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Medical Imaging Technologies and Healthcare Infrastructure: Artificial Intelligence-Based Analysis of Global Trends

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ABSTRACT Medical imaging technologies have a critical role in improving healthcare efficiency, diagnostic accuracy, and patient outcomes. This study investigates the global distribution of advanced medical imaging devices such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and mammography across OECD countries between 2015 and 2023 using OECD health data. Using correlation and regression analyses, this research explores the relationships between imaging device density, healthcare infrastructure capacity, population size, and healthcare expenditures. The analysis reveals a strong positive correlation between imaging device availability and healthcare infrastructure capacity ($\rho = 0.77$), as well as a robust association with population size ($\rho = 0.87$). In contrast, healthcare expenditures demonstrate a weaker relationship with these variables ($\rho \approx 0.41 - 0.55$), indicating that strategic planning is essential beyond mere budget increases. K-Means clustering and Principal Component Analysis (PCA) categorize countries into distinct groups according to imaging technology availability and infrastructure capacity. Integration of artificial intelligence (AI) within medical imaging is highlighted as a promising approach for enhancing early diagnosis, reducing unnecessary healthcare utilization, and improving operational efficiency. Findings emphasize that effective healthcare policies should focus not only on increasing budgets but also on targeted resource allocation, infrastructure optimization, and adoption of advanced AI technologies.

KEYWORDS
Artificial intelligence
Medical imaging technologies
Healthcare infrastructure
Regression analysis
OECD health data
CT
MRI
PET
Healthcare expenditures
Clustering analysis
Principal component analysis

INTRODUCTION

Medical imaging technologies are foundational elements of contemporary healthcare systems, playing a critical role in enhancing diagnostic precision, clinical decision-making, and treatment planning. The widespread use of advanced imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and mammography has substantially improved early disease detection and patient outcomes across many developed nations (Lei *et al.* 2024; Deng *et al.* 2024). However, significant disparities remain in access to these technologies, particularly between high-income and lower-income countries.

In recent years, the integration of artificial intelligence (AI) into medical imaging has introduced transformative capabilities that go beyond conventional imaging. AI-powered tools, including deep learning algorithms, convolutional neural networks, and computer-aided diagnosis (CAD) systems have enhanced lesion detection, reduced noise in low-dose CT (LDCT) images, and improved diagnostic efficiency (Zubair *et al.* 2024). Countries such as South Korea, Germany, and the Netherlands have pioneered the deployment of AI-supported imaging workflows, demonstrating the potential of AI to elevate diagnostic quality and streamline radiology operations. Despite these advances, global adoption of AI-enhanced imaging remains uneven and often limited by infrastructure, budgetary constraints, and policy readiness.

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Effective utilization of imaging technologies depends not only on equipment acquisition but also on the broader healthcare infrastructure in which these technologies are embedded. Numerous studies have confirmed that medical imaging device availability correlates strongly with healthcare infrastructure indicators, including hospital bed density, intensive care unit (ICU) availability, and qualified personnel (Rhodes *et al.* 2012; Phua *et al.* 2020). In countries with well-developed healthcare systems, access to high-performance imaging is facilitated by complementary investments in institutional capacity, workforce, and information systems. In contrast, infrastructure deficiencies often constrain device utilization in lower-resourced settings (Murthy *et al.* 2015).

Although previous research has explored the associations between population size, healthcare expenditures, and imaging technology distribution (Jones 2024; Hou *et al.* 2020), the role of AI integration and strategic planning in shaping such distributions remains underexplored. Existing studies rarely assess how technological readiness and digital health policies intersect with economic and demographic factors to influence the deployment of imaging technologies. Furthermore, healthcare expenditures alone have proven insufficient to explain the variability in imaging device density, highlighting the importance of targeted infrastructure planning and resource optimization.

This study aims to investigate the global distribution of advanced medical imaging devices across OECD countries over the period 2015 to 2023. This time frame was selected based on data availability and completeness in the OECD Health Statistics database, as well as to capture critical developments during the COVID-19 pandemic, which significantly impacted healthcare investments and imaging needs. By employing multivariate statistical techniques, correlation analysis, regression modeling, K-Means clustering, and principal component analysis (PCA), this research examines the relationships between imaging device density, healthcare infrastructure capacity, population dynamics, and healthcare spending. Additionally, it evaluates the strategic implications of AI integration in improving imaging accessibility and infrastructure efficiency. The findings aim to provide evidence-based recommendations for health policymakers to support equitable, efficient, and AI-informed imaging infrastructure planning across diverse healthcare contexts.

LITERATURE REVIEW

Recent literature from 2015 to 2024 has examined the evolving relationship between medical imaging technologies and healthcare infrastructure, focusing on two main dimensions: (1) the integration of artificial intelligence (AI) into advanced imaging modalities such as CT, MRI, and PET, and its impact on clinical effectiveness; and (2) the influence of demographic variables, population structure, income distribution, healthcare spending, and digital capacity on the equitable distribution of imaging technologies.

AI-Based Medical Imaging Applications

Artificial intelligence has fundamentally reshaped diagnostic imaging, particularly in radiology. Convolutional neural networks (CNNs) and deep learning algorithms have been shown to enhance lesion detection, classification, and segmentation in CT and MRI images, significantly improving diagnostic workflows (Deng *et al.* 2024; Hwang *et al.* 2024). In the context of PET imaging, AI-based models have improved molecular image analysis and contributed to advanced applications in drug development and immunotherapy (McGale *et al.* 2024). Countries like South Korea, Germany, and the Netherlands have led large-scale initiatives to incorporate AI-supported imaging systems into clinical practice, reflecting both technical maturity and policy-driven strategies (Hwang *et al.* 2024). However, gaps in infrastructure and workforce readiness remain critical barriers in middle- and low-income settings.

Hybrid Imaging Technologies: PET/CT and PET/MRI

Hybrid imaging modalities such as PET/CT and PET/MRI integrate anatomical and functional imaging to enhance diagnostic precision. While PET/CT remains dominant due to speed and cost-efficiency, PET/MRI offers superior soft tissue contrast, especially valuable in oncology (Lei *et al.* 2024). The incorporation of AI into hybrid imaging technologies remains an emerging but promising trend, offering benefits such as enhanced image reconstruction, faster processing times, and improved targeting for personalized therapy (McGale *et al.* 2024).

Low-Dose CT (LDCT) and Deep Learning Techniques

Growing concern over radiation exposure in CT imaging, particularly in lung cancer screening has driven the adoption of low-dose CT (LDCT). However, the reduced image quality in LDCT can hinder accurate diagnosis. Recent studies have demonstrated that deep learning-based denoising algorithms significantly enhance LDCT image clarity, enabling safer, high-frequency screenings without compromising diagnostic reliability (Zubair *et al.* 2024). These AI-driven solutions are particularly critical in resource-constrained environments where cost-effective yet accurate imaging is required.

Healthcare Infrastructure and Device Distribution

The distribution of medical imaging devices is strongly associated with national healthcare infrastructure metrics such as ICU capacity, hospital bed density, and trained personnel availability (Rhodes *et al.* 2012; Phua *et al.* 2020). High-income countries typically exhibit higher device density due to their established institutional frameworks and sustained investments. In contrast, countries with infrastructure deficits face limited diagnostic reach, regardless of healthcare spending levels (Murthy *et al.* 2015). Recent models suggest that capital investment, not merely operational expenditure, better predicts device acquisition trends across countries (Organisation for Economic Co-operation and Development (OECD) 2023).

Optimal Infrastructure Planning and Socioeconomic Determinants

Healthcare capacity planning increasingly incorporates variables such as population aging, chronic disease prevalence, mortality rates, and epidemiological transitions (Hou *et al.* 2020). However, emerging research emphasizes the role of income inequality, urban–rural divide, and health service accessibility in determining whether technological investments translate into actual clinical usage (Jones 2024). Countries with similar income levels often exhibit vastly different imaging accessibility outcomes due to differing investment priorities and policy efficiency. AI-based predictive modeling tools are increasingly utilized to optimize device placement, hospital capacity, and staff allocation (Hwang *et al.* 2024).

Digital Transformation and Health Information Technologies

The integration of information technology into healthcare systems has transformed operational management, diagnostics, and resource optimization. Tools such as electronic health records (EHR), health information exchanges (HIE), and AI-enhanced analytics platforms enable data-driven decision-making across both clinical and administrative domains (Agarwal *et al.* 2010). IT integration has been linked to reduced operational costs, better inventory control, improved service coverage, and ultimately, improved patient outcomes (Fichman *et al.* 2011). These systems form the backbone for AI deployment, ensuring that technological advances are embedded within an actionable infrastructure.

MATERIAL AND METHODS

This study adopts a quantitative research design to analyze the global distribution of medical imaging devices and their relationship with healthcare infrastructure capacity across OECD countries. The selected time frame, 2015–2023, was determined based on the completeness and consistency of OECD Health Statistics data across countries. This period also encompasses the COVID-19 pandemic years (2020–2022), which significantly influenced healthcare investment priorities, diagnostic demand, and infrastructure strain.

The dataset includes detailed indicators on the number of imaging devices per country, including computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and mammography units, as well as national population size, total healthcare expenditures, and general healthcare infrastructure indicators (e.g., hospital bed availability and ICU capacity). To explore the relationships between variables and underlying structures, the following analytical techniques were applied:

Correlation analysis was used to evaluate linear associations between device density, infrastructure capacity, population, and healthcare expenditure. Linear regression analysis assessed the predictive strength of these variables on imaging device availability, focusing on statistical significance and R^2 values. K-Means clustering was implemented to categorize countries based on similarity in device density and infrastructure. The optimal number of clusters (k=5) was identified using the elbow method, minimizing within-cluster sum of squares. Principal Component Analysis (PCA) was applied to standardized variables using Python's scikit-learn library. PCA helped identify latent dimensions, such as population-driven demand versus infrastructure-driven supply, that explain cross-national variability in device deployment. All statistical analyses were performed using SPSS version 28 and Python (pandas, numpy, matplotlib, scikit-learn) to ensure reproducibility and analytical robustness.

RESULTS

Growth Trends in Medical Imaging Devices

Between 2015 and 2023, the total number of medical imaging devices increased substantially across most OECD countries. CT and MRI devices experienced steady growth, driven by technological advancements, expanded clinical applications, and the increasing adoption of AI-supported diagnostic workflows. In contrast, PET device growth was more gradual, constrained by higher costs and limited specialist use cases (Figure 1).

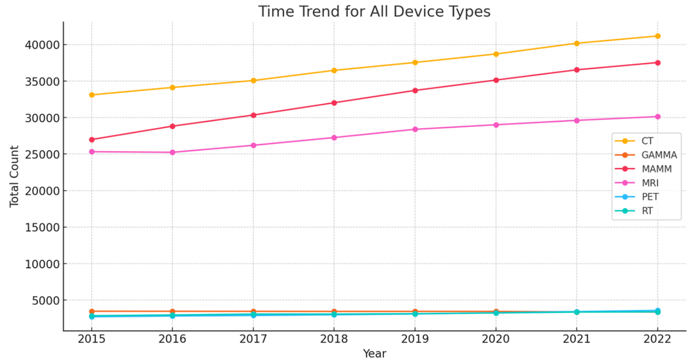

Figure 1 Annual Growth Trend of Medical Imaging Devices

Device availability showed pronounced variation among OECD nations. Countries such as Germany, Italy, South Korea, and Australia recorded the highest availability of CT scanners. MRI and PET scanners were predominantly concentrated in high-income countries such as Italy, France, Germany, and South Korea. In contrast, lower-income countries, including Mexico, Romania, and Turkey, exhibited significantly lower device densities, often limited by capital investment and workforce constraints (Figure 2).

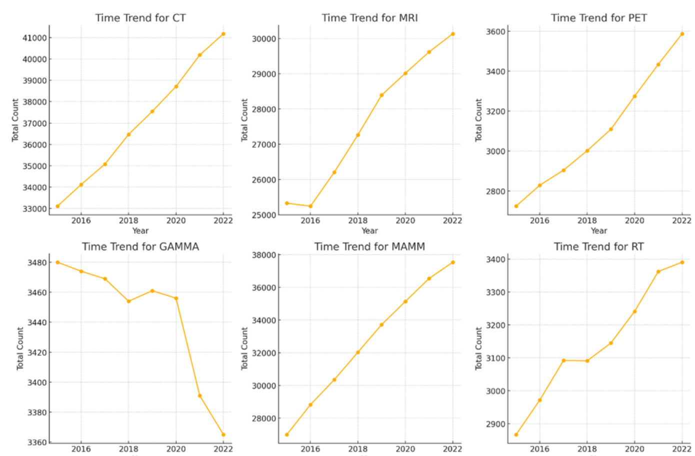

Figure 2 Time Trend of Medical Devices

Per Capita Medical Device Distribution

An analysis of per capita device density revealed that smaller, high-income countries such as Iceland, Denmark, and South Korea maintained the highest device availability per 100,000 population. Conversely, countries with large populations, such as Turkey and Mexico, displayed lower per capita values, despite possessing high absolute numbers of devices. This suggests that national population size can obscure disparities in accessibility when using total counts alone.

Correlation and Regression Analysis

Correlation analysis revealed strong positive associations between imaging device density and healthcare infrastructure capacity ($\rho = 0.77$), as well as population size ($\rho = 0.87$). In contrast, healthcare expenditures exhibited weaker correlations with device density ($\rho \approx 0.41 - 0.55$), indicating that fiscal inputs alone are not sufficient to explain technology diffusion.

Linear regression modeling confirmed that infrastructure capacity was the most significant predictor of device density ($R^2 = 0.827$,

$p < 0.01$), reinforcing the importance of investment in physical and institutional capacity alongside procurement strategies.

Clustering Analysis and PCA

Using K-Means clustering ($k = 5$), countries were grouped based on similarities in imaging device density and healthcare infrastructure. The highest-density cluster included the United States, Germany, and Japan, while mid-tier clusters featured countries such as Turkey, Poland, and Hungary. Low-density clusters encompassed Romania, Mexico, and Lithuania.

PCA results showed that the first two principal components explained a substantial portion of the variance. The first component was driven primarily by population size and device availability, while the second reflected infrastructure indicators such as hospital beds per capita. Interestingly, healthcare expenditure did not load heavily on either component, further supporting the idea that structural capacity and policy prioritization—rather than spending levels—are primary determinants of imaging availability (Figure 3).

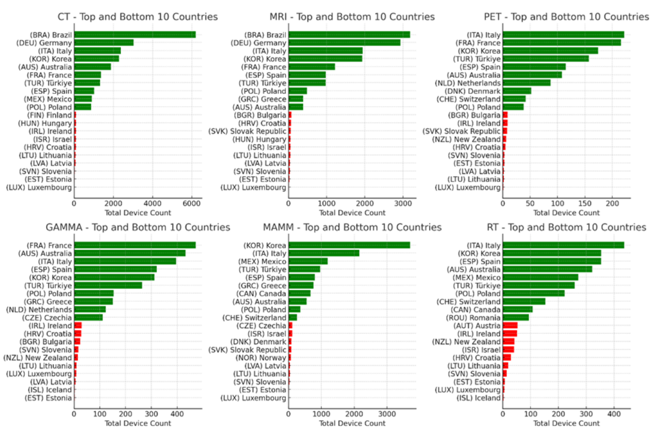

Figure 3 Comparison of Medical Imaging Device Availability: Top and Bottom 10 Countries

Medical Device Distribution by Population

Detailed device distribution analysis by population and income level highlighted structural inequities. Countries such as Australia, Greece, and South Korea ranked highest in per capita CT availability, while South Korea, Finland, and Germany led in MRI density. PET device access was highest in Denmark, the Netherlands, and Switzerland, while Romania, Lithuania, and Mexico ranked lowest.

Mammography distribution followed similar patterns: wealthier countries demonstrated higher access, while lower-income nations lagged behind. Gamma devices (e.g., gamma cameras for nuclear medicine) were found predominantly in Western Europe, with significantly limited availability in Turkey, Romania, and Mexico. Radiotherapy device distribution was similarly uneven, Italy, South Korea, and Spain exhibited the highest per capita RT density, while Estonia, Slovenia, and Luxembourg ranked lowest.

These variations are closely tied to health policy strategies, income distribution, and national investment models. Countries with strong healthcare governance and capital planning maintained high per capita access, even when overall population size was small (Figure 4).

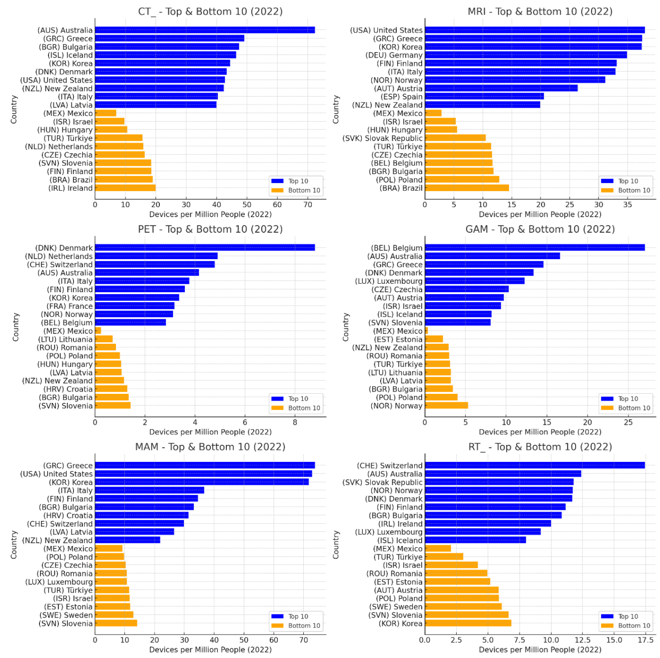

Figure 4 Medical Device Distribution by Population

K-Means Clustering and PCA Results

To further explore patterns of similarity among OECD countries regarding imaging technology deployment and healthcare infrastructure, both K-Means clustering and Principal Component Analysis (PCA) were conducted.

K-Means Clustering Results: K-Means clustering was applied to standardized data including imaging device density (CT, MRI, PET, Mammography), hospital bed availability, and population size. The elbow method was used to determine the optimal number of clusters, with $k = 5$ selected based on minimization of within-cluster sum of squares (WCSS). The resulting five clusters showed clear stratification by healthcare development levels:

Cluster 1 – High Density, High Infrastructure: Countries such as Germany, Japan, and the United States showed both high imaging device density and robust infrastructure, reflecting sustained investment and mature healthcare systems.

Cluster 2 – High Per Capita but Small Population: Iceland, Denmark, and Finland stood out for their extremely high per capita device availability, despite relatively small populations. These countries have high health expenditure per capita and strong national planning frameworks.

Cluster 3 – Mid-Range Device Availability with Strong Infrastructure: South Korea, France, and Italy had relatively balanced device distributions, supported by universal health coverage and active AI adoption in radiology.

Cluster 4 – Moderate Density, Growing Capacity: Countries like Turkey, Hungary, and Poland fell into this intermediate category. They showed moderate device availability and growing infrastructure, often supported by recent health transformation programs.

Cluster 5 – Low Density, Limited Capacity: Mexico, Romania, and Lithuania were clustered due to limited imaging infrastructure, low device-per-capita ratios, and overall constrained healthcare budgets.

This analysis reveals that imaging device distribution is not solely dependent on healthcare expenditure, but rather on broader institutional capacity, policy prioritization, and long-term capital investment strategies.

Principal Component Analysis (PCA) Results: PCA was conducted on the same standardized dataset to uncover the underlying structure influencing imaging technology distribution. The first two principal components (PC1 and PC2) explained 78.5% of the total variance.

PC1 (Population-Infrastructure Component): Heavily loaded with population size, hospital bed density, and overall device counts, this component reflects the scale and institutional readiness of national healthcare systems.

PC2 (Technology Efficiency Component): Primarily associated with per capita device availability and mammography coverage, this component differentiates between high-efficiency systems and those with uneven or resource-constrained allocation. Interestingly, healthcare expenditure did not significantly load onto either component, supporting earlier regression findings that spending levels alone are insufficient predictors of imaging technology diffusion. Instead, structural indicators, such as population health demand and infrastructure scale, emerged as more critical.

Countries such as South Korea and Germany showed strong performance across both components, while Turkey, Mexico, and Romania loaded high on PC1 (population) but low on PC2 (per capita efficiency), suggesting challenges in translating investment into accessible services.

DISCUSSION

This study offers comprehensive insights into the global landscape of medical imaging technologies, revealing the extent to which their availability is shaped by healthcare infrastructure, demographic realities, and policy direction. Consistent with prior research (Rhodes *et al.* 2012; Phua *et al.* 2020), the results confirm a strong association between imaging device density and hospital bed capacity, signifying that physical infrastructure remains a foundational determinant of technology diffusion. High-income countries with mature institutional frameworks, such as Germany, South Korea, and Japan, demonstrate higher imaging accessibility, while resource-constrained nations lag behind, despite increasing healthcare budgets (Murthy *et al.* 2015).

Importantly, the findings challenge the assumption that healthcare expenditure alone ensures equitable technology access. Regression and PCA analyses clearly illustrate that spending levels have weaker explanatory power than infrastructure indicators and population-driven demand (Hou *et al.* 2020; Jones 2024). This underscores the necessity of incorporating capital investment data and strategic planning variables into future assessments. A system may invest heavily in healthcare, yet without operational efficiency or infrastructure readiness, the impact on imaging accessibility remains limited.

The study also highlights the transformative potential of artificial intelligence in medical imaging, particularly in enhancing diagnostic precision and reducing operational burden. AI-supported low-dose CT and PET/MRI modalities, as discussed in recent literature (Lei *et al.* 2024; Zubair *et al.* 2024), exemplify the shift towards data-driven, personalized diagnostics. Countries with advanced digital ecosystems (e.g., South Korea) are actively integrating AI tools into radiology workflows, but adoption remains uneven across the OECD, often constrained by infrastructure, workforce readiness, and policy frameworks.

Moreover, the COVID-19 pandemic, covered within the study's 2015–2023 timeline served as an inflection point, prompting urgent diagnostic capacity expansion in several countries. However, those with pre-established infrastructure and coordinated planning responded more effectively, reinforcing the idea that system resilience stems from long-term investment, not crisis-driven funding alone.

The intersection between imaging technologies and healthcare economics is deeply mediated by information technology integration. Tools like EHR systems, AI-based analytics, and digital hospital infrastructure enhance not only decision-making but also cost-efficiency and outcome optimization (Fichman *et al.* 2011). The synergy between physical infrastructure and digital capabilities will be essential as healthcare systems transition toward more predictive, preventive, and personalized models.

CONCLUSION

Ensuring equitable access to advanced medical imaging technologies requires more than increasing healthcare expenditure. Evidence presented in this research points to the primacy of infrastructure development, population-based planning, and capital investment over general budget growth. Countries with effective alignment between these domains tend to achieve both higher device availability and more balanced per capita distribution. The role of artificial intelligence is becoming increasingly central, particularly in improving diagnostic precision, operational efficiency, and healthcare outcomes. However, technological integration must be accompanied by investments in digital infrastructure, workforce readiness, and ethical governance to be effective. The disparity in AI readiness among OECD countries reflects broader systemic differences in healthcare strategy and innovation adoption.

Future policy efforts should prioritize the creation of AI-compatible healthcare environments where imaging technologies are part of a broader ecosystem, combining hardware, data infrastructure, and clinical intelligence. In addition, upcoming research should expand on this work by incorporating longitudinal device usage data, national capital investment indicators, and digital health maturity indices. Such multidimensional analyses will better inform strategic decisions and foster more resilient, inclusive, and technologically adaptive healthcare systems.

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Ethical standard

The author has no relevant financial or non-financial interests to disclose.

Availability of data and material

Data used in this study are publicly available through the OECD Health Statistics database.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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