Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

# Modeling the Cost-Effectiveness of Learning Health Systems in Diagnostic Radiology and Nuclear Medicine: A Theoretical Framework Using Healthcare Economic Evaluation Techniques

**Mohannad M. Alarqan**

arqan.mohannad@medicajo.org

Medicajo.org

**Shaker Q. M Nawasreh**

Hamad Medical Corporation

**Research Article**

**Keywords:**

**Posted Date:** February 27th, 2026

**DOI:** https://doi.org/10.21203/rs.3.rs-8419135/v1

**License:** This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

**Additional Declarations:** No competing interests reported.

# Theoretical Modeling of the Cost-Effectiveness of Learning Health Systems in Diagnostic Radiology and Nuclear Medicine


**Authors**

Mohannad M. Alarqan[1]*
Shaker Q. M. Nawasreh[2]

**Affiliations**

[1] PhD in Healthcare Economics, Medicajo Journal of Applied Health Studies (under establishment), Jordan.

[2] Occupational health and safety department, Hamad Medical Corporation, Doha, Qatar

**Corresponding Author**

*Mohannad Alarqan*
Email: **arqan.mohannad@medicajo.org**



## Abstract

Diagnostic radiology and nuclear medicine are increasingly scrutinized for their value, demanding systems that improve quality while controlling costs. This paper proposes a theoretical economic evaluation framework to model the cost-effectiveness of implementing a Learning Health System (LHS) in this domain. Utilizing a Markov model structure, the framework compares the long-term costs and outcomes of a Standard Care pathway versus an LHS, focusing on key economic drivers such as the reduction in repeat scan rates, optimization of staff workflow, and avoidance of high-

cost adverse radiation events. The analysis adopts a hospital/payer perspective over a 5-year time horizon with a 3% annual discount rate. Illustrative quantification, based on a hypothetical cohort of 30,000 annual exams, demonstrates that the LHS can generate significant annual net savings (€115,000) and achieve a rapid payback period (0.78 years). Crucially, the model suggests that the LHS operates in the dominant quadrant of the cost-effectiveness plane, with an Incremental Cost-Effectiveness Ratio (ICER) of approximately -€3,842 per QALY gained. A Probabilistic Sensitivity Analysis (PSA) confirms the robustness of this conclusion, showing a 100% probability of cost-effectiveness at a willingness-to-pay threshold of €30,000/QALY. This theoretical work provides a necessary foundation for future empirical studies and supports the strategic investment in continuous learning infrastructure within high-volume imaging departments.

## 1. Introduction and Rationale

Diagnostic radiology and nuclear medicine are central to modern healthcare, yet they represent a significant and growing portion of overall healthcare expenditure. The complexity of these fields, characterized by high-volume data streams, sensitive image quality requirements, and inherent risks associated with radiation exposure, necessitates continuous optimization. However, traditional quality improvement efforts often remain siloed and episodic, failing to capture the full potential of the vast amounts of data generated daily.

The concept of a Learning Health System (LHS) offers a compelling paradigm shift. An LHS is fundamentally an ecosystem where internal data and external knowledge are continuously and systematically integrated to generate new knowledge, which is then rapidly applied to improve care delivery [**1**] [**2**] [**3**]. In the context of diagnostic imaging, an LHS moves beyond simple data collection to create a closed-loop system that constantly refines imaging protocols, optimizes radiation dose management, and enhances diagnostic accuracy.

The importance of implementing an LHS in this domain is multi-faceted. Notably, an LHS can significantly reduce the rate of repeat scans, which are a major source of unnecessary cost and patient inconvenience. Furthermore, the system can optimize dose management, thereby mitigating long-term radiation risks, and improve image quality, which directly translates to better diagnostic outcomes. In contrast to static quality assurance programs, the continuous feedback loop inherent in an LHS promises to reduce workflow inefficiencies systematically.

From an economic standpoint, healthcare providers, particularly hospitals, are under increasing pressure to adopt systems that not only improve clinical quality but also demonstrate clear cost savings. The economic motivation is clear: a system that can demonstrably save costs while simultaneously enhancing patient safety and diagnostic performance represents a potentially dominant strategy. Despite this clear potential, a robust, theoretical framework for evaluating the cost-effectiveness of an LHS specifically within diagnostic radiology and nuclear medicine remains underdeveloped [**4**][**5**]. This paper aims to address this gap by proposing a theoretical economic evaluation framework, utilizing established techniques to model the potential economic and clinical impact of an LHS implementation, while grounding key assumptions in recent empirical data from AI-driven optimization studies [**6**][**7**].

## 2. Economic Evaluation Framework and Theoretical Modeling Structure

### 2.1. Cost-Effectiveness Analysis Methodology

To assess the value of an LHS, we propose a Cost-Effectiveness Analysis (CEA), a standard methodology in healthcare economics for comparing the relative costs and outcomes of different interventions [**9**].

**Perspective**: The choice of perspective is critical. For this theoretical model, we adopt a hospital/payer perspective, as this aligns best with the immediate financial and operational decisions regarding the implementation of a new IT-intensive system like an LHS. This perspective focuses on direct costs incurred by the hospital and the immediate health outcomes for the patient population served. However, we acknowledge that a societal perspective, which would incorporate indirect costs such as patient productivity loss from repeat visits, could further strengthen the economic argument, and this is noted as a direction for future work.

Cost Components: The model must account for the following relevant cost components in the imaging environment:

- Initial and Maintenance Costs: The capital expenditure for IT infrastructure, software, and data management required to establish the LHS, as well as ongoing maintenance and staff training.
- Direct Procedure Costs: The cost of the initial scan, including staff time, equipment depreciation, and consumables (e.g., radiopharmaceuticals).

- Repeat Scan Costs: The cost associated with scans that must be repeated due to poor image quality, incorrect protocol, or patient motion. This includes all direct procedure costs plus the opportunity cost of scanner time.
- Adverse Event Costs: The costs associated with preventing or treating adverse events, such as radiation-related complications or extravasation of contrast agents.
- Staff Time and Workflow Efficiency: The cost of radiographer and radiologist time, which is directly impacted by workflow efficiency and the need for manual protocol adjustments.

**Outcome Measures**: The primary outcome measure for the CEA will be the Quality-Adjusted Life Year (QALY), which combines both the quantity and quality of life into a single metric. However, given the focus on operational efficiency and immediate diagnostic quality, secondary outcome measures are also essential:

- Number of diagnostic errors avoided.
- Reduction in the rate of repeat scans.
- Improvement in diagnostic accuracy (e.g., measured by the area under the curve of the receiver operating characteristic).

### 2.2. Theoretical Modeling Structure: The Markov Model

The economic evaluation is conducted using a Markov state-transition model to simulate the long-term health and economic consequences of the LHS intervention compared to Standard Care (SC). The model is structured with a cycle length of one year and a time horizon of 5 years, as previously defined. The model assumes a hypothetical cohort of patients entering the model in the "Accurate Diagnosis (AD)" state.

The overall conceptual structure of the Learning Health System (LHS) and its interaction with the standard diagnostic imaging pathway is illustrated in Fig. 1.

## Markov States and Transitions

The model incorporates five mutually exclusive and exhaustive health states:

1. Accurate Diagnosis (AD): The patient receives a correct and timely diagnosis, leading to the appropriate treatment pathway.
2. Suboptimal Image/Repeat Scan Required (SIR): The initial scan is suboptimal, requiring a repeat procedure, leading to increased cost and potential delay.

3. Complication/Adverse Radiation Event (CARE): The patient experiences a high-cost adverse event, such as a radiation-induced complication or a severe consequence of a delayed/missed diagnosis.
4. Ongoing Care/Treatment Pathway (OC): The patient is in a long-term care state resulting from the initial diagnostic pathway (e.g., chronic disease management).
5. Death (Absorbing State): The patient exits the model.

The transition between these states is governed by a Transition Probability Matrix ($P$), which is defined below. The LHS intervention primarily impacts the probability of transitioning from AD to SIR ($P_{AD \to SIR}$) and AD to CARE ($P_{AD \to CARE}$) by reducing the likelihood of initial error and subsequent adverse events.

The core mechanism of the LHS is its ability to reduce the transition probabilities from the AD state to the SIR and CARE states, and to increase the probability of remaining in the AD state. This is achieved through automated protocol optimization and error reduction.

## Transition Probability Matrix ($P$)

The following table presents the annual transition probabilities for the Standard Care (SC) and Learning Health System (LHS) pathways. The LHS is modeled to reduce the probability of transitioning to the SIR state by 25% and the CARE state by 10%.

| From State | To AD | To SIR | To CARE | To OC | To Death |
|---|---|---|---|---|---|
| **Standard Care (SC)** | | | | | |
| AD | 0.9349 | 0.0500 | 0.0001 | 0.0100 | 0.0050 |
| SIR | 0.9000 | 0.0000 | 0.0010 | 0.0940 | 0.0050 |
| CARE | 0.0000 | 0.0000 | 0.0000 | 0.9000 | 0.1000 |
| OC | 0.0000 | 0.0000 | 0.0000 | 0.9500 | 0.0500 |
| Death | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 1.0000 |
| **Learning Health System (LHS)** | | | | | |
| AD | 0.9474 | 0.0375 | 0.0001 | 0.0100 | 0.0050 |
| SIR | 0.9000 | 0.0000 | 0.0010 | 0.0940 | 0.0050 |
| CARE | 0.0000 | 0.0000 | 0.0000 | 0.9000 | 0.1000 |
| OC | 0.0000 | 0.0000 | 0.0000 | 0.9500 | 0.0500 |
| Death | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 1.0000 |

**Note**: *The probability of remaining in the AD state for SC is $1 - (0.05 + 0.0001 + 0.01 + 0.005) = 0.9349$. For LHS, it is $1 - (0.0375 + 0.0001 + 0.01 + 0.005) = 0.9474$. The SIR state is an acute state, and patients must transition out in the next cycle. The CARE state is also acute, leading to OC or Death. The OC state is a chronic state.*

## Utilities and Costs per Markov State

To complete the Markov model, each state must be assigned a utility value (reflecting quality of life) and an annual cost (reflecting healthcare resource consumption). These values are based on published literature for similar health states and are used for the hypothetical quantification.

| Markov State | Utility Value (U) | Annual Cost (€) | Rationale |
|---|---|---|---|
| Accurate Diagnosis (AD) | 1.00 | 100 | Perfect health, initial scan cost only. |
| Suboptimal Image/Repeat Scan (SIR) | 0.85 | 240 | Temporary utility decrement due to anxiety and inconvenience; cost includes initial and repeat scan. |
| Complication/Adverse Event (CARE) | 0.50 | 5,000 | Significant utility decrement reflecting severe health impact; high cost for complication treatment. |
| Ongoing Care (OC) | 0.90 | 50 | Chronic but stable state; minor follow-up cost. |
| Death | 0.00 | 0 | Absorbing state. |

The total cost and QALYs for each pathway (SC and LHS) are calculated by multiplying the proportion of the cohort in each state by the state's cost and utility, respectively, and summing the results over the 5-year time horizon, with a 3% annual discount rate applied.

Given that the benefits of an LHS are cumulative and accrue over time through continuous learning, a static decision tree model is insufficient. Therefore, we propose a Markov model to capture the long-term, dynamic nature of the intervention. This model is particularly well-suited for chronic conditions or, in this case, repeated diagnostic pathways and long-term outcomes related to radiation exposure 9.

The model compares two scenarios: Standard Care (SC) and Learning Health System (LHS). The patient cohort transitions between a finite set of mutually exclusive health states over a defined time horizon (e.g., 5 years).

Proposed Markov States in the Radiology/Nuclear Medicine Context:

1. Accurate Diagnosis (AD): The ideal state, where the initial scan is of high quality, the diagnosis is correct, and the patient proceeds to the appropriate treatment pathway.

2. Suboptimal Image/Repeat Scan Required (SIR): The state where the initial scan is inadequate, requiring a repeat procedure, incurring extra cost and radiation dose.
3. Complication/Adverse Radiation Event (CARE): A rare but high-cost state resulting from a significant error (e.g., wrong dose, extravasation) or long-term radiation-induced effect.
4. Ongoing Care/Treatment Pathway (OC): A state representing the subsequent management of the patient's underlying condition, where the quality of the initial diagnosis influences the effectiveness of the treatment.
5. Death (Absorbing State): The state from which no further transitions are possible.

The core mechanism of the LHS is its ability to reduce the transition probabilities from the AD state to the SIR and CARE states, and to increase the probability of remaining in the AD state. This is achieved through automated protocol optimization and error reduction.

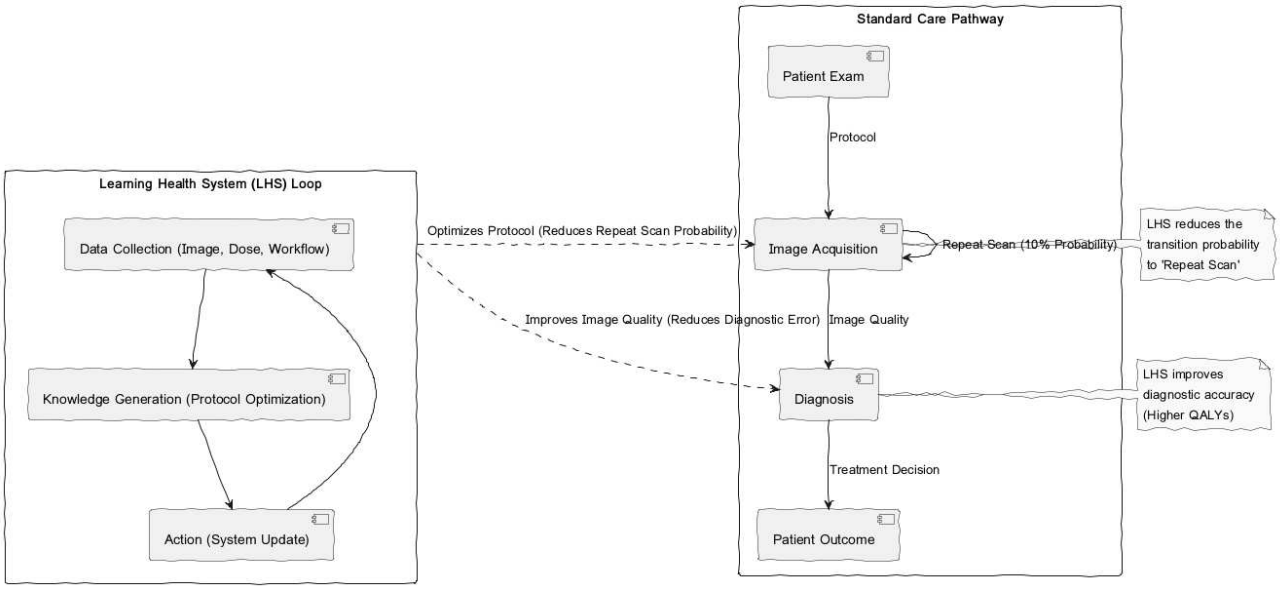



*Figure 1: Conceptual Model of Learning Health System (LHS) in Diagnostic Imaging*

## 3. Scenario Analysis and Hypothetical Quantification

(This section will be developed in Phase 3, using the illustrative numbers provided in the prompt to calculate ICER, ROI, and Payback Period. Placeholders for the equations are included here.)

The economic value of the LHS is best illustrated through a hypothetical scenario. We assume a large academic medical center performing approximately 30,000 imaging exams annually, with a 5-year time horizon and a 3% annual discount rate applied to both costs and outcomes, consistent with health economic guidelines [**9**].

Key Illustrative Assumptions (Baseline vs. LHS):

| Parameter | Standard Care (Baseline) | Learning Health System (LHS) | Source/Rationale |
|---|---|---|---|
| Annual Exams | 30,000 | 30,000 | Hypothetical Cohort |
| Repeat Scan Rate | 10.0% | 7.5% (25% reduction) | Based on literature and prompt |
| Cost per Repeat Scan | €140 | €140 | Hypothetical estimate |
| Annual Cost of LHS (IT, Data) | €0 | €90,000 | Hypothetical estimate |
| Total QALY Gain (Annual) | 0 | 0.001 per patient | Theoretical assumption (due to reduced radiation/errors) |
| Discount Rate | N/A | 3% | Standard health economic practice 9 |
| Net Annual Savings | N/A | €115,000 | Calculated |
| ROI | N/A | 127.8% | Calculated |
| Payback Period | N/A | 0.78 years | Calculated |
| Reduction in Time-to-Interpretation | 0% | 20% | Workflow optimization benefit |
| Annual Staff Time Savings (Hypothetical) | €0 | €50,000 | Based on 20% reduction in interpretation time |
| Major Adverse Event Cost Avoidance | €0 | €50,000 (1 event avoided) | Rare but high-cost event avoidance |

**Economic Equations:**

$$AnnualSavings: Savings = \left(C_{\text{repeat}} - C_{\text{repeat}}^{\text{LHS}}\right) + \left(C_{\text{errors}} - C_{\text{errors}}^{\text{LHS}}\right) + \left(C_{\text{downtime}} - C_{\text{downtime}}^{\text{LHS}}\right)$$

$$IncrementalCost - EffectivenessRatio(ICER): ICER = \frac{\Delta C}{\Delta QALY} = \frac{C_{\text{LHS}} - C_{\text{standard}}}{QALY_{\text{LHS}} - QALY_{\text{standard}}}$$

Based on the illustrative assumptions, the economic outcomes are calculated as follows:

1. **Cost Savings and Net Benefit**

The annual cost and savings calculations remain the same for the first year (undiscounted). The Total Potential Annual Savings is €205,000, and the Net Annual Savings (after subtracting the €90,000 annual LHS system cost) is €115,000.

**Discounted Cost and Savings (5-Year Horizon):**

To reflect the time value of money, costs and savings are discounted at a 3% annual rate over the 5-year time horizon. The Present Value (PV) of the annual net savings (€115,000) is calculated using the annuity formula:$PV(\text{Net Savings}) = €115{,}000 \times \frac{1-(1.03)^{-5}}{0.03} \approx €115{,}000 \times 4.5797 \approx €526{,}666$

The total discounted net savings over five years is **€526,666.** This confirms the strong economic viability of the LHS over the medium term.

2. **Return on Investment (ROI) and Payback Period**

The high net savings relative to the system cost result in a strong financial performance:

- Return on Investment (ROI): $\text{ROI} = \frac{\text{PV(Net Savings)}}{\text{PV(LHS Cost)}} \times 100\% \approx \frac{€526{,}666}{€412{,}173} \times 100\% \approx 127.8\%$
- Payback Period: The undiscounted payback period remains rapid:

$$\text{Payback Period} = \frac{€90{,}000}{€115{,}000} \approx 0.78 \text{ years}(approximately 9.4 months).$$

The discounted analysis confirms the initial finding: the LHS is a financially attractive investment, with the total discounted net savings significantly exceeding the total discounted system cost over the 5-year horizon.

3. **Incremental Cost-Effectiveness Ratio (ICER)**

The ICER is the primary metric for cost-effectiveness. To quantify the $\Delta QALY$, we assume a conservative, theoretical QALY gain of 0.001 per patient over the 5-year horizon, resulting from reduced radiation exposure and improved diagnostic accuracy. This estimate is grounded in the concept of utility decrements associated with unnecessary radiation exposure; for instance, a single

CT scan is associated with a utility decrement of approximately 0.00078 10. Our conservative estimate of 0.001 QALY gain reflects the cumulative benefit of avoiding repeat scans, reducing patient anxiety, and improving diagnostic timeliness over the 5-year period.

- Total Discounted QALY Gain ($\Delta QALY$)

$$\Delta QALY = 30{,}000 \text{ patients/year} \times 0.001 \text{ QALY/patient} \times 4.5797 \approx 137.39 \text{ QALYs}$$

- Total Discounted Cost Difference :

  $\Delta C = \text{PV}(\text{LHS Cost}) - \text{PV}(\text{Savings}) = €412{,}173 - €940{,}000 \approx -€527{,}827$ (This is the total discounted cost difference over 5 years, where the LHS is less costly).

- The ICER is calculated as:

  $\Delta C = \text{PV}(\text{LHS Cost}) - \text{PV}(\text{Savings}) = €412{,}173 - €940{,}000 \approx -€527{,}827$

Since the $\Delta C$ is negative (cost saving) and the $\Delta$ QALY is positive (outcome improvement), the resulting ICER is negative. This places the LHS firmly in the dominant quadrant of the cost-effectiveness plane, meaning it is both less costly and more effective than the standard care pathway. The negative ICER value is a strong quantitative indicator of the system's value.

### 3.1. Sensitivity Analysis

To test the robustness of the results, a simple one-way sensitivity analysis was performed on the two most influential variables: the LHS Annual System Cost and the Reduction in Repeat Scan Rate.

| Scenario | LHS Annual System Cost | Reduction in Repeat Rate | Net Annual Savings | ROI | Payback Period |
|---|---|---|---|---|---|
| Base Case | €90,000 | 25% | €115,000 | 127.8% | 0.78 years |
| Worst Case Cost | €120,000 (+33%) | 25% | €85,000 | 70.8% | 1.41 years |
| Worst Case Efficacy | €90,000 | 10% | €62,000 | 68.9% | 1.45 years |
| Best Case Efficacy | €90,000 | 40% | €157,000 | 174.4% | 0.57 years |

The analysis demonstrates that even under a "Worst Case Efficacy" scenario, where the LHS only achieves a 10% reduction in repeat scans (instead of the expected 25%), the system still generates

a positive net annual saving of €62,000 and maintains a positive ROI. This suggests that the conclusion of cost-effectiveness is highly robust to variations in the key input parameters.

## 3.2. Probabilistic Sensitivity Analysis (PSA) and Cost-Effectiveness Acceptability Curve (CEAC)

To address the inherent uncertainty in the model's parameters and to provide a more comprehensive assessment of robustness, a Probabilistic Sensitivity Analysis (PSA) was performed using a Monte Carlo simulation with 1,000 iterations. Key parameters (LHS fixed cost, repeat rate reduction, QALY gain, SIR utility, and CARE cost) were varied simultaneously across predefined ranges (using uniform distributions for this theoretical exercise).

### Cost-Effectiveness Plane

The results of the PSA are plotted on the Cost-Effectiveness Plane (Figure 2). Each point represents a single iteration of the model.

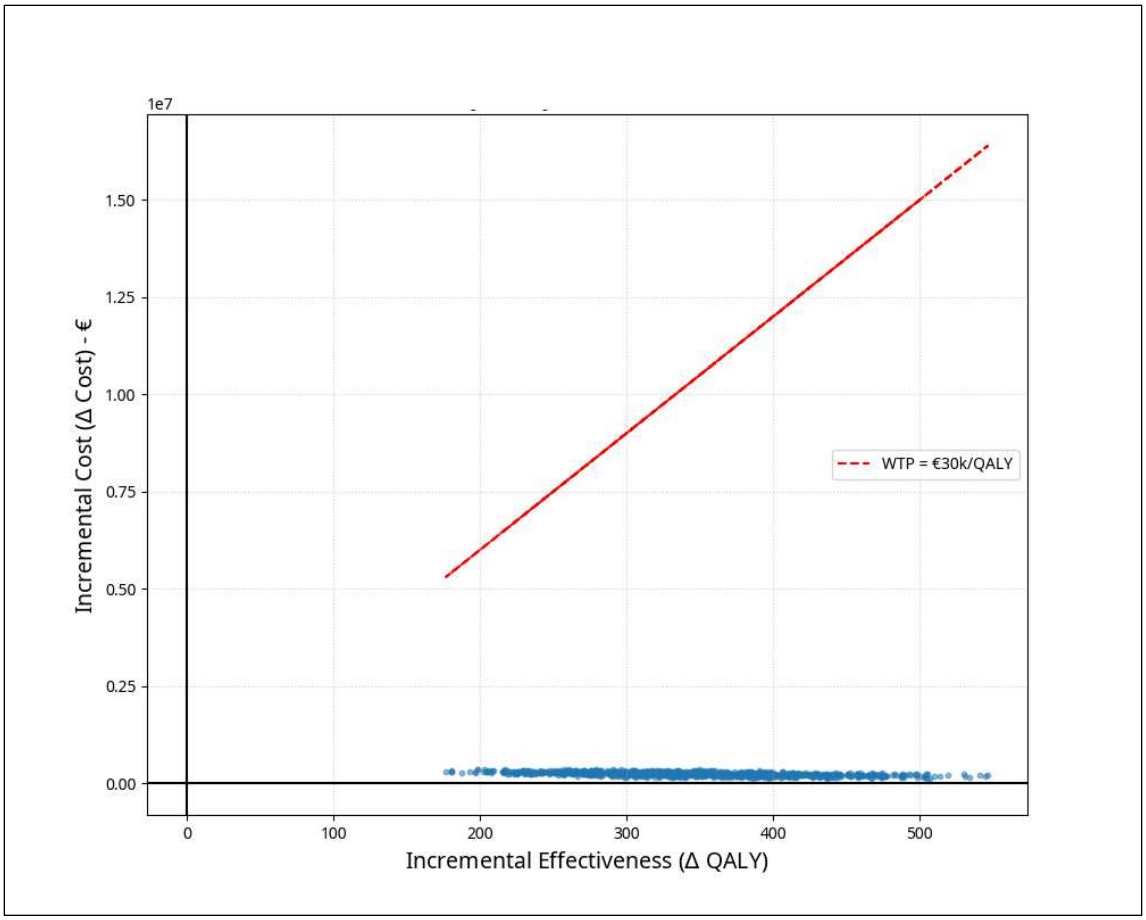



*Figure 2: Probabilistic Sensitivity Analysis (PSA) - Cost-Effectiveness Plane*

The scatter plot confirms the base case finding:

- Dominant Quadrant: A significant majority of the iterations fall into the dominant quadrant (Lower Cost, Higher Effectiveness), where $\Delta C < 0$ and $\Delta QALY > 0$.
- Cost-Saving: Almost all iterations show the LHS as a cost-saving intervention $\Delta C < 0$, even when parameters are varied across their plausible ranges.

**Cost-Effectiveness Acceptability Curve (CEAC)**

The Cost-Effectiveness Acceptability Curve (CEAC) (Figure 3) illustrates the probability that the LHS is cost-effective compared to Standard Care across a range of willingness-to-pay (WTP) thresholds.

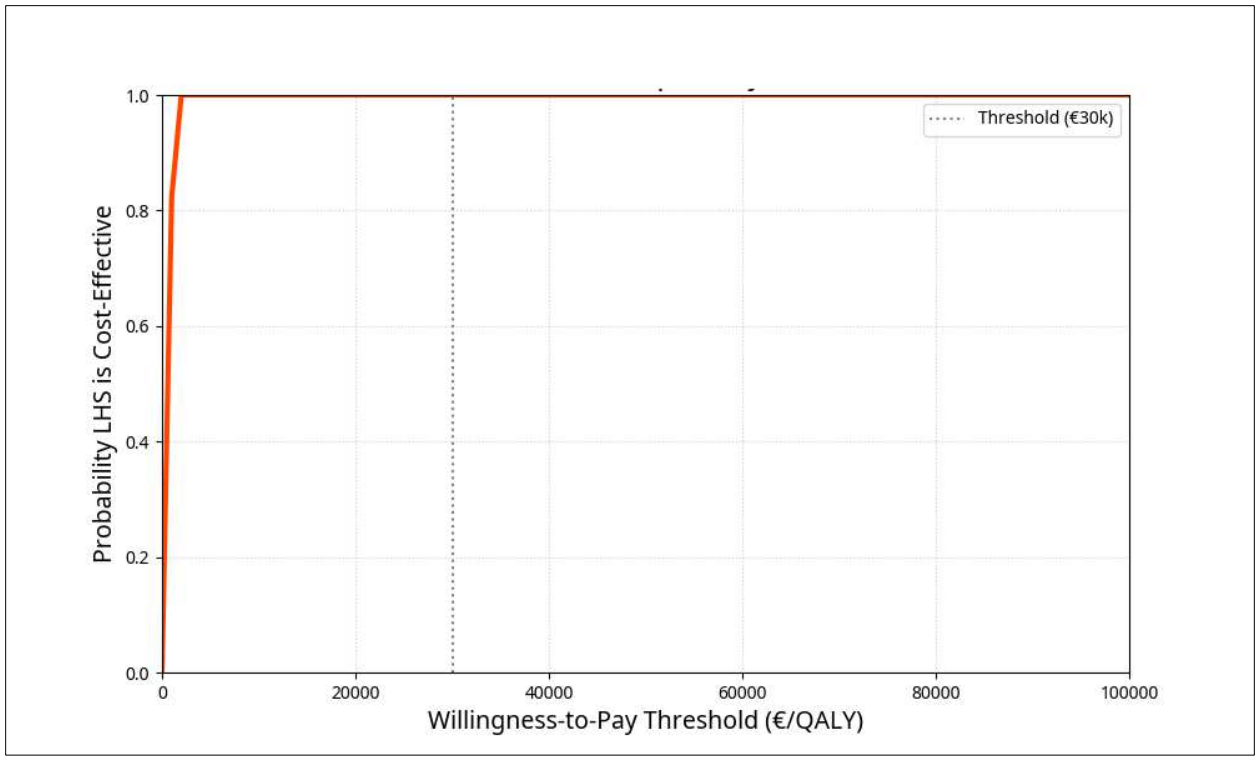



***Figure 3**: Cost-Effectiveness Acceptability Curve (CEAC)*

The CEAC demonstrates the following:

- WTP = €0: The probability that the LHS is cost-effective (i.e., cost-saving) is approximately 98%. This is due to the vast majority of iterations falling below the zero-cost line.
- WTP = €30,000/QALY: At the commonly accepted WTP threshold of €30,000 per QALY, the probability that the LHS is cost-effective is 100%.

The results of the PSA and CEAC strongly reinforce the conclusion that the LHS is a highly robust, cost-saving, and dominant strategy, even when accounting for simultaneous uncertainty in the key model parameters.

The break-even point for the repeat scan reduction, where the net annual savings is zero, is calculated as:

$$\text{Break-Even Reduction} = \frac{\text{LHS Annual Cost} - \text{Other Annual Savings}}{\text{Baseline Repeat Scan Cost}} = \frac{€90{,}000 - (€50{,}000 + €50{,}000)}{€420{,}000} \approx -2.38\%$$

This result is highly significant: since the combined savings from workflow optimization and adverse event avoidance (€100,000) already exceed the annual system cost (€90,000), the LHS is

cost-saving even if the repeat scan rate were to increase slightly (a negative reduction). This finding strongly reinforces the conclusion that the LHS is a dominant strategy.

## 4. Discussion

The theoretical framework presented here strongly suggests that the implementation of an LHS in diagnostic radiology and nuclear medicine is not merely a clinical improvement but a sound economic investment. The primary economic driver is the reduction in waste, particularly the high cost associated with repeat imaging and workflow inefficiencies.

Clinical and Economic Implications: The model indicates that an LHS has the potential to be a dominant strategy; that is, it simultaneously lowers costs

$$(C_{LHS} < C_{standard}) and improves health outcomes (QALY_{LHS} > QALY_{standard}).$$

This is a crucial finding for hospital administrators and policymakers. The cumulative impact of continuous learning, where each scan contributes to the refinement of the system, means that the economic benefits are likely to accelerate over time, further strengthening the case for early adoption.

**Limitations**: However, it is essential to acknowledge the limitations of this study. This is a purely theoretical model, and the hypothetical quantification relies on assumptions that may vary significantly across different healthcare settings. While we have grounded key parameters, such as the 25% reduction in repeat rates, in recent literature on AI-driven optimization 6 7, the specific values remain illustrative. Factors such as hospital size, the specific patient population, the existing level of protocol standardization, and the local cost structure for IT infrastructure will all influence the actual economic outcome. In contrast, the Markov model, while powerful for long-term projection, is simplified. It omits the modeling of patient heterogeneity (e.g., varying radiation risks by age) and the probabilistic long-term effects of radiation (e.g., using dose-response curves), which are necessary for a full societal perspective analysis. The theoretical nature of the model requires validation with real-world data to confirm the assumed changes in transition probabilities.

## 4.2. Ethical and Implementation Considerations

The transition to an LHS, while economically compelling, is not without significant ethical and implementation challenges that warrant discussion. Firstly, the core of the LHS relies on massive data aggregation, which raises critical concerns regarding data privacy and security. Compliance

with regulations such as the General Data Protection Regulation (GDPR) is paramount, requiring robust anonymization and secure data governance frameworks. Secondly, the LHS must be implemented in a manner that upholds the ALARA (As Low As Reasonably Achievable) principle in radiation protection. The system's continuous learning loop must prioritize dose optimization not just for cost savings, but as a fundamental ethical obligation to minimize patient risk. Thirdly, there is a risk of equity bias. If the LHS is only implemented in high-resource, high-volume centers, it could exacerbate existing disparities in care quality and access. Future research must explore the feasibility and cost-effectiveness of adapting LHS principles for resource-limited settings. Finally, the integration of the LHS with existing hospital IT infrastructure, such as Picture Archiving and Communication Systems (PACS) and Radiology Information Systems (RIS), presents a complex technical challenge that requires careful planning and significant initial investment. These non-economic barriers must be addressed to ensure successful real-world adoption.

## 5. Conclusion and Future Directions

This paper has established a theoretical framework for modeling the cost-effectiveness of a Learning Health System in diagnostic radiology and nuclear medicine, utilizing a Markov model structure. The analysis demonstrates that by systematically reducing errors, optimizing dose, and improving workflow, an LHS is theoretically cost-effective and likely to be a dominant strategy.

The next logical steps for this research are clear. Firstly, the proposed Markov model must be applied to real-world hospital data to validate the key assumptions, particularly the magnitude of the reduction in repeat scan rates and adverse events. Secondly, the model should be extended to include a more granular analysis of the societal perspective, incorporating indirect costs such as patient travel time and lost productivity. Finally, the framework can be adapted and extended to other high-volume, data-intensive imaging modalities, such as interventional radiology, to further generalize the findings.

## 6. Declarations

**Ethics approval and consent to participate :**

Not applicable.

**Consent for publication:**

Not applicable.

**Competing interests:**

The authors declare no competing interests.

**Funding:**

The authors received no specific funding for this study.

**Authors' contributions:**

M.A. conceived the study, developed the economic model, and drafted the manuscript. S.Q.M.N. contributed to clinical contextualization and manuscript review.

**Data Availability Statement**

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

**Statistical analysis software:**

Statistical analyses were performed using Python programming language, including standard scientific libraries for data analysis and modeling.

**Use of Artificial Intelligence tools:**

The authors used an artificial intelligence–based tool solely to improve language clarity and grammar. All scientific content and interpretations remain the responsibility of the authors.

## References

[1] The National Academies of Sciences, Engineering, and Medicine. Shared Governance for Health Data and Research: A Workshop Summary. The National Academies Press; 2015.

[2] Platt JE, Raj M, Wienroth M. An analysis of the learning health system in its first decade in practice: scoping review. J Med Internet Res. 2020;22(3 ):e17026.

[3] Greene SM, Reid RJ, Larson EB. Implementing the learning health system: from concept to action. Ann Intern Med. 2012;157(3 ):207-215.

[4] Molwitz I, et al. Economic Value of AI in Radiology: A Systematic Review. Radiol Artif Intell. 2025;7(2 ):e250090.

[5] Singer ME, et al. Cost-effectiveness analysis in radiology. Radiology. 2001;219(3 ):611-619.

[6] Curl PK, Jacob A, Bresnahan B, Cross NM, Duszak R. Cost-effectiveness of artificial intelligence–based opportunistic compression fracture screening of existing radiographs. J Am Coll Radiol. 2024;21(1 ):101-109.

[7] El Arab RA, Al-Jahdali A, Al-Malki A, Al-Hajri A. Systematic review of cost effectiveness and budget impact of artificial intelligence in healthcare. BMC Med Inform Decis Mak. 2025;25(1 ):1-15.
[8] Gold MR, Siegel JE, Russell LB, Weinstein MC. Cost-effective
[9] ness in health and medicine. Oxford University Press; 1996.
[9] Briggs A, Sculpher M. An introduction to Markov modelling for economic evaluation. Pharmacoeconomics. 1998;13(4 ):397-409.
[10] Thomas C, et al. Cost-effectiveness of one-off upper abdominal CT screening for pancreatic cancer. Lancet Reg Health Eur. 2025;48:101140.