Appendix

Table A1. LNSs (LNSs) and Corresponding Locations.

LNSs	Locations
2L	Left upper paratracheal lymph node
2R	Right upper paratracheal lymph node
3A	Pre-vascular lymph node
3P	Post-tracheal lymph node
4L	Left lower paratracheal lymph node
4R	Right lower paratracheal lymph node
5	Sub-aortic lymph node
6	Para-aortic lymph node
7	Subcarinal lymph node
8	Paraesophageal lymph node below carina
9	Pulmonary ligament lymph node
10	Hilar lymph node
11	Interlobar lymph node
12	Pulmonary lobar lymph node
13	Pulmonary segmental lymph node
14	Subsegmental lymph node

A1 Definition Rules for LNS labels

The LNS (defined in Table A1) labels are assigned based on the following rules:

- If a LNS was dissected (dissection total is non-zero) and found to have no metastasis (pathological examination shows no cancer cells), the label is 0 (no metastasis);
- If a LNS was dissected and found to have metastasis (pathological examination shows cancer cells), the label is 1 (metastasis present);
- If a LNS was not dissected, the label is None, indicating unknown metastasis status.

The format of the patient data is structured as shown in Table A2.

Table A2. LNS Metastasis Example Data.

Patient	2L	3A	3P	4L	5	6	7	8	9	10	11	12	13	14
A				1		1	0	0	1	1	0			
B				0		1			1	0	1			

A2 Data Splitting and Task Specifications

The dataset was split strictly by patient to avoid data leakage, resulting in 733 patients for training, 85 patients for validation, and 101 patients for testing. This patient-level partition was consistently used throughout both the LNS status prediction stage and the AI-powered decision support system evaluation.

For the LNS status prediction stage, the primary objective was to predict the unknown status of certain LNSs given the known statuses of others. During training, a known LNS status within each patient (as illustrated in Table A2) was randomly masked by setting its label to -1, while retaining the remaining known statuses as input information. This masking operation defines one training sample (or instance). For a patient with N known LNS statuses, N such training instances were generated by masking each known status in turn. Repeating this procedure for all patients in the training set produced the final training dataset for the mask-and-predict task. Each training batch consisted of a fixed number of these masked instances. The loss function for this task was defined as the cross-entropy classification loss between the predicted status of the masked LNS and its ground-truth status, followed by backpropagation. For validation and testing, the $\mathrm{AUC}_{\mathrm{LNS}}$ metric was computed by applying the same mask-and-predict procedure to the corresponding validation and test data, measuring the binary classification performance.

For the evaluation of the AI-powered decision support system, the model parameters were kept frozen without any further training. To simulate the intraoperative diagnosis process on the test set, a subset of LNS statuses (depending on the experimental configuration) was randomly selected as the initially known statuses. The model was then used to predict the unknown statuses of the remaining LNSs. Finally, the patient-level overall precision and recall were calculated based on these predictions.

A3 Graph Construction

As shown in Tables A3–A5, we constructed three clinical knowledge graphs: K1, K2, and K3, representing anatomical proximity, rule transfer mode, and discovered transfer paradigms among LNSs, respectively. In these graphs, each LNS was treated as a node, and the adjacency relationships between LNSs were encoded as undirected edges with binary weights (0 or 1) to indicate the presence or absence of a connection.

For the node embedding, each node was first represented by its categorical type, which was then embedded using the PyTorch `nn.Embedding` module. The overall graph-structured data was created according to the adjacency relationships described in the knowledge graphs. These graphs were then used as prior knowledge inputs for the graph neural network module, enabling graph-based encoding of the anatomical and clinical relationships among LNSs.

Table A3. Adjacency matrix of the K1 knowledge graph, where K1 represents clinical prior knowledge based on anatomic proximity of LNSs.

	2L	2R	3A	3P	4L	4R	5	6	7	8	9	10	11	12	13	14
2L	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
2R	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
3A	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
3P	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
4L	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0
4R	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0
5	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0
6	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0
7	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0

Table A4. Adjacency matrix of the K2 knowledge graph, where K2 represents the clinical rule transfer mode among LNSs.

	2L	2R	3A	3P	4L	4R	5	6	7	8	9	10	11	12	13	14
2L	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2R	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3A	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
3P	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0
4L	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0
4R	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0
5	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
9	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
10	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0
11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0
12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0

Table A5. Adjacency matrix of the K3 knowledge graph, where K3 represents the discovered transfer paradigms among LNSs.

	2L	2R	3A	3P	4L	4R	5	6	7	8	9	10	11	12	13	14
2L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
2R	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0
3A	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
3P	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0
4L	0	0	0	0	0	0	0	1	0	0	0	1	1	1	0	0
4R	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	1
5	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
6	0	0	0	0	1	0	1	0	0	1	0	1	1	0	0	0
7	0	1	0	1	0	1	0	0	0	1	1	0	0	1	1	1
8	0	0	0	0	0	0	0	1	1	0	0	1	0	0	1	0
9	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0
10	0	0	0	0	1	1	0	1	0	1	0	0	1	1	1	0
11	0	0	0	0	1	0	0	1	0	0	0	1	0	1	1	1
12	0	1	1	1	1	1	0	0	1	0	0	1	1	0	1	1
13	1	0	1	0	0	0	0	0	1	1	0	1	1	1	0	1
14	0	0	0	0	0	1	0	0	1	0	0	0	1	1	1	0