches, will speed up this adoption.[42-43]

Radiology is transitioning to value-based service, along with the rest of the healthcare system. Value-Based radiology focuses on delivering high-quality care to patients while reducing costs and improving outcomes. AI will be a critically important tool in transforming radiology practice by enhancing the accuracy and quality of diagnosis and improving the productivity of radiology practices with optimized workflow. Creating and documenting the values of diagnostic services will become a high priority, as will metrics that explicitly gauge bias and equity. This transition process will create demand for many new AI tools, AI orchestration tools, and Intelligence Management Systems (IMS) will be increasingly essential.

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