Enhancing HTA model adaptations with AI: Leveraging large language models and R-Shiny for local cost-effectiveness analyses

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R for HTA Annual Workshop | June 10th , 2025

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Today’s discussion topics

Opening remarks, context & objectives

Country requirements & concept presentation

Case study: Using LLMs and R-Shiny for model adaptation

Key takeaways

Opening remarks, context & objectives

Background

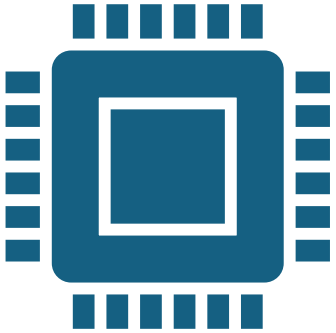
Global pharma companies build global HTA models.

Local affiliates face challenges adapting them:

- Limited manpower.
- Limited access to country-specific data.
- Bandwidth constraints.

Adaptation processes are manual, slow, error-prone.

What are LLMs & R-Shiny?



LLMs: AI tools that understand and generate text, helping HTA teams automate data extraction and interpretation and fill local data gaps.

R-Shiny: Open-source framework that enables the creation of interactive/transparent web applications from R.

Session objectives

01

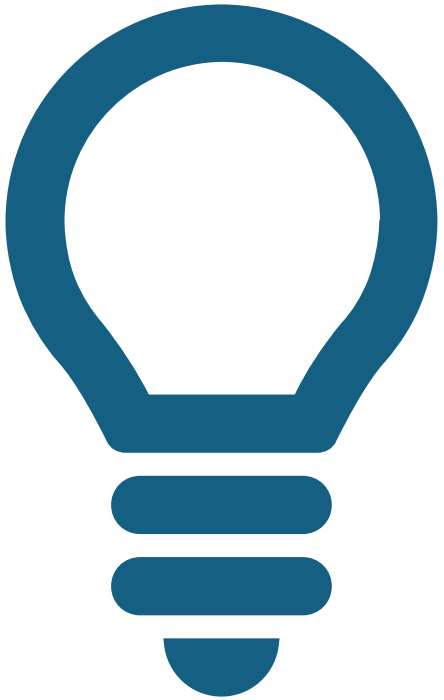
Simplify and accelerate local model adaptation.

02

Enhance reproducibility in economic model involving local adaptations.

03

Free up teams to focus on interpretation, not data cleaning.



Country requirements & concept presentation

Country specific needs

Why adapt global models?

- Clinical differences (treatment standards)
- Cost variations (healthcare pricing)
- Epidemiological differences (incidence, survival)
- Utility differences (HRQoL values)

Ignoring these leads to loss of relevance or HTA rejection.

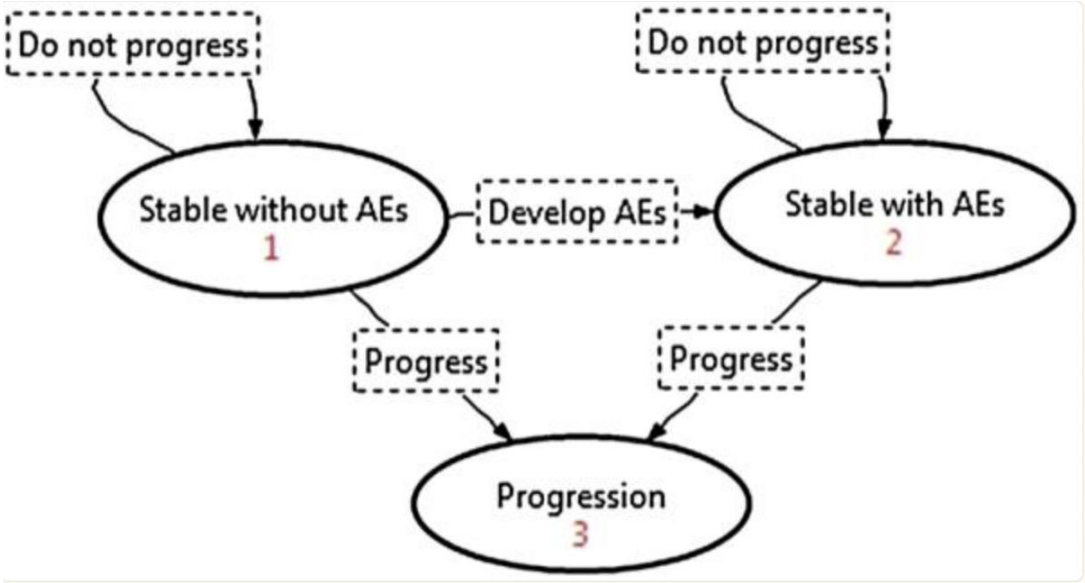
Challenges in model adaptation

- Data unavailability or poor accessibility
- Inconsistent model documentation
- Time-consuming manual parameter updates
- Risk of human error

AI-enhanced step-by-step adaptation

Step	Action	How AI Helps
1	Identify model components needing localization	NLP parsing of model files
2	Extract local parameters	Prompt-based search across local datasets
3	Search and recommend replacements	Intelligent data queries
4	Modify model dynamically	Auto-suggest edits
5	Quality control	AI-generated checklists
6	Documentation generation	Auto-documented assumptions and sources

We adapted a global Markov model to UK and Canada requirements using LLMs + R-Shiny



Case study based on a global cost-effectiveness model originally published by Diaby et al. 2014. *Breast Cancer Res Treat*. 147(2):433–441.

Markov model compares everolimus + exemestane vs. exemestane alone for HR+/HER2– metastatic breast cancer in U.S., with lifetime horizon and 6-week cycles.

Model adaptation for UK and Canada to explore localized HTA requirements.

Case study: Using LLMs and R-Shiny for model adaptation

Input parameters to be localized include cost, utilities and transition probabilities

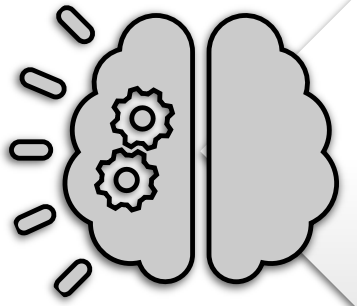
United Kingdom (NICE / NHS)

- Costs: NHS Reference Costs (NHS Digital)
- Utilities: EQ-5D from NICE evidence summaries (NICE TA Documents)
- Transitions: UK cancer registry (Cancer Research UK)

Canada (CADTH / CIHI)

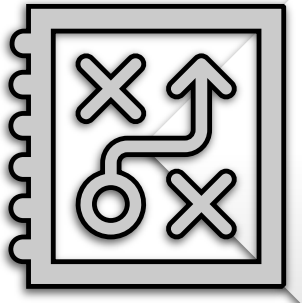
- Costs: CIHI Case Costing and Public Drug Plans (CIHI Database)
- Utilities: Canadian health utility compendium (Canadian Utility Compendium)
- Transitions: Canadian Cancer Registry (Statistics Canada)

Implementing model adaptations



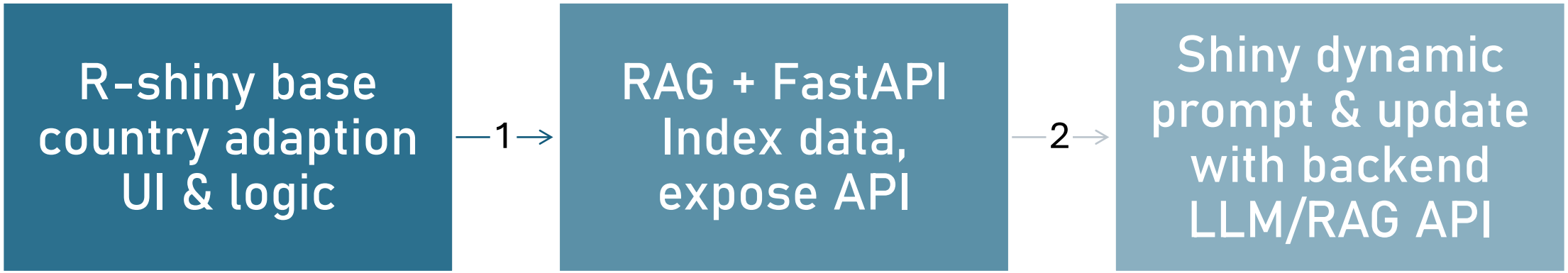
AI-powered Retrieval-Augmented Generation (RAG) used to:

- Search and extract local clinical and economic parameters.
- Maintain traceability and documentation of all substitutions.



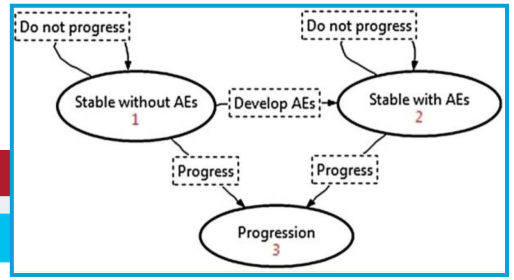
R-Shiny interface dynamically applies updates to the model structure and reruns simulations.

LLM & R-Shiny Setup

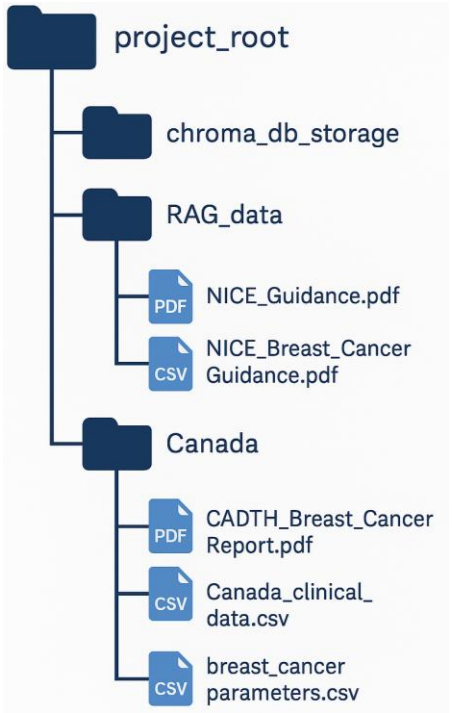


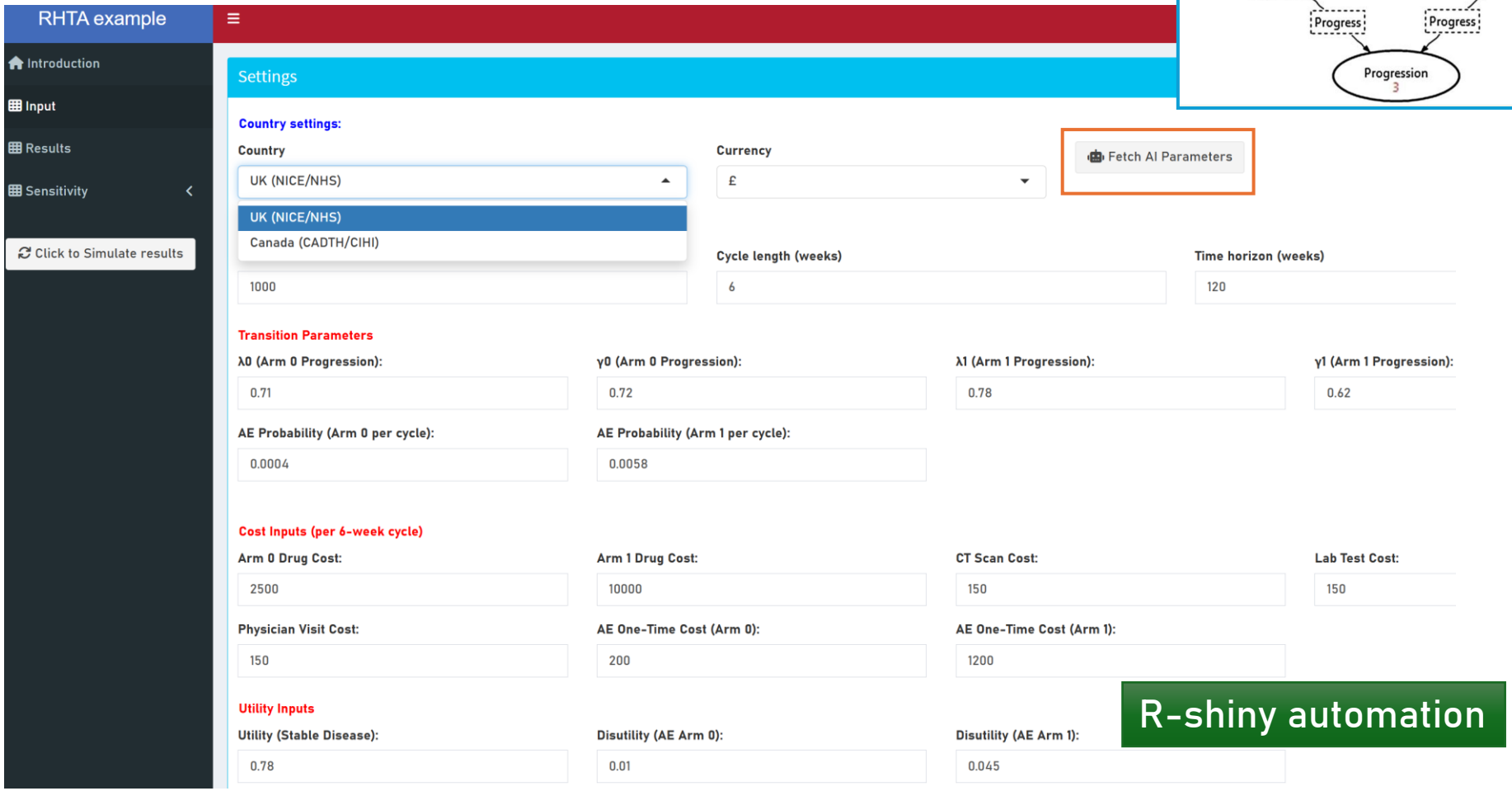
LLMs + R-SHINY ILLUSTRATION

R-Shiny + LLM + RAG overview



RAG data structure





R-shiny automation

Indexed in ChromaDB

FastAPI + Ollama API

R to call LLM (llama2, DeepSeek, etc.) with RAG

Example data for RAG

Country-specific model for HTA

Prompt: *"Extract standard clinical and economic parameters for breast cancer treatment in UK"*

Context:

CSV files

PDF files

text	country	source	topic
Breast cancer progression rate is 0.07 per cycle, according to Cancer Research UK (2023). Gamma factor is 0.55.	UK	Cancer Research UK 2023	Clinical Parameters
Arm 0 treatment cost is £200 per 6-week cycle (NHS Digital, 2022). Arm 1 treatment cost is £10,000 per 6-week cycle.	UK	NHS Digital 2022	Cost
Utilities for stable disease state are reported as 0.72 based on EQ-5D measures (NICE TA123).	UK	NICE TA123	Quality of Life
In Canada, breast cancer progression rate is 0.065 per cycle, with gamma factor 0.56 (Canadian Cancer Registry, 2023).	Canada	Canadian Cancer Registry 2023	Clinical Parameters
Arm 0 cost: CAD 300; Arm 1 cost: CAD 12,000 per 6-week cycle (CIHI Case Costing 2023).	Canada	CIHI Case Costing 2023	Cost
Utility for stable disease in Canada is 0.71 based on EQ-5D from the Canadian Utility Compendium (2022).	Canada	Canadian Utility Compendium	Quality of Life

NICE_Guidance.pdf

Clinical Effectiveness

In the clinical trials reviewed, the median progression-free survival for patients receiving exemestane alone was 5.7 months, compared with 11.0 months for those receiving everolimus plus exemestane. The hazard ratio for progression was 0.45 (95% CI: 0.38–0.54), indicating a significant benefit for the combination therapy. The incidence of grade 3/4 adverse events was 23% in the exemestane group and 45% in the combination group.

Costs and Resource Use

The cost of everolimus (10 mg daily) is £2,500 per 28-day cycle, while exemestane costs £125 per 28-day cycle. Administration and monitoring costs are estimated at £150 per cycle. The cost of managing adverse events was estimated at £1,200 per event (grade 3/4).

Updated model results with AI fetched local parameters

Fetch AI Parameters

Simulation Results

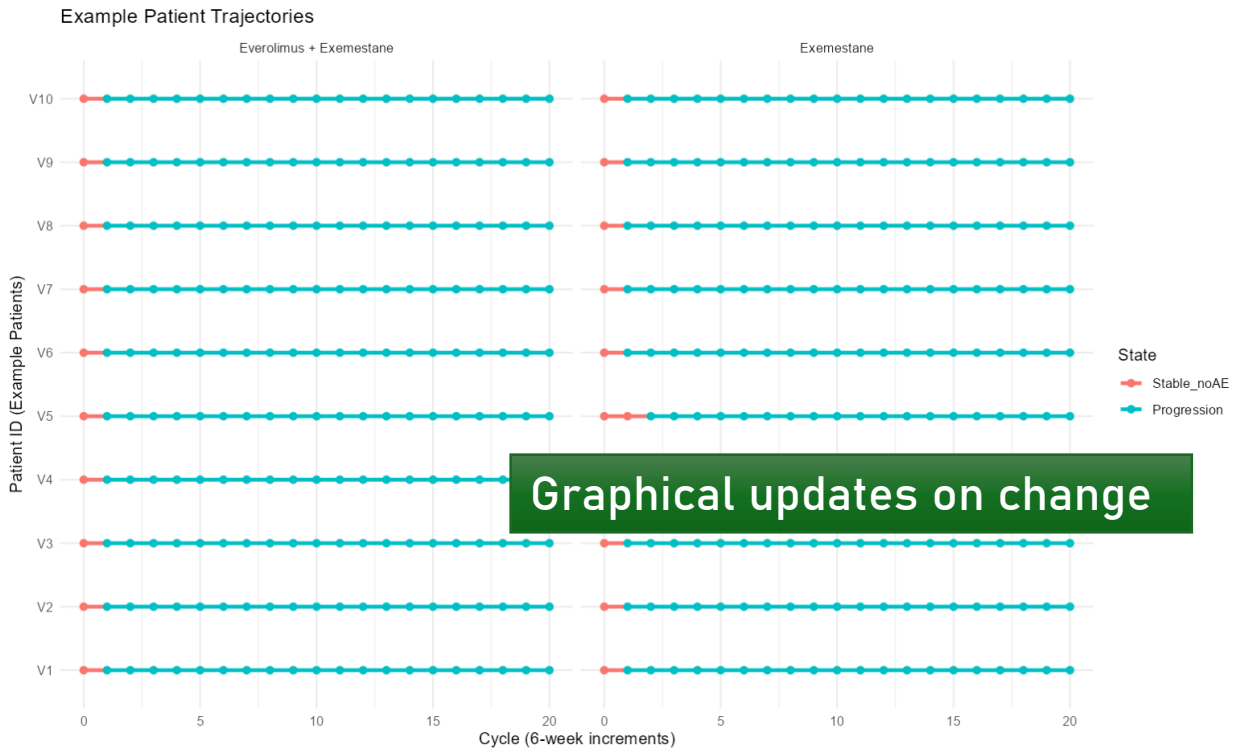
```
Country Selected: UK (NICE/NHS)

Microsimulation results (n = 1000 patients per arm):
Arm 0 (Exemestane): Avg Cost £ 271.6 , Avg QALYs: 0.008
Arm 1 (Everolimus + Exemestane): Avg Cost £ 1266.85 , Avg QALYs: 0.011

ICER:  £ 384209.3  per QALY gained
```

Dynamic update with AI parameters

Example Patient Trajectories



Graphical updates on change

AI Answer & Traceability

```
📊 AI Extracted Parameters:
lambda0: 0.71
gamma0: 0.72
lambda1: 0.78
cost_rx0: 2500
cost_rx1: 10000
cost_ct: 150
cost_lab: 150
cost_visit: 150
cost_AE0: 200
cost_AE1: 1200
utility_stable: 0.78

✅ Updated Parameters: lambda0, gamma0, lambda1, cost_rx0, cost_rx1, cost_ct, cost_lab, cost_visit, cost_AE0, cost
⚠ Using Default: gamma1, p_AE0, p_AE1, disutility_AE0, disutility_AE1

📚 Sources Context Used:
ID: CSV, Source: CSV, Topic: Quality of Life, Country: Canada
ID: CSV, Source: CSV, Topic: Quality of Life, Country: UK
ID: NICE_Guidance.pdf, Source: NICE_Guidance.pdf, Topic: NA, Country: UK
ID: NICE_Breast_Cancer_Guidance.pdf, Source: NICE_Breast_Cancer_Guidance.pdf, Topic: NA, Country: UK
ID: CSV, Source: CSV, Topic: Cost, Country: UK
```

AI's raw response in JSON format

Track parameters with RAG data source

Show 5 entries Search:

	source	country	row	topic
1	CSV	Canada	6	Quality of Life
2	CSV	UK	3	Quality of Life
3	NICE_Guidance.pdf	UK		
4	NICE_Breast_Cancer_Guidance.pdf	UK		
5	CSV	UK	2	Cost

Showing 1 to 5 of 5 entries Previous 1 Next

Download Sources (.csv)

Downloadable RAG source for validation

Unlocking the Potential of LLMs + R-Shiny in HEOR – Key takeaways

Interactive dashboards, powered by LLMs, that present complex data in visually compelling and easily digestible format can be created using Shiny.

Stakeholders can be provided access to Shiny apps, enabling real-time adaptation/collaboration and informed decision-making.

Flexibility allows development of interactive models that can be deployed in several markets.

Customized, dynamic reports consolidating key health economics insights can be leveraged by LLMs and produce robust adapted models, improving efficiency.

R-Shiny applications can be deployed on cloud platforms, ensuring scalability and secure access to health economic data and analyses representing the reality of each markets.

Questions

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