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Lean Six Sigma Alongside AI in Radiology

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Abstract

Radiology departments play a very pivotal role in the diagnosis of and care for patients. However, these departments predominantly suffer from inefficiencies such as long waiting times, heavy workloads, and high diagnostic rates. These result from fragmented scheduling, manual processes, and limited decision-support tools. This study proposes a transformative approach through the integration of LSS methodologies with advanced hardware and AI-driven software to enhance operational efficiency and diagnostic accuracy. It integrates the Lean principles on waste removal, Six Sigma to reduce the variability of processes, and AI tools for automating workflows and decision support. Key interventions will be the adoption of automated image scanners, AI-powered diagnostic assistance, and centralized workflow management systems to optimize scheduling, machine utilization, and radiologist productivity. Pilot implementation of these solutions will be done and further refined, with tracking key metrics including patient wait times, diagnostic accuracy, and radiologist throughput, to measure impact. The expected outcomes are a 30% reduction in patient wait times, a 20% increase in diagnostic accuracy, and improved radiologist productivity. The use of AI aims at smoothening workflows to achieve more patient satisfaction and minimize errors and thereby improve the quality of care as a whole. In summary, these findings set forth a scalable model for radiology departments to drive toward improved efficiencies and outcomes, allowing for faster and more accurate diagnoses in an increasingly demanding healthcare environment. This research underlines the potential of combining LSS and AI in solving critical challenges in radiology and improving the delivery of patient care.

Keywords
Lean Six Sigma, AI-driven Software, Diagnostic Accuracy, Workflow Optimization, Patient Wait Times

1. Introduction
Radiology has evolved as a pillar of modern diagnostic medicine, enabling physicians to detect, monitor, and treat a wide range of conditions with high precision. Nevertheless, even at the center, radiology departments continue to face systemic inefficiencies that detract from clinical performance and patient experience. Waiting times, diagnostic errors, and bureaucratic bottlenecks have been long-standing issues, having a tendency to result in delayed treatment, compromised quality of care, and physician burnout.

These inefficiencies are commonly caused by outdated scheduling systems, isolated workflows, and too many manual processes. A lack of built-in decision-support tools and automation slows image acquisition speed and accuracy, as well as interpretation and reporting. With healthcare organizations increasingly under pressure to deliver quicker and more reliable services, radiology needs to undergo process innovation. This research proposes a revolutionary solution by merging Lean Six Sigma (LSS) techniques with artificial intelligence-powered tools and the latest imaging technology to render radiology procedures more effective. Lean will be used to eliminate non-value-added processes, whereas Six Sigma techniques will be implemented to control process variation and diagnostic errors. Artificial intelligence will concurrently support radiologists in automated low-level tasks and in enhancing diagnostic correctness.

1.1 Objectives

1. Develop an AI-Assisted Diagnostic Model
Create a machine learning model that will identify common abnormalities in X-ray images with high specificity and sensitivity, such as fractures, pneumonia, and tumors.

2. Integrate AI into Radiology Workflow
Create a model to incorporate the AI model seamlessly into existing radiology workflows such that real-time image analysis and decision support to radiologists are enabled.

3. Quantify Diagnostic Accuracy and Efficiency Gains
Evaluate the impacts of AI integration on diagnostic quality, time-to-diagnosis, and radiologist consistency with the critical performance indicators (KPIs) by Lean Six Sigma metrics.

4. Reduce Process Variation and Error Rates
Use Six Sigma practices to measure and minimize diagnostic errors and process variation before and after AI integration.

5. Enhance Radiologist Productivity
To what extent the AI reduce radiologists' cognitive and administrative burden by doing such tedious tasks as image triaging and initial annotation.

6. Develop a Scalable Implementation Plan
Create a scalable implementation plan that considers hospital size, case load, and IT infrastructure, optimizing the applicability of the AI solution to the radiology departments.

2. Literature Review

Literature Review: Lean Six Sigma and Artificial Intelligence in Radiology Workflow Optimization
Radiology sections are increasingly turning to Lean Six Sigma (LSS) practices and artificial intelligence (AI) to address entrenched problems with scheduling inefficiencies, diagnostic delays, and operational bottlenecks. This literature review integrates findings across peer-reviewed publications, case reports, and technical reviews to show the emerging role of process improvement and AI tools in radiological service optimization.

A pioneering work by Dowell et al. (2017) proved that the deployment of LSS in interventional radiology improved scheduling efficiency considerably and decreased procedure delays, which reflected the model's ability to rationalize complicated workflows. In the same vein, Roth et al. (2010) implemented LSS methods on magnetic resonance imaging (MRI) processes, significantly reducing patient throughput times for liver and knee scans. These results were corroborated by a systematic review by Rutman et al. (2020) which established that LSS deployments uniformly improved quality measures and patient satisfaction across radiology practices.

Outside imaging modality-based uses, Sahin and Yilmaz (2012) applied Six Sigma to optimize diagnostic imaging turnaround time and report precision, with an observed reduction in errors and increased process standardization. Hwang and Choi (2016) echoed these findings, emphasizing the correlation between reduced wait times and increased patient satisfaction when Lean principles were adopted in a Korean hospital’s radiology department. In a similar context, Fadhilah and Ayubi (2023) demonstrated that LSS tools like DMAIC (Define, Measure, Analyze, Improve, Control) could significantly cut radiology wait times in a resource-limited setting.

From operational initiatives Yaduvanshi and Sharma (2017) discussed systemic challenges in applying LSS to healthcare operations, particularly to environments with weak infrastructure or training capabilities. They highlighted leadership commitment and cultural change to achieve long-term process improvements. Early adoption studies, e.g. Workman-Germann and Woodward-Hagg (2006), cite that even basic Lean tools like value stream mapping could have starting point gains when being implemented as part of hospital-scale initiatives.

The use of AI to support LSS in radiology has become increasingly popular in recent years. Acosta et al. (2024) assessed AI-supported radiology reporting and found that AI-drafted reports simulated by AI enhanced radiologist productivity without compromising diagnostic quality. Supplementing this Baltruschat et al. (2020) created an AI solution to optimize chest X-ray worklists, allowing for more prompt interpretations of urgent cases. Wismueller et al. (2022) created an AI-powered QA system (AQUARIUS) to minimize diagnostic inequalities, envisioning a future where AI plays a central role in real-time quality assurance.

Moreover, Thompson et al. (2023) explored AI-supported triage algorithms and achieved impressive waiting time reductions for patients through automated prioritization—a concept consonant with Lean's waste-reduction philosophy. Cherry and Seshadri (2020) also highlighted that AI analytics can be supplemented with statistical Six Sigma principles to lower costs and variability in diagnostic processes. Zhang et al. (2015) and Porter & Catalani-Davies (2020) summed up that integrating LSS with data-driven methodology provides a strong framework for continuous improvement in interventional as well as diagnostic radiology.

In brief, the literature evidence is that Lean Six Sigma provides a data-driven, disciplined method of improving radiology processes and that AI technologies offer powerful mechanisms for automation, triage, and quality control. The convergence of the two areas has great potential to transform radiology departments into more efficient, accurate, and patient-centric operations.

3. Methods

Data Collection and Sources:
We will utilize publicly available datasets such as the NIH ChestX-ray14 and Stanford's CheXpert dataset, which consist of thousands of labeled radiographic images with common thoracic pathologies. These datasets will provide a solid foundation for training and testing our AI diagnostic model. Other operational data—wait times, report turnaround times, and error rates—will be simulated from case studies of published hospital reports and anonymized clinical data where possible.

Machine Learning Development:
A CNN model architecture will be trained in a supervised learning approach. Data will be split into training (70%), validation (15%), and testing (15%) subsets. Model performance will be evaluated based on sensitivity, specificity, precision, recall, and area under the ROC curve (AUC). Preprocessing will include normalization, augmentation, and de-identification of sensitive information.

Lean Six Sigma Workflow Evaluation:
A baseline of current radiology workflows will be mapped with SIPOC (Suppliers, Inputs, Process, Outputs, Customers) diagrams and value stream mapping. Key performance indicators (KPIs) will be defined based on Lean Six Sigma concepts (e.g., DPMO—defects per million opportunities, cycle time, and first-time yield). Post-intervention metrics will be collected after AI integration to measure improvements.

Validation and Simulation:
To model deployment, a digital twin of a radiology department will be created using process simulation software (e.g., Simul8 or Arena). This will enable iterative testing of the AI-augmented workflow under varying patient volumes and resource constraints.

Ethical Considerations:
All data used will be anonymized and sourced from open-access databases. There will be no use of patient-identifiable data, and the study will be carried out within institutional ethical guidelines for research using AI and healthcare data.

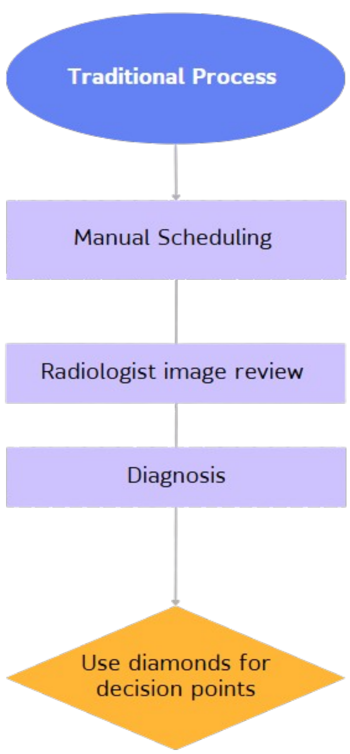
4. Data Collection

This study will collect data from two primary sources: publicly available radiographic image datasets and simulated operational performance data from radiology departments. The primary imaging datasets used will be NIH ChestX-ray14 and Stanford's CheXpert, both of which contain thousands of chest X-rays with a range of clinically significant conditions marked, such as pneumonia, pleural effusion, and cardiomegaly. These data sets will supply a varied and standardized foundation for model training and testing. All images will be preprocessed, including normalization and augmentation, in order to maximize model robustness and prevent overfitting in model training. The ground-truth annotated pathologies in the data sets will serve as a basis for ground truth for supervised learning algorithms.

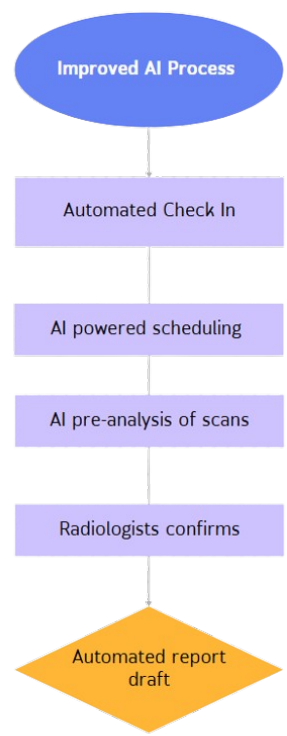
Synthetic operating data will concurrently be generated in parallel to replicate actual radiology department workflows. This includes time-based metrics like patient wait times, image acquisition time, report turnaround time, and radiologist workload. These simulated values will be expressed through parameters that have been collected from published hospital case studies and academic literature. Lean Six Sigma methodologies will be used to create a baseline image of current performance, using tools like value stream mapping and process analysis to identify inefficiencies and delays in diagnostic processes.

The imaging and workflow data will be utilized to train and test the AI diagnosis system, calculate its impact on operating performance, and enable simulation modeling of radiology departments operating under various loads. All data utilized in this study will be anonymized and handled according to ethical standards and data protection rules.

The flowcharts below show the comparison between the traditional process and our proposed process:



Traditional Process



AI Process

5. Conclusion

As radiology continues to serve as a critical pillar of modern healthcare, addressing its operational inefficiencies and diagnostic challenges is essential to improving patient outcomes and clinical performance. This research proposes a comprehensive, data-driven solution by integrating Lean Six Sigma methodologies with artificial intelligence to streamline workflows, reduce variability, and enhance diagnostic accuracy. Through the collection and analysis of radiographic imaging data and simulated operational metrics, this study aims to demonstrate how AI can function as a reliable decision-support tool while Lean Six Sigma provides a framework for sustainable process improvement. The goal is to create a scalable model that can be applied across diverse healthcare settings, delivering faster diagnoses, improved resource utilization, and higher-quality care. By aligning technological innovation with proven quality improvement strategies, this approach has the potential to transform radiology into a more efficient, precise, and patient-centered discipline.

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Biographies

L. Taylor Starr is a distinguished engineer, educator, and entrepreneur with extensive experience in systems engineering, aerospace, and industrial process improvement. Holding master's degrees in industrial engineering from the University of Texas at Arlington and Human-Centered Design Engineering from the University of Washington, as well as a bachelor's degree in Aeronautical and Industrial Technology from Tennessee State University, she has built a career at the intersection of engineering, education, and innovation. With over a decade of experience at Lockheed Martin, Starr has held key roles in project management, business development, and space systems engineering. Her expertise in Lean Six Sigma (Master Black Belt) has driven process efficiencies across aerospace and defense sectors. In academia, she has served as an engineering faculty member at Cedar Valley College and a graduate research assistant at the University of Texas at Arlington, contributing to advancements in engineering education and research. As the founder and CEO of ESTe²M Builders, Starr is dedicated to inspiring the next generation of STEM leaders through hands-on learning experiences. Her work focuses on fostering confidence, creativity, and competence in young learners through innovative STEM education initiatives. With a passion for bridging industry and education, she continues to shape the future of engineering and technology.

Noah Noronha is a driven mechanical engineering student at Texas A&M University with a strong foundation in mathematics, physics, and computational analysis. With a 4.0 GPA across both Texas A&M and community college coursework, he has completed advanced studies in calculus, differential equations, and university physics. He has secured a Co-Op position with Trane Technologies as a Systems Engineer; an opportunity rarely offered to freshmen. His responsibilities will include HVAC systems analysis and optimization, further developing his technical and problem-solving skills. Additionally, he is an intern in NASA's NCAS program, gaining hands-on experience with aerospace engineering and research. Noah's research focuses on artificial intelligence and neurodiversity in STEM, collaborating with Texas A&M faculty on a machine learning training program for high-functioning autistic individuals. His work has been accepted for presentation at the 2025 ASEE Conference in Montreal, Canada. He is also pursuing Lean Six Sigma Green Belt certification, researching process improvement in the radiology field. His involvement with ASME, where he placed third in an engineering challenge, further reflects his commitment to innovation. Through his research and industry experience, Noah aims to bridge mechanical engineering with AI-driven optimization and system efficiency.

Ibrahim Amin is a software engineering student at Texas A&M University with a strong foundation in programming, artificial intelligence, and process optimization. With a 4.0 GPA, he has gained expertise in Python, JavaScript, and cloud computing through coursework and certifications, further enhancing his ability to apply software engineering principles to real-world challenges. He is currently involved in a research project on artificial intelligence and neurodiversity in STEM, working alongside faculty at Texas A&M University. His research focuses on leveraging machine learning to support high-functioning autistic individuals in technical careers, utilizing natural language processing to develop personalized support tools. His work has been accepted for presentation at the 2025 ASEE Conference in Montreal, Canada. Additionally, Ibrahim is pursuing Lean Six Sigma Green Belt certification, researching the application of DMAIC (Define, Measure, Analyze, Improve, Control) methodologies to process improvements in the radiology field. His findings are expected to be presented at the North American Conference on Industrial Engineering and Operations Management in 2025. With prior experience in software debugging at Glennmore Technologies and a track record of building AI-based applications, Ibrahim is committed to integrating machine learning, process optimization, and software engineering to solve complex challenges in both industry and research.

David Kadari is a biomedical engineering student at Texas A&M University with a strong foundation in programming, artificial intelligence, and process optimization. With a 4.0 GPA, he has gained expertise in Python, JavaScript, and machine learning frameworks, equipping him with the technical skills necessary to tackle complex engineering problems. He is currently involved in a research project on artificial intelligence and neurodiversity in STEM, working alongside faculty at Texas A&M University. His research focuses on leveraging machine learning to support high-functioning autistic individuals in technical careers, utilizing natural language processing to develop personalized support tools. His work has been accepted for presentation at the 2025 ASEE Conference in Montreal, Canada. Additionally, David is pursuing Lean Six Sigma Green Belt certification, researching the application of DMAIC (Define, Measure, Analyze, Improve, Control) methodologies to process improvements in the radiology field. His findings are expected to be presented at the North American Conference on Industrial Engineering and Operations Management in 2025. With a passion for software development and AI-driven solutions, David is committed to integrating machine learning, process optimization, and software engineering to create innovative and impactful advancements in both research and industry.