



Causal Representation Learning under Informative Missingness for Clinical Multimodal Prediction and Offline Decision-Making

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Clinical Missingness Is MNAR

- Clinical EHR data are **systematically incomplete** rather than randomly incomplete.
- The probability that a modality or measurement is observed often depends on **latent patient state and clinician decision-making**.
- This is a **missing-not-at-random (MNAR) problem**, not a nuisance that can be removed by imputation alone.
- We study two scales of informative missingness:
 - Patient-level MMNAR**: which modalities are available for a patient.
 - Step-level monitoring intensity MNAR**: how often variables are measured over time.

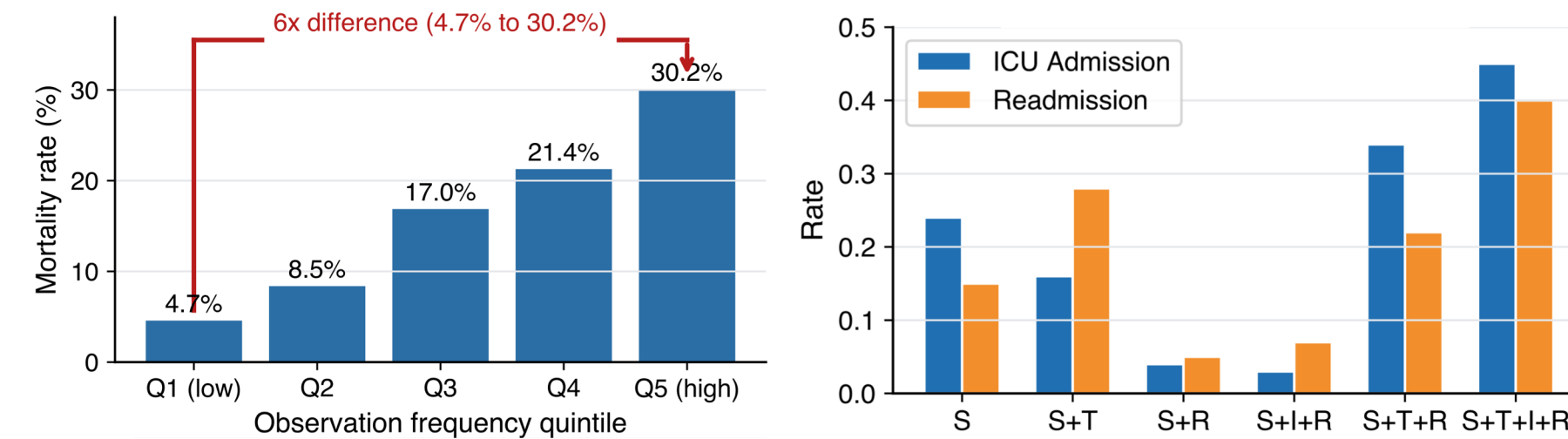


Figure 1 and 2. Informative missingness in clinical data.

The Thesis Question and Dataset

How should observation patterns in multimodal clinical data — at both patient and step levels — be modeled to learn representations that are sufficient for prediction and control, and what methodological interventions correct the distinct failure modes that arise when such patterns are ignored?

INSTANTIATION I: STATIC EPISODE-LEVEL PREDICTION.

- MIMIC-IV cohort: 20,000 adult ICU patients.
- Modalities: structured EHR, chest X-ray, discharge summary, radiology report.
- Tasks: 30-day readmission, post-discharge ICU admission, 180-day mortality.

INSTANTIATION II: SEQUENTIAL DECISION-MAKING.

- MIMIC-III, MIMIC-IV and eICU cohort.
- 72-hour window $\rightarrow H = 18$ decision steps at 4-hour intervals
- Action space: IV fluids and vasopressors.

Unified Causal View of MNAR in Clinical Multimodal Learning

STATIC SETTING (PATIENT-LEVEL MODALITY MISSINGNESS)

- Latent health $h_i^* \rightarrow$ multimodal contents x_i
- Latent health $h_i^* \rightarrow$ observation pattern δ_i
- Latent health $h_i^* \rightarrow$ clinical outcome y_i
- Critical extra edge: $\delta_i \rightarrow y_i$ directly ($\uparrow$ tests $\rightarrow$ earlier interv. $\rightarrow$ chg. outcome)

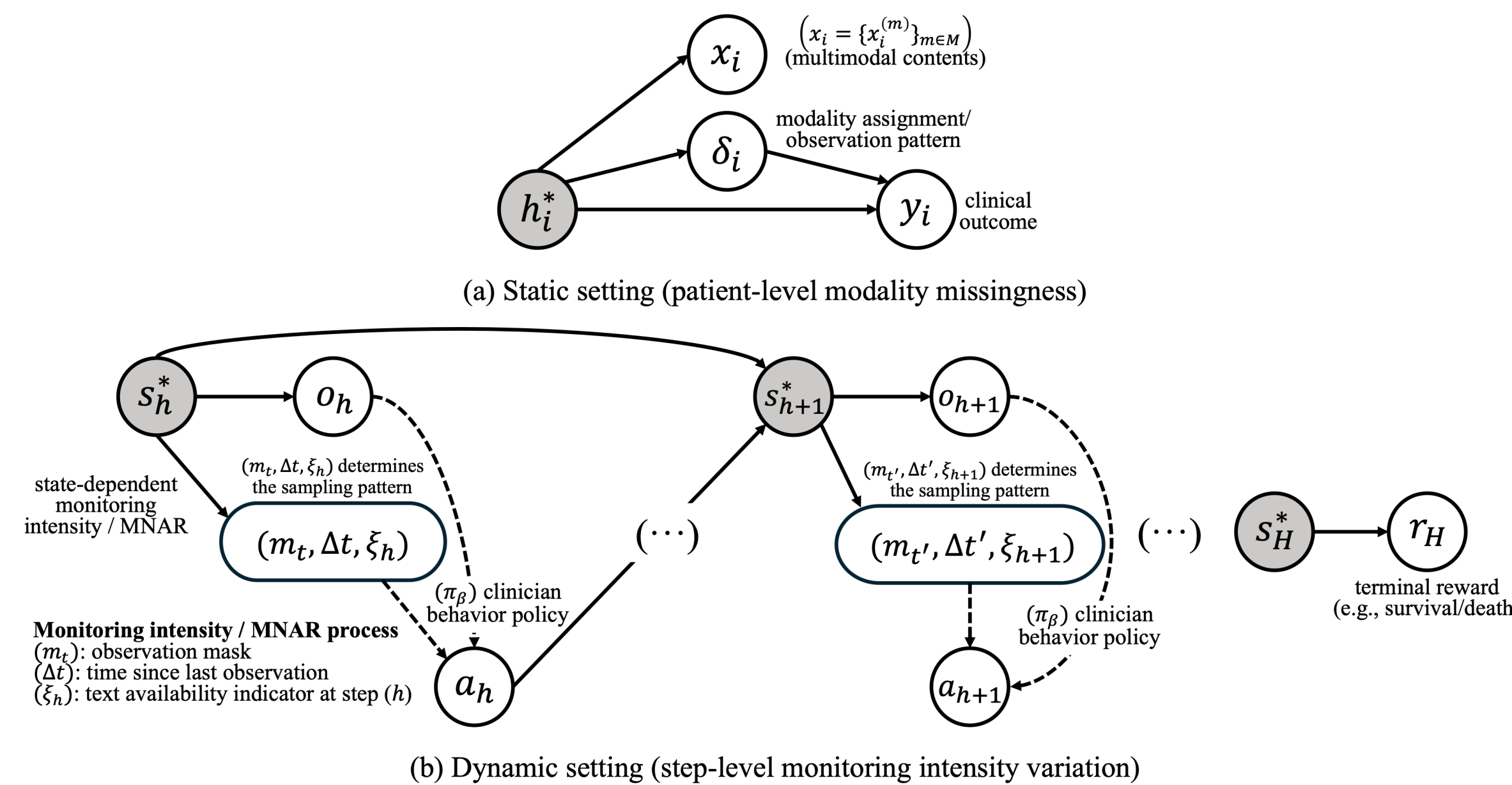


Figure 3. Unified causal structure for clinical multimodal learning under MNAR.

DYNAMIC SETTING (STEP-LEVEL MONITORING INTENSITY)

- Latent state $s_h^* \rightarrow$ observations o_h and monitoring intensity $(m_t, \Delta t, \xi_h)$
- $(s_h^*, a_h) \rightarrow s_{h+1}^*$ (treatment changes the patient's state)
- Terminal state $s_H^* \rightarrow$ reward r_H (survival or death)

Methodology

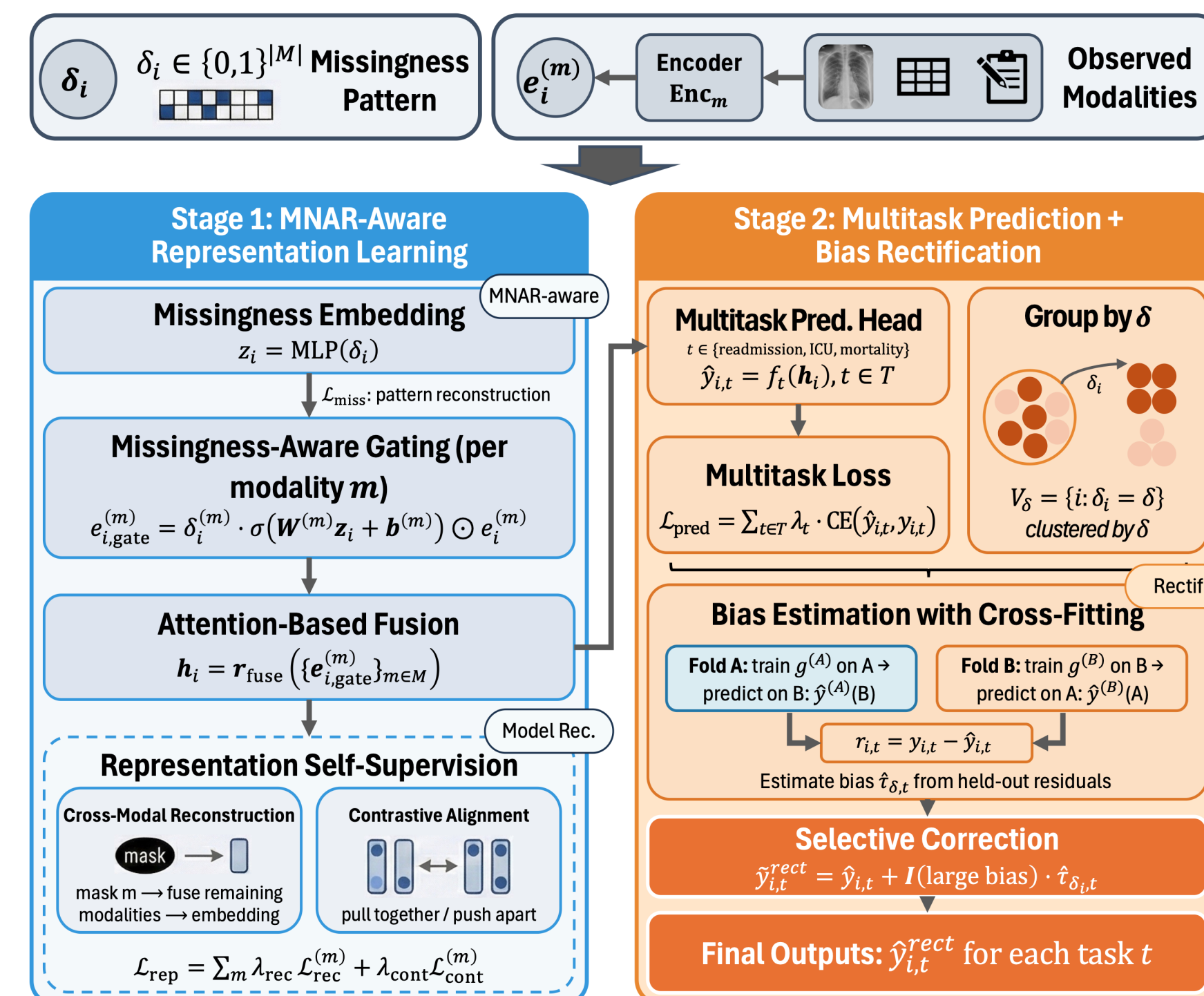


Figure 4. Instantiation I (static MMNAR prediction): two-stage pipeline for patient-level multimodal learning under informative missingness.

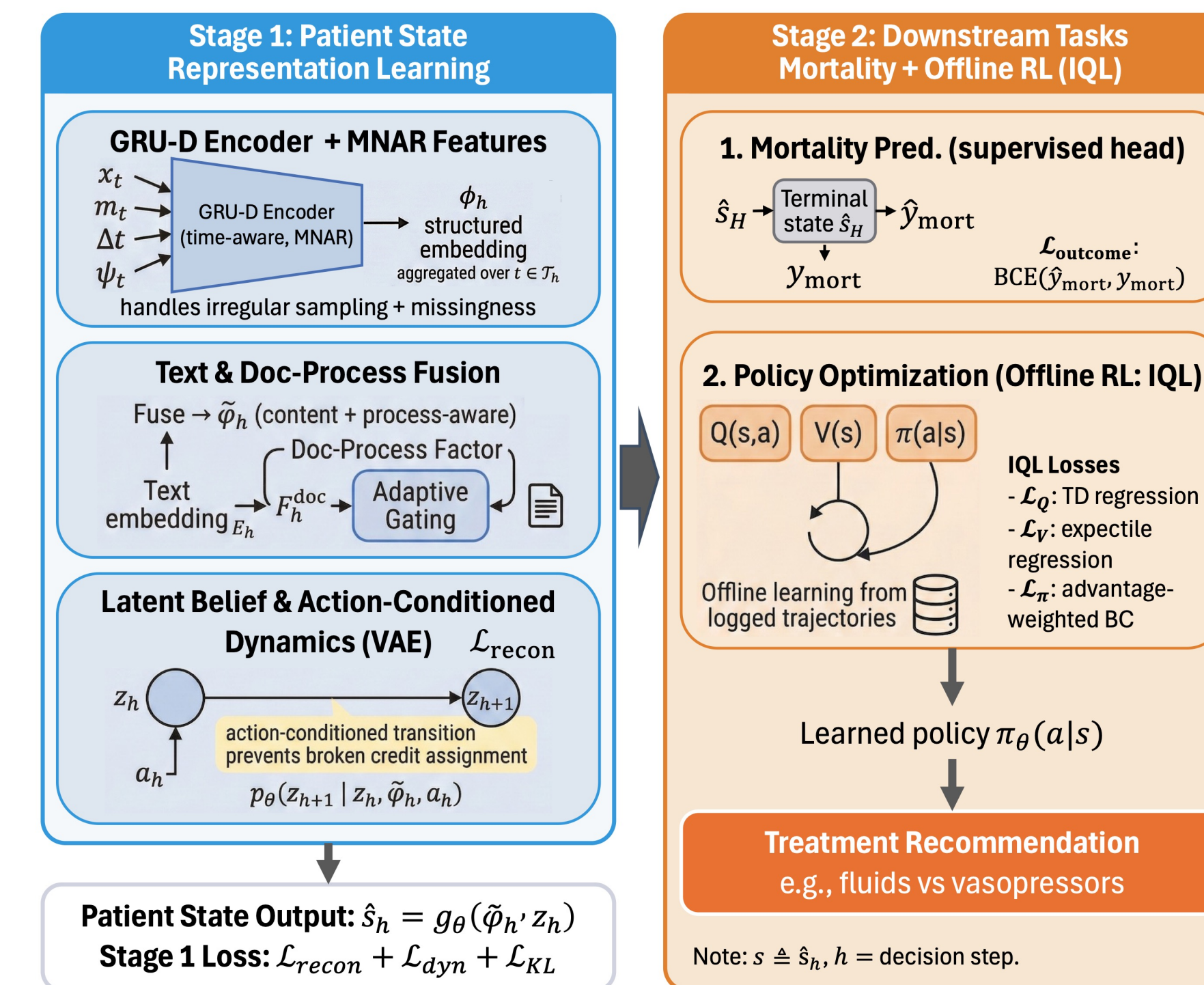


Figure 5. Instantiation II (dynamic MNAR offline control): MNAR-aware state learning and downstream policy optimization.

Results

Results I: Static Prediction under MMNAR

Task	Best Baseline	Ours	Gain
ICU Admission (MIMIC-IV)	0.869 (DrFuse)	0.982	+13.0%
30-Day Readmission (MIMIC-IV)	0.799 (MUSE+)	0.866	+8.4%
In-Hospital Mortality (MIMIC-IV)	0.905 (MUSE+)	0.947	+4.6%

Our method outperforms all 13 baselines on both MIMIC-IV and eICU.

Results II: Offline Decision-Making under Dynamic MNAR

Method	MIMIC-IV FQE	vs. Clinician	eICU FQE	vs. Clinician
Clinician (BC)	0.521	—	0.534	—
CQL	0.418	−19.8%	0.408	—
Tabular Q (AI Clinician)	0.491	−5.8%	0.478	—
Ours (IQL)	0.634	+21.7%	0.604	+13.1%

Our policy outperforms clinician behavior and all RL baselines on both datasets.

Robustness and Cross-Institutional Generalization

Shift Severity	Ours	MUSE+	Gap
None (original)	0.866	0.799	+6.7%
Mild (KL = 0.2)	0.854	0.771	+8.3%
Moderate (KL = 0.5)	0.838	0.734	+10.4%
Severe (KL = 1.0)	0.812	0.687	+12.5%

Protocol	Train $\rightarrow$ Test	FQE	vs. Clinician
In-distribution	MIMIC-IV $\rightarrow$ MIMIC-IV	0.634	+21.7%
Zero-shot transfer	MIMIC-IV $\rightarrow$ eICU	0.568	+6.4%
Fine-tuned transfer	MIMIC-IV + eICU FT $\rightarrow$ eICU	0.594	+11.2%