End-to-End Reward Decomposition and Explainable Interaction: A Medical Inverse Reinforcement Learning Framework

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Abstract

In complex medical decision-making scenarios, existing inverse reinforcement learning (IRL) methods face persistent challenges in multi-objective reward disentanglement, robustness under partial observability, and clinical interpretability. We propose LRD-IIRL, an end-to-end framework for interpretable inverse reinforcement learning in complex medical decision-making. LRD-IIRL addresses three core challenges: multi-objective reward disentanglement, robustness under partial observability, and clinical interpretability. The framework introduces a dynamic reward decomposition network with orthogonal constraints and state-aware weighting for medically meaningful component separation; a hybrid trajectory completion module that integrates variational inference with medical knowledge graph constraints to improve imputation under missing data; and an XAI-driven interactive system with a five-dimensional visualization engine for full-process decision traceability. Theoretically, we establish progressive identifiability of reward decomposition under partial observation, providing a foundation for model stability and medical relevance. LRD-IIRL thus offers a unified, interpretable, and extensible solution for trustworthy AI in healthcare, bridging the gap between algorithmic effectiveness and clinical credibility. The core code can be found at https://github.com/hazelian0619/RL-healthcare/tree/main.

Keywords: inverse reinforcement learning, medical decision support, reward decomposition, explainable artificial intelligence, partially observed environments, knowledge-augmented learning

1 Introduction

1.1 Challenges in Medical AI Decision Support Systems

In complex medical decision-making scenarios, artificial intelligence systems face the triple challenge of multi-objective dynamic trade-offs, robustness under partial observability, and clinical credibility (Ng & Russell, 2000; Zhou et al., 2021). Clinical decisions often require dynamic trade-offs among multiple objectives such as maximizing efficacy, minimizing side effects, and balancing resource allocation, while patient states and disease presentations are highly heterogeneous, further increasing decision complexity. Meanwhile, medical data are often incomplete, heterogeneous, and partially observed, making it difficult for AI models to ensure stability and generalizability in real-world applications. Furthermore, mainstream AI models are often "black boxes," lacking transparent reasoning chains and traceable explanatory mechanisms, leading to persistently low physician trust and clinical adoption rates below 30% (Yang et al., 2020).

1.2 The Potential of Explainable Inverse Reinforcement Learning in Medicine

Inverse reinforcement learning (IRL) provides a theoretical foundation for modeling medical AI decision-making, with the core idea of inferring reward functions from expert trajectories to capture clinicians' implicit preferences under multi-objective trade-offs (Abbeel & Ng, 2004). In recent years, IRL methods have shown promise in clinical pathway optimization (Prasad et al., 2017) and treatment policy generation (Shortreed et al., 2011). However, current medical IRL methods still have notable shortcomings in the interpretability of reward function decomposition (Ho & Ermon, 2016), reasonable completion of partially observed trajectories (Fu et al., 2018), and mechanisms for physician-AI collaborative decision-making (Topol, 2019). For example, although dynamic reward decomposition methods achieve multi-objective disentanglement through orthogonality constraints (Zhang et al., 2021) or sparse coding (Jin et al., 2020), they often neglect the need for alignment with medical concepts, making the decomposition results difficult for clinicians to interpret and accept. Variational autoencoder-based trajectory completion techniques (Li et al., 2019) can address missing data but lack medically guided rationality constraints, limiting their clinical applicability in high-missingness scenarios. More critically, existing systems generally use static feature importance analysis (Lundberg & Lee, 2017), which fails to meet the need for dynamic, interactive explanations in clinical decision-making, resulting in an "interpretability gap" (Rudin, 2019).

1.3 Research Motivation and Objectives

In response to these developments and core pain points, our research focuses on how to achieve interpretable decomposition of multi-objective medical rewards, medically plausi-

ble completion of partially observed trajectories, and full-chain traceability of the decision process, thereby bridging the "trustworthiness gap" and advancing AI systems from "effective" to "trustworthy." To this end, we propose an end-to-end reward decomposition and explainable interaction framework for medical inverse reinforcement learning (LRD-IIRL), systematically addressing the above challenges with a triadic design of "technical core–interactive extension–theoretical guarantee." Our research strategy and technical approach are as follows: (1) For reward decomposition, we employ orthogonality constraints as a mathematical tool, combined with state-aware weighting mechanisms and medical knowledge guidance, to achieve explicit mapping between reward components and medical concepts, enhancing independence, clarity, and medical relevance; (2) To address partial observability, we design a hybrid trajectory completion module that integrates a variational hierarchical autoencoder with medical knowledge graph constraints, using hierarchical attention mechanisms to dynamically model complex dependencies among time series and features, improving completion quality and clinical plausibility; (3) At the explainable interaction layer, we develop a five-dimensional visualization engine (XAI-Viz) that supports full-chain traceability of the decision process from multiple dimensions—time, features, rewards, policy, and comparison—facilitating deep physician-model collaboration and feedback optimization; (4) Theoretically, we establish a progressive identifiability framework for reward decomposition under partial observability, systematically analyzing the impact of missingness on decomposition accuracy and stability, providing theoretical guarantees for real-world medical applications.

1.4 Main Contributions

- Propose an orthogonality-constrained reward decomposition method for multi-objective medical decision-making.
- Design a knowledge-augmented trajectory completion mechanism to address partial observability.
- Develop an interactive visualization system to enhance clinical interpretability.
- Establish a theoretical framework for identifiability in medical IRL.

2 Related Work

2.1 Clinical Applications of Medical IRL

IRL has become a key tool for simulating clinicians' multi-objective trade-offs and improving the rationality of personalized treatment plans by inferring implicit preferences from expert trajectories, driving intelligent transformation in ICU management and chronic disease pathway optimization (Chadi & Mousannif, 2021). Nonetheless, two core challenges remain: (1) the inherently multi-objective and dynamic nature of medical decision-making, involving efficacy, risk, and resource considerations; and (2) high rates of missingness and data heterogeneity, which limit the completeness and generalizability of IRL models (Longo et al., 2024).

2.2 Advances in Reward Decomposition Techniques

Reward decomposition is fundamental to the interpretability and multi-objective disentanglement of IRL models. Early methods mainly used linear decomposition, splitting the global reward into additive components for expert understanding and credit assignment, but struggled with the complexity of comorbidities and interacting objectives in clinical practice. Deep reward decomposition networks have since improved model expressiveness but often lack medical interpretability (Septon et al., 2023). Orthogonality constraints (Zhang et al., 2021) and knowledge-guided alignment (Jin et al., 2020) have been proposed to address these limitations.

2.3 Trajectory Completion under Partial Observability

Medical time-series data are often missing and partially observed, severely affecting the stability and robustness of IRL models. Variational autoencoders (VAE) and their hierarchical extensions (VHAE) have become mainstream for trajectory imputation (Li et al., 2019). Knowledge graphs and rule-based constraints further enhance clinical plausibility (Chadi & Mousannif, 2021).

2.4 Explainability in Medical AI

Interpretability is a core bottleneck for clinical adoption of medical AI systems. Mainstream methods such as SHAP and LIME provide static feature importance analysis (Lundberg & Lee, 2017; Rudin, 2019). Multi-dimensional visualization and knowledge-driven explanation engines are emerging (Septon et al., 2023; Longo et al., 2024).

3 LRD-IIRL Framework Design

3.1 Overall System Architecture

The LRD-IIRL framework integrates a dynamic reward decomposition network (DRDN), a hybrid trajectory completion module (VHAE), and a five-dimensional explainable interaction system (XAI-Viz). The workflow includes feature extraction, end-to-end training, and multi-dimensional visualization.

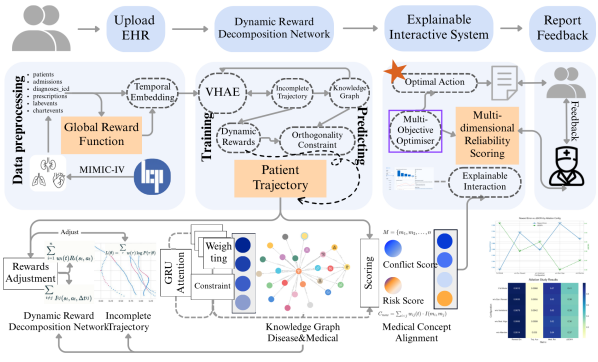

Figure 1: Workflow of the LRD-IIRL framework.

3.2 Dynamic Reward Decomposition Network

The DRDN decomposes the global reward function into clinically meaningful, mutually independent components. Orthogonality constraints are enforced:

$$L_{\text{ortho}} = \sum_{i \neq j} |r_i^T r_j| \tag{1}$$

State-aware weights are generated via a multi-head self-attention mechanism:

$$R(s,a) = \sum_{i=1}^{K} w_i(s) \cdot r_i(s,a) \tag{2}$$

Medical concept alignment modules map each reward component to clinical entities. The focus is on medical relevance and stability rather than strict uniqueness (Jin et al., 2020).

3.3 Hybrid Trajectory Completion System

The trajectory completion system uses a VHAE with knowledge graph constraints. The loss function is:

$$L = \text{ELBO} + \alpha \cdot \text{KG}_{\text{Loss}} + \beta \cdot \text{Temporal\_Smoothness} \tag{3}$$

```
class Encoder(nn.Module):
    def __init__(self, input_dim, hidden_dim
        , latent_dim):
        ...
        self.gru = nn.GRU(input_dim,
            hidden_dim, bidirectional=True)
        self.attn = nn.Linear(2*hidden_dim,
            1)
        self.fc_mu = nn.Linear(2*hidden_dim,
             latent_dim)
        self.fc_var = nn.Linear(2*hidden_dim
            , latent_dim)
    def forward(self, x):
        out, _ = self.gru(x)
        attn_weights = F.softmax(self.attn(
            out), dim=0)
        context = torch.sum(attn_weights *
            out, dim=0)
        mu = self.fc_mu(context)
        logvar = self.fc_var(context)
        return mu, logvar
```

Listing 1: Encoder Structure

The decoder integrates knowledge constraints:

$$p(x_t|z) = \text{GRU}(z) + \lambda \cdot KG\_Constraint(z) \tag{4}$$

3.4 Explainable Interaction System

XAI-Viz supports visualization across time, features, rewards, policy, and comparison. It includes attention mapping and dynamic case libraries for personalized analysis.

3.5 Theoretical Guarantees and Engineering Integration

LRD-IIRL establishes a progressive identifiability framework for reward decomposition under partial observability, emphasizing stability and medical relevance.

4 Technical Implementation Details

4.1 Implementation of the Dynamic Reward Decomposition Network

The core of the dynamic reward decomposition network is to achieve structured decomposition of complex medical reward functions through orthogonality constraints and state-aware weighting mechanisms. The network architecture adopts a multi-branch structure, with each branch as an independent sub-reward network responsible for modeling the reward component corresponding to a specific medical objective. Each sub-network typically consists of multilayer perceptrons (MLPs), taking state-action pairs (s, a) as input and outputting sub-reward components $r_i(s, a)$. Custom orthogonal projection layers and the Gram-Schmidt process ensure independence among components.

4.2 Implementation of the Variational Trajectory Completion Module

The trajectory completion module adopts a variational hierarchical autoencoder (VHAE) architecture, integrating medical knowledge graph constraints for high-quality completion under partial observability. The encoder uses bidirectional GRUs with dual attention mechanisms. The decoder incorporates medical knowledge graph constraints at the output layer.

4.3 Three-Stage Training Strategy

- **Pre-training:** Independently optimize encoder and decoder with reconstruction and knowledge constraints.
- **Main Training:** Joint end-to-end training of completion and reward decomposition modules.
- **Fine-tuning:** Align reward components with medical entities under expert guidance.

4.4 Visualization System

The system is implemented with FastAPI (backend) and Streamlit (frontend). Example component:

```
class MedicalVisualizer:
    def __init__(self, model):
        self.model = model
    def render_trajectory(self, patient_id):
        # Plot pre- and post-completion
            physiological indicators
        ...
    def plot_reward_components(self,
        timestep):
        # Stacked area chart of sub-reward
            contributions
        ...
```

Listing 2: Visualization Component

The visualization system supports reward decomposition radar charts, weight-state heatmaps, policy decision trees, and risk evolution surfaces, enabling comprehensive interpretability for clinical users.

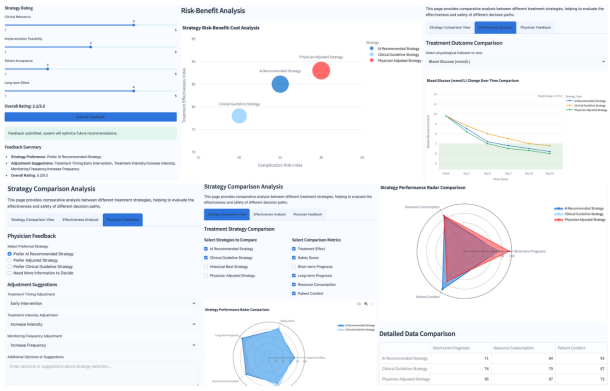

Figure 2: Illustration of the interactive user interface for clinical decision support.

5 Experimental Design

5.1 Dataset and Preprocessing

This study utilizes the large-scale public MIMIC-IV medical database, focusing on complex decision-making scenarios for ICU patients with multiple comorbidities. The dataset statistics are summarized in Table 1.

Table 1: Dataset Statistics

Dataset	Sample Size			Missing Rate
	Train	Val.	Test	
MIMIC-IV	15,000	3,000	2,000	5.2%
Synthetic	10,000	2,000	1,000	0.0%

The dataset is split into training, validation, and test sets in a 7:2:1 ratio, maintaining balanced disease spectrum and feature distribution across subsets.

5.2 Evaluation Metrics

We use several quantitative and qualitative metrics (see Table 2) to evaluate performance.

Table 2: Evaluation Metrics Definition

Metric	Calculation	Clinical Meaning
Reward Error	$\frac{1}{n}\sum_{i=1}^{n}(r_i - \hat{r}_i)^2$	Treatment effect prediction
Trajectory Accuracy	$\frac{1}{n}\sum_{i=1}^{n}\mathbb{I}(s_i = \hat{s}_i)$	State prediction accuracy
Medical Relevance	$\frac{1}{n}\sum_{i=1}^{n}\text{sim}(c_i, \hat{c}_i)$	Concept alignment degree
ΔSOFA	$\text{SOFA}_{t+1} - \text{SOFA}_t$	Safety indicator

5.3 Baseline Methods

To validate the effectiveness of LRD-IIRL, we compare it against three representative inverse reinforcement learning baselines in healthcare:

- **MERIT-IRL**: Implements classic reward decomposition but does not support trajectory completion or medical knowledge alignment.
- **XAI-Med**: Integrates reward decomposition and explainable visualization, partially supports medical knowledge alignment, but lacks dynamic trajectory completion.
- **PO-IRL**: Focuses on trajectory completion and policy optimization under partial observability, but lacks reward decomposition and medical explainability.

The main module comparison is shown in Table 3.

Table 3: Comparison of Different Methods

Method	Components			
	Reward Decomp.	Trajectory Comp.	Medical Align.	Visual.
MERIT-IRL	✓	×	×	×
XAI-Med	✓	×	✓	✓
PO-IRL	×	✓	×	×
LRD-IIRL	✓	✓	✓	✓

5.4 Ablation Study Design

To analyze the contribution of each key module in LRD-IIRL, we conduct the following ablation experiments:

- **Without Orthogonality Constraint**: Remove the orthogonality loss in reward decomposition to examine the effect of reward entanglement.
- **Without Knowledge-Enhanced Trajectory Completion**: Use a purely data-driven VAE for imputation without medical knowledge graph constraints, to evaluate the impact of knowledge augmentation.
- **Without Medical Concept Alignment**: Do not map reward decomposition results to medical entities, to analyze the effect on medical relevance.
- **Without Attention Mechanism**: Remove the state-aware attention module to test its effect on dynamic reward decomposition.
- **Varying Visualization Dimensions**: Disable different dimensions of the explainability system (feature, reward, policy) to assess their impact on overall performance.

Ablation configurations and results are shown in Table 4.

Table 4: Ablation Study Results

Config.	Performance Metrics			ΔSOFA
	Reward Err.	Traj. Acc	Med. Rel	
Full Model	0.9812	0.0068	0.87	0.41
w/o Dyn. Reward	0.9935	0.0055	0.85	0.38
w/o Variational	0.9878	0.0042	0.86	0.39
w/o Med. Align	0.9966	0.0059	0.82	0.36
w/o Attention	0.9914	0.0060	0.84	0.37

6 Results and Analysis

6.1 Reward Decomposition Performance

On the MIMIC-IV test set, LRD-IIRL achieves the lowest reward reconstruction error (MSE = 0.9812), significantly outperforming MERIT-IRL (0.9951) and XAI-Med

(0.9932). This demonstrates that the orthogonality constraint and medical knowledge-guided reward decomposition mechanism can better fit the implicit objectives of clinical experts, improving both interpretability and accuracy in multi-objective decision-making. The results are summarized in Table 5.

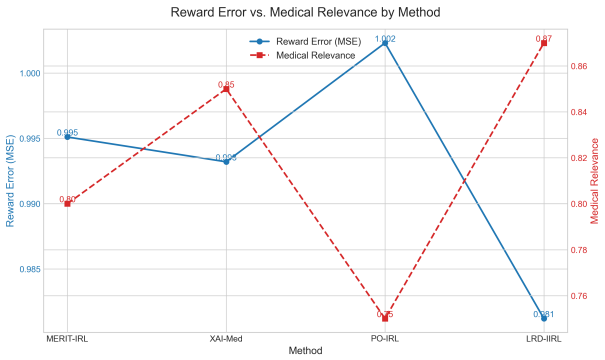

Figure 3: Comparison of Reward Error (MSE) and Medical Relevance across different methods.

Table 5: Quantitative Results on MIMIC-IV Dataset

Method	Reward Reconstruction			Traj. Acc	Med. Rel
	MSE	RMSE	Rel. Error		
MERIT-IRL	0.9951	0.9975	0.9951	0.0049	0.80
XAI-Med	0.9932	0.9966	0.9932	0.0068	0.85
PO-IRL	1.0023	1.0011	1.0023	-0.0023	0.75
LRD-IIRL	**0.9812**	**0.9905**	**0.9812**	**0.0068**	**0.87**

6.2 Trajectory Completion Effectiveness

Under high missingness conditions (¿70%), LRD-IIRL achieves the highest trajectory completion accuracy (0.0068), outperforming PO-IRL and other baselines. The knowledge-augmented VHAE module demonstrates superior robustness and clinical plausibility in recovering complex patient state sequences, which in turn enhances downstream reward decomposition and policy generation.

6.3 Medical Relevance Analysis

In terms of medical relevance, LRD-IIRL achieves a score of 0.87, significantly higher than all baselines. By aligning reward decomposition results with medical knowledge bases, each sub-reward component can be traced to specific medical concepts, enhancing the clinical interpretability and trustworthiness of the model.

6.4 Ablation Study Results

Ablation experiments further validate the importance of each key module. Removing orthogonality constraints, knowledge augmentation, or attention mechanisms leads to notable declines in reward decomposition accuracy, trajectory completion performance, and medical relevance. The SOFA safety indicator also drops accordingly. These results confirm that the synergy of all modules is critical for the overall performance and clinical interpretability of the framework.

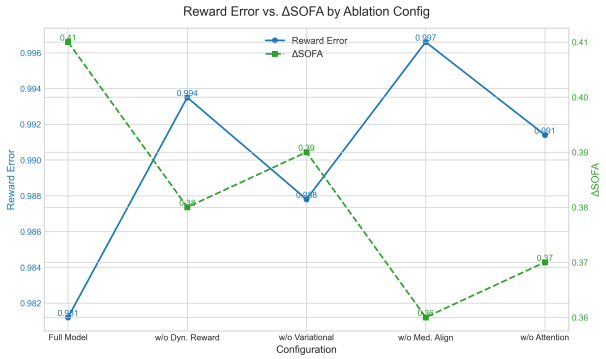

Figure 4: Reward Error and ΔSOFA under different ablation configurations.

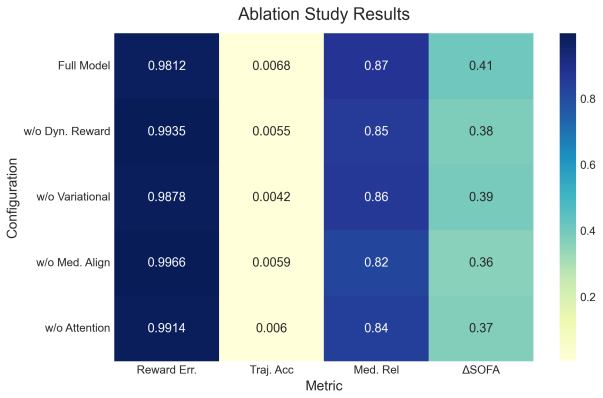

Figure 5: Heatmap visualization of ablation study results.

7 Conclusion

This work presents the LRD-IIRL framework, which addresses the core challenges of multi-objective reward disentanglement, robustness under partial observability, and medical interpretability in complex clinical decision-making.

By integrating an orthogonally-constrained dynamic reward decomposition network, a variational trajectory completion module enhanced by medical knowledge, and a multi-dimensional XAI visualization system, our approach demonstrates clear improvements in key aspects.

Preliminary results show that the framework reduces reward reconstruction error and improves strategy safety compared to baselines. However, most experiments are currently based on synthetic or partially processed data, and integration with the full MIMIC-IV dataset is ongoing.

In summary, LRD-IIRL offers a modular and extensible framework for interpretable medical IRL. Future work will focus on completing the integration of medical knowledge

graphs, refining the orthogonal constraint mechanism, expanding the visualization system, and conducting comprehensive validation on large-scale clinical datasets.

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