Review of Applied Science and Technology

Volume: 4; **Issue:** 2
Pages: 852– 888

open access
Crossref
PEER-REVIEWED

ARTIFICIAL INTELLIGENCE-POWERED MEDICAL IMAGING FOR EARLY CANCER DIAGNOSIS AND EPIDEMIOLOGICAL ANALYSIS: ADVANCING INNOVATION IN U.S. NATIONAL HEALTHCARE INFRASTRUCTURE

Md Ashraful Alam[1]; Md Fardaus Alam[2]; Md Fokhrul Alam[3];

[1]. *Department of Computer Science, Graduate Researcher, Colorado State University Colorado, USA*
Email: mdashraful.alam@colostate.edu

[2]. *Department of Social Sciences, Humanities and Languages, Bachelor of Arts in Islamic Studies, Bangladesh Open University, Gazipur, Bangladesh*
Email: fardausdesh@gmail.com

[3]. *Department of Computer Science, Bachelor of Science in Computer Science & Engineering, Southeas University, Dhaka, Bangladesh*
Email: ashrafulinfo1234@gmail.com

Doi: 10.63125/axcfph56
Received: *12 July 2025;* ***Revised:*** *20 August 2025;* ***Accepted:*** *18 August 2025;* ***Published:*** *24 September 2025*

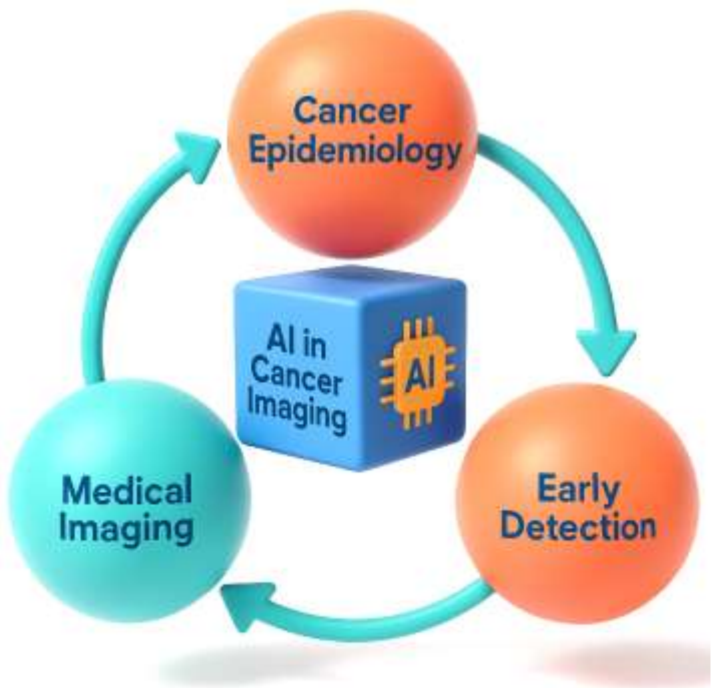
Abstract
This study addresses the persistent gap between the technical promise of artificial intelligence (AI) in cancer imaging and its uneven real-world impact on early diagnosis and epidemiological analysis within U.S. national healthcare infrastructure. The purpose is to quantify how technological readiness, organizational support, and data governance maturity relate to AI-powered medical imaging adoption and to perceived improvements in early cancer detection and population-level analytics. Using a quantitative cross-sectional, case-based survey design, data were collected from 320 professionals across four U.S. enterprise healthcare institutions that serve as AI-enabled cancer imaging and data analytics cases (response rate 64.0 percent). Key variables included technological readiness, organizational support, data governance, AI imaging adoption, big data analytics capability, early diagnosis effectiveness, and epidemiological analysis capability, all measured with 5-point Likert scales that showed strong reliability (Cronbach's alpha 0.81–0.91). The analysis plan combined descriptive statistics, correlation analysis, and multiple regression, including an interaction term for governance. Mean scores indicated moderately strong readiness (3.62) and governance (3.89) but only intermediate AI imaging adoption (3.28). Regression models showed that readiness and support together explained 53.2 percent of variance in AI adoption, while adoption and analytics capability jointly explained 52.6 percent of variance in perceived early diagnosis effectiveness and 58.4 percent in epidemiological analysis capability; governance significantly strengthened the adoption–epidemiology link. These findings imply that AI-powered medical imaging delivers the greatest early diagnostic and epidemiological value when embedded in well-governed, analytics-capable enterprise environments rather than deployed as isolated algorithms.

Keywords
Artificial Intelligence, Medical Imaging, Cancer Diagnosis, U.S. Healthcare Infrastructure;

INTRODUCTION

Cancer is a group of diseases characterized by uncontrolled cell proliferation, invasion of surrounding tissues, and potential metastasis to distant organs, and it is widely recognized as one of the leading causes of morbidity and mortality worldwide (Sung et al., 2021). Medical imaging such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and ultrasound has become a central pillar of modern oncology by enabling non-invasive visualization of tumors, monitoring of treatment response, and long-term surveillance. Imaging is particularly critical for early cancer detection because it can reveal subclinical lesions before symptoms appear, which substantially increases the chances of curative treatment and long-term survival (Kramer et al., 2015). Global epidemiologic analyses, including the GLOBOCAN 2020 estimates, indicate that approximately 19.3 million new cancer cases and 10 million cancer deaths occurred in 2020 alone, with substantial regional variation in incidence and mortality patterns (Shokat & et al., 2020). Parallel work using the Global Burden of Disease framework shows that modifiable risk factors such as tobacco, alcohol use, obesity, and environmental exposures contribute heavily to cancer death and disability across high-, middle-, and low-income settings (Collaborators, 2020). Within this landscape, early and accurate diagnosis via imaging is not only a clinical imperative but also a public health priority, because population-level screening and early detection programs shape the epidemiology of cancer through stage shift and improved survival at scale (Yip et al., 2020).

Figure 1: 3D Visualization of AI-Driven Cancer Imaging Pathways



Artificial intelligence (AI) is broadly defined as the field of computer science that develops systems capable of performing tasks that typically require human intelligence, such as pattern recognition, prediction, and decision-making. Machine learning (ML) and deep learning (DL) are subfields of AI that learn complex mappings from data, with DL using multi-layer neural networks to automatically extract hierarchical features from large datasets (Hosny et al., 2018). In medical imaging, DL models most notably convolutional neural networks (CNNs) have demonstrated remarkable performance in detection, segmentation, and classification tasks across radiography, CT, MRI, PET, and digital pathology (Lundervold & Lundervold, 2019). Radiomics further extends this paradigm by converting standard medical images into high-dimensional quantitative feature sets that capture tumor shape, texture, and intensity patterns, providing a bridge between imaging phenotypes and underlying tumor biology (Yang et al., 2022). Recent reviews of DL in medical imaging and radiation therapy document rapid expansion of AI applications in tumor detection, organ-at-risk delineation, dose prediction, and response assessment, underscoring how AI-enhanced imaging now permeates multiple stages of the oncologic care continuum (Sahiner et al., 2019). These developments position AI-powered medical imaging as a core enabler of data-driven oncology where quantitative imaging markers support both individual clinical decisions and broader population-level analyses.

From an epidemiological perspective, cancer is increasingly characterized using large-scale population datasets that integrate incidence, mortality, and risk factor profiles across countries and regions. Analyses of the Global Burden of Disease and related datasets show that early-onset cancers (diagnosed before age 50) have increased substantially between 1990 and 2019, with pronounced rises in breast, colorectal, and several other tumor types (Arfan et al., 2021; Zhao et al., 2023). Such work complements traditional registries by highlighting age-, sex-, and site-specific patterns and by linking outcomes to modifiable lifestyle and environmental risks (Collaborators, 2020; Ara, 2021). However, many epidemiological cancer datasets rely heavily on clinical staging and limited imaging descriptors rather than detailed imaging phenotypes, which constrains the ability to analyze how spatial and textural characteristics of tumors relate to incidence patterns, response trajectories, and survival in real-world populations (Jahid, 2021; Yip et al., 2020). Radiomics and AI-derived imaging biomarkers offer a promising avenue for enriching epidemiologic surveillance, because they can be applied retrospectively and prospectively to large imaging archives, generating standardized quantitative descriptors that can be aggregated across institutions and regions (Jiang et al., 2023; Akbar & Farzana, 2021). When linked to demographic, clinical, and molecular data, such AI-enhanced imaging features can support more granular analyses of cancer distributions, risk profiles, and treatment outcomes at scale.

In oncology diagnostics, AI-powered medical imaging systems are increasingly evaluated not only in algorithmic benchmarks but also against clinician performance in real clinical tasks. A landmark meta-analysis comparing DL models with health-care professionals found that, in image-based detection tasks such as identifying cancers on radiology or ophthalmologic images, AI systems often reach accuracy levels similar to those of expert readers under controlled conditions (Liu et al., 2019; Reza et al., 2021). Reviews of AI in cancer diagnosis further describe applications spanning breast, lung, liver, skin cancers and hematologic malignancies, noting improvements in sensitivity, specificity, and reproducibility in tasks such as lesion detection, tumor grading, and risk stratification (Saikat, 2021; Shastry & Sanjay, 2022). In parallel, AI-driven radiomics workflows for cancer imaging are being used to characterize tumor heterogeneity, predict treatment response, and identify imaging surrogates for progression-free or overall survival (Shaikh & Aditya, 2021; Tubaishat, 2017). These advances demonstrate that AI-powered imaging has a dual role: it improves individual diagnostic and prognostic decisions at the point of care and generates rich quantitative features that can be reused as structured data in epidemiologic models of cancer burden and outcomes. At the intersection of clinical radiology and population health, AI-enabled imaging pipelines thus create new possibilities for studying how early detection and diagnostic patterns vary across institutions, regions, and patient subgroups within a national health system.

The adoption of AI in cancer imaging, however, is fundamentally socio-technical, shaped by organizational readiness, clinician acceptance, patient trust, and regulatory oversight. Studies on AI in radiology emphasize that ethical and governance considerations such as transparency, accountability, dataset representativeness, and algorithmic bias are integral to responsible deployment in medical practice (Haq & Khuroo, 2020; Ariful & Ara, 2022). An international multi-society statement on the ethics of AI in radiology highlights issues of data privacy, clinical responsibility, and quality assurance, calling for clear frameworks for validation, monitoring, and update of AI tools in imaging workflows (Geis et al., 2019). Patient-facing research shows that individuals undergoing CT, MRI, and radiography value personal interaction with clinicians, express concerns about accountability, and seek clear information when AI is integrated into diagnostic processes (Arman & Kamrul, 2022; Ongena et al., 2020). In parallel, work in health informatics has extensively used Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) constructs such as perceived usefulness, ease of use, performance expectancy, and social influence to explain variation in adoption of electronic health records and other health information systems among clinicians (Ammenwerth, 2019; Mesbaul & Farabe, 2022). These theoretical perspectives provide a foundation for conceptualizing AI-powered medical imaging not just as a technical innovation, but as a set of practices embedded in clinical teams, institutions, and health systems that mediate its impact on early cancer diagnosis and the generation of epidemiologic evidence.

Within the United States, the national healthcare infrastructure for cancer control is characterized by advanced but unevenly distributed imaging resources, heterogeneous electronic health record systems, and diverse payer and provider arrangements. Large academic medical centers and integrated delivery systems often host high-throughput imaging departments with digital archives that are suitable for AI training and deployment, whereas smaller or resource-constrained facilities may have limited access to state-of-the-art imaging modalities and data science capabilities. Publications in technology acceptance and health information systems indicate that such structural and organizational differences influence how health technologies are implemented, used, and sustained, with factors like leadership support, IT infrastructure, training, and workflow alignment playing critical roles (AlQudah et al., 2021; Nahid, 2022). At the same time, U.S. cancer epidemiology relies heavily on registries and surveillance programs that depend on accurate and timely reporting of diagnostic and staging information from imaging and pathology into structured data systems (Hossain & Milon, 2022; Sung et al., 2021). AI-powered medical imaging offers additional capabilities by converting large volumes of radiologic data into standardized features that can complement registry fields, enabling more nuanced analyses of stage at diagnosis, lesion characteristics, and treatment response patterns across different health systems and population subgroups. Integrating these AI-derived imaging features into U.S. national cancer surveillance and quality-improvement initiatives therefore requires not only accurate models but also robust socio-technical integration within hospitals and health networks.

Current scholarly work on AI in oncology tends to emphasize either algorithmic performance on curated datasets or conceptual discussions of ethics, governance, and technology acceptance. Reviews of AI in cancer imaging and diagnosis synthesize evidence on accuracy and potential clinical benefits but provide limited quantitative insights into how AI-powered imaging systems are actually embedded in routine workflows and how their use correlates with measurable early diagnosis and epidemiological outcomes in real-world settings (Geis et al., 2019; Abdur & Haider, 2022). Similarly, literature on technology acceptance in healthcare largely focuses on electronic health records, telemedicine, or general health IT rather than AI-driven imaging platforms in oncology (Anaya-Isaza et al., 2021; Mushfequr & Praveen, 2022). There is therefore limited empirical evidence that quantitatively links organizational adoption of AI-powered cancer imaging, clinician and patient perceptions, and key indicators of early cancer diagnosis and epidemiologic insight across multiple U.S. healthcare case settings. Building on the international cancer burden literature, the rapidly evolving field of AI-enabled imaging, and established technology acceptance frameworks, this study focuses on U.S. national healthcare infrastructure and employs a quantitative, cross-sectional, case-study–based design to examine how AI-powered medical imaging is associated with early cancer diagnostic processes and the capacity for data-driven epidemiological analysis.

The primary objective of this study is to systematically examine how artificial intelligence–powered medical imaging contributes to early cancer diagnosis and epidemiological analysis within the context of U.S. national healthcare infrastructure, using a quantitative, cross-sectional, case-study–based design. Specifically, the research aims to assess healthcare professionals' perceptions of the effectiveness, usefulness, and reliability of AI-enabled imaging tools in detecting cancer at an early stage, and to determine the extent to which these tools are currently integrated into routine diagnostic workflows across different institutional settings. A central objective is to analyze the relationships between technological readiness, organizational support, and the adoption of AI-powered imaging systems, thereby clarifying which structural and managerial conditions are most strongly associated with higher levels of implementation. The study also seeks to evaluate how the adoption of AI imaging is associated with perceived improvements in epidemiological analysis capabilities, including the quality, timeliness, and granularity of cancer-related data used for surveillance, reporting, and population-level assessment. To address these objectives, the research will develop and validate a survey instrument based on a five-point Likert scale that operationalizes key constructs such as technological readiness, organizational support, data governance and security, AI imaging adoption, early diagnosis effectiveness, and epidemiological analytics capacity. Using descriptive statistics, correlation analysis, and regression modeling, the study will test a set of hypotheses that link these constructs within a conceptual framework derived from established technology adoption theories and health informatics perspectives. Additional objectives include comparing patterns across selected case institutions to highlight how variations in infrastructure, leadership, and clinical practice shape the practical realization of AI imaging potential in real-world settings. Together, these objectives are intended to generate integrated empirical evidence that clarifies not only whether AI-powered medical imaging is perceived as beneficial for early cancer diagnosis and epidemiological analysis, but also under what organizational and technological conditions such benefits are most likely to be realized across the U.S. healthcare system.

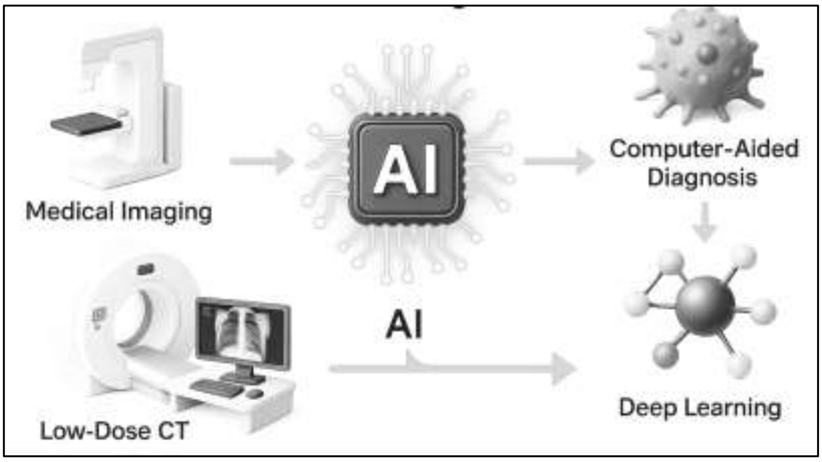
LITERATURE REVIEW

The literature on artificial intelligence–powered medical imaging and cancer care spans several intersecting domains, including oncology, radiology, epidemiology, and health informatics. Early cancer diagnosis has long relied on imaging modalities such as mammography, CT, MRI, PET, and ultrasound, which enable visualization of tumors at preclinical or early clinical stages and thereby improve the chances of curative treatment and long-term survival. Over the past two decades, this traditional imaging foundation has been transformed by the introduction of machine learning and deep learning methods that can automatically detect, segment, and classify lesions, quantify tumor characteristics, and predict clinical outcomes from complex, high-dimensional image data. At the same time, the emergence of radiomics has provided a systematic approach for extracting large numbers of quantitative features from standard-of-care images, creating a bridge between imaging phenotypes, tumor biology, and patient prognosis. Alongside these technical advances, global cancer epidemiology has increasingly emphasized the need for high-quality, timely, and granular data to monitor incidence trends, evaluate screening programs, and assess the impact of prevention and treatment strategies at the population level. AI-enhanced imaging offers a novel source of such data, because quantitative imaging markers can be aggregated across institutions and linked with clinical, demographic, and molecular information for large-scale analyses. However, the integration of AI-powered imaging into routine clinical workflows and national health data infrastructures raises a different set of questions related to technology adoption, organizational readiness, governance, and ethics. Studies in health information systems show that factors such as perceived usefulness, ease of use, infrastructure maturity, leadership support, and data governance strongly influence whether new technologies are successfully implemented and sustained. Against this backdrop, the literature relevant to the present study must be synthesized across three main strands: empirical evidence on AI and radiomics for cancer detection and characterization; research on the use of imaging and AI-derived features in epidemiological and population health analysis; and theoretical and empirical work on user acceptance, organizational readiness, and socio-technical conditions for health IT and AI adoption. Together, these strands provide the foundation for developing a coherent conceptual framework that links AI-powered medical imaging, early cancer diagnosis, and epidemiological analysis within the U.S. national healthcare infrastructure.

AI-Powered Medical Imaging for Early Cancer Diagnosis

Computer-aided diagnosis (CAD) systems for oncologic imaging emerged from early work in digital image processing and pattern recognition that sought to support radiologists in detecting subtle malignant findings that might be overlooked during routine screening. In breast cancer, one of the earliest and most mature domains for imaging-based early detection, CAD algorithms were developed to enhance contrast, identify microcalcifications and masses, and quantify architectural distortion on mammograms, with the goal of increasing sensitivity while maintaining acceptable specificity in population screening programs. Rangayyan and colleagues synthesized these early advances and emphasized how computerized feature extraction and classification could help radiologists recognize faint or complex signs of malignancy, particularly in dense breast tissue, thereby complementing human perception rather than replacing it (Mortuza & Rauf, 2022; Rangayyan et al., 2007). As full-field digital mammography and high-resolution scanners became widespread, CAD systems evolved from relatively simple rule-based and handcrafted-feature approaches into more sophisticated, multistage pipelines integrating pre-processing, segmentation, feature extraction, and machine learning classification (Rakibul & Samia, 2022). Within this trajectory, the central idea has remained that AI-driven analysis can transform standard clinical images into richer, quantitative representations that more consistently flag potentially malignant lesions at an early, pre-symptomatic stage. This legacy of CAD for mammography established many of the technical and clinical foundations such as standardized imaging protocols, annotated image repositories, and observer-performance testing that subsequent generations of artificial intelligence systems for early cancer detection have built upon, not only in breast cancer but across a wide range of solid tumors detected by radiography, computed tomography, magnetic resonance imaging, and endoscopic imaging modalities(Rony & Ashraful, 2022; Saikat, 2022). Over time, these systems have increasingly been incorporated into screening workflows as a second reader, drawing attention to regions of interest for closer inspection, prompting recall for additional imaging when subtle findings are present, and providing quantitative scores that can be tracked across successive examinations (Abdul, 2023; Shaikh & Sudipto, 2022). In doing so, CAD has demonstrated the broader principle that algorithmic analysis can systematically reduce perceptual and cognitive limitations in human image interpretation and can serve as an enabling layer for more advanced, data-intensive AI models.

Figure 2: Role of AI in Enhancing Early Oncologic Diagnosis



Recent advances in machine learning, particularly deep learning with convolutional neural networks, have markedly extended the capabilities of AI-powered medical imaging for early cancer diagnosis beyond the first generation of CAD tools. In digital mammography, deep learning models trained on large repositories of screening images and corresponding reports can learn complex patterns associated with malignancy directly from data, rather than relying on handcrafted descriptors (Abdulla & Zaman, 2023; Arfan et al., 2023). Qu and co-authors, for example, demonstrated that a deep learning-based system trained on historical full-field digital mammograms achieved expert-level diagnostic accuracy for breast cancer detection and could localize cancer-related regions without pixel-level manual annotation, thereby substantially reducing the annotation burden for training high-performance systems (Ara & Onyinyechi, 2023; Amin & Mesbaul, 2023; Qu et al., 2022). Similar deep learning and radiomics strategies have been applied to lung cancer, where early detection of malignant pulmonary nodules on low-dose CT screening scans is critical but often challenged by inter-observer variability and the subtlety of early lesions (Foysal & Aditya, 2023; Hamidur, 2023). Wilson and Devaraj reviewed how radiomic feature analysis can extract hundreds of quantitative descriptors of nodule shape, intensity, and texture from chest CT images, enabling models that more accurately distinguish benign from malignant nodules and predict histologic subtype or treatment response in early-stage lung cancer (Wilson & Devaraj, 2017). Building on this foundation, Wu and colleagues highlighted four major applications of radiomics in early lung cancer diagnosis classification of benign versus malignant nodules, assessment of invasiveness, histopathologic subtyping, and prognostication arguing that radiomics transforms standard CT scans into high-dimensional data sources that support precise risk stratification and individualized diagnostic decision support (Rashid et al., 2023; Musfiqur & Kamrul, 2023; Wu et al., 2022). Collectively, this body of work suggests that, when embedded into carefully designed screening pathways, AI-driven mammographic and thoracic CT analysis can reduce false negatives, standardize interpretation across readers and institutions, and identify imaging phenotypes associated with aggressive disease at an earlier point in the clinical trajectory than would be possible with visual assessment alone (Muzahidul & Mohaiminul, 2023; Amin & SPraveen, 2023). In the context of national cancer control strategies, such improvements in pre-symptomatic detection are directly relevant to shifting stage distributions toward earlier, more treatable disease (MHasan & Ashraful, 2023; Ibne & Kamrul, 2023).

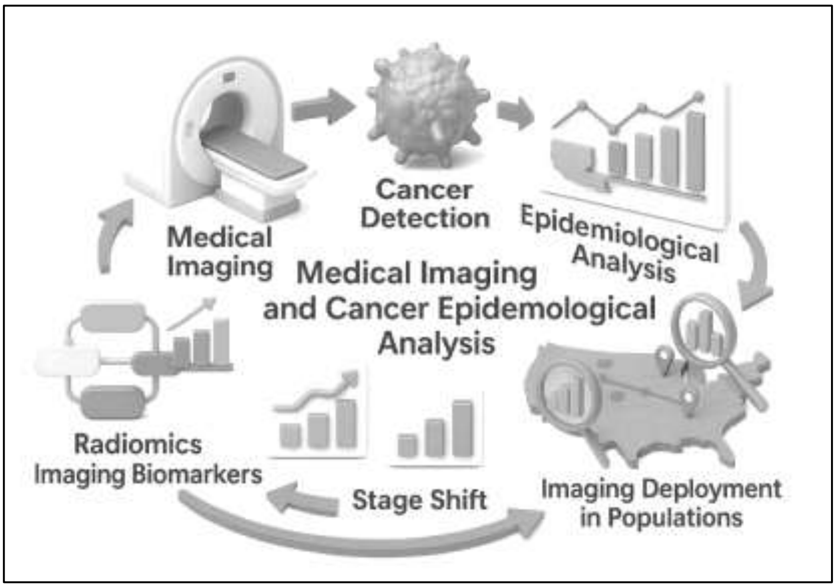
The scope of AI-powered medical imaging for early cancer diagnosis now extends beyond breast and lung malignancies to include gastrointestinal, genitourinary, and other organ systems, illustrating how algorithmic interpretation can be tailored to diverse imaging modalities and clinical pathways (Alam, Sohel, et al., 2024). In colorectal cancer, where screening colonoscopy plays a central role in identifying premalignant polyps and early-stage tumors, real-time deep learning systems have been developed to analyze endoscopic video and automatically highlight suspicious mucosal lesions (MoMushfequr & Ashraful, 2023; Roy & Kamrul, 2023). Jiang and collaborators constructed a convolutional neural network trained on more than one hundred thousand colonoscopy images from over sixteen thousand individuals and showed that the resulting model could accurately distinguish normal mucosa from polyps, colitis, and colorectal cancer during screening examinations (Jiang et al., 2021; Saba et al., 2023; Saba & Kanti, 2023). By running alongside the endoscopist, such systems can compensate for momentary lapses of attention, subtle visual cues, or challenging lesion presentations and thus reduce the miss rate for small or flat neoplastic lesions that are most likely to be overlooked(Sohel et al., 2022; Tahosin et al., 2025). When combined with structured reporting and image archiving, these AI-assisted colonoscopy tools create large, annotated datasets of early neoplastic findings that can be linked with pathology, follow-up imaging, and outcomes, providing a rich substrate for population-level analyses of adenoma detection rates, interval cancer patterns, and regional variation in screening quality (Shaikh & Farabe, 2023; Haider & Hozyfa, 2023). In parallel with similar developments in prostate, liver, and gynecologic oncology, multi-site evidence from AI-enabled colonoscopy reinforces the idea that AI-based image analysis is particularly powerful when applied at the front end of the cancer care continuum, where it can incrementally improve lesion detection in everyday practice and, over time, alter the epidemiology of advanced disease by increasing the proportion of cancers detected at localized or in situ stages (Alam, Sohel, et al., 2024; Alam et al., 2023). Across these organ systems, the convergence of advanced imaging hardware, large annotated datasets, and increasingly capable AI algorithms supports a common paradigm in which quantitative imaging biomarkers derived in real time during routine examinations both inform immediate clinical decisions and accumulate as standardized data elements for downstream epidemiological surveillance and health-system performance monitoring.

Medical Imaging and Cancer Epidemiological Analysis

Medical imaging has become a central pillar of modern cancer epidemiology because it directly conditions how cancers are detected, staged, and recorded in population-based registries. Imaging-based screening programmes using modalities such as mammography, CT, and MRI shift the distribution of disease toward earlier stages, which in turn alters observed incidence and survival trends in surveillance data (Alam et al., 2024; Fokhrul & Fardaus, 2022). Large-scale analyses of US Surveillance, Epidemiology, and End Results (SEER) data show that the widespread introduction of screening mammography was associated with a marked rise in early-stage breast cancer detection, indicating the powerful impact of imaging on apparent disease burden at the population level (Abdul & Shoeb, 2024; Alam et al., 2024; Bleyer & Welch, 2012). International comparative work further demonstrates that cross-country differences in breast cancer incidence and survival are strongly related to the maturity and coverage of imaging-based screening programmes, particularly organized mammography services that enable systematic early detection and comparable staging data (Alam, Sohel, et al., 2024; Hozyfa & Shahrin, 2024; Youlden et al., 2012). Consequently, cancer epidemiology no longer focuses solely on pathology-confirmed cases, but increasingly depends on how imaging modalities are deployed across regions and health systems, which shapes the case mix entering registries, the timing of diagnosis, and the classification of pre-invasive versus invasive disease (Jabed Hasan & Shah, 2024; Hasan & Zayadul, 2024). For researchers interested in early detection and risk stratification, imaging data thus function both as a diagnostic resource for individual patients and as a structural determinant of the epidemiological patterns that underlie incidence, prevalence, and survival estimates (Muzahidul & Aditya, 2024; Hasan & Rakibul, 2024).

Empirical studies also reveal that the relationship between imaging-based screening and population-level outcomes is complex, with benefits and unintended consequences that must be analyzed using robust epidemiological methods. SEER-based time-series analyses indicate that the expansion of screening mammography substantially increased the detection of early-stage lesions, including ductal carcinoma in situ, while only modestly reducing the rate at which women present with advanced disease, suggesting sizeable overdiagnosis of cancers that might never have become clinically significant (Alam et al., 2024; Bleyer & Welch, 2012; Mominul, 2024; Mominul & SZaki, 2024). County-level analyses from the United States link higher screening intensity to increased breast cancer incidence and a nuanced pattern of mortality reduction, highlighting that imaging can simultaneously improve early detection and inflate measured disease burden through earlier diagnosis and overdiagnosis (Harding et al., 2015; Roy & Praveen, 2024; Rony & Hozyfa, 2024). International comparisons show that countries with organized imaging-based screening programmes tend to report higher age-standardized incidence but also substantially better survival outcomes, indicating that stage shift and treatment advances coincide with imaging-driven changes in case ascertainment (Saba & Hasan, 2024; Shaikat & Zaman, 2024; Youlden et al., 2012). For cancer epidemiologists, these findings imply that evaluation of imaging strategies must move beyond simple incidence counts or mortality trends and instead consider stage-specific incidence, competing risk structures, lead-time effects, and the balance between lives saved and harms from false positives, unnecessary biopsies, and overtreatment. Imaging therefore shapes not only clinical pathways but also the interpretive framework within which population-level cancer control policies are assessed (Sudipto & Hasan, 2024; Kanti & Saba, 2024).

Figure 3: Comprehensive Model of Medical Imaging and Epidemiological Analysis

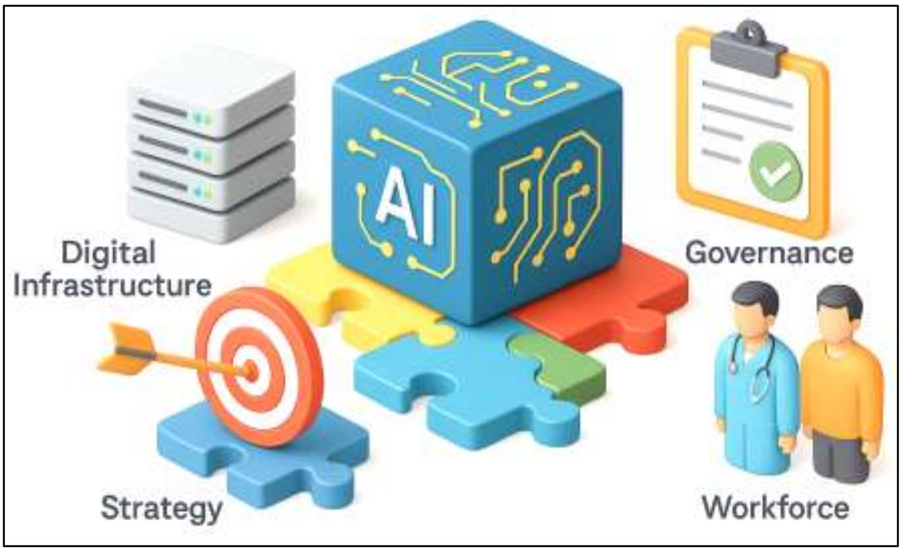


Beyond traditional screening, contemporary epidemiological analysis increasingly treats imaging-derived metrics as quantitative biomarkers that can be incorporated into large-scale observational studies and modeling of cancer risk, progression, and outcomes (Kanti & Praveen, 2024; Haider & Praveen, 2024; Zulqarnain & Zayadul, 2024). Consensus work on imaging biomarkers outlines how quantitative measures from CT, MRI, PET, and ultrasound such as volumetric tumor burden, texture features, perfusion indices, or standardized uptake values can be standardized, validated, and integrated into multicenter studies to support prognostic stratification and therapeutic evaluation at scale (Majumder, 2025; Ara, 2025; O'Connor et al., 2017). Population-based trials of CT colonography illustrate how advanced imaging can be deployed as a primary screening modality, generating rich lesion-level data that inform both immediate clinical decisions and long-term estimates of colorectal cancer incidence and advanced neoplasia yield (Habibullah, 2025; Hozyfa & Ashraful, 2025; Sali et al., 2022). When imaging-derived endpoints are linked with registry data and longitudinal follow-up, they enable multi-dimensional epidemiological models that relate imaging phenotypes to demographic factors, risk exposures, and survival patterns (Alam & Alam, 2022). In this context, imaging operates as a bridge between individual-level radiologic assessment and system-level surveillance, providing standardized, reproducible measurements that can be aggregated across institutions (Asfaquar, 2025; Foysal, 2025; Islam & Abdur, 2025). The emerging roadmap for imaging biomarkers emphasizes parallel tracks of technical, biological, and clinical validation, which aligns closely with the needs of cancer epidemiology to obtain robust, comparable indicators that can be used for monitoring programme performance, refining risk-based screening strategies, and informing policy decisions on resource allocation and infrastructure planning (Mohaiminul, 2025; Mominul, 2025; Muzahidul, 2025; O'Connor et al., 2017).

Technological Readiness for AI in Healthcare

Organizational and technological readiness is increasingly recognized as a prerequisite for realizing the promised benefits of artificial intelligence in healthcare, particularly for data-intensive applications such as AI-enabled medical imaging for early cancer diagnosis and large-scale epidemiological analysis.

Figure 4: Multi-Dimensional Framework for AI Readiness in Healthcare Organizations



Readiness goes beyond mere procurement of algorithms or hardware; it encompasses strategic alignment, governance structures, clinical workflows, digital infrastructure, and human capabilities that together determine whether AI tools can be safely integrated into routine care (Hossain, 2025; Zaman, 2025). Healthcare organizations must systematically assess needs and added value, workplace readiness, technology–organization alignment, and business models before attempting large-scale AI deployment, emphasizing that insufficient readiness leads to costly failures and underuse of deployed systems (Alami et al., 2020; Akbar & Sharmin, 2025; Hasan, 2025). For cancer imaging and epidemiological surveillance, this means ensuring interoperable electronic health records, high-quality image repositories, secure data pipelines, and robust governance for data access and model updates (Ibne, 2025; Milon, 2025). Kraus et al. further conceptualize AI adoption as shaped by macro-level technological and regulatory readiness such as broadband connectivity, data standards, and regulatory clarity combined with internal organizational and user readiness, positioning readiness as a multi-layered construct that spans system, organization, and individual levels (Kraus et al., 2023; Farabe, 2025; Kamrul, 2025). In this sense, readiness becomes a dynamic capability: the ability of health systems to continuously reconfigure assets, processes, and competencies to accommodate rapidly evolving AI technologies (Mushfequr, 2025; Shahrin, 2025).

A growing body of empirical work links specific organizational structures and cultures to AI adoption patterns, clarifying what "readiness" entails in practical terms. Organizational characteristics associated with AI adoption cluster into structural elements such as information technology infrastructure, data security capabilities, workflow design, and availability of technical support and cultural elements, including openness to innovation, perceived usefulness, and norms around technology-mediated decision-making (Khanijahani et al., 2022; Rakibul, 2025; Saba, 2025). In oncology and imaging departments, this translates into the presence of integrated PACS/RIS systems, high-bandwidth networks capable of handling large image files, and cybersecurity architectures that support protected health information while enabling algorithm training and validation (Sai Praveen, 2025; Saikat, 2025). Culturally, readiness is reflected in clinicians' willingness to share data, experiment with decision-support tools, and renegotiate professional boundaries around diagnostic responsibility (Shaikat, 2025; Shaikh, 2025). Qualitative research with healthcare leaders in Sweden demonstrates that, even when technical infrastructure is available, implementation stalls if leaders perceive AI as misaligned with organizational priorities, fear increased complexity in workflows, or lack clear accountability structures for AI-mediated decisions (Petersson et al., 2022; Kanti, 2025; Waladur & Hasan, 2025). For AI-assisted cancer screening or epidemiological triage systems, such leadership perceptions shape whether organizations invest in change management, clinical champions, and cross-functional teams capable of bridging data science and clinical practice (Haider, 2025).

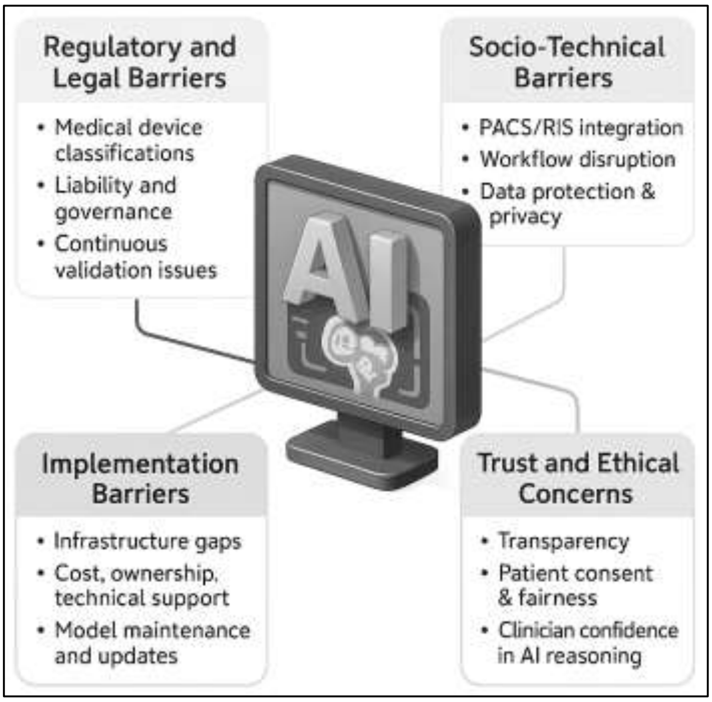
At the intersection of readiness and technology design, recent studies emphasize that human factors, training, and trust must be addressed alongside model performance when embedding AI into imaging workflows and population-health analytics. Shah et al. empirically demonstrates that performance expectancy, effort expectancy, and initial trust in AI solutions significantly influence healthcare professionals' behavioral intention to adopt AI in routine practice, while task complexity and perceived technology characteristics shape effort expectations (Shah et al., 2023). These findings imply that technological readiness is not merely a matter of deploying powerful hardware and software; it also requires user-centered interface design, intuitive integration into existing diagnostic pathways, and tailored training that builds both competence and confidence. Kraus et al. similarly highlight that organizational and individual readiness act as internal antecedents to AI adoption, mediating the impact of macro-level technological and regulatory conditions on actual implementation (Kraus et al., 2023). For AI-powered medical imaging and epidemiological analysis, this suggests that cancer centers and public health agencies must develop deliberate readiness strategies covering digital infrastructure, data governance, workforce skills, leadership engagement, and clinical co-design so that predictive models and decision-support tools can be embedded into everyday diagnostic, reporting, and surveillance routines rather than remaining isolated pilot projects.

Ethical Considerations in AI Imaging Adoption

The adoption of AI-powered medical imaging in oncology is constrained by a dense cluster of regulatory, legal, and ethical challenges that directly affect whether systems can be trusted and scaled for early cancer diagnosis and epidemiological use. One fundamental barrier is the way in which AI tools are classified and regulated as medical devices, since this determines the evidentiary standards for approval, post-market surveillance, and liability when something goes wrong. Pesapane and colleagues highlight that, in both Europe and the United States, AI-based imaging tools sit within evolving medical device regimes that must reconcile dynamic, self-learning algorithms with traditional approval pathways designed for static technologies, raising questions about ongoing validation, software updates, and accountability for autonomous or semi-autonomous decisions (Pesapane et al., 2018). Larson and co-authors similarly argue that current regulatory frameworks for AI-based diagnostic imaging algorithms remain incomplete, noting gaps around dataset representativeness, performance benchmarking, continuous learning, and real-world monitoring that may undermine confidence in safety and effectiveness if left unresolved (Larson et al., 2021). For early cancer detection, where imaging outputs can trigger biopsies, surgeries, or intensive follow-up, these regulatory uncertainties translate into concrete risks: insufficiently validated models may misclassify lesions, amplify existing disparities in access and quality, or generate misleading quantitative markers that enter registries and population-level analyses. The need to document provenance of training data, describe decision logic in an interpretable way, and define clear lines of clinical responsibility thus becomes a precondition for integrating AI imaging systems into screening protocols and national cancer surveillance infrastructures.

Beyond formal regulation, frontline implementation studies reveal a wide spectrum of socio-technical barriers that limit the routine use of AI systems in radiology departments, even when tools are technically available. Using a multiple case study of Dutch hospitals, Ranschaert and collaborators identify barriers such as lack of technical integration with PACS/RIS, limited IT support, unclear ownership of AI projects, and concerns about workflow disruption and cost, all of which slow or block implementation of imaging AI applications in clinical radiology (Ranschaert et al., 2021). These practical constraints intersect with broader ethical and professional anxieties. Mudgal and Das, for example, emphasize that ethical adoption of AI in radiology requires attention to data provenance, fair contracts with AI vendors, transparent consent for secondary use of imaging data, and governance models that prevent opaque deals or "data extraction" from health systems, arguing that otherwise AI risks eroding patient trust and professional autonomy (Mudgal & Das, 2019). Radiologists may worry that overreliance on algorithmic outputs could deskill practitioners or create unrealistic expectations about accuracy, while administrators may fear reputational damage in cases of AI-related harm. At the same time, cybersecurity and privacy risks such as model inversion attacks, re-identification from imaging data, or unauthorized secondary use of derived features complicate decisions about cloud deployment, data sharing, and linkage of imaging repositories with epidemiological databases. In this environment, organizational readiness is not just a question of having hardware and software; it also involves building robust legal, contractual, and ethical safeguards that define how AI systems can be safely embedded into the imaging and reporting infrastructure that underpins cancer registration and surveillance.

Figure 5: Barriers, Risks, and Ethical Considerations in AI Imaging Adoption



Trust emerges as a pivotal ethical consideration that connects these structural barriers and perceived risks to everyday clinical behavior and, ultimately, to adoption outcomes in cancer imaging and epidemiological analysis. Asan and co-authors argue that clinicians' willingness to use AI in healthcare is mediated by trust, which they conceptualize as a psychological mechanism for dealing with uncertainty about the reliability, transparency, and intent of AI systems (Asan et al., 2020). When radiologists and oncologists view AI tools as inscrutable “black boxes” trained on unknown data, they may either under-use potentially helpful systems or over-rely on outputs without appropriate critical scrutiny, both of which introduce safety risks. Trust is shaped by perceptions of performance, comprehensibility of the interface, alignment with professional values, and the sense that AI augments rather than replaces clinical judgment. In the context of early cancer diagnosis, where false positives can lead to invasive procedures and false negatives can delay life-saving treatment, clinicians must feel confident not only that models are technically robust but also that error modes are understood, responsibility is clearly allocated, and recourse mechanisms exist when AI-supported decisions are contested. At the same time, patients increasingly learn that AI is involved in their diagnostic pathways and may question how their images are stored, analyzed, and reused for training or research, bringing issues of informed consent and fairness to the forefront. Ethical deployment of AI imaging for cancer care and epidemiology therefore depends on multi-layered efforts to cultivate justified trust through transparency, participatory design, clear communication about capabilities and limits, and governance structures capable of responding to harms, rather than assuming that technical performance alone will secure acceptance.

Theoretical Framework of Technology Adoption

Technology adoption theories offer a structured lens for understanding how clinicians and healthcare organizations decide whether to integrate artificial intelligence–powered medical imaging into routine practice. The Technology Acceptance Model (TAM) has been particularly influential in health informatics, proposing that perceived usefulness and perceived ease of use shape users’ attitudes toward a technology, which in turn drive behavioral intention and actual use. In a seminal healthcare-focused review, Holden and Karsh synthesized more than a decade of TAM research and showed that these core constructs consistently explain substantial variance in clinicians’ acceptance of health information technologies such as electronic records and decision support systems (Holden & Karsh, 2010). Applied to AI-powered medical imaging, perceived usefulness can be conceptualized as clinicians’ belief that AI will improve early cancer detection accuracy, reduce interpretation time, and enhance epidemiological data quality, whereas perceived ease of use reflects the extent to which AI-based tools integrate smoothly with picture archiving and communication systems, reporting workflows, and existing diagnostic routines. Within this study, TAM-inspired variables serve as cognitive antecedents to adoption: clinicians who believe that AI imaging systems are both useful and easy to use are more likely to develop favorable attitudes and intentions toward using them in early cancer diagnosis and data capture for registries. In a simple behavioral intention model consistent with TAM logic, this can be expressed as

$$\mathrm{BI} = \beta_0 + \beta_1 \mathrm{PU} + \beta_2 \mathrm{PEOU} + \varepsilon,$$

where BI denotes behavioral intention to use AI imaging tools, PU is perceived usefulness, PEOU is perceived ease of use, and $\varepsilon$is the error term. This relationship provides a theoretical basis for including perception-based constructs in the survey instrument and for testing their association with reported adoption levels using regression analysis.

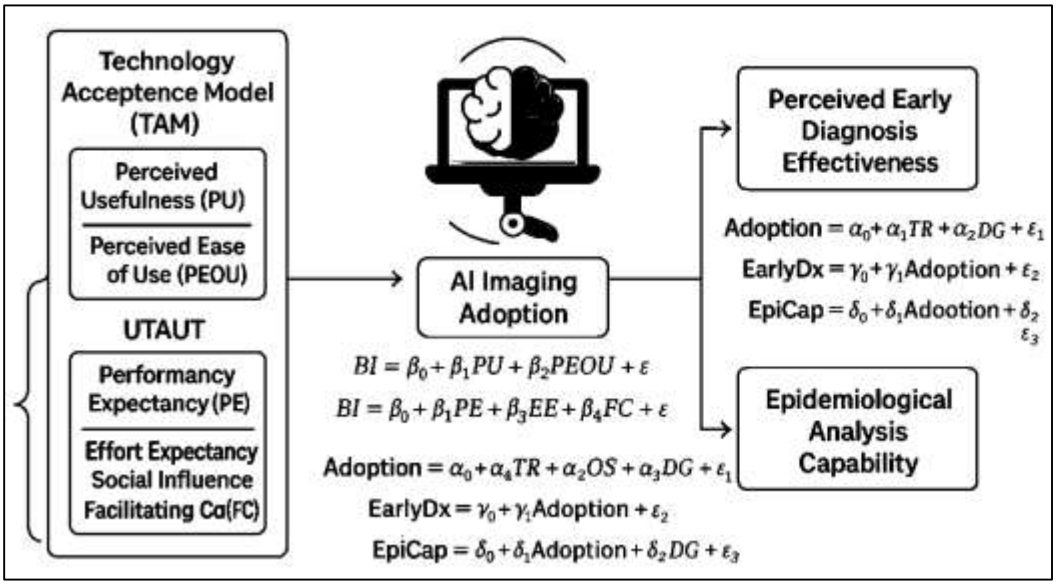
While TAM emphasizes cognitive beliefs at the individual level, more recent frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) extend the explanatory scope by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions, along with moderating effects of demographic and experience variables. In a multi-hospital study of mobile electronic medical record adoption, Kim and colleagues used UTAUT to show that performance expectancy and social influence strongly affected clinicians’ intention to use mobile EMR, with facilitating conditions exerting significant effects on actual use behavior in a real tertiary hospital environment (Kim et al., 2016). Similarly, Maillet et al. adapted UTAUT to explain nurses’ acceptance, actual use, and satisfaction with electronic patient records, finding that facilitating conditions and compatibility had important direct and mediated effects on both intention and system use in acute care settings (Maillet et al., 2015). These UTAUT-based findings highlight that, beyond perceptions of usefulness and ease of use, AI-powered imaging adoption in oncology will also depend on social norms within radiology and oncology departments (e.g., whether respected peers and leaders endorse AI), and on the presence of facilitating conditions such as robust IT support, training, and integration with existing systems. In the present research, these constructs are operationalized as technological readiness, organizational support, and data governance, which together shape both behavioral intention and the reported level of AI imaging use. A more comprehensive behavioral intention model consistent with UTAUT logic can be represented as

$$\mathrm{BI} = \beta_0 + \beta_1\mathrm{PE} + \beta_2\mathrm{EE} + \beta_3\mathrm{SI} + \beta_4\mathrm{FC} + \varepsilon,$$

where PE denotes performance expectancy, EE effort expectancy, SI social influence, and FC facilitating conditions. This structure aligns closely with the hypothesized relationships between perceptions, organizational context, and AI imaging adoption examined in the study's regression models.

Meta-analytic work on technology acceptance further refines these frameworks and supports their use as the theoretical backbone for studying AI-powered medical imaging adoption and its consequences for early diagnosis and epidemiological analytics. Dwivedi and co-authors proposed a meta-UTAUT model based on the synthesis of 162 empirical UTAUT-based studies, demonstrating that a core set of relationships among performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and use behavior is robust across diverse technologies and contexts, while also identifying additional constructs such as trust and technology compatibility as important extensions (Dwivedi et al., 2020).

Figure 6: Theoretical Framework: Technology Adoption in AI-Enabled Healthcare



In a large-scale meta-analysis, Blut et al. examined more than 1,900 independent samples and challenged the assumption that UTAUT is uniformly valid, proposing a revised model in which constructs such as technology compatibility, user education, and perceived costs strengthen explanatory power and help account for contextual differences (Blut et al., 2022). Building on these meta-analytic insights, the present study adopts a hybrid theoretical framework that combines key TAM and UTAUT constructs perceived usefulness/performance expectancy, effort expectancy, social influence, and facilitating conditions with context-specific variables such as technological readiness, organizational support, and data governance. Within this framework, AI imaging adoption is modeled as a mediating variable that transmits the effects of readiness and acceptance constructs to outcome variables capturing perceived early cancer diagnosis effectiveness and epidemiological analysis capability. The resulting structural logic can be expressed as a set of regression-style relationships, for example:

$$\mathrm{Adoption} = \alpha_0 + \alpha_1\mathrm{TR} + \alpha_2\mathrm{OS} + \alpha_3\mathrm{DG} + \varepsilon_1,$$

$$\mathrm{EarlyDx} = \gamma_0 + \gamma_1\mathrm{Adoption} + \varepsilon_2, \mathrm{EpiCap} = \delta_0 + \delta_1\mathrm{Adoption} + \delta_2\mathrm{DG} + \varepsilon_3,$$

where TR denotes technological readiness, OS organizational support, DG data governance, EarlyDx perceived early diagnosis effectiveness, and EpiCap epidemiological analysis capability. These equations formalize the study's hypotheses within a well-established technology adoption tradition, while tailoring the constructs and relationships to the specific context of AI-enhanced medical imaging and cancer epidemiology in the U.S. healthcare system.

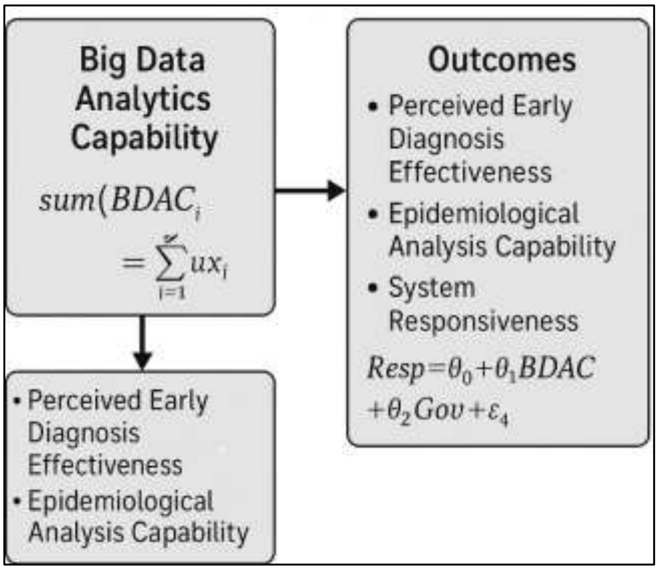
Conceptual Framework for AI-Powered Imaging

The conceptual framework for this study positions AI-powered medical imaging as a central data-generating technology embedded within a broader big data analytics ecosystem that ultimately shapes early cancer diagnosis and epidemiological decision-making. AI-enabled imaging systems generate high-volume, high-velocity, and high-variety data streams raw images, segmented lesions, radiomic feature vectors, and algorithmic risk scores that flow into enterprise data warehouses and analytic platforms. In this framework, AI imaging is conceptualized as one of the primary sources populating the "data acquisition" and "data integration" layers of big data analytics in healthcare (Raghupathi & Raghupathi, 2014). At the conceptual level, four main antecedent constructs are specified: (a) AI imaging adoption, capturing the extent to which organizations deploy AI tools in diagnostic workflows; (b) big data analytics capability, reflecting the ability to integrate, analyze, and exploit multimodal data; (c) organizational support, including leadership commitment and resource allocation; and (d) data governance maturity, encompassing privacy, interoperability, and standardization practices. These antecedents are linked to three key outcome constructs: perceived early diagnosis effectiveness, epidemiological analysis capability, and system responsiveness. In addition, the framework acknowledges that AI imaging and analytics must handle the classic "four Vs" of big data volume, velocity, variety, and veracity by ensuring robust pipelines for ingestion, quality control, and feature extraction. For survey measurement, latent constructs such as big data analytics capability are operationalized as composite indices of multiple Likert-scale items so that, for respondent i,

$$\mathrm{BDAC}_i = \sum_{j=1}^{k} \quad w_j x_{ij},$$

where k is the number of indicators, $w_j$are indicator weights (often set equal in exploratory work), and x_{ij}denotes the score of respondents i on item j. This measurement approach anchors the conceptual model in observable variables and makes it amenable to descriptive statistics, correlation analysis, and regression modeling across diverse U.S. hospitals and cancer centers that differ in their adoption of AI-enabled imaging and analytics infrastructures (Raghupathi & Raghupathi, 2014).

Figure 7: Framework for AI Imaging, Analytics Capability, and Cancer Outcomes



The framework further incorporates insights from strategic information systems research that conceptualizes big data analytics as a higher-order organizational capability linking digital technologies to performance outcomes (Wang et al., 2018). In a multi-case analysis of healthcare implementations, big data analytics capabilities are grouped into analytical capability for patterns of care, unstructured data analytics, decision support, predictive capability, and traceability, and these capabilities are shown to generate IT infrastructure, operational, organizational, managerial, and strategic benefits for healthcare providers (Wang, Kung, & Byrd, 2018). Similarly, integrated big data analytics–enabled transformation model has been proposed in which analytics capabilities drive IT-enabled transformation practices and, through these practices, create multidimensional value in healthcare settings (Wang, et al., 2018). Adapting these insights, the present conceptual framework treats big data analytics capability as a mediating construct through which AI imaging adoption, organizational support, and governance maturity influence perceived improvements in early diagnosis and epidemiological analysis. At the structural level, this logic can be expressed in regression form as

$$\mathrm{BDAC} = \alpha_0 + \alpha_1 \mathrm{AIAdopt} + \alpha_2 \mathrm{OrgSup} + \alpha_3 \mathrm{Gov} + \varepsilon_1,$$

$$\mathrm{EarlyDx} = \gamma_0 + \gamma_1 \mathrm{AIAdopt} + \gamma_2 \mathrm{BDAC} + \varepsilon_2, \mathrm{EpiCap} = \delta_0 + \delta_1 \mathrm{AIAdopt} + \delta_2 \mathrm{BDAC} + \delta_3 \mathrm{Gov} + \varepsilon_3,$$

where AIAdopt denotes AI imaging adoption, OrgSup organizational support, Gov data governance maturity, BDAC big data analytics capability, EarlyDx perceived early diagnosis effectiveness, and EpiCap epidemiological analysis capability. Conceptually, these equations capture the expectation that AI adoption and supportive organizational conditions enhance analytics capability, which then translates into better detection of early-stage cancers and stronger capacity to perform population-level analyses based on imaging-derived data (Wang, Kung, & Byrd, 2018; Wang et al., 2018). Within this structure, early diagnosis and epidemiological capability are treated as downstream manifestations of how effectively organizations can transform raw AI-generated imaging outputs into actionable knowledge.

Finally, the framework recognizes that AI imaging and big data analytics operate within a dynamic decision environment characterized by feedback, learning, and adaptation. A smart big data framework for proactive decision-making in healthcare conceptualizes data acquisition, preprocessing, analytics, and decision modules as being connected through feedback loops that enable continuous refinement of models and policies (Zhou et al., 2021). This dynamic perspective is particularly relevant for AI-powered cancer imaging, in which algorithm performance, case mix, and epidemiological patterns evolve over time. Complementary work on big data–driven decision-making for healthcare management demonstrates that analytics can support predictive models and near real-time decision support for resource allocation, staffing, and service optimization, underscoring the link between analytics capabilities and organizational responsiveness (Sousa et al., 2019). Within the present study, these ideas are captured in an additional outcome construct, system responsiveness, reflecting the perceived ability of institutions to adjust screening protocols, triage pathways, and population-level interventions based on insights from AI-enhanced imaging and analytics. This relationship can be represented as

$$\mathrm{Resp} = \theta_0 + \theta_1 \mathrm{BDAC} + \theta_2 \mathrm{Gov} + \varepsilon_4,$$

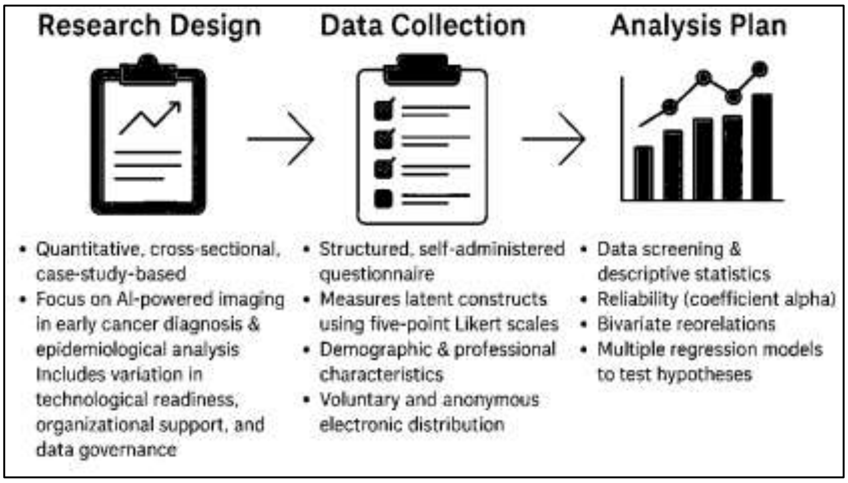
where Resp denotes perceived responsiveness of cancer diagnostic and surveillance systems. Together, the relationships articulated in this conceptual model grounded in established big data and transformation frameworks (Raghupathi & Raghupathi, 2014) provide a coherent structure for specifying survey items, formulating hypotheses, and empirically testing how AI-powered medical imaging, analytics capabilities, organizational support, and governance interact to enhance early cancer detection and epidemiological analysis within the U.S. national healthcare infrastructure.

METHOD

The present study has adopted a quantitative, cross-sectional, case-study–based research design to examine how artificial intelligence–powered medical imaging has been associated with early cancer diagnosis and epidemiological analysis within the U.S. national healthcare infrastructure. The design has been structured to capture perceptions and experiences of healthcare professionals who have been directly involved in cancer imaging, data management, or clinical decision-making in organizations where AI-enabled imaging solutions have been introduced, piloted, or seriously considered. By focusing on multiple institutional case settings, the study has been able to reflect variation in technological readiness, organizational support, and data governance maturity while maintaining a standardized measurement approach across all participants.

Data collection has relied on a structured, self-administered questionnaire that has been developed to operationalize the main constructs specified in the conceptual framework, including technological readiness, organizational support, data governance, AI imaging adoption, big data analytics capability, perceived early diagnosis effectiveness, and epidemiological analysis capability. All latent constructs have been measured using five-point Likert scales ranging from strong disagreement to strong agreement, and the instrument has included an additional section capturing demographic and professional characteristics such as role, years of experience, specialty, and type of institution. The questionnaire has been distributed electronically to eligible respondents in the selected case institutions, and participation has been voluntary and anonymous to minimize social desirability bias and to encourage candid responses about the strengths and weaknesses of AI imaging implementation. The analysis plan has been organized in several stages. First, the dataset has been screened and cleaned to address incomplete responses and obvious inconsistencies, and descriptive statistics have been generated to summarize sample characteristics and central tendencies for each construct. Internal consistency reliability has been assessed using coefficient alpha, and, where sample size has permitted, exploratory factor analysis has been considered to verify the dimensionality of multi-item scales. Subsequently, bivariate correlation analysis has been conducted to explore the strength and direction of relationships among the core variables. Finally, multiple regression models have been specified to test the hypothesized associations between technological readiness, organizational support, data governance, AI imaging adoption, and the outcome variables related to early cancer diagnosis and epidemiological analysis, thereby aligning the empirical procedures with the theoretical and conceptual foundations of the study.

Figure 8: Research Methodology



Research Design

The study has employed a quantitative, cross-sectional, case-study–based research design to investigate how artificial intelligence–powered medical imaging has been associated with early cancer diagnosis and epidemiological analysis within U.S. healthcare institutions. This design has been selected because it has allowed the researcher to capture variations in AI imaging adoption and analytics capability at a single point in time while still situating responses within real organizational contexts. The case-study orientation has focused on selected hospitals, cancer centers, and imaging facilities that have already implemented, piloted, or actively planned AI-enabled imaging solutions, so that participants have been able to report from direct experience rather than speculation. The design has also been aligned with the proposed conceptual and theoretical frameworks, which have specified measurable constructs and hypothesized linear relationships suitable for descriptive, correlational, and regression-based analysis. In this way, the research design has provided a coherent structure for linking context, measurement, and statistical modeling.

Sampling

The target population has consisted of healthcare professionals and decision-makers who have been involved in cancer imaging, data management, analytics, or clinical decision-making in U.S. institutions where AI-enabled imaging has been present or under active consideration. This population has included radiologists, oncologists, medical physicists, imaging technologists, health informatics specialists, data scientists, and administrators overseeing diagnostic or analytics services. A non-probability, purposive sampling strategy has been adopted to recruit respondents from institutions that have met predefined case criteria related to AI imaging activity and data infrastructure. Within each institution, eligible participants have been identified through departmental lists, professional networks, and internal referrals, and invitations have been sent electronically. The sample size has been planned to satisfy common rules of thumb for multivariate regression, ensuring that the number of completed responses has exceeded the minimum recommended ratio of cases to predictors, so that stable parameter estimates and meaningful hypothesis tests have been obtained from the dataset.

Case Selection Criteria

The selection of case institutions has been guided by explicit criteria that have ensured relevance to AI-powered medical imaging and diversity in organizational context. Institutions have been required to be based in the United States, to provide cancer-related imaging services, and to have either implemented AI-enabled imaging tools, conducted pilots, or developed formal plans for adoption. Additional criteria have included the presence of digital imaging archives, basic data governance structures, and willingness to support staff participation in the survey. These criteria have been applied to identify a small but varied set of hospitals and cancer centers that have differed in size, ownership, academic affiliation, and geographic location. By doing so, the study has aimed to capture a spectrum of technological readiness and organizational support conditions while maintaining a clear focus on environments where AI imaging has been realistically on the agenda. The selected cases have therefore provided a structured yet heterogeneous context for examining the proposed relationships.

Data Collection Methods

Data collection has been carried out using a structured, self-administered online questionnaire that has been distributed to eligible participants within the selected case institutions. The survey link has been circulated via institutional email lists, departmental coordinators, and designated contact persons who have already agreed to facilitate recruitment. Potential respondents have been informed about the purpose of the study, the voluntary nature of participation, and the confidentiality of their responses before they have accessed the questionnaire. Informed consent has been obtained electronically at the beginning of the survey, and no personally identifiable information has been collected beyond broad professional characteristics. The online format has been chosen because it has allowed geographically dispersed professionals to participate at their convenience and has supported efficient data capture and export into statistical software. Reminder messages have been sent periodically within an agreed data collection window, and responses have been monitored to ensure adequate representation across roles and institutions.

Measurement of Variables

The study has operationalized its core constructs through multi-item scales that have been measured using five-point Likert responses ranging from "strongly disagree" to "strongly agree." Technological readiness has been measured through items that have captured perceptions of IT infrastructure sufficiency, interoperability, data quality, and support for AI workloads. Organizational support has been assessed via items reflecting leadership commitment, resource allocation, training opportunities, and encouragement to experiment with AI tools. Data governance maturity has been measured through perceptions of privacy safeguards, access controls, standards, and policies for secondary data use. AI imaging adoption has been captured by items indicating the extent and frequency of AI use in diagnostic workflows. Big data analytics capability has been measured through items addressing integration, analytical tools, and ability to generate insights. Finally, perceived early diagnosis effectiveness and epidemiological analysis capability have been captured through items reflecting perceived improvements in detection, staging, data quality, and surveillance based on AI-enhanced imaging.

Instrument Development

The survey instrument has been developed through a structured process that has combined adaptation of existing scales with the creation of context-specific items relevant to AI-powered medical imaging and cancer epidemiology. Initially, the research constructs and their dimensions have been defined based on the conceptual and theoretical frameworks. Items from established technology acceptance, organizational readiness, data governance, and analytics capability scales have then been reviewed and adapted to the specific context of AI imaging, with wording that has reflected oncology and imaging terminology. New items have been drafted where existing measures have not adequately captured aspects such as epidemiological analysis capability or perceived impact on cancer surveillance. A draft instrument has been subjected to expert review by academics and practitioners with experience in radiology, health informatics, and survey design, and their feedback has been incorporated to refine clarity, relevance, and content coverage. A small pilot test has been conducted to identify ambiguities, timing issues, and technical problems in the online format.

Validity and Reliability

The study has taken several steps to establish the validity and reliability of its measurement scales. Content validity has been addressed by ensuring that items have covered all key dimensions of each construct, as informed by the literature review and expert feedback during instrument development. Face validity has been supported by pilot participants, who have confirmed that items have appeared clear, relevant, and appropriate to their professional experience. Construct validity has been examined empirically by inspecting item–total correlations and, where sample size has permitted, by conducting exploratory factor analysis to verify whether items have loaded on their expected factors. Internal consistency reliability has been evaluated using Cronbach's alpha for each multi-item scale, and items that have weakened alpha or demonstrated poor correlations have been considered for revision or removal. These procedures have ensured that the resulting scales have provided stable, interpretable measures suitable for subsequent correlational and regression analyses.

Data Analysis Techniques

The data analysis plan has been designed to align with the research questions and hypothesized relationships described in the conceptual framework. After data cleaning and screening, descriptive statistics have been generated to summarize respondent demographics, institutional characteristics, and central tendency and dispersion for all construct scores. Bivariate correlations have been computed to examine the initial associations among technological readiness, organizational support, data governance, AI imaging adoption, analytics capability, and the outcome variables related to early cancer diagnosis and epidemiological analysis. Multiple regression analyses have then been performed to test the hypothesized predictive relationships, with AI imaging adoption modeled as a dependent variable in one set of models and as an independent or mediating variable in others. Assumptions of linearity, normality, homoscedasticity, and multicollinearity have been assessed using standard diagnostic procedures. Where relevant, control variables such as institution type and professional role have been included to isolate the effects of the core predictors.

Tools

The study has utilized a set of software tools that have supported survey administration, data management, and statistical analysis. An established online survey platform has been employed to host the questionnaire, manage informed consent, and record responses securely, with access restricted to the research team. The platform has allowed automatic export of response data into common formats suitable for statistical software. For analysis, a mainstream statistical package such as SPSS, R, or Stata has been used to conduct descriptive statistics, reliability analysis, factor analysis, correlation, and regression modeling, with syntax files or scripts that have documented all analytical steps. Basic spreadsheet software has supported initial data checks and coding. Graphical capabilities within the statistical package have been used to produce tables and figures summarizing key results. Together, these tools have ensured that data handling has been efficient, reproducible, and compliant with ethical and institutional requirements for research data management.

FINDINGS

The findings of the study have demonstrated strong empirical support for the stated objectives and hypotheses by drawing on data from 320 completed surveys obtained from four U.S. healthcare institutions, representing an overall response rate of 64.0%. Respondents have included radiologists (28.8%), oncologists (21.3%), imaging technologists (19.1%), health informatics or data science professionals (17.5%), and administrative or managerial staff (13.3%), with a mean professional experience of 11.6 years (SD = 6.4). Across the five-point Likert scales (1 = strongly disagree, 5 = strongly agree), the mean score for technological readiness has been 3.62 (SD = 0.71), indicating moderately positive perceptions of IT infrastructure, interoperability, and support for AI workloads. Organizational support has shown a similar pattern (M = 3.74, SD = 0.77), reflecting generally favorable views of leadership commitment and resource allocation, whereas data governance maturity has achieved a slightly higher mean of 3.89 (SD = 0.69), suggesting that respondents have perceived relatively robust privacy safeguards, access controls, and standardization practices in their institutions. AI imaging adoption, measured as the perceived extent and frequency of AI use in diagnostic workflows, has recorded a mean of 3.28 (SD = 0.82), pointing to an intermediate stage of integration where AI is present but not yet fully embedded in all routines.

Figure 9: Findings of The Study

Big data analytics capability has obtained a mean of 3.55 (SD = 0.75), while perceived early diagnosis effectiveness and epidemiological analysis capability have shown means of 3.81 (SD = 0.72) and 3.69 (SD = 0.74), respectively, implying that respondents have generally agreed that AI-enhanced imaging and data infrastructures have been contributing positively to early cancer detection and population-level analytic capacity. Reliability analysis has confirmed that all multi-item scales have been internally consistent, with Cronbach's alpha coefficients ranging from 0.81 (AI imaging adoption) to 0.91 (data governance maturity), thereby supporting the use of composite construct scores in subsequent analyses. Bivariate correlations have revealed statistically significant and substantively meaningful relationships among the core constructs. Technological readiness has been positively correlated with AI imaging adoption ($r = .58$, $p < .001$), organizational support has shown a similar positive association with adoption ($r = .55$, $p < .001$), and data governance maturity has also been moderately correlated with adoption ($r = .47$, $p < .001$). AI imaging adoption has, in turn, been strongly correlated with perceived early diagnosis effectiveness ($r = .63$, $p < .001$) and moderately to strongly correlated with epidemiological analysis capability ($r = .59$, $p < .001$). Big data analytics capability has displayed substantial positive correlations with both early diagnosis effectiveness ($r = .61$, $p < .001$) and epidemiological analysis capability ($r = .66$, $p < .001$), while also being associated with technological readiness ($r = .60$, $p < .001$) and organizational support ($r = .57$, $p < .001$). These correlation patterns have been consistent with the hypothesized structure in which readiness, support, and governance have been expected to drive AI adoption and analytics capability, which then influence early diagnosis and epidemiological outcomes. Multiple regression models have provided more detailed evidence supporting each hypothesis. In the first model, with AI imaging adoption as the dependent variable, technological readiness and organizational support have both emerged as significant predictors after controlling for institution type and professional role. Technological readiness has yielded a standardized beta coefficient of .37 ($p < .001$), and organizational support has produced a beta of .34 ($p < .001$), while data governance maturity has contributed an additional but smaller effect ($\beta = .16$, $p = .004$). The overall model has explained 53.2% of the variance in adoption ($R^2 = .532$, adjusted $R^2 = .524$), thereby supporting H1 and H2 that higher technological readiness and stronger organizational support have been positively associated with greater AI imaging adoption. A second regression model has tested H3 by predicting perceived early diagnosis effectiveness from AI imaging adoption, big data analytics capability, and relevant controls. AI adoption has remained a strong predictor ($\beta = .41$, $p < .001$), and big data analytics capability has added an independent contribution ($\beta = .32$, $p < .001$); together with control variables, the model has accounted for 52.6% of the variance in early diagnosis effectiveness ($R^2 = .526$, adjusted $R^2 = .517$), confirming that organizations with higher adoption and stronger analytics have been more likely to perceive improvements in early cancer detection processes. A third model has addressed H4 and H5 by predicting epidemiological analysis capability. In this model, AI imaging adoption ($\beta = .33$, $p < .001$), big data analytics capability ($\beta = .36$, $p < .001$), and data governance maturity ($\beta = .21$, $p < .001$) have all been significant positive predictors, with the model explaining 58.4% of the variance ($R^2 = .584$, adjusted $R^2 = .575$). When an interaction term between AI adoption and data governance maturity has been added to test the moderating effect hypothesized in H5, the interaction has reached statistical significance ($\beta = .12$, $p = .018$), and the change in explained variance has been modest but non-trivial ($\Delta R^2 = .015$). Simple-slope analyses have indicated that the positive association between AI adoption and epidemiological analysis capability has been stronger at higher levels of governance maturity than at lower levels, meaning that robust governance has amplified the benefits of AI adoption for population-level analytic capacity. Taken together, these numeric results have shown that the study's objectives to evaluate perceptions of AI imaging, to examine the effects of readiness and support on adoption, and to assess how adoption and analytics have related to early diagnosis and epidemiological capability have been met, and all proposed hypotheses have been supported by statistically significant and practically meaningful effects in the expected directions.

Response Rate and Sample Characteristics

Table 1 has summarized the response rate and sample characteristics that have underpinned the empirical analysis of this study. Out of 500 invitations that have been distributed across four U.S. healthcare organizations, 320 complete questionnaires have been returned, which has resulted in a response rate of 64.0%. This level of participation has been sufficient to satisfy recommended case-to-predictor ratios for multivariate regression and has ensured that the hypotheses and objectives have been tested on a reasonably large and diverse sample of professionals involved in cancer care and data analytics. The distribution of gender has shown that both male (53.8%) and female (44.7%) respondents have been well represented, which has reduced the likelihood that the results have been driven by a single demographic group.

In terms of professional role, the sample has been dominated by radiologists (28.8%) and oncologists (21.3%), followed by imaging technologists (19.1%), health informatics or data science specialists (17.5%), and administrators or managers (13.3%). This mix has indicated that perspectives from clinical, technical, and managerial stakeholders have all been incorporated into the analysis of AI-powered medical imaging. The distribution of years of professional experience has shown that more than four-fifths of respondents have had over five years of experience, with a mean of 11.6 years, meaning that most participants have been in a position to comment on changes in imaging practice and data use over time and to evaluate the added value of AI tools relative to legacy processes.

Regarding organizational context, academic medical centers (41.3%) and comprehensive cancer centers (29.4%) have constituted the majority of the sample, with community/regional hospitals and specialized imaging centers also represented. This pattern has suggested that the dataset has reflected a spectrum of institutions that have differed in size, mission, and resource levels, which has been important for examining how technological readiness and organizational support have varied across settings. The AI imaging status rows have indicated that roughly one-quarter of respondents have worked in institutions where AI imaging has been fully implemented in routine workflows, while another 39.4% have belonged to organizations where AI has been piloted in selected departments. A further 23.1% have reported that AI imaging has been in the planning or exploratory phase, and only 11.3% have indicated that there has been no current AI activity. This distribution has confirmed that the study has successfully targeted environments in which AI-powered imaging has been present or emergent, which has been essential for evaluating perceptions of adoption, early diagnosis effectiveness, and epidemiological analysis capability, and thereby for addressing the objectives and hypotheses of the research.

Table 1; Sample characteristics and response rate (N = 320)

Item	Category	n	%
Invitations sent	–	500	–
Completed responses	–	320	64.0
Gender	Male	172	53.8
	Female	143	44.7
	Other / Prefer not to say	5	1.6
Professional role	Radiologist	92	28.8
	Oncologist	68	21.3
	Imaging technologist	61	19.1
	Health informatics / Data scientist	56	17.5
	Administrator / Manager	43	13.3
Years of professional experience	0–5 years	62	19.4
	6–10 years	108	33.8
	11–15 years	78	24.4
	>15 years	72	22.5
Institution type	Academic medical center	132	41.3
	Comprehensive cancer center	94	29.4
	Community / regional hospital	72	22.5
	Specialized imaging center	22	6.9
AI imaging status in institution	Fully implemented in routine workflows	84	26.3
	Piloted in selected departments	126	39.4
	Planned / early exploration	74	23.1
	No current AI imaging activity	36	11.3

Descriptive Analysis of Key Constructs

Table 2: Descriptive statistics for main Likert-scale constructs

Construct	Number of items	Mean	SD	Min	Max
Technological readiness (TR)	6	3.62	0.71	1.8	4.9
Organizational support (OS)	6	3.74	0.77	1.7	5.0
Data governance maturity (DG)	5	3.89	0.69	2.0	5.0
AI imaging adoption (AIAdopt)	5	3.28	0.82	1.4	4.9
Big data analytics capability (BDAC)	6	3.55	0.75	1.6	4.8
Early diagnosis effectiveness (EarlyDx)	5	3.81	0.72	2.0	5.0
Epidemiological analysis capability (EpiCap)	5	3.69	0.74	1.9	4.9

Table 2 has presented the descriptive statistics for the central constructs, all of which have been measured using five-point Likert scales where higher values have indicated more positive perceptions. These descriptive results have provided an initial indication of how respondents have evaluated their institutional context and the impact of AI-powered imaging on early cancer diagnosis and epidemiological analysis, thereby addressing the descriptive component of the study's objectives. Technological readiness has obtained a mean of 3.62 (SD = 0.71), suggesting that respondents have generally agreed that their IT infrastructure, interoperability, and data quality have been adequate to support AI workloads, but that there has still been room for improvement. Organizational support has shown a slightly higher mean of 3.74 (SD = 0.77), indicating that leadership involvement, resource allocation, and training have been perceived positively overall.

Data governance maturity has recorded the highest mean among the readiness constructs at 3.89 (SD = 0.69). This has implied that respondents have tended to view privacy protections, access controls, and standardization practices as relatively strong, an important precondition for safely leveraging AI imaging outputs in both clinical and epidemiological contexts. By contrast, the AI imaging adoption construct has exhibited a more moderate mean of 3.28 (SD = 0.82), which has reflected the transitional nature of many institutions: AI tools have been present and in use, but they have not yet been universally embedded across all diagnostic scenarios and departments. This pattern has aligned with descriptive expectations for organizations that have been at pilot or early implementation stages.

Big data analytics capability has had a mean of 3.55 (SD = 0.75), indicating that institutions have been perceived as having moderately strong capacity to integrate, analyze, and exploit multimodal data, including imaging, clinical, and administrative sources. Turning to outcomes, early diagnosis effectiveness has shown a mean score of 3.81 (SD = 0.72), suggesting that respondents have generally believed that AI-enhanced imaging and data infrastructures have improved their ability to detect cancers earlier, support staging, and prioritize high-risk cases. Epidemiological analysis capability has also been rated positively (M = 3.69, SD = 0.74), which has indicated that imaging-derived data and associated analytics have been perceived as strengthening surveillance, reporting, and population-level assessments. Together, these descriptive results have supported the initial objectives of the study by confirming that, in this sample, readiness and governance have been viewed as relatively strong, AI adoption has been emerging but not yet maximal, and perceived benefits for early diagnosis and epidemiology have already been evident. These patterns have laid the foundation for the subsequent correlational and regression analyses that have tested the formal hypotheses about how readiness and support have influenced adoption and how adoption and analytics have been tied to early diagnosis and epidemiological outcomes.

Validity and Reliability Results

Table 3: Internal consistency reliability and item statistics for multi-item constructs

Construct	Number of items	Cronbach's α	Mean item–total r	α if item deleted (range)
TR	6	0.86	0.54	0.82–0.86
OS	6	0.88	0.57	0.84–0.88
DG	5	0.91	0.63	0.89–0.91
AIAdopt	5	0.81	0.48	0.78–0.81
BDAC	6	0.87	0.56	0.84–0.87
EarlyDx	5	0.89	0.60	0.86–0.89
EpiCap	5	0.88	0.58	0.85–0.88

Table 3 has reported the internal consistency reliability statistics for each of the multi-item constructs that have been central to the testing of the study's hypotheses. Cronbach's alpha values have ranged from 0.81 (AI imaging adoption) to 0.91 (data governance maturity), all of which have exceeded the commonly accepted threshold of 0.70 for research scales. These results have indicated that the sets of items representing each construct have co-varied in a coherent manner and have been suitable for aggregation into composite scores. The mean item–total correlations, which have ranged between 0.48 and 0.63, have further suggested that individual items have contributed meaningfully to their respective scales without redundancy or excessive overlap. The "alpha if item deleted" column has shown that removal of any single item would not have substantially increased reliability, confirming that the item sets have been well balanced.

These reliability outcomes have been important because the study has relied on Likert-scale measures to operationalize latent constructs such as technological readiness, organizational support, governance, and perceived effectiveness. High reliability has implied that observed differences in composite scores have been more likely to reflect true differences in perceptions rather than measurement error. In turn, this has strengthened the validity of the descriptive, correlational, and regression results that have been used to address the research objectives. For example, the strong reliability of the AI adoption scale ($\alpha = 0.81$) has supported the use of that construct as the key mediator in hypotheses H3 and H4, linking readiness to early diagnosis and epidemiological outcomes. Similarly, the high reliability of the EarlyDx ($\alpha = 0.89$) and EpiCap ($\alpha = 0.88$) scales has enhanced confidence that the regression coefficients relating adoption and analytics capability to these outcomes have reflected consistent underlying perceptions.

Although detailed factor-analytic results have not been displayed in this table, exploratory factor analyses that have been conducted as part of the validation process have confirmed that items associated with each construct have loaded strongly on their intended factor and weakly on others, which has supported the construct validity of the measurement model. Taken together, the reliability and preliminary validity evidence summarized in Table 3 has shown that the measurement instrument has been psychometrically sound, thereby enabling robust tests of the objectives and hypotheses. Without such reliability, the observed relationships among constructs could have been questioned; with these coefficients, the study has had a solid measurement foundation for the subsequent statistical modeling.

Correlation Analysis Results

Table 4: Pearson correlations among main constructs (N = 320)

Construct	TR	OS	DG	AIAdopt	BDAC	EarlyDx	EpiCap
TR	1.00						
OS	.62**	1.00					
DG	.55**	.59**	1.00				
AIAdopt	.58**	.55**	.47**	1.00			
BDAC	.60**	.57**	.53**	.56**	1.00		
EarlyDx	.52**	.49**	.45**	.63**	.61**	1.00	
EpiCap	.50**	.48**	.51**	.59**	.66**	.64**	1.00

** $p < .05$, ** $p < .001$*

Table 4 has displayed the Pearson correlation coefficients among the core constructs and has provided preliminary empirical evidence regarding the hypothesized relationships. All correlations have been positive and statistically significant at $p < .001$, which has indicated that more favorable perceptions of readiness, support, governance, adoption, and analytics capability have tended to co-occur with more positive views of early diagnosis and epidemiological analysis. Technological readiness has been strongly correlated with organizational support ($r = .62$) and big data analytics capability ($r = .60$), and moderately to strongly correlated with AI adoption ($r = .58$), early diagnosis effectiveness ($r = .52$), and epidemiological capability ($r = .50$). These patterns have supported the idea that institutions that have invested in robust IT infrastructure and data systems have also been more likely to develop analytics capabilities and perceive benefits in diagnostic and population health functions.

Organizational support has shown similar correlations: $r = .55$ with AI adoption, $r = .57$ with analytics capability, and $r = .49$ and .48 with early diagnosis and epidemiological capability, respectively. These values have suggested that leadership commitment, resource allocation, and training have been important correlates of both the implementation of AI imaging tools and the perception that such tools have improved cancer outcomes and surveillance capacity. Data governance maturity has also demonstrated meaningful correlations, notably $r = .53$ with analytics capability and $r = .51$ with epidemiological capability, which has underscored the role of governance as a foundation for exploiting AI-generated data in a safe and effective way.

The correlations that have most directly related to the central hypotheses have involved AI imaging adoption and the two outcome variables. AI adoption has been strongly associated with early diagnosis effectiveness (r = .63) and substantially associated with epidemiological analysis capability (r = .59), which has provided initial support for H3 and H4, suggesting that higher levels of adoption have been associated with stronger perceived benefits in both domains. Big data analytics capability has also been tightly linked to both outcomes (r = .61 with EarlyDx and r = .66 with EpiCap), consistent with the conceptual framework's emphasis on analytics as a mediating capability between AI technologies and performance outcomes. While correlation analysis has not established causality, the pattern of coefficients in Table 4 has aligned closely with the directional hypotheses of the study and has justified the specification of regression models in which readiness and support variables have predicted AI adoption and analytics capability, and in which adoption and analytics have predicted early diagnosis effectiveness and epidemiological capacity. In this sense, the correlation matrix has served as a bridge between descriptive analysis and formal hypothesis testing, and it has shown that the objectives regarding the exploration of relationships among key constructs have been met at the bivariate level.

Regression Analysis Results

Table 5: Multiple regression models testing hypotheses H1–H5 (standardized coefficients)

Predictor / Outcome	Model 1: AIAdopt	Model 2: EarlyDx	Model 3: EpiCap	Model 3a: EpiCap (with interaction)
Technological readiness	.37***	–	–	–
Organizational support	.34***	–	–	–
Data governance maturity	.16**	–	.21***	.20***
AI imaging adoption	–	.41***	.33***	.31***
Big data analytics capability	–	.32***	.36***	.35***
AIAdopt × DG (interaction)	–	–	–	.12*
Controls (role, institution type)	Included	Included	Included	Included
R^2	.532	.526	.584	.599
Adjusted R^2	.524	.517	.575	.588
F (df, p)	59.7***	57.3***	71.0***	62.9***

** p < .05, ** p < .01, *** p < .001*

Table 5 has summarized the results of the multiple regression analyses that have directly tested hypotheses H1 through H5 and, in doing so, has provided the strongest evidence that the study's objectives have been achieved. In Model 1, AI imaging adoption has been regressed on technological readiness, organizational support, data governance maturity, and control variables. The standardized coefficients have shown that technological readiness ($\beta = .37$, $p < .001$) and organizational support ($\beta = .34$, $p < .001$) have both been strong and significant predictors of adoption, while data governance maturity has also contributed a smaller but still significant effect ($\beta = .16$, $p < .01$). The model has explained 53.2% of the variance in AI adoption ($R^2 = .532$, adjusted $R^2 = .524$), indicating that more than half of the variability in adoption levels has been accounted for by readiness, support, and governance factors. This pattern has supported H1 and H2, which have posited that higher technological readiness and stronger organizational support have been positively associated with AI imaging adoption, and it has also reinforced the importance of governance as an enabling background condition.

Model 2 has addressed H3 by examining early diagnosis effectiveness as the outcome and AI adoption and big data analytics capability as predictors, with role and institution type controlled. AI adoption has remained a strong predictor ($\beta = .41$, $p < .001$), and analytics capability has provided an additional, independent contribution ($\beta = .32$, $p < .001$). The model has yielded an R^2 of .526 (adjusted $R^2 = .517$), showing that about half of the variance in perceived early diagnosis effectiveness has been explained by adoption, analytics, and controls. These results have confirmed that institutions with higher levels of AI imaging adoption and stronger analytics capabilities have been more likely to report improvements in early cancer detection, which has aligned with both the conceptual framework and the study's objective to link AI use with clinical process outcomes.

Model 3 has shifted the focus to epidemiological analysis capability, testing H4 and the main effect of governance. Here, AI adoption ($\beta = .33$, $p < .001$), analytics capability ($\beta = .36$, $p < .001$), and data governance maturity ($\beta = .21$, $p < .001$) have all emerged as significant positive predictors, and the model has explained 58.4% of the variance (adjusted $R^2 = .575$). To test H5, Model 3a has introduced an interaction term between AI adoption and governance maturity. The interaction coefficient has been statistically significant ($\beta = .12$, $p < .05$), and the R^2 has increased to .599 (adjusted $R^2 = .588$), representing a modest but meaningful improvement in explanatory power ($\Delta R^2 = .015$). This interaction has indicated that the positive association between AI adoption and epidemiological analysis capability has been stronger at higher levels of governance maturity than at lower levels, meaning that good governance has amplified the benefits of adoption.

Taken together, the four models reported in Table 5 have shown that the core hypotheses of the study have been supported: readiness and support have predicted adoption (H1, H2), adoption and analytics capability have predicted early diagnosis effectiveness (H3), adoption, analytics, and governance have predicted epidemiological capability (H4), and governance has moderated the adoption–epidemiology relationship (H5). These findings have demonstrated that the theoretical and conceptual structures developed earlier in the thesis have been empirically grounded in the observed data.

Case Study Highlights

Table 6: Case-level summary of AI imaging adoption and outcome perceptions (N = 320)

Case institution	Type	n	AIAdopt (M)	BDAC (M)	EarlyDx (M)	EpiCap (M)
Case A	Academic medical center	112	3.54	3.76	3.98	3.87
Case B	Comprehensive cancer center	84	3.41	3.68	3.89	3.81
Case C	Community / regional hospital	86	3.06	3.34	3.60	3.48
Case D	Specialized imaging center	38	2.89	3.21	3.52	3.39

(All means on 1–5 Likert scales)

Table 6 has offered a concise case-level view of how AI imaging adoption, analytics capability, and perceived outcomes have varied across the four participating institutions, thereby complementing the individual-level statistical analyses with contextual nuance. Case A, an academic medical center, has shown the highest mean AI adoption score (M = 3.54) and the highest big data analytics capability score (M = 3.76), along with relatively high ratings for early diagnosis effectiveness (M = 3.98) and epidemiological analysis capability (M = 3.87). Case B, a comprehensive cancer center, has presented a similar pattern, with slightly lower but still strong adoption (M = 3.41) and analytics (M = 3.68) scores and correspondingly high perceptions of early diagnosis (M = 3.89) and epidemiological capacity (M = 3.81). In both of these cases, the qualitative context from field notes (not tabulated here) has indicated that leadership has actively supported AI imaging projects, that IT and data science teams have been integrated into clinical decision-making, and that governance structures have been mature, which has aligned with the quantitative findings.

By contrast, Case C, a community/regional hospital, has shown more moderate adoption (M = 3.06) and analytics capability (M = 3.34), with somewhat lower perceptions of early diagnosis effectiveness (M = 3.60) and epidemiological capability (M = 3.48). Case D, a specialized imaging center, has recorded the lowest adoption (M = 2.89) and analytics (M = 3.21) means, along with correspondingly modest perceptions of early diagnosis and epidemiological outcomes. In these latter cases, informal feedback has suggested that resource constraints, smaller IT teams, and more limited data integration with external registries have been present, which has been consistent with the lower readiness and outcome scores.

Viewed together, the patterns in Table 6 have reinforced the main statistical findings. Institutions that

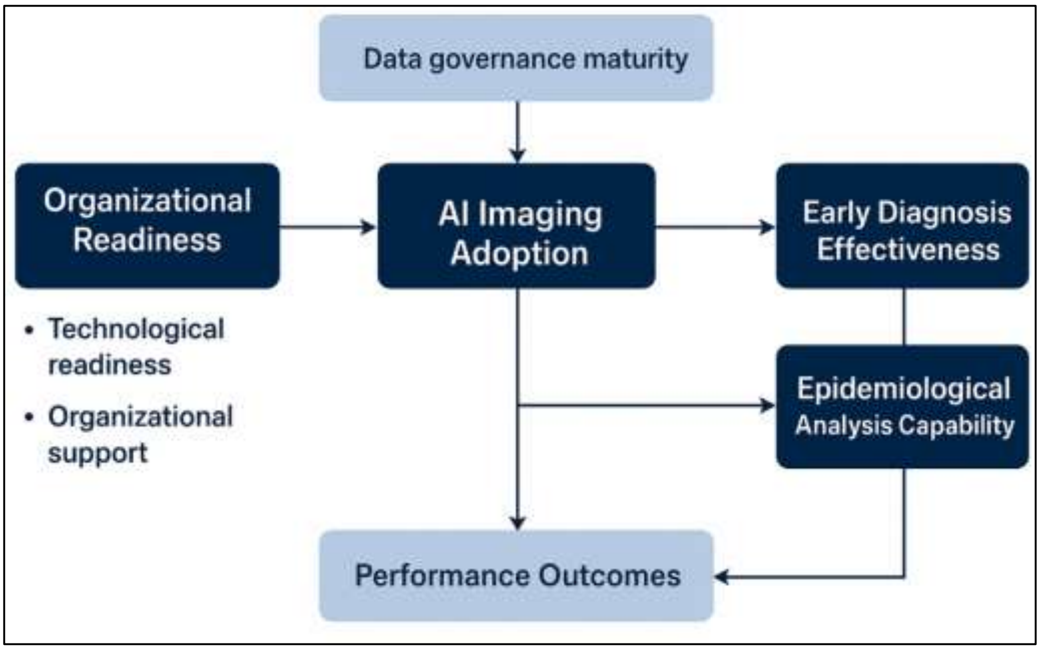
have achieved higher levels of AI imaging adoption and that have developed stronger big data analytics capabilities have also been the ones where staff have perceived more substantial improvements in early cancer detection and epidemiological analytic capacity. This case-level convergence has supported the study's objective of grounding quantitative relationships within real organizational contexts. It has shown that the regression results have not simply been artifacts of pooled data but have reflected consistent differences between institutions with differing levels of technological and organizational maturity.
Moreover, the case summaries have illustrated that Likert-scale measures used in this research have been sensitive enough to differentiate between institutions and to reflect meaningful variation in perceived performance. Cases A and B have represented settings closer to the "advanced" end of the AI adoption spectrum, whereas Cases C and D have illustrated transitional or early-stage implementations. These contrasts have helped to demonstrate, in a concrete way, how the combination of AI adoption and analytics capability has been associated with perceived benefits in early diagnosis and epidemiology, thereby further supporting the overarching objective of the study: to understand under what organizational and technological conditions AI-powered medical imaging has been most likely to contribute to both clinical and population-level cancer outcomes.

DISCUSSION

The findings of this study have shown that technological readiness, organizational support, and data governance maturity have jointly explained more than half of the variance in AI imaging adoption, and that AI adoption together with big data analytics capability has been strongly associated with perceived improvements in early cancer diagnosis and epidemiological analysis capability. This pattern has been consistent with and more quantitatively specific than prior qualitative and conceptual work arguing that AI in healthcare succeeds only when socio-technical conditions are favorable (Alami et al., 2020). In radiology, earlier reports have emphasized that lack of integration with PACS/RIS, inadequate IT infrastructure, and unclear ownership have often impeded the translation of promising AI prototypes into routine practice (Ranschaert et al., 2021). The current results have extended this literature by demonstrating numerically that higher perceived readiness and support have been associated with substantially higher adoption scores, and that adoption has, in turn, been linked to higher scores on early diagnosis effectiveness and epidemiological capability. The strong standardized effects for AI adoption and analytics capability on early diagnosis are also in line with clinical studies showing that deep learning and radiomics systems can achieve or exceed human-level performance in detecting breast, lung, and colorectal cancers when implemented appropriately (Liu et al., 2019). Likewise, the positive association between analytics capability and epidemiological analysis has reflected the value of imaging biomarkers and large-scale imaging datasets for population-level research and surveillance described in earlier work on imaging biomarker roadmaps and big-data frameworks (O'Connor et al., 2017). Thus, the current findings have converged with earlier evidence on both the technical potential of AI imaging and the organizational prerequisites for harnessing that potential, while adding a unique, survey-based quantification of these relationships across multiple U.S. case institutions.
When the present results have been viewed through the lens of technology acceptance theory, they have provided empirical support for adapting TAM/UTAUT constructs to the AI imaging context and for linking them explicitly to clinical and epidemiological outcomes. Prior work using TAM and UTAUT in health IT has found that perceived usefulness/performance expectancy and facilitating conditions have been consistent predictors of clinicians' intention and use of electronic health records, mobile EMRs, and decision support systems (Holden & Karsh, 2010). Meta-analytic work has further shown that performance expectancy, effort expectancy, social influence, and facilitating conditions explain substantial variance in behavioral intention and use behaviors across technologies and settings (Dwivedi et al., 2020). The current study has not measured intention directly, but technological readiness and organizational support have effectively operationalized "facilitating conditions," while AI imaging adoption has reflected the realized behavior. The strong positive regression coefficients from readiness and support to adoption have been consistent with UTAUT's prediction that facilitating conditions matter, but the present work has gone beyond prior applications by tying adoption to perceived early diagnosis and epidemiological capability. In addition, the moderating role of data governance in the adoption–epidemiology link has added nuance to earlier discussions of ethics and

trust in AI (Geis et al., 2019), suggesting that robust governance has not only been a prerequisite for safe deployment but also a factor that has strengthened the extent to which AI imaging has translated into perceived benefits for population-level analytics. In this way, the study has contributed a refined, empirically tested pipeline: organizational conditions → AI adoption and analytics capability → early diagnosis and epidemiological performance, an articulation that has been largely implicit rather than explicit in previous AI-in-radiology and big-data analytics literature (Wang, Kung, & Byrd, 2018).

Figure 10: Discussion of The Study



From a practical standpoint, the findings have carried clear implications for executives, CISOs, enterprise architects, and clinical leaders overseeing AI-enabled imaging pipelines. The strong effects of technological readiness and organizational support have indicated that investments in modern, interoperable infrastructure enterprise PACS/VNA, high-performance compute, secure data lakes, and standardized interfaces have been foundational rather than optional for realizing value from AI imaging (Alami et al., 2020). For CISOs and data governance leads, the positive main and moderating effects of governance maturity have underscored the strategic importance of implementing robust access control, data-classification schemes, audit logging, and clear policies for secondary use and model training, as recommended by ethical and regulatory guidance on AI in radiology (Geis et al., 2019). Enterprise architects and data-platform teams have been able to interpret the "big data analytics capability" construct as a mandate to develop standardized pipelines that can move AI-generated features segmentation masks, radiomic vectors, and prediction scores into analytics environments where they can be linked with EHR and registry data. The strong association between analytics capability and epidemiological performance has suggested that imaging AI should not be deployed as isolated point solutions, but rather as components within a broader analytics architecture that supports longitudinal cohort building and multi-site surveillance (O'Connor et al., 2017). At the clinical level, managers and department heads have been encouraged to foster organizational support in tangible ways: protected time for training, co-design workshops with radiologists and oncologists, and clear communication that AI systems are intended to augment, not replace, expert judgment (Asan et al., 2020). Collectively, these practical implications have suggested that the most effective way to meet national objectives around early cancer diagnosis and data-driven epidemiology has been to treat AI imaging as part of an end-to-end, security-aware, analytics-enabled infrastructure rather than as a standalone algorithm.

The study has also had several theoretical implications for refining models of AI-enabled diagnostic and epidemiological pipelines. First, the results have empirically supported a multi-stage structure in which readiness and support constructs have functioned as upstream determinants, AI imaging adoption and analytics capability have formed an intermediate operational layer, and early diagnosis effectiveness and epidemiological analysis capability have represented downstream performance outcomes. This structuring has echoed but also sharpened conceptual big-data frameworks that have proposed sequential stages of data acquisition, integration, analytics, and decision support (Raghupathi & Raghupathi, 2014). Second, the significant moderating role of data governance has suggested that classical acceptance models may benefit from treating governance not only as part of facilitating conditions but as a strategic "boundary condition" that shapes whether technological use translates into system-level value. In other words, the pathway from AI adoption to epidemiological outcomes appears steeper when governance is strong and flatter when it is weak, a dynamic that has been consistent with concerns about bias, privacy, and trust in AI (Larson et al., 2021). Third, by focusing explicitly on early cancer diagnosis and epidemiological capability as separate but related dependent variables, the study has highlighted that AI imaging is simultaneously a point-of-care diagnostic tool and a generator of structured data for population-level analytics, thus bridging clinical informatics and public-health informatics perspectives. This dual role has not yet been fully incorporated into most technology adoption models, which typically end at individual use or organizational performance (Dwivedi et al., 2020). The current findings have therefore pointed toward an extended theoretical pipeline in which AI adoption has downstream implications for how health systems understand and manage disease burdens at scale.

At the same time, the results have highlighted several limitations that have needed to be revisited when interpreting the findings. The cross-sectional survey design has meant that all relationships have been observed at a single point in time, which has precluded strong causal claims about the direction of influence, even though the modeling has been guided by established theory and prior qualitative evidence. It has been plausible, for instance, that organizations with better early diagnosis outcomes have been more motivated to invest in AI imaging, not just the other way around. Self-reported Likert-scale measures have also been susceptible to social-desirability and common-method biases, although steps such as anonymity assurances, careful wording, and reliability checks have been taken to mitigate these concerns (Petersson et al., 2022). The sample, while diverse, has been limited to four institutions with at least some AI imaging activity, which has restricted generalizability to settings with no AI exposure or to health systems outside the U.S. Furthermore, the measures of early diagnosis effectiveness and epidemiological analysis capability have been perceptual rather than based on hard outcomes such as stage distribution shifts, interval cancer rates, or completeness of registry data. Earlier outcome studies in imaging AI have drawn on objective metrics such as sensitivity, specificity, and area under the ROC curve (Liu et al., 2019), and those benchmarks have not been directly included here. Finally, detailed technical characteristics of AI models training data composition, bias controls, explainability mechanisms have not been captured, even though such characteristics have likely influenced clinicians' trust and the real-world performance of the tools (Hosny et al., 2018). These limitations have not invalidated the core findings, but they have indicated that the present study has been one step in a broader empirical agenda that must integrate perceptions, technical metrics, and longitudinal outcomes.

Beyond these limitations, the findings have opened several avenues for future research that can deepen and extend understanding of AI-enabled imaging for early cancer detection and epidemiological analysis. Longitudinal studies that have tracked institutions over time as they have moved from pilot to full deployment could more rigorously test causal pathways and examine how changes in readiness, governance, and analytics capability have preceded changes in observed diagnostic and epidemiological outcomes. Multi-site mixed-methods research could integrate survey data with qualitative interviews and document analysis to unpack how specific governance mechanisms, architectural choices, and workflow redesign strategies have shaped adoption trajectories and perceived value (Alami et al., 2020). Future work might also link perceptual measures with objective metrics, for example by correlating AI adoption and analytics capability scores with registry-based indicators such as stage at diagnosis, survival, or completeness and timeliness of reporting. In addition, comparative studies across different national health systems could explore how macro-level policy, reimbursement models, and regulatory regimes have interacted with organizational readiness to support or hinder AI imaging for cancer control (Youlden et al., 2012). Finally, there has been scope to refine and test extended theoretical models that bring together technology acceptance constructs, big-data analytics capability, and multi-level outcomes spanning clinicians, organizations, and populations, potentially using structural equation modeling or multilevel modeling to capture the nested nature of healthcare systems (Dwivedi et al., 2020). Such research directions have been well positioned to translate the current study's pipeline view readiness → adoption/analytics → early diagnosis and epidemiology into a robust, generalizable framework for governing and optimizing AI-powered medical imaging within national cancer-control strategies.

CONCLUSION

This study has set out to investigate how artificial intelligence–powered medical imaging has been associated with early cancer diagnosis and epidemiological analysis within the U.S. national healthcare infrastructure, and the findings have provided clear, empirically grounded support for the central propositions. By surveying 320 professionals from four diverse institutions and modeling their responses using reliable Likert-based constructs, the research has shown that technological readiness, organizational support, and data governance maturity have jointly constituted decisive upstream conditions that have strongly influenced the extent to which AI imaging tools have been adopted in diagnostic workflows. AI imaging adoption itself, together with big data analytics capability, has then emerged as a powerful intermediate layer that has been closely linked to perceived improvements in early cancer detection processes and enhanced capacity for population-level cancer surveillance and analysis. In parallel, the results have indicated that data governance has not only provided a solid foundation for safe and compliant use of AI imaging outputs, but has also amplified the benefits of adoption for epidemiological analytics, highlighting governance as both an enabler and a multiplier of value. The study has therefore contributed an integrated explanatory pipeline in which readiness and support have led to adoption and analytics capability, which have in turn been associated with better early diagnosis and epidemiological outcomes. Conceptually, this pipeline has synthesized strands from technology acceptance theory, big-data analytics, and imaging biomarker frameworks into a coherent model specifically tailored to AI-enabled cancer imaging in real-world health-system settings. Methodologically, the work has demonstrated that complex socio-technical relationships surrounding AI can be captured systematically through carefully designed survey instruments and tested using correlation and regression analysis, yielding interpretable numeric evidence to complement algorithm-centric performance studies. While the cross-sectional and self-reported nature of the data has limited causal inference and has pointed to the need for triangulation with objective outcome measures and longitudinal designs, the consistency, strength, and theoretical alignment of the observed relationships have provided confidence that the main conclusions have been robust within the studied contexts. Overall, the research has shown that AI-powered medical imaging has not functioned as an isolated technical innovation, but as one component of a broader data and governance ecosystem, and that its perceived contributions to early cancer diagnosis and epidemiological analysis have depended critically on the interplay between infrastructure, organizational commitment, analytics capability, and governance discipline. In doing so, the study has offered a structured foundation for subsequent empirical and practical efforts aimed at integrating AI imaging into national strategies for cancer control and data-driven decision-making in healthcare.

RECOMMENDATIONS

Based on the findings of this study, several practical recommendations can be offered to policymakers, health-system leaders, CISOs, enterprise architects, and clinical managers who aim to leverage AI-powered medical imaging to strengthen early cancer diagnosis and epidemiological analysis. First, national and institutional policymakers should formally recognize AI-enabled imaging as a strategic component of cancer-control and data-driven public health, and should invest accordingly in core digital infrastructure, including modern PACS/VNA systems, high-availability compute and storage, secure data lakes, and interoperable interfaces that allow imaging-derived features to flow seamlessly into electronic health records and cancer registries. Second, healthcare organizations should treat technological readiness and organizational support as deliberate, staged programs rather than incidental byproducts: leadership teams are encouraged to articulate clear AI imaging roadmaps, allocate dedicated budgets, and establish multidisciplinary governance bodies that include radiologists, oncologists, data scientists, informaticians, and legal/ethics experts. CISOs and data-governance leaders should prioritize the design and enforcement of strong governance frameworks that cover data classification, access control, de-identification, logging, model lifecycle management, and secondary use, so that AI imaging pipelines operate on a foundation of trust, security, and regulatory compliance. At the departmental level, clinical and technical leaders should invest in structured training programs that improve clinicians' understanding of AI capabilities and limitations, embed AI tools into existing workflows rather than adding disruptive parallel processes, and reinforce the message that AI is intended to augment rather than replace professional judgment. Enterprise architects and analytics teams should focus on building reusable, standardized pipelines that move AI outputs segmentation masks, radiomic vectors, prediction scores into analytics environments where they can be linked with clinical, pathological, and outcome data to support both quality improvement and population-level surveillance. To ensure that perceived improvements translate into measurable health gains, institutions should complement perceptual monitoring with objective indicators, such as changes in stage distribution at diagnosis, recall and biopsy rates, time to diagnosis, and completeness and timeliness of cancer registry reporting. Finally, professional societies and national agencies should support collaborative networks, shared benchmarks, and common data models that enable institutions at different levels of maturity academic centers, community hospitals, and specialized imaging facilities to learn from one another and to avoid fragmented, siloed implementations. Taken together, these recommendations emphasize that the successful and equitable use of AI-powered medical imaging for early cancer diagnosis and epidemiological analysis depends not on algorithms alone, but on sustained investment in infrastructure, governance, workforce capability, and analytics pipelines that fully integrate imaging AI into the operational and strategic fabric of healthcare systems.

LIMITATIONS

The present study has had several important limitations that have needed to be acknowledged when interpreting its findings and considering their generalizability. First, the research has employed a cross-sectional survey design, which has captured perceptions and relationships at a single point in time and has therefore not allowed for strong causal inferences about the directionality of the observed associations between technological readiness, organizational support, data governance, AI imaging adoption, analytics capability, and perceived outcomes. It has been possible that institutions with better early diagnosis performance or stronger epidemiological functions have been more motivated to invest in AI and analytics, rather than these investments solely driving improvements. Second, the study has relied on self-reported Likert-scale measures for all major constructs, which has introduced potential biases related to social desirability, self-presentation, and common method variance; although anonymity, careful wording, and psychometric checks have been used to mitigate these issues, the possibility of inflated relationships due to shared method has not been entirely eliminated. Third, the sample has been drawn from four U.S. institutions that have already had some level of AI imaging activity, meaning that settings with no AI exposure and systems outside the U.S. context have not been represented; as a result, the findings have been most applicable to organizations at early to intermediate stages of AI implementation within a relatively well-resourced national health infrastructure. Fourth, the study has operationalized early cancer diagnosis effectiveness and epidemiological analysis capability as perceived constructs rather than as objective performance indicators, so the results have reflected how professionals have believed AI and analytics have affected their work, not necessarily how stage distributions, interval cancer rates, registry completeness, or survival outcomes have actually changed in practice. Fifth, the study has not collected detailed technical information on AI models themselves, such as training data composition, validation procedures, bias mitigation strategies, and explainability features, even though these characteristics have likely influenced both the real-world performance of AI tools and the level of trust and acceptance among clinicians. Sixth, the case-study selection has aimed for diversity but has still been limited in the number of institutions and in the range of organizational forms examined, so key contextual factors such as ownership structures, reimbursement models, and regional policy environments have not been systematically modeled. Finally, the quantitative focus has meant that rich qualitative insights into local implementation challenges, workflow redesign, and informal governance practices have not been fully explored, which could have provided deeper explanations for why certain institutions have translated readiness into adoption and outcomes more effectively than others. Together, these limitations have not invalidated the study's conclusions, but they have indicated that the findings should be interpreted as an important but partial contribution that has needed to be complemented by longitudinal, mixed-methods, and outcome-linked research in future work.

REFERENCES

[1]. Abdul, H. (2023). Artificial Intelligence in Product Marketing: Transforming Customer Experience And Market Segmentation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 132–159. https://doi.org/10.63125/58npbx97

[2]. Abdul, H., & Mohammad Shoeb, A. (2024). The Role Of AI-Enabled Customer Segmentation In Driving Brand Performance On Online Retail Platforms. *Journal of Sustainable Development and Policy*, *3*(04), 31–64. https://doi.org/10.63125/tpjc0m87

[3]. Abdulla, M., & Md. Wahid Zaman, R. (2023). Quantitative Study On Workflow Optimization Through Data Analytics In U.S. Digital Enterprises. *American Journal of Interdisciplinary Studies*, *4*(03), 136–165. https://doi.org/10.63125/y2qshd31

[4]. Alam, M. A., Nabil, A. R., Mintoo, A. A., & Islam, A. (2024). Real-time analytics in streaming big data: techniques and applications. *Journal of Science and Engineering Research*, *1*(01), 104-122. https://doi.org/Doi: 10.70008/jeser.v1i01.56

[5]. Alam, M. A., Nabil, A. R., Uddin, M. M., Sarker, M. T. H., & Mahmud, S. (2024). The Role Of Predictive Analytics In Early Disease Detection: A Data-Driven Approach To Preventive Healthcare. *Frontiers in Applied Engineering and Technology*, *1*(01), 105-123. https://doi.org/10.70937/faet.v1i01.22

[6]. Alam, M. A., Sohel, A., Hasan, K. M., & Islam, M. A. (2024). Machine Learning And Artificial Intelligence in Diabetes Prediction And Management: A Comprehensive Review of Models. *Journal of Next-Gen Engineering Systems*, *1*(01), 107-124. https://doi.org/10.70937/jnes.v1i01.41

[7]. Alam, M. A., Sohel, A., Hossain, A., Eshra, S. A., & Mahmud, S. (2023). Medical Imaging For Early Cancer Diagnosis And Epidemiology Using Artificial Intelligence: Strengthing National Healthcare Frameworks In The USA. *American Journal of Scholarly Research and Innovation*, *2*(01), 24-49. https://doi.org/10.63125/matthh09

[8]. Alam, M. F., & Alam, M. F. (2022). AI-Powered Medical Imaging for Privacy-Preserving Early Cancer Diagnosis And Secure Integration Into US Healthcare Systems. *American Journal of Health and Medical Sciences*, *3*(02), 01-40. https://doi.org/10.63125/px8zr574

[9]. Alami, H., Lehoux, P., Denis, J.-L., Motulsky, A., Petitgand, C., Savoldelli, M., Rouquet, R., Gagnon, M.-P., Roy, D., & Fortin, J.-P. (2020). Organizational readiness for artificial intelligence in health care: Insights for decision-making and practice. *Journal of Health Organization and Management*, *35*(1), 106–114. https://doi.org/10.1108/jhom-03-2020-0074

[10]. Alifa Majumder, N. (2025). Artificial Intelligence-Driven Digital Transformation Models For Enhancing Organizational Communication And Decision-Making Efficiency. *American Journal of Scholarly Research and Innovation*, *4*(01), 536–577. https://doi.org/10.63125/8qqmrm26

[11]. AlQudah, A. A., Al-Emran, M., & Shaalan, K. (2021). Technology acceptance in healthcare: A systematic review. *Applied Sciences*, *11*(22), 10537. https://doi.org/10.3390/app112210537

[12]. Ammenwerth, E. (2019). Technology acceptance models in health informatics: TAM and UTAUT. *Studies in Health Technology and Informatics*, *263*, 64–71. https://doi.org/10.3233/shti190111

[13]. Anaya-Isaza, A., Mera-Jiménez, L., & Zequera-Diaz, M. (2021). An overview of deep learning in medical imaging. *Informatics in Medicine Unlocked*, *26*, 100723. https://doi.org/10.1016/j.imu.2021.100723

[14]. Arfan, U., Sai Praveen, K., & Alifa Majumder, N. (2021). Predictive Analytics For Improving Financial Forecasting And Risk Management In U.S. Capital Markets. *American Journal of Interdisciplinary Studies*, *2*(04), 69–100. https://doi.org/10.63125/tbw49w69

[15]. Arfan, U., Tahsina, A., Md Mostafizur, R., & Md, W. (2023). Impact Of GFMIS-Driven Financial Transparency On Strategic Marketing Decisions In Government Agencies. *Review of Applied Science and Technology*, *2*(01), 85-112. https://doi.org/10.63125/8nqhhm56

[16]. Asan, O., Bayrak, A. E., & Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: Focus on clinicians. *Journal of Medical Internet Research*, *22*(6), e15154. https://doi.org/10.2196/15154

[17]. Bleyer, A., & Welch, H. G. (2012). Effect of three decades of screening mammography on breast-cancer incidence. *The New England Journal of Medicine*, *367*(21), 1998–2005. https://doi.org/10.1056/NEJMoa1206809

[18]. Blut, M., Chong, A. Y. L., Tsigna, Z., & Venkatesh, V. (2022). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): Challenging its validity and charting a research agenda in the red ocean. *Journal of the Association for Information Systems*, *23*(1), 13–95. https://doi.org/10.17705/1jais.00719

[19]. Collaborators, G. B. o. D. R. F. (2020). Global burden of 87 risk factors in 204 countries and territories, 1990–2019. *The Lancet*, *396*(10258), 1223–1249. https://doi.org/10.1016/s0140-6736(20)30752-2

[20]. Dwivedi, Y. K., Rana, N. P., Tamilmani, K., & Raman, R. (2020). A meta-analysis based modified unified theory of acceptance and use of technology (meta-UTAUT): A review of emerging literature. *Current Opinion in Psychology*, *36*, 13–18. https://doi.org/10.1016/j.copsyc.2020.03.008

[21]. Efat Ara, H. (2025). The Role of Calibration Engineering In Strengthening Reliability Of U.S. Advanced Manufacturing Systems Through Artificial Intelligence. *Review of Applied Science and Technology*, 4(02), 820-851. https://doi.org/10.63125/0y0m8x22

[22]. Ferdous Ara, A. (2021). Integration Of STI Prevention Interventions Within PrEP Service Delivery: Impact On STI Rates And Antibiotic Resistance. *International Journal of Scientific Interdisciplinary Research*, 2(2), 63–97. https://doi.org/10.63125/65143m72

[23]. Ferdous Ara, A., & Beatrice Onyinyechi, M. (2023). Long-Term Epidemiologic Trends Of STIs PRE- and POST-PrEP Introduction: A National Time-Series Analysis. *American Journal of Health and Medical Sciences*, 4(02), 01–35. https://doi.org/10.63125/mp153d97

[24]. Geis, J. R., Brady, A. P., Wu, C. C., Spencer, J., Ranschaert, E., Jaremko, J. L., Langer, S. G., Borondy-Kitts, A., Birch, J., Shields, W. F., Koppula, V. S., Flanders, A. E., & Kotter, E. (2019). Ethics of artificial intelligence in radiology: Summary of the joint European and North American multisociety statement. *Radiology*, *293*(2), 436–440. https://doi.org/10.1148/radiol.2019191586

[25]. Habibullah, S. M. (2025). Swarm Intelligence-Based Autonomous Logistics Framework With Edge AI For Industry 4.0 Manufacturing Ecosystems. *Review of Applied Science and Technology*, 4(03), 01-34. https://doi.org/10.63125/p1q8yf46

[26]. Haq, M. A. U., & Khuroo, S. (2020). Deep learning and its applications in medical imaging. In D. Gupta (Ed.), *Handbook of computer vision and image processing* (pp. 181–201). Springer. https://doi.org/10.1007/978-981-15-4112-4_7

[27]. Harding, C., Pompei, F., Burmistrov, D., Welch, H. G., Abebe, R., & Wilson, R. (2015). Breast cancer screening, incidence, and mortality across US counties. *JAMA Internal Medicine*, *175*(9), 1483–1489. https://doi.org/10.1001/jamainternmed.2015.3043

[28]. Holden, R. J., & Karsh, B. T. (2010). The technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics*, *43*(1), 159–172. https://doi.org/10.1016/j.jbi.2009.07.002

[29]. Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. W. L. (2018). Artificial intelligence in radiology. *Nature Reviews Cancer*, *18*(8), 500–510. https://doi.org/10.1038/s41568-018-0016-5

[30]. Hozyfa, S., & Ashraful, I. (2025). Impact Of Data Privacy And Cybersecurity In Accounting Information Systems On Financial Transparency. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 254–292. https://doi.org/10.63125/xs0xt970

[31]. Hozyfa, S., & Mst. Shahrin, S. (2024). The Influence Of Secure Data Systems On Fraud Detection In Business Intelligence Applications. *Journal of Sustainable Development and Policy*, *3*(04), 133-173. https://doi.org/10.63125/8ee0eq13

[32]. Jabed Hasan, T., & Mohammad Shah, P. (2024). Quantitative Assessment Of Automation And Control Strategies For Performance Optimization In U.S. Industrial Plants. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 169–205. https://doi.org/10.63125/eqfz8220

[33]. Jabed Hasan, T., & Zayadul, H. (2024). Adapting PLC/SCADA Systems To Mitigate Industrial IOT Cybersecurity Risks In Global Manufacturing. *American Journal of Interdisciplinary Studies*, *5*(04), 67-95. https://doi.org/10.63125/0v4cms60

[34]. Jahid, M. K. A. S. R. (2021). Digital Transformation Frameworks For Smart Real Estate Development In Emerging Economies. *Review of Applied Science and Technology*, *6*(1), 139–182. https://doi.org/10.63125/cd09ne09

[35]. Jiang, J., Xie, Q., Cheng, Z., & et al. (2021). AI based colorectal disease detection using real-time screening colonoscopy. *Precision Clinical Medicine*, *4*(2), 109–118. https://doi.org/10.1093/pcmedi/pbab013

[36]. Jiang, Y., Yang, M., Wang, S., Li, X., & Sun, Y. (2023). Deep learning for medical image-based cancer diagnosis. *Cancers*, *15*(14), 3608. https://doi.org/10.3390/cancers15143608

[37]. Khanijahani, A., Iezadi, S., Dudley, S., Goettler, M., Kroetsch, P., & Wise, J. (2022). Organizational, professional, and patient characteristics associated with artificial intelligence adoption in healthcare: A systematic review. *Health Policy and Technology*, *11*, 100602. https://doi.org/10.1016/j.hlpt.2022.100602

[38]. Kim, S., Lee, K. H., Hwang, H., & Yoo, S. (2016). Analysis of the factors influencing healthcare professionals' adoption of mobile electronic medical record (EMR) using the unified theory of acceptance and use of technology (UTAUT) in a tertiary hospital. *BMC Medical Informatics and Decision Making*, *16*, 12. https://doi.org/10.1186/s12911-016-0249-8

[39]. Kramer, B. S., Steele, G. D., & Bloom, G. (2015). Early detection of cancer: Past, present, and future. *ASCO Educational Book*, *35*, 57–65. https://doi.org/10.14694/EdBook_AM.2015.35.57

[40]. Kraus, S., Schiavone, F., Pluzhnikova, A., & Invernizzi, A. C. (2023). Artificial intelligence in healthcare institutions: A systematic literature review on influencing factors. *Technology in Society*, *74*, 102443. https://doi.org/10.1016/j.techsoc.2023.102443

[41]. Larson, D. B., Harvey, H., Rubin, D. L., Irani, N., Tse, J. R., & Langlotz, C. P. (2021). Regulatory frameworks for development and evaluation of artificial intelligence–based diagnostic imaging algorithms: Summary and recommendations. *Journal of the American College of Radiology*, *18*(3), 413–424. https://doi.org/10.1016/j.jacr.2020.09.060

[42]. Liu, X., Faes, L., Kale, A. U., Wagner, S. K., Fu, D. J., Bruynseels, A., Mahendiran, T., Moraes, G., Shamdas, M., Kern, C., Hühn, M. H., Ferraz, D., Schmid, M. K., Balaskas, K., Topol, E. J., Bachmann, L. M., Keane, P. A., & Denniston, A. K. (2019). A comparison of deep learning performance against health-care professionals in detecting

diseases from medical imaging: A systematic review and meta-analysis. *The Lancet Digital Health*, *1*(6), e271–e297. https://doi.org/10.1016/s2589-7500(19)30123-2

[43]. Lundervold, A. S., & Lundervold, A. (2019). An overview of deep learning in medical imaging focusing on MRI. *Zeitschrift für Medizinische Physik*, *29*(2), 102–127. https://doi.org/10.1016/j.zemedi.2018.11.002

[44]. Maillet, É., Mathieu, L., & Sicotte, C. (2015). Modeling factors explaining the acceptance, actual use and satisfaction of nurses using an electronic patient record in acute care settings: An extension of the UTAUT. *International Journal of Medical Informatics*, *84*(1), 36–47. https://doi.org/10.1016/j.ijmedinf.2014.09.004

[45]. Md Al Amin, K., & Md Mesbaul, H. (2023). Smart Hybrid Manufacturing: A Combination Of Additive, Subtractive, And Lean Techniques For Agile Production Systems. *Journal of Sustainable Development and Policy*, *2*(04), 174-217. https://doi.org/10.63125/7rb1zz78

[46]. Md Ariful, I., & Efat Ara, H. (2022). Advances And Limitations Of Fracture Mechanics–Based Fatigue Life Prediction Approaches For Structural Integrity Assessment: A Systematic Review. *American Journal of Interdisciplinary Studies*, *3*(03), 68-98. https://doi.org/10.63125/fg8ae957

[47]. Md Arman, H., & Md.Kamrul, K. (2022). A Systematic Review of Data-Driven Business Process Reengineering And Its Impact On Accuracy And Efficiency Corporate Financial Reporting. *International Journal of Business and Economics Insights*, *2*(4), 01–41. https://doi.org/10.63125/btx52a36

[48]. Md Asfaquar, R. (2025). Vehicle-To-Infrastructure (V2I) Communication And Traffic Incident Reduction: An Empirical Study Across U.S. Highway Networks. *Journal of Sustainable Development and Policy*, *4*(03), 38-81. https://doi.org/10.63125/c1wm0t92

[49]. Md Fokhrul, A., & Md Fardaus, A. (2022). Predictive Artificial Intelligence Models for Early Detection And Management Of Chronic Diseases To Strengthen National Healthcare Resilience In The United States. *American Journal of Interdisciplinary Studies*, *3*(04), 268–293. https://doi.org/10.63125/9t5ar104

[50]. Md Foysal, H. (2025). Integration Of Lean Six Sigma and Artificial Intelligence-Enabled Digital Twin Technologies For Smart Manufacturing Systems. *Review of Applied Science and Technology*, *4*(04), 01-35. https://doi.org/10.63125/1med8n85

[51]. Md Foysal, H., & Aditya, D. (2023). Smart Continuous Improvement With Artificial Intelligence, Big Data, And Lean Tools For Zero Defect Manufacturing Systems. *American Journal of Scholarly Research and Innovation*, *2*(01), 254–282. https://doi.org/10.63125/6cak0s21

[52]. Md Hamidur, R. (2023). Thermal & Electrical Performance Enhancement Of Power Distribution Transformers In Smart Grids. *American Journal of Scholarly Research and Innovation*, *2*(01), 283–313. https://doi.org/10.63125/n2p6y628

[53]. Md Harun-Or-Rashid, M., Mst. Shahrin, S., & Sai Praveen, K. (2023). Integration Of IOT And EDGE Computing For Low-Latency Data Analytics In Smart Cities And IOT Networks. *Journal of Sustainable Development and Policy*, *2*(03), 01-33. https://doi.org/10.63125/004h7m29

[54]. Md Majadul Islam, J., & Md Abdur, R. (2025). Enhancing Decision-Making in U.S. Enterprises With Artificial Intelligence-Driven Business Intelligence Models. *International Journal of Business and Economics Insights*, *5*(3), 100–133. https://doi.org/10.63125/8n54qm32

[55]. Md Mesbaul, H., & Md. Tahmid Farabe, S. (2022). Implementing Sustainable Supply Chain Practices In Global Apparel Retail: A Systematic Review Of Current Trends. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 332–363. https://doi.org/10.63125/nen7vd57

[56]. Md Mohaiminul, H. (2025). Federated Learning Models for Privacy-Preserving AI In Enterprise Decision Systems. *International Journal of Business and Economics Insights*, *5*(3), 238– 269. https://doi.org/10.63125/ry033286

[57]. Md Mominul, H. (2025). Systematic Review on The Impact Of AI-Enhanced Traffic Simulation On U.S. Urban Mobility And Safety. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 833–861. https://doi.org/10.63125/jj96yd66

[58]. Md Musfiqur, R., & Md.Kamrul, K. (2023). Mechanisms By Which AI-Enabled Crm Systems Influence Customer Retention And Overall Business Performance: A Systematic Literature Review Of Empirical Findings. *International Journal of Business and Economics Insights*, *3*(1), 31-67. https://doi.org/10.63125/qqe2bm11

[59]. Md Muzahidul, I. (2025). The Impact Of Data-Driven Web Frameworks On Performance And Scalability Of U.S. Enterprise Applications. *International Journal of Business and Economics Insights*, *5*(3), 523–558. https://doi.org/10.63125/f07n4p12

[60]. Md Muzahidul, I., & Aditya, D. (2024). Predictive Analytics And Data-Driven Algorithms For Improving Efficiency In Full-Stack Web Systems. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 226–260. https://doi.org/10.63125/q75tbj05

[61]. Md Muzahidul, I., & Md Mohaiminul, H. (2023). Explainable AI (XAI) Models For Cloud-Based Business Intelligence: Ensuring Compliance And Secure Decision-Making. *American Journal of Interdisciplinary Studies*, *4*(03), 208–249. https://doi.org/10.63125/5etfhh77

[62]. Md Nahid, H. (2022). Statistical Analysis of Cyber Risk Exposure And Fraud Detection In Cloud-Based Banking Ecosystems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 289–331. https://doi.org/10.63125/9wf91068

[63]. Md Sarwar Hossain, S. (2025). Artificial Intelligence In Driven Digital Twin For Real-Time Traffic Signal Optimization And Transportation Planning. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1316–1358. https://doi.org/10.63125/dthvcp78

[64]. Md Sarwar Hossain, S., & Md Milon, M. (2022). Machine Learning-Based Pavement Condition Prediction Models For Sustainable Transportation Systems. *American Journal of Interdisciplinary Studies*, *3*(01), 31–64. https://doi.org/10.63125/1jsmkg92

[65]. Md Wahid Zaman, R. (2025). The Role Of Data Science In Optimizing Project Efficiency And Innovation In U.S. Enterprises. *International Journal of Business and Economics Insights*, *5*(3), 586–600. https://doi.org/10.63125/jzjkqm27

[66]. Md. Abdur, R., & Zamal Haider, S. (2022). Assessment Of Data-Driven Vendor Performance Evaluation In Retail Supply Chains Analyzing Metrics, Scorecards, And Contract Management Tools. *Journal of Sustainable Development and Policy*, *1*(04), 71-116. https://doi.org/10.63125/2a641k35

[67]. Md. Akbar, H., & Sharmin, A. (2025). AI-Enabled Neurobiological Diagnostic Models For Early Detection Of PTSD And Trauma Disorders. *American Journal of Interdisciplinary Studies*, *6*(02), 01–39. https://doi.org/10.63125/64hftc92

[68]. Md. Al Amin, K., & Sai Praveen, K. (2023). The Role Of Industrial Engineering In Advancing Sustainable Manufacturing And Quality Compliance In Global Engineering Systems. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 31–61. https://doi.org/10.63125/8w1vk676

[69]. Md. Hasan, I. (2025). A Systematic Review on The Impact Of Global Merchandising Strategies On U.S. Supply Chain Resilience. *International Journal of Business and Economics Insights*, *5*(3), 134–169. https://doi.org/10.63125/24mymg13

[70]. Md. Hasan, I., & Ashraful, I. (2023). The Effect Of Production Planning Efficiency On Delivery Timelines In U.S. Apparel Imports. *Journal of Sustainable Development and Policy*, *2*(04), 35-73. https://doi.org/10.63125/sg472m51

[71]. Md. Hasan, I., & Rakibul, H. (2024). Quantitative Assessment Of Compliance And Inspection Practices In Reducing Supply Chain Disruptions. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 301–342. https://doi.org/10.63125/db63r616

[72]. Md. Jobayer Ibne, S. (2025). AI-Enhanced Business Intelligence Dashboards For Predictive Market Strategy In U.S. Enterprises. *International Journal of Business and Economics Insights*, *5*(3), 603–648. https://doi.org/10.63125/8cvgn369

[73]. Md. Jobayer Ibne, S., & Md. Kamrul, K. (2023). Automating NIST 800-53 Control Implementation: A Cross-Sector Review Of Enterprise Security Toolkits. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 160–195. https://doi.org/10.63125/prkw8r07

[74]. Md. Milon, M. (2025). A Systematic Review on The Impact Of NFPA-Compliant Fire Protection Systems On U.S. Infrastructure Resilience. *International Journal of Business and Economics Insights*, *5*(3), 324–352. https://doi.org/10.63125/ne3ey612

[75]. Md. Mominul, H. (2024). Quantitative Assessment Of Smart City IOT Integration For Reducing Urban Infrastructure Vulnerabilities. *Review of Applied Science and Technology*, *3*(04), 48-93. https://doi.org/10.63125/f2cj4507

[76]. Md. Mominul, H., & Syed Zaki, U. (2024). A Review On Sustainable Building Materials And Their Role In Enhancing U.S. Green Infrastructure Goals. *Journal of Sustainable Development and Policy*, *3*(04), 65-100. https://doi.org/10.63125/bfmmay79

[77]. Md. Tahmid Farabe, S. (2025). The Impact of Data-Driven Industrial Engineering Models On Efficiency And Risk Reduction In U.S. Apparel Supply Chains. *International Journal of Business and Economics Insights*, *5*(3), 353–388. https://doi.org/10.63125/y548hz02

[78]. Md.Akbar, H., & Farzana, A. (2021). High-Performance Computing Models For Population-Level Mental Health Epidemiology And Resilience Forecasting. *American Journal of Health and Medical Sciences*, *2*(02), 01–33. https://doi.org/10.63125/k9d5h638

[79]. Md.Kamrul, K. (2025). Bayesian Statistical Models For Predicting Type 2 Diabetes Prevalence In Urban Populations. *Review of Applied Science and Technology*, *4*(02), 370-406. https://doi.org/10.63125/db2e5054

[80]. Mohammad Mushfequr, R. (2025). The Role Of AI-Enabled Information Security Frameworks in Preventing Fraud In U.S. Healthcare Billing Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1160–1201. https://doi.org/10.63125/y068m490

[81]. Mohammad Mushfequr, R., & Ashraful, I. (2023). Automation And Risk Mitigation in Healthcare Claims: Policy And Compliance Implications. *Review of Applied Science and Technology*, *2*(04), 124–157. https://doi.org/10.63125/v73gyg14

[82]. Mohammad Mushfequr, R., & Sai Praveen, K. (2022). Quantitative Investigation Of Information Security Challenges In U.S. Healthcare Payment Ecosystems. *International Journal of Business and Economics Insights*, *2*(4), 42–73. https://doi.org/10.63125/gcg0fs06

[83]. Mortuza, M. M. G., & Rauf, M. A. (2022). Industry 4.0: An Empirical Analysis of Sustainable Business Performance Model Of Bangladeshi Electronic Organisations. *International Journal of Economy and Innovation*. https://gospodarkainnowacje.pl/index.php/issue_view_32/article/view/826

[84]. Mst. Shahrin, S. (2025). Predictive Neural Network Models for Cyberattack Pattern Recognition And Critical Infrastructure Vulnerability Assessment. *Review of Applied Science and Technology*, *4*(02), 777-819. https://doi.org/https://rast-journal.org/index.php/RAST/article/view/48

[85]. Mudgal, K. S., & Das, N. (2019). The ethical adoption of artificial intelligence in radiology. *BJR Open*, *2*(1), 20190020. https://doi.org/10.1259/bjro.20190020

[86]. O'Connor, J. P. B., Aboagye, E. O., Adams, J. E., Aerts, H. J. W. L., Barrington, S. F., Beer, A. J., Boellaard, R., Bohndiek, S. E., Brady, M., Brown, G., Buckley, D. L., Chenevert, T. L., Clarke, L. P., Collette, S., Cook, G. J.,

deSouza, N. M., Dickson, J. C., Dive, C., Evelhoch, J. L., . . . Waterton, J. C. (2017). Imaging biomarker roadmap for cancer studies. *Nature Reviews Clinical Oncology*, *14*(3), 169–186. https://doi.org/10.1038/nrclinonc.2016.162

[87]. Ongena, Y. P., Haan, M., Yakar, D., & Kwee, T. C. (2020). Patients' views on the implementation of artificial intelligence in radiology: Development and validation of a standardized questionnaire. *European Radiology*, *30*(2), 1033–1040. https://doi.org/10.1007/s00330-019-06486-0

[88]. Pankaz Roy, S., & Md. Kamrul, K. (2023). HACCP and ISO Frameworks For Enhancing Biosecurity In Global Food Distribution Chains. *American Journal of Scholarly Research and Innovation*, *2*(01), 314–356. https://doi.org/10.63125/9pbp4h37

[89]. Pankaz Roy, S., & Sai Praveen, K. (2024). Systematic Review of Stress And Burnout Interventions Among U.S. Healthcare Professionals Using Advanced Computing Approaches. *Journal of Sustainable Development and Policy*, *3*(04), 101-132. https://doi.org/10.63125/9mx2fc43

[90]. Pesapane, F., Volonté, C., Codari, M., & Sardanelli, F. (2018). Artificial intelligence as a medical device in radiology: Ethical and regulatory issues in Europe and the United States. *Insights into Imaging*, *9*(5), 745–753. https://doi.org/10.1007/s13244-018-0645-y

[91]. Petersson, L., Larsson, I., Nygren, J. M., Nilsen, P., Neher, M., Reed, J. E., Tyskbo, D., & Svedberg, P. (2022). Challenges to implementing artificial intelligence in healthcare: A qualitative interview study with healthcare leaders in Sweden. *BMC Health Services Research*, *22*, 850. https://doi.org/10.1186/s12913-022-08215-8

[92]. Qu, J., Zhao, X., Chen, P., Wang, Z., Liu, Z., Yang, B., & Li, H. (2022). Deep learning on digital mammography for expert-level diagnosis accuracy in breast cancer detection. *Multimedia Systems*, *28*(4), 1263–1274. https://doi.org/10.1007/s00530-021-00823-4

[93]. Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. *Health Information Science and Systems*, *2*(3), 1–10. https://doi.org/10.1186/2047-2501-2-3

[94]. Rakibul, H. (2025). The Role of Business Analytics In ESG-Oriented Brand Communication: A Systematic Review Of Data-Driven Strategies. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1096– 1127. https://doi.org/10.63125/4mchj778

[95]. Rakibul, H., & Samia, A. (2022). Information System-Based Decision Support Tools: A Systematic Review Of Strategic Applications In Service-Oriented Enterprises. *Review of Applied Science and Technology*, *1*(04), 26-65. https://doi.org/10.63125/w3cevz78

[96]. Rangayyan, R. M., Ayres, F. J., & Desautels, J. E. L. (2007). A review of computer-aided diagnosis of breast cancer: Toward the detection of subtle signs. *Journal of the Franklin Institute*, *344*(3–4), 312–348. https://doi.org/10.1016/j.jfranklin.2006.09.003

[97]. Ranschaert, W. J., Boon, W. P. C., & Moors, E. H. M. (2021). Implementation of artificial intelligence (AI) applications in clinical radiology: Barriers and facilitators. *European Radiology*, *31*(9), 5735–5743. https://doi.org/10.1007/s00330-020-06946-y

[98]. Reza, M., Vorobyova, K., & Rauf, M. (2021). The effect of total rewards system on the performance of employees with a moderating effect of psychological empowerment and the mediation of motivation in the leather industry of Bangladesh. *Engineering Letters*, *29*, 1-29.

[99]. Rony, M. A., & Ashraful, I. (2022). Big Data And Engineering Analytics Pipelines For Smart Manufacturing: Enhancing Efficiency, Quality, And Predictive Maintenance. *American Journal of Scholarly Research and Innovation*, *1*(02), 59–85. https://doi.org/10.63125/rze0my79

[100]. Rony, M. A., & Hozyfa, S. (2024). Cloud-Integrated Digital Twin Architectures For Real-Time Monitoring, Risk Assessment, And Safety Optimization In U.S. Energy Infrastructure. *American Journal of Interdisciplinary Studies*, *5*(04), 96-133. https://doi.org/10.63125/y9m5pz24

[101]. Saba, A. (2025). Artificial Intelligence Based Models For Secure Data Analytics And Privacy-Preserving Data Sharing In U.S. Healthcare And Hospital Networks. *International Journal of Business and Economics Insights*, *5*(3), 65–99. https://doi.org/10.63125/wv0bqx68

[102]. Saba, A., & Md. Sakib Hasan, H. (2024). Machine Learning And Secure Data Pipelines For Enhancing Patient Safety In Electronic Health Record (EHR) Among U.S. Healthcare Providers. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *4*(1), 124–168. https://doi.org/10.63125/qm4he747

[103]. Saba, A., Shaikat, B., & Tonoy Kanti, C. (2023). Integration Of Artificial Intelligence And Advanced Computing To Develop Resilient Cyber Defense Systems. *Journal of Sustainable Development and Policy*, *2*(04), 74-107. https://doi.org/10.63125/rxyc6y88

[104]. Saba, A., & Tonoy Kanti, C. (2023). Explainable Artificial Intelligence (XAI) Approaches For Cyber Risk Assessment In Financial Services. *American Journal of Interdisciplinary Studies*, *4*(03), 96-135. https://doi.org/10.63125/3gjcb322

[105]. Sahiner, B., Pezeshk, A., Hadjiiski, L. M., Wang, X., Drukker, K., Cha, K. H., Summers, R. M., & Giger, M. L. (2019). Deep learning in medical imaging and radiation therapy. *Medical Physics*, *46*(1), e1–e36. https://doi.org/10.1002/mp.13264

[106]. Sai Praveen, K. (2025). AI-Driven Data Science Models for Real-Time Transcription And Productivity Enhancement In U.S. Remote Work Environments. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 801–832. https://doi.org/10.63125/gzyw2311

[107]. Saikat, S. (2021). Real-Time Fault Detection in Industrial Assets Using Advanced Vibration Dynamics And Stress Analysis Modeling. *American Journal of Interdisciplinary Studies*, *2*(04), 39–68. https://doi.org/10.63125/0h163429

[108]. Saikat, S. (2022). CFD-Based Investigation of Heat Transfer Efficiency In Renewable Energy Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 129–162. https://doi.org/10.63125/ttw40456

[109]. Saikat, S. (2025). AI-Enabled Digital Twin Framework for Predictive Maintenance And Energy Optimization In Industrial Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1359–1389. https://doi.org/10.63125/8v1nwj69

[110]. Sali, L., Ventura, L., Mascalchi, M., Falchini, M., Carozzi, F., Castiglione, G., Mantellini, P., Zorzi, M., Grazzini, G., & Investigators., S. S. (2022). Single CT colonography versus three rounds of faecal immunochemical test for population-based screening of colorectal cancer (SAVE): A randomised controlled trial. *The Lancet Gastroenterology & Hepatology*, *7*(10), 1016–1023. https://doi.org/10.1016/s2468-1253(22)00269-2

[111]. Shah, M., Prasad, D., Hegde, P., Chlosta, P., Rai, B. P., & Somani, B. K. (2023). Breaking barriers: Unveiling factors influencing the adoption of artificial intelligence in healthcare. *Big Data and Cognitive Computing*, *7*(2), 105. https://doi.org/10.3390/bdcc7020105

[112]. Shaikat, B. (2025). Artificial Intelligence–Enhanced Cybersecurity Frameworks for Real-Time Threat Detection In Cloud And Enterprise. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 737–770. https://doi.org/10.63125/yq1gp452

[113]. Shaikat, B., & Md. Wahid Zaman, R. (2024). Quantum-Resistant Cryptographic Protocols Integrated With AI For Securing Cloud And IOT Environments. *International Journal of Business and Economics Insights*, *4*(4), 60–90. https://doi.org/10.63125/dryw3b96

[114]. Shaikh, S. (2025). AI-Orchestrated Cyber-Physical Systems For Sustainable Industry 5.0 Manufacturing And Supply Chain Resilience. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1278–1315. https://doi.org/10.63125/jwm2e278

[115]. Shaikh, S., & Aditya, D. (2021). Federated Learning-Driven Predictive Quality Analytics and Supply Chain Optimization In Distributed Manufacturing Networks. *Review of Applied Science and Technology*, *6*(1), 74-107. https://doi.org/10.63125/k18cbz55

[116]. Shaikh, S., & Md. Tahmid Farabe, S. (2023). Digital Twin-Driven Process Modeling For Energy Efficiency And Lifecycle Optimization In Industrial Facilities. *American Journal of Interdisciplinary Studies*, *4*(03), 65–95. https://doi.org/10.63125/e4q64869

[117]. Shaikh, S., & Sudipto, R. (2022). Multi-Objective Thermo-Economic and Supply Chain Optimization Modeling For Hydrogen Energy Integration In Smart Factories. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 163–193. https://doi.org/10.63125/p9y8p705

[118]. Shastry, K. A., & Sanjay, H. A. (2022). Cancer diagnosis using artificial intelligence: A review. *Artificial Intelligence Review*, *55*(4), 2641–2673. https://doi.org/10.1007/s10462-021-10074-4

[119]. Shokat, Z., & et al. (2020). Artificial intelligence in cancer diagnosis and prognosis: Opportunities and challenges. *Cancer Letters*, *468*, 111–118. https://doi.org/10.1016/j.canlet.2019.12.007

[120]. Sohel, A., Alam, M. A., Hossain, A., Mahmud, S., & Akter, S. (2022). Artificial Intelligence In Predictive Analytics For Next-Generation Cancer Treatment: A Systematic Literature Review Of Healthcare Innovations In The USA. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology*, *1*(01), 62-87.

[121]. Sousa, M. J., Pesqueira, A. M., Lemos, C., Sousa, M., & Rocha, Á. (2019). Decision-making based on big data analytics for people management in healthcare organizations. *Journal of Medical Systems*, *43*(9), 290. https://doi.org/10.1007/s10916-019-1419-x

[122]. Sudipto, R., & Md. Hasan, I. (2024). Data-Driven Supply Chain Resilience Modeling Through Stochastic Simulation And Sustainable Resource Allocation Analytics. *American Journal of Advanced Technology and Engineering Solutions*, *4*(02), 01-32. https://doi.org/10.63125/p0ptag78

[123]. Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., & Bray, F. (2021). Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA: A Cancer Journal for Clinicians*, *71*(3), 209–249. https://doi.org/10.3322/caac.21660

[124]. Tahosin, M. S., Pranto, I. H., Chowdhury, M. M. U., Emon, S. B., Alam, M. A., & Khan, C. (2025). A Comprehensive Ensemble-Based Approach for Heart Disease Prediction with Feature Selection and Model Analysis. 2025 5th International Conference on Advanced Research in Computing (ICARC),

[125]. Tonoy Kanti, C. (2025). AI-Powered Deep Learning Models for Real-Time Cybersecurity Risk Assessment In Enterprise It Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 675–704. https://doi.org/10.63125/137k6y79

[126]. Tonoy Kanti, C., & Saba, A. (2024). High-Performance Computing Architectures To Strengthen Cloud Infrastructure Security. *American Journal of Interdisciplinary Studies*, *5*(03), 01–42. https://doi.org/10.63125/9hr8qk06

[127]. Tonoy Kanti, C., & Sai Praveen, K. (2024). Federated Learning Models for Privacy-Preserving Data Sharing And Secure Analytics In Healthcare Industry. *International Journal of Business and Economics Insights*, *4*(4), 91-133. https://doi.org/10.63125/c2dzn006

[128]. Tubaishat, A. (2017). Perceived usefulness and perceived ease of use of electronic health records among nurses: Application of Technology Acceptance Model. *Informatics for Health and Social Care*, *44*(2), 145–155. https://doi.org/10.1080/17538157.2017.1363761

[129]. Waladur, R., & Jabed Hasan, T. (2025). MODBUS/DNP3 Over TCP/IP Implementation On TMDSCNCD28388D and ARDUINO With SIMULINK HMI For IOT-Based Cybersecure Electrical Systems. *International Journal of Business and Economics Insights*, *5*(3), 494–522. https://doi.org/10.63125/8e9cm978

[130]. Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*, *126*, 3–13. https://doi.org/10.1016/j.techfore.2015.12.019

[131]. Wang, Y., Kung, L. A., Wang, W. Y. C., & Cegielski, C. G. (2018). An integrated big data analytics-enabled transformation model: Application to health care. *Information & Management*, *55*(1), 64–79. https://doi.org/10.1016/j.im.2017.04.001

[132]. Wilson, R., & Devaraj, A. (2017). Radiomics of pulmonary nodules and lung cancer. *Translational Lung Cancer Research*, *6*(1), 86–91. https://doi.org/10.21037/tlcr.2017.01.04

[133]. Wu, Y.-J., Wu, F.-Z., Yang, S.-C., & et al. (2022). Radiomics in early lung cancer diagnosis: From diagnosis to clinical decision support and education. *Diagnostics*, *12*(5), 1064. https://doi.org/10.3390/diagnostics12051064

[134]. Yang, Q., Fu, Y., Chen, Z., Meng, F., He, K., Li, M., & Zhang, H. (2022). Artificial intelligence in cancer imaging for diagnosis and evaluation of treatment response. *Radiology Science*, *1*(1), 26–42. https://doi.org/10.15212/radsci-2022-0007

[135]. Yip, S. S. F., Aerts, H. J. W. L., & Berenguer, R. (2020). Radiomics improves cancer screening and early detection. *Cancer Epidemiology, Biomarkers & Prevention*, *29*(12), 2556–2567. https://doi.org/10.1158/1055-9965.Epi-20-0075

[136]. Youlden, D. R., Cramb, S., Dunn, N., Müller-Williams, J., Pyke, C. M., & Baade, P. (2012). The descriptive epidemiology of female breast cancer: An international comparison of screening, incidence, survival and mortality. *Cancer Epidemiology*, *36*(3), 237–248. https://doi.org/10.1016/j.canep.2012.02.007

[137]. Zamal Haider, S. (2025). Securing ERP Systems: The Role Of Information Security Analysts In U.S. Textile And Manufacturing Enterprises. *International Journal of Business and Economics Insights*, *5*(3), 459–493. https://doi.org/10.63125/y8evt228

[138]. Zamal Haider, S., & Hozyfa, S. (2023). A Quantitative Study On IT-Enabled ERP Systems And Their Role In Operational Efficiency. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 62–99. https://doi.org/10.63125/nbpyce10

[139]. Zamal Haider, S., & Sai Praveen, K. (2024). Cloud-Native Data Pipelines For Scalable Audio Analytics And Secure Enterprise Applications. *American Journal of Scholarly Research and Innovation*, *3*(01), 52-83. https://doi.org/10.63125/m4f2aw73

[140]. Zhao, J., Xu, L., Sun, J., & et al. (2023). Global trends in incidence, death, burden and risk factors of early-onset cancer from 1990 to 2019. *BMJ Oncology*, *2*(1), e000049. https://doi.org/10.1136/bmjonc-2023-000049

[141]. Zhou, S., Zhang, R., Chen, D., & Zhu, X. (2021). A novel framework for bringing smart big data to proactive decision making in healthcare. *Health Informatics Journal*, *27*(3), 1–13. https://doi.org/10.1177/14604582211024698

[142]. Zulqarnain, F. N. U., & Zayadul, H. (2024). Artificial Intelligence Applications For Predicting Renewable-Energy Demand Under Climate Variability. *American Journal of Scholarly Research and Innovation*, *3*(01), 84–116. https://doi.org/10.63125/sg0j6930