

SurgViVQA: Temporally-Grounded Video Question Answering for Surgical Scene Understanding

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Abstract

Purpose: Video Question Answering (VideoQA) in the surgical domain aims to enhance intraoperative understanding by enabling AI models to reason over temporally coherent events rather than isolated frames. Current approaches are limited to static image features, and available datasets often lack temporal annotations, ignoring the dynamics critical for accurate procedural interpretation.

Methods: We propose SurgViVQA, a surgical VideoQA model that extends visual reasoning from static images to dynamic surgical scenes. It uses a Masked Video–Text Encoder to fuse video and question features, capturing temporal cues like motion and tool–tissue interactions, which a fine-tuned LLM then decodes into coherent answers. To evaluate its performance, we curate REAL-Colon-VQA, a colonoscopic video dataset including motion questions and diagnostic attributes, with out-of-template questions with rephrased or semantically altered formulations to evaluate model robustness.

Results: Experimental validation on REAL-Colon-VQA and the public EndoVis18-VQA dataset shows that SurgViVQA outperforms existing image-based VQA benchmark models, especially on keyword accuracy, improving over PitVQA by +11% on REAL-Colon-VQA and +9% on EndoVis18-VQA. A perturbation study on the questions further confirms improved generalizability and robustness to variations in question phrasing.

Conclusion: SurgViVQA and the REAL-Colon-VQA dataset provide a framework for temporally-aware understanding in surgical VideoQA, enabling AI models to interpret dynamic procedural contexts.

Keywords: Surgical VideoQA, Temporal Reasoning, Vision-Language Model, Medical Video Understanding

1 Introduction

During minimally invasive procedures, surgeons must interpret complex and dynamic visual scenes to guide critical decisions [1]. Understanding these scenes requires modeling not only the spatial content within individual frames but also temporal dependencies across sequences. Subtle temporal cues, such as instrument motion, unfolding anatomy, lesion progression, or endoscope movement, are critical for assessing surgical progress and preventing complications.

General purpose Large Language Models (LLMs) offer a promising framework for interpreting such visual surgical data, as they can combine image understanding with advanced textual reasoning, despite missing clinical knowledge [2, 3]. However, current surgical Visual Question Answering (VQA) systems remain limited. Foundational approaches, such as SurgicalGPT [4], extend image–text transformers by integrating visual–text embeddings into a GPT-2 decoder for autoregressive generation. Similarly, PitVQA [5] combines a ViT image encoder with a cross-attention text encoder and GPT-2 decoder, grounding visual features into textual tokens. Despite these advances, both models operate on isolated frames, formulate answers as fixed classes or frame-level predictions, and fail to model cause–effect relationships, temporal dependencies, or dynamic aspects of surgical procedures.

The challenge is compounded by the datasets themselves. Most surgical VQA datasets lack temporal annotations and evaluate models in an in-template manner, where test questions closely mirror training examples [5–7]. This encourages text-biased strategies, limiting the ability to assess model performance under rephrased or semantically varied questions, which are crucial for real-world clinical applications. Consequently, models may generate linguistically plausible answers that fail to convey the key clinical information.

Meanwhile, general-purpose Vision–Language Models (VLMs) demonstrate strong zero-shot performances on generic visual tasks, particularly demonstrating impressive linguistic robustness, but face significant challenges in surgical contexts. Trained on natural images and everyday semantics, they often fail to detect subtle cues such as mucosal texture, illumination artifacts, or tool–tissue interactions [2, 3].

In this paper, we overcome these challenges through a temporally-aware VideoQA architecture and a large-scale colonoscopic dataset designed to capture clinically meaningful temporal dynamics. Our key contributions are as follows:

- We propose SurgViVQA, a VideoQA architecture that processes short temporal clips of 8 frames, integrating tube-masked video embeddings with question representations to learn unified spatiotemporal features. These are processed by an LLM (e.g., GPT-2, Qwen3) for open-ended, contextually coherent answer generation.
- We introduce REAL-Colon-VQA, a colonoscopic video dataset annotated with temporally coherent Question and Answer (Q&A) pairs that capture clinically relevant events such as tool usage, lesion motion, and endoscope navigation. The dataset enables both in-template and out-of-template evaluations, including question perturbations designed to test robustness to linguistic variability.
- We extensively evaluate our framework on REAL-Colon-VQA and EndoVis18-VQA, demonstrating superior performance in temporal reasoning, semantic robustness, and keyword-level accuracy compared to state-of-the-art image-based baselines.

2 Methodology

2.1 Proposed Method: SurgViVQA

As in Fig. 1, SurgViVQA processes surgical video clips and questions through a Masked Video–Text Encoder, producing temporally-aware multimodal embeddings that are decoded by a LoRA-adapted LLM to generate context-grounded answers.

Masked-Video Embeddings

Unlike static images, videos exhibit temporal continuity, meaning that adjacent frames often contain slowly evolving semantics such as instrument motion, camera movement, or tissue deformation. This results in strong temporal redundancy and correlation, where visual content remains largely unchanged between consecutive frames. Masked visual modeling has been proposed to learn effective visual representations by reconstructing hidden parts of the input [8]. In videos, a clip of T frames of size $H \times W$ can be represented as a sequence of spatiotemporal **cubes**, where each cube covers a small spatial region over a short temporal span. With cubes of size $t \times h \times w$, the clip forms a token grid of $\frac{T}{t} \times \frac{H}{h} \times \frac{W}{w}$, each represented by a D -dimensional feature vector. To encourage temporal understanding during training, high-ratio masking is applied in **tubes**, where all cubes at the same spatial location across the temporal dimension are simultaneously hidden. This design forces the model to reconstruct missing content without relying on low-level temporal continuity, instead leveraging high-level semantic reasoning, capturing tool interactions, and anatomical dynamics across time.

Architecture

Masked Video–Text Encoder: To capture temporal dynamics in surgical procedures, Masked Video–Text Encoder consists of a video encoder and a text encoder with a built-in cross-attention mechanism. It integrates tube-masked video embeddings with

question representations, allowing each question token to attend to the full temporal sequence of visual features. This produces unified embeddings that capture tool interactions, and anatomical dynamics, suitable for surgical VideoQA.

LLM with LoRA Adaptation: The fused video–text embeddings are passed into a causal, frozen LLM (e.g., GPT-2, Qwen3) enhanced with Low-Rank Adaptation (LoRA) [9] for efficient fine-tuning. The decoder is built from stacked transformer blocks with multi-head self-attention, layer normalization, and feed-forward layers. Self-attention allows each token to incorporate information from previous tokens, capturing sequential dependencies, while multi-head attention enables the model to attend to different aspects of the input. This module generates open-ended, free-form responses autoregressively, producing coherent and detailed answers grounded in the video–text context.

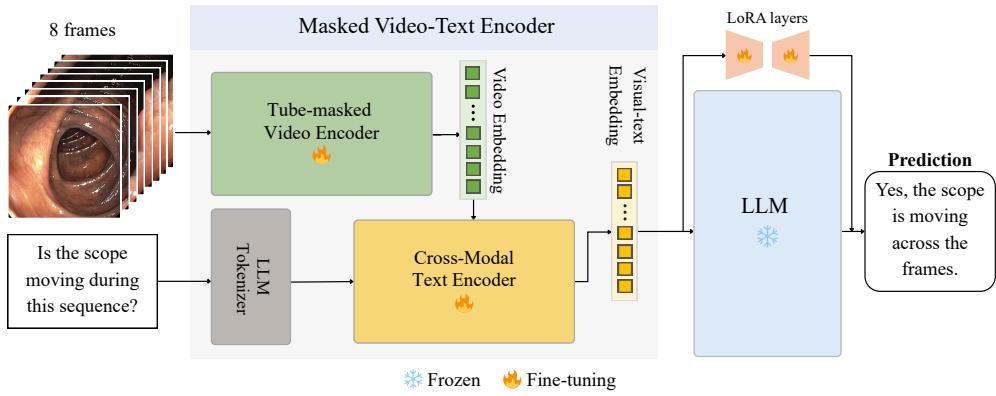


Fig. 1 **SurgViVQA:** The architecture integrates a Masked Video–Text Encoder with a LoRA-adapted LLM to generate context-grounded answers from surgical videos.

2.2 Proposed Dataset: REAL-Colon-VQA

We introduce REAL-Colon-VQA, extending REAL-Colon dataset [10], to benchmark for surgical VideoQA in colonoscopy. Each procedure was reviewed frame-by-frame to annotate endoscope motion (advancing, withdrawing, exiting), tool usage (catheter, snare, forceps), visibility, occlusions, flushing, and illumination mode (white light vs. narrow band image). Lesion attributes (location, size in millimetres, histopathology) were inherited from the clinically verified REAL-Colon annotations [10].

From these annotations we automatically generate QA pairs targeting spatial and temporal reasoning. Questions are created from clinically validated templates and paraphrased into semantically equivalent variants to assess linguistic robustness. Each question has two answers: (i) a short factual answer (e.g. “yes”, “catheter”, “advancing”), and (ii) a longer descriptive answer providing context.

Each QA pair is linked to an eight frame video clip. The clip is built by sampling one frame every 4 frames in the original 30 fps video (stride = 4), i.e. frames $t, t+4, t+8, \dots$,

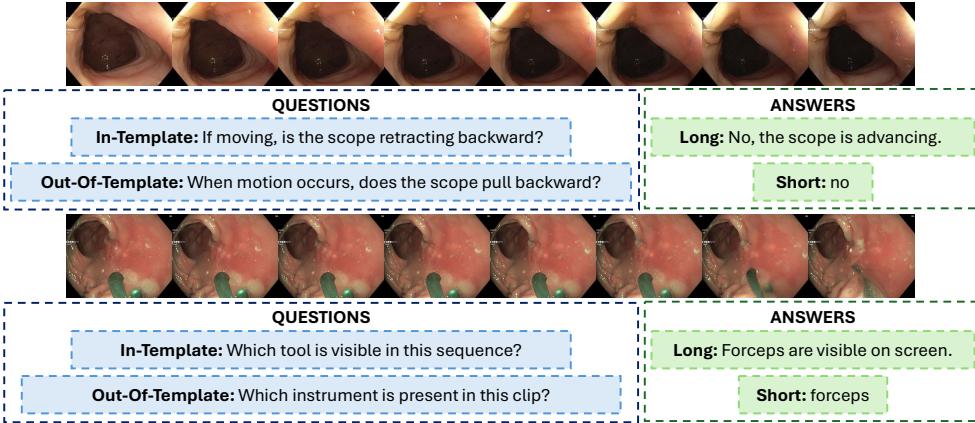


Fig. 2 Example from the REAL-Colon-VQA dataset.

rather than eight strictly consecutive frames. At 30 fps this yields a time span of 28 frames ≈ 0.93 s, large enough to capture scene evolution without expanding the window too much. This preserves short term dynamics such as scope trajectory, lesion motion, flushing, illumination changes, and occlusions. A question is marked true for a clip only if the underlying clinical or visual condition holds for most frames in that clip, making supervision explicitly temporal rather than single frame. On average, questions are 41 characters (about 7.5 words); short answers average 4.2 characters (1 word), long answers 38 characters (about 6.8 words).

REAL-Colon-VQA spans 18 question categories across six reasoning domains: Instruments (tool presence/identity), Sizing (lesion extent), Diagnosis (histopathology), Positions (anatomical site and on-screen location), Operation Notes (illumination, visibility, flushing, occlusion), and Movement (scope and lesion motion). This extends prior surgical VQA datasets such as EndoVis18-VQA [6], PitVQA [5], Kvasir-VQA [7] and SSG-VQA [11] by explicitly modelling temporal events (e.g. scope advancement, lesion drift), which are not captured in those datasets as reported in Table 1. The final dataset contains 5,200 instances for each answer type (short and long). Unlike existing surgical VQA benchmarks, which operate on isolated frames or frame-level classification, REAL-Colon-VQA links motion cues, visibility conditions, and diagnostic attributes to short video clips, providing (to our knowledge) the first colonoscopic VideoQA dataset that jointly supports temporal and diagnostic reasoning in real endoscopic footage.

3 Experiments and Results

3.1 Dataset

In addition to our released REAL-Colon-VQA dataset (Section 2.2), split into 4,450 training instances and 750 testing instances, we conduct our experiments on the publicly available EndoVis18-VQA dataset [6, 12], comprising 13,790 QA pairs extracted

Table 1 Comparison of surgical VQA datasets. REAL-Colon-VQA is the only video-based dataset with out-of-template questions, and short/long answers.

Category	EndoVis18-VQA [6, 12]	PitVQA [5]	Kvasir-VQA [7]	SSG-VQA [11]	REAL-Colon-VQA
Procedure	Nephrectomy	Transsphenoidal	Colon/Gastroscopy	Cholecystectomy	Colonoscopy
Video-based	✗	✗	✗	✗	✓
Out-of-template	✓	✗	✗	✗	✓
Short-answer	✗	✗	✗	✗	✓
#Steps	0	19	1	0	0
#Instruments	6	18	1	6	3
#Positions	4	5	3	3	2
#Sizing	0	0	1	0	1
#Diagnosis	0	0	2	0	1
#Operation Notes	13	14	7	10	5
#Movement	0	0	0	0	5

from 2,086 surgical scenes across 14 nephrectomy videos. The questions address anatomical structures, tool–tissue interactions, and instrument locations, and the answers belong to 18 discrete classes (1 kidney, 13 tool–tissue interactions, and 4 instrument locations). We follow the original official split, consisting of 1,560 frames and 10,574 QAs for training, and 447 frames with 3,216 QAs for validation. For the image-level setting, we retain the dataset in its original form, while, for the video-level setting, we construct 8-frame clips and retain only samples for which all 8 consecutive frames are available and aligned with the final frame’s QA annotation. To assess robustness beyond template-based formulations, we perform out-of-template evaluation using a perturbed version of the original questions as in [12].

3.2 Implementation Details

Our SurgViVQA architecture is implemented in PyTorch using HuggingFace repositories, with a Masked Video–Text Encoder built from pre-trained Video Masked Autoencoders (VideoMAE) [8] video encoder and the Bootstrapping Language–Image Pre-training (BLIP) cross-attention text encoder [13] to fuse video and question representations. To adapt VideoMAE to the 8-frame setting, the patch-embedding and final LayerNorm layers are kept unfrozen, while the rest of the encoder remains frozen, as pre-training was done with 16 frames. The LLM is fine-tuned on the task using LoRA. For GPT-2, the low-rank adapters are applied to the attention (c_attn) and projection (c_proj) layers, while for Qwen the adapters target the query, key, value, and output projection layers (q_proj, k_proj, v_proj, o_proj). The model is trained for 60 epochs using the Adam optimizer with a learning rate of 2×10^{-7} , and optimized with Binary Cross-Entropy (BCE) loss. For fairness, all comparative baselines of SOTA, such as SurgicalGPT and PitVQA, are retrained using their official repositories. Visual-language models (VLMs) are used at inference with zero-shot modality injection via an extensive prompt that efficiently describes the environmental setting. Experiments are conducted on NVIDIA H100.

3.3 Results

To comprehensively evaluate SurgViVQA, we employ a suite of automatic metrics capturing both lexical precision and semantic fidelity. BLEU-4 (BLE-4) measures

4-gram overlap between generated and reference answers, reflecting linguistic accuracy, while ROUGE-L (ROU-L) and METEOR (MET) assess semantic coherence with human responses. Given the clinical context, we place particular emphasis on Keyword Accuracy (K-ACC), which evaluates whether the model explicitly generates the correct surgical or anatomical term within its response, providing a direct measure of factual grounding and clinical relevance. Table 2 reports quantitative comparisons on EndoVis18-VQA and REAL-Colon-VQA, including both in-template and out-of-template evaluations for robustness and generalization.

For in-template performance, our proposed SurgViVQA with GPT-2 as LLM achieves the best results across all metrics, with Keyword Accuracy of 48.3% on EndoVis18-VQA and 63.2% on REAL-Colon-VQA, outperforming PitVQA by roughly 9% and 11%, respectively. BLEU-4, ROUGE-L, and METEOR scores also improve substantially, showing that factual grounding gains do not come at the expense of linguistic fluency. Notably, SurgViVQA achieves results close to large zero-shot vision-language models, despite using only 364M trainable parameters, compared to multi-billion parameter VLMs like Qwen2.5-VL-3B-Instruct [14] (3B parameters), MedGemma-4B [15] (4B parameters), InternVL3-1B [16] (1B parameters) and VideoLLaMA3-2B [17] (2B parameters). This highlights the efficiency and domain

Table 2 Performance comparison of baseline models, zero-shot and our SurgViVQA model across datasets, reporting in-template and out-of-template metrics. All metrics are in percentages (%). Best results in **bold**; second-best underlined.

REAL-Colon-VQA																	
Model	LLM	In-template						Out-of-template									
		BLE-4		ROU-L		MET		K-ACC		BLE-4		ROU-L		MET		K-ACC	
Base	SurgicalGPT [4]	gpt2	Image	14.93	47.85	52.36	33.33	12.35	42.87	50.49	46.67						
	PitVQA [5]	gpt2	Image	<u>64.55</u>	<u>78.48</u>	<u>79.99</u>	54.13	<u>23.63</u>	<u>50.03</u>	<u>53.22</u>	42.93						
	Qwen [14]	-	Image	4.53	45.70	46.83	49.33	0.50	38.80	40.77	50.27						
	MedGemma [15]	-	Image	18.09	36.92	31.86	49.47	5.31	30.96	27.80	34.13						
Zero-Shot	InternVL3 [16]	-	Video	7.13	43.90	54.31	68.67	3.87	32.10	44.34	53.73						
	VideoLLaMA3 [17]	-	Video	2.74	33.01	42.22	17.60	1.78	26.17	35.15	21.47						
	Ours	SurgViVQA	qwen	Video	60.09	74.36	75.32	59.73	16.84	37.69	35.26	38.00					
	Ours	SurgViVQA	gpt2	Video	71.98	82.85	84.11	<u>63.20</u>	31.19	53.62	54.89	47.73					
EndoVis18-VQA																	
Model	LLM	In-template						Out-of-template [12]									
		BLE-4		ROU-L		MET		K-ACC		BLE-4		ROU-L		MET		K-ACC	
Base	SurgicalGPT [4]	gpt2	Image	29.55	58.60	57.99	4.00	2.52	43.97	44.99	11.85						
	PitVQA [5]	gpt2	Image	<u>81.73</u>	86.18	83.28	40.35	<u>17.57</u>	46.87	45.49	9.73						
	Qwen [14]	-	Image	19.04	57.60	68.60	51.22	11.92	52.77	63.72	46.90						
	MedGemma [15]	-	Image	8.23	44.32	64.19	37.90	7.74	40.74	<u>61.59</u>	<u>37.86</u>						
Zero-Shot	InternVL3 [16]	-	Video	5.62	51.50	55.33	32.21	0.57	38.73	38.73	21.99						
	VideoLLaMA3 [17]	-	Video	3.28	52.01	54.66	40.90	0.57	38.73	39.51	35.89						
	Ours	SurgViVQA	qwen	Video	79.05	<u>87.98</u>	<u>84.70</u>	46.30	0.60	12.33	8.10	0.99					
	Ours	SurgViVQA	gpt2	Video	84.94	89.65	86.08	<u>48.27</u>	24.84	<u>50.86</u>	50.13	9.23					

specificity of our architecture. For out-of-template evaluations, all models show a drop in performance, reflecting the challenge of generalizing to unseen question types. SurgViVQA with Qwen shows particularly strong degradation on EndoVis18-VQA, likely due to limited adaptation to surgical-specific terminology and procedural dynamics, whereas SurgViVQA with GPT-2 maintains higher robustness. Despite this, SurgViVQA suffers less than image-only baselines, indicating that temporal fusion contributes to robustness. The remaining gap is likely due to the limited diversity of question types in training, which constrains generalization. Fig. 3 presents a qualitative comparison of the predictions produced by all evaluated models on both in-template and out-of-template samples from the REAL-Colon-VQA dataset.

Sequence								
	In-template				Out-of-template			
Question	Ground Truth		In-template		Out-of-template			
Ground Truth	If moving, is the scope retracting backward? No, the scope is advancing.				When motion occurs, does the scope pull backward? No, the scope is advancing.			
SurgicalGPT	Yes, the scope retracts backward.		✗	No, the scope does not pull backward.		✗		
PitVQA	No, the scope is advancing.		✓	No, the scope stays within the patient.		✗		
Qwen	The scope is retracting backward.		✗	The scope is advancing forward.		✓		
MedGemma	No. The scope is stationary.		✗	The scope is retracting backward.		✗		
InternVL3	Yes, the scope is retracting backward.		✗	No, the scope does not pull backward.		✓		
VideoLLaMA	The scope in the video is not retracting backward; it appears to be stationary with a slight movement towards the upper region of the colon.		✗	The scope does not pull backward; it advances forward during the video.		✓		
SurgViVQA (qwen)	No, the scope is advancing.		✓	No, the scope is advancing.		✓		
SurgViVQA (gpt2)	No, the scope is advancing.		✓	No, the scope is advancing.		✓		

Fig. 3 qualitative comparison of predictions from all models on in-template and out-of-template example from the REAL-Colon-VQA dataset

3.4 Ablation Study

We evaluate our method on the EndoVis18-VQA dataset through two complementary ablation studies: (1) analysis of different temporal feature extractors as video encoders paired with GPT-2, and (2) evaluation of keyword penalization in the weighted BCE loss to mitigate missing critical keywords in generated answers.

(1) *Temporal Feature Extractors*: To assess the contribution of different temporal feature extractors (Temporal F. E.), we conducted an ablation study on the in-template EndoVis18-VQA dataset comparing X-CLIP [18], ViViT [19], TimeSformer [20], VideoMamba [21] and VideoMAE [8], with the latter used as the tube-masked video encoder, all paired with the same GPT-2, as reported in Table 3. Our experiments show that VideoMAE consistently achieves the best performance across BLEU,

Table 3 Performance of different video encoders paired with GPT-2 on in-template EndoVis18-VQA. All metrics are reported in percentages (%). Best results are in **bold**; second-best results are underlined.

Temporal F. E.	BLEU-3	BLEU-4	ROUGE-2	ROUGE-L	METEOR
X-CLIP [18]	83.41	78.81	<u>85.81</u>	88.80	86.79
ViViT [19]	84.08	78.27	<u>82.74</u>	86.89	84.02
TimeSformer [20]	84.73	81.02	82.63	86.31	83.02
VideoMAE [8]	88.44	84.94	89.62	89.66	<u>86.08</u>
VideoMamba [21]	<u>87.96</u>	<u>84.47</u>	85.76	89.06	85.64

ROUGE, and METEOR metrics, highlighting its superior ability to capture spatiotemporal features in surgical video clips. VideoMamba provides competitive results, but falls slightly behind VideoMAE, emphasizing the importance of encoder design for effective video representation. Overall, the results demonstrate that selecting a high-capacity video encoder is crucial for generative surgical VQA performance.

(2) *Keyword Penalization*: To address the issue of missing crucial keywords in generated answers (e.g., predicting "lung" instead of "kidney"), we introduce a penalization term in the weighted BCE loss. Let $y_i \in 0, 1$ denote the reference label for token i , \hat{y}_i the predicted probability, and \mathcal{K} the set of keywords in the reference. The modified loss is defined as:

$$\mathcal{L}_{WBCE} = \frac{1}{N} \sum_{i=1}^N w_i \text{BCE}(y_i, \hat{y}_i), \quad w_i = \begin{cases} \lambda & \text{if token } i \text{ is a keyword} \\ 1 & \text{otherwise} \end{cases} \quad (1)$$

where N is the total number of tokens in the answer and λ is the keyword weighting factor, which increases the penalty for mispredicting keywords, encouraging the model to focus on correctly predicting critical keywords.

We experiment with different values of λ , specifically [1, 2, 5, 10, 25, 50], and compare their effect on keyword accuracy and overall language generation performance using our SurgViVQA with GPT2 as LLM on EndoVis18-VQA dataset. The setting

Table 4 Performance of SurgViVQA with GPT2 as LLM and different keyword penalization λ in the weighted BCE loss on EndoVis18-VQA dataset. Metrics are reported in percentages (%). Best results in **bold**; second-best results are underlined.

Model	λ	In-template				Out-of-template			
		BLE-4	ROU-L	MET	K-ACC	BLE-4	ROU-L	MET	K-ACC
SurgViVQA (GPT2)	1	84.94	89.65	86.08	48.27	24.85	50.86	50.13	9.23
	2	<u>84.71</u>	89.75	86.17	<u>48.61</u>	25.14	50.92	50.13	9.12
	5	84.53	90.71	87.83	48.42	<u>25.68</u>	<u>51.08</u>	<u>50.14</u>	8.81
	10	83.92	91.87	89.78	49.03	27.91	52.09	50.76	<u>11.47</u>
	25	80.31	90.81	<u>88.66</u>	46.45	25.14	50.92	50.13	9.12
	50	80.16	<u>90.93</u>	88.65	46.83	12.38	43.80	46.70	12.08

$\lambda = 1$ corresponds to the standard BCE loss formulation, i.e., without the inclusion of the penalization term. As shown in Table 4, incorporating keyword penalization demonstrates promising potential. Moderate penalization ($\lambda = 10$) yields the best trade-off between language fluency and keyword accuracy, while excessively large values degrade performance, confirming that overemphasizing keywords harms overall generation quality. However, with proper tuning of λ , this technique could be further leveraged to improve both keyword accuracy and overall generation quality.

4 Discussions and Conclusions

In this study, we introduced SurgViVQA, a temporally-aware VideoQA model for dynamic surgical procedures, along with REAL-Colon-VQA, a colonoscopic video dataset annotated with temporally coherent Q&A pairs. SurgViVQA integrates a Masked Video–Text Encoder to combine short video clips with question features, capturing subtle motion and tool–tissue interactions, which are then decoded by a fine-tuned LLM into contextually coherent answers. Ablation studies indicate that tube-masked video encoders most effectively capture spatiotemporal dynamics, while keyword penalization in the loss function further improves the accurate generation of clinically critical terms, together contributing to the enhanced performance of SurgViVQA. Evaluations on REAL-Colon-VQA and EndoVis18-VQA demonstrate that SurgViVQA consistently outperforms image-based baselines across lexical, semantic, and clinically grounded metrics, including Keyword Accuracy. Notably, out-of-template results indicate that the model generalizes better than image-only baselines, although performance decreases under unseen linguistic formulations, highlighting the potential benefits of more diverse question sampling to further improve robustness. Overall, these findings emphasize the critical role of temporal modeling in surgical VideoQA, showing that integrating motion and sequence dynamics enhances both factual accuracy and linguistic fluency. Future work will focus on improving out-of-domain generalization through more varied question types and extending temporal reasoning beyond 8 frames, aiming to provide surgeons with more reliable, context-aware, and temporally-informed decision support. Additionally, further studies could explore proper fine-tuning strategies for vision–language models to achieve better alignment with the surgical domain.

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Code availability. The source code of this work, along with the REAL-Colon-VQA dataset annotations and the pre-trained weights of the SurgViVQA model, is available at <https://github.com/madratak/SurgViVQA>.

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