

Deep Learning-Based Prediction System for Surgical Difficulty in Rectal Cancer Patients Using MRI Pelvimetry

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Purpose: This study presents a system that automatically predicts the difficulty of laparoscopic total mesorectal excision (TME) using magnetic resonance imaging (MRI) pelvimetry and the clinical characteristics of the patients with rectal cancer, using deep learning (DL) technology and statistical analysis.

Materials and Methods: Colorectal MRI data were collected from patients with rectal cancer and input into the segmentation model for DL training, followed by automatic measurement of pelvimetry parameters from the segmentation results. The measured parameters and preoperative clinical data of the patients were statistically analyzed to identify clinically correlated predictors of surgical difficulty. Finally, using the selected predictors, a logistic nomogram was generated for the prediction of surgical difficulty.

Results: The segmentation models yielded Dice similarity coefficients (DSC) of 92.7%–95.7%, and the automatic measurement results exhibited high correlation with the manual measurement results. The identified predictors were age, tumor location from the anal verge, interspinous distance, angle δ , and mesorectal fat area. The C-index of the generated nomogram was 0.852.

Conclusion: The system provides standard guidance for the examination of the difficulty of TME that could potentially be used in clinical settings. A follow-up study could develop this idea to fully automate the entire process with a simple user interface to provide objective predictions and explanations.

Key Words: Rectal cancer, deep learning, pelvimetry, MRI

Received: September 24, 2024 **Revised:** November 6, 2025

Accepted: November 19, 2025 **Published online:** April 1, 2026

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•The authors have no potential conflicts of interest to disclose.

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INTRODUCTION

Colorectal cancer is one of the most common malignancies globally, leading to a high number of deaths each year.¹ Surgical resection continues to be the most commonly used and effective treatment option for patients with colorectal cancer. Among various types, the surgical procedure for rectal cancer is known to be the most complicated process due to the anatomic complexity of the pelvis.² At present, as minimally invasive surgery emerges as the latest surgical trend with various advantages, laparoscopic surgery has been widely adopted for the treatment of such patients.^{3,4} In particular, total mesorectal excision (TME), which is a method of completely removing the rectum together with the enveloping lymphovascular fatty tissue (mesorectum) through sharp and precise dissection, is consid-

ered a standard technique for rectal cancer surgery that leads to positive oncologic outcomes.^{5,6}

Various preoperative assessments may help predict surgical difficulty and hence achieve better oncological outcomes.⁷ The difficulty of rectal cancer surgery is affected by various clinical factors and the pelvic structures of patients.⁸ It is reported that the difficulty of surgery generally increases in men, those with high body mass index (BMI), and patients with a narrow and deep pelvis.^{9,10} Since the pelvic structure significantly affects the difficulty of surgery, it is crucial to examine the pelvic structure before surgery.^{11,12} The structure of the pelvis can be evaluated using various pelvimetric parameters with magnetic resonance imaging (MRI).¹³ Pelvic measurement techniques were originally studied mostly in obstetrics and gynecology; however, many colorectal experts now utilize pelvic measurement with the development of laparoscopic technology.¹⁴

There have been various attempts to evaluate surgical difficulty of laparoscopic TME using patient clinical data and pelvic structure.^{10,15–18} Baik, et al.¹⁹ analyzed factors that affected the pathological quality of the resected specimen after TME and reported that patients with a narrow obstetric conjugate or shorter interspinous distance should be considered high-risk patients as they result in poor postoperative specimen quality. Ferko, et al.²⁰ used MRI and computed tomography (CT) images to define various pelvimetric parameters that could potentially influence the performance of TME and found that the angle between the lower and upper borders of the pubic symphysis and promontory was statistically correlated with the overall quality of TME. Some studies used CT images only, rather than MRI, to emphasize the importance of pelvic cross-sectional measurement.^{11,21}

Despite the existence of study results regarding evaluation of surgical difficulty that highlight the importance of its prediction for better surgical outcomes, surgical difficulty assessments are rarely utilized in the actual clinical settings.²² The reason could be not only due to different parameters that can affect surgical difficulty, but also because the procedure of measuring pelvic parameters is complicated and time-consuming. Moreover, a standard indicator for measuring surgical difficulty does not exist; hence, the prediction is a subjective process that lacks inter-rater reliability.²³

To resolve the obstacles that could be raised in the process of assessing the difficulty of TME, application of artificial intelligence (AI) to the process could be one of the solutions. In particular, deep learning (DL) in the medical field is a rising technology that has been widely incorporated in various medical fields recently, including prediction, diagnosis, and treatment of diseases.^{24–27} Especially, the application of DL using medical images has developed diversely as DL in the computer vision (CV) area has exponentially advanced over the years. DL research using radiology images is one of the fastest growing technologies among them. DL in CV is specialized in tasks such as finding abnormalities on medical images by finding se-

mantic features of images, or segmenting various organs and tissue areas inside the body to obtain anatomical indicators.^{28–30} In rectal cancer, previous studies mainly focused on diagnosing and classifying rectal cancer by detecting the tumor in medical images, while studies regarding evaluation of surgical difficulties do not exist yet.^{31,32} Application of AI technology using convolutional neural network (CNN) can shorten the time taken for examining pelvic anatomy by automating the process.³³ This study aimed to develop a system that can automatically predict the difficulty of laparoscopic TME using MRI pelvimetry and clinical characteristics of patients with rectal cancer.

MATERIALS AND METHODS

Overview

The overall workflow of the study is divided into three sections: DL segmentation, automatic measurement, and statistical analysis with nomogram formation. Preoperative clinical data and colorectal MRI data are collected from the patients with rectal cancer, and pelvimetry parameters are measured from the selected MRI slices. These slices are also input to the segmentation model for DL training, followed by automatic measurement of pelvimetry parameters from the segmentation results. Subsequently, the measured parameters and preoperative clinical data of the patients are statistically analyzed to identify clinically correlative predictors of surgical difficulty. Finally, using the selected predictors, a nomogram is generated for the prediction of surgical difficulty.

The data preprocessing, DL training, and generation of the post-segmentation algorithm were performed using Python (version 3.7.0; Python Software Foundation, Wilmington, DE, USA), and statistical analyses were done using SPSS (version 23.0; IBM Corp., Armonk, NY, USA) and R (version 4.2.0; R Core Team, Vienna, Austria). The code used for this study is available in <https://github.com/chrstnkgng/PelvMR>.

Patients

From January 2017 to February 2022, the medical records for patients who received laparoscopic TME for rectal cancer at Gachon University Gil Medical Center were retrospectively reviewed. Rectal cancer patients who underwent low anterior resection (LAR) or ultra-LAR (uLAR) by a single surgeon (JHB) were considered for inclusion in the study population. Patients who underwent emergency operations, open procedures, Hartmann's operations and transanal approaches such as abdominoperineal resection or intersphincteric resection were excluded. Four hundred two patients were selected for the study, including 297 for DL training and 105 for clinical assessment and statistical analysis.

Patients were classified according to surgical difficulty based on pelvic dissection time (PDT). Preoperative clinical data and the parameters in MRI pelvimetry were examined to identify

predictors of surgical difficulty in laparoscopic rectal surgery.

This study was approved by the Institutional Review Board of Gil Medical Center (No. GCIRB2021-311). Informed consent was waived as this study was retrospective.

MRI pelvimetry

The parameters in MRI pelvimetry were examined to identify predictors of surgical difficulty. MRI parameters were classified into three categories: length, angle, and area. The measurement was performed in sagittal view and axial view of colorectal MRI using software of the INFINTT Picture Archiving and Communication Systems.

In the sagittal view, six lengths and four angles were measured from a selected image presenting a pubic symphysis and a coccygeal tip. In axial view, two lengths and three areas were

measured from selected images presenting the rectal area, interspinous distance, and intertuberos distance. A total of 15 parameters were measured and each parameter was described as follows: 1) pelvic inlet length: distance between sacral promontory and superior aspect of pubic symphysis; 2) pelvic outlet length: distance between tip of the coccyx and inferior aspect of pubic symphysis; 3) pubic height: distance between superior and inferior aspect of pubic symphysis; 4) sacral length: distance between sacral promontory and tip of the coccyx; 5) pelvic depth: perpendicular distance between pelvic inlet and tip of the coccyx; 6) sacral depth: perpendicular distance between sacral length and the deepest portion of the sacrococcygeal hollow; 7) angle α : angle between pelvic inlet and the deepest sacrococcygeal point based on the sacral promontory; 8) angle β : angle between the extension of pelvic

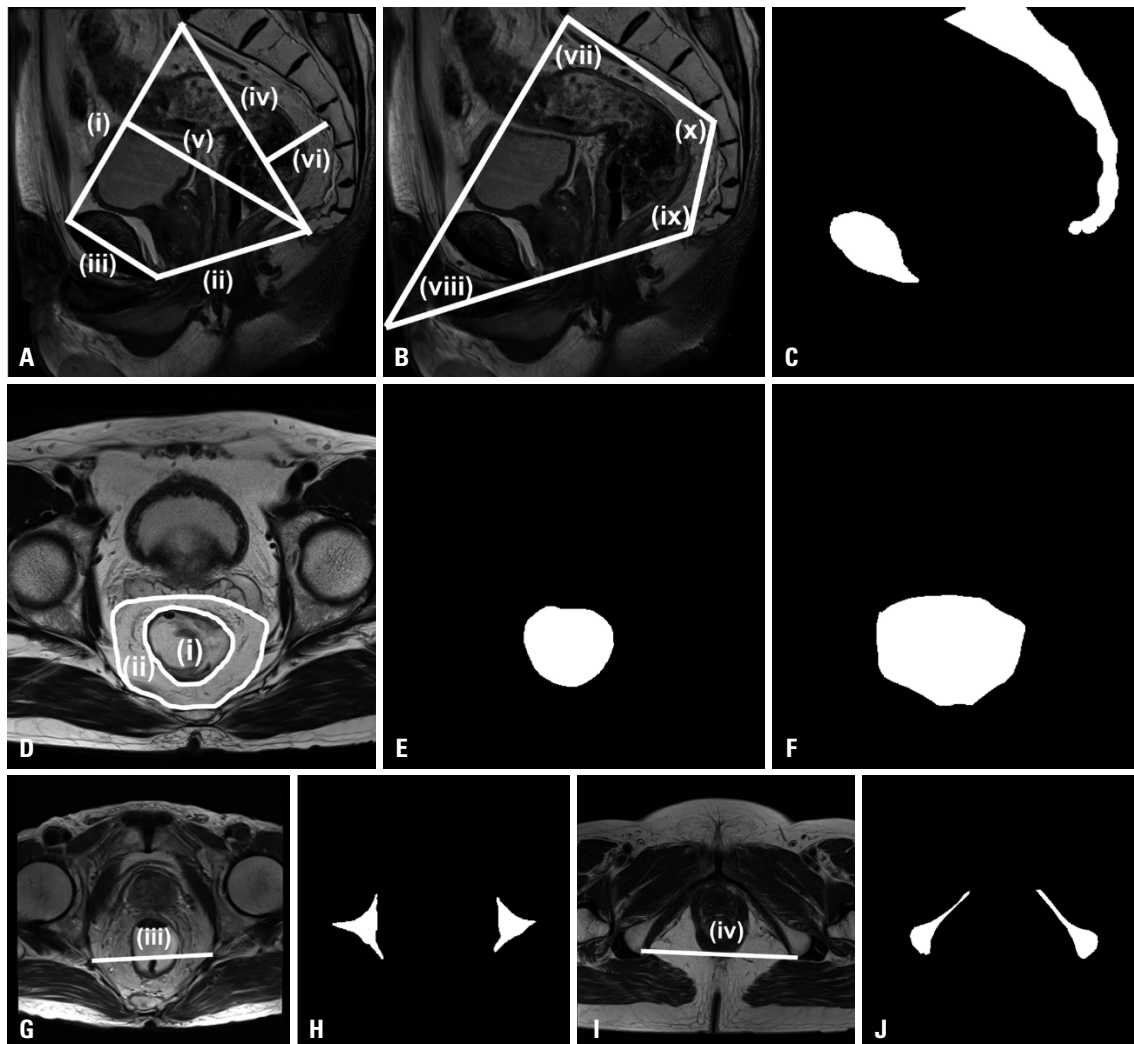


Fig. 1. MRI pelvimetry parameters and GT images of segmented areas. (A) Slice of a sagittal view showing length parameters: (i) pelvic inlet, (ii) pelvic outlet, (iii) pubic depth, (iv) sacral length, (v) pelvic depth, and (vi) sacral depth. (B) Slice of a sagittal view showing angle parameters: (vii) angle α , (viii) angle β , (ix) angle γ , and (x) angle δ . (C) GT image of a sagittal view showing the coccygeal tip and pubic symphysis. (D) Slice of an axial view showing the rectum and mesorectum: (i) rectum, (ii) mesorectum. (E) GT image of an axial view showing the rectum. (F) GT image of an axial view showing the mesorectum. (G) Slice of an axial view showing the interspinous distance. (H) GT image of an axial view showing the ischial spines. (I) Slice of an axial view showing the intertuberos distance. (J) GT image of an axial view showing the ischial tuberosities. MRI, magnetic resonance imaging; GT, ground truth.

inlet and pelvic outlet; 9) angle γ : angle between pelvic outlet and the deepest sacrococcygeal point; 10) angle δ : angle between sacral promontory and the tip of the coccyx based on the deepest sacrococcygeal point; 11) interspinous distance: distance between tips of ischial spines; 12) intertuberos distance: distance between the lowest points of the ischial tuberosities; 13) mesorectal area: area obtained by summing rectal area and mesorectal fat in the axial view including interspinous distance; 14) rectal area: area corresponding to rectum in the axial view including interspinous distance; and 15) mesorectal fat area: area where the rectal area is removed from the mesorectal area.

The parameters and areas needed for the segmentation process are shown in Fig. 1.

DL dataset

Colorectal MRI images from 297 patients who received laparoscopic TME for rectal cancer were used for the DL model development, and 105 images from 105 patients with clinical data were used for test and statistical analysis. For the examination, T2-weighted MRI images were taken preoperatively using a 3-Tesla magnetic resonance imager (Siemens Magnetom Verio, Siemens, Germany). The MRI slices used for model training were selected by the clinical experts. The MRI slices were determined based on the slice selection that was generally used for manual pelvimetry measurement. In the sagittal view, slices with clear view of the apex of the coccyx were selected, whereas in the axial view, slices with clear view of ischial spines and ischial tuberosities were selected. Selected MRI slices from the sagittal view were input to segment coccygeal tip and pubic symphysis, whereas MRI slices from the axial view were used for the segmentation of rectum, mesorectum, ischial spines, and ischial tuberosities. To overcome the difficulties that could be raised by a small dataset, three slices that clearly outline the desired segmentation area were taken from the set of images of each patient. The final number of images used for the training was: 852 images for the coccygeal tip and pubic symphysis, 889 for the mesorectum and rectum, 831 for the ischial spines, and 810 for the ischial tuberosities. After the training, the models were tested with 105 images that were selected for clinical evaluation. These testing images are clinical data for which human measurements exist, and they were not included in the training set.

The data preprocessing was performed before the DL training. First, the bone and tissue areas in the MRI images that needed to be segmented were manually annotated by clinical experts. They were further generated as mask images for use as the ground truth (GT) images for the DL training. For better contrast, all raw MRI images were processed with the contrast limited adaptive histogram equalization technique after the conversion from Digital Imaging and Communications in Medicine to Portable Network Graphics (PNG) format. All images were resized to 256×256 pixels from the original resolution

of 512×512 pixels. Additionally, the PNG-converted images were normalized using the standard ImageNet-based normalization [mean=(0.485, 0.456, 0.406), std=(0.229, 0.224, 0.225)] before being used as input to the DL model.

Segmentation using DL

For the segmentation of pelvic MRI, a U-Net3+ architecture was used, which is an upgraded version of a U-Net model.^{34,35} U-Net3+ is a CNN for semantic segmentation, with the utilization of full-scale skip connections and improved loss. To maximize the accuracy of pelvimetry measurements, it is crucial to clearly distinguish objects and achieve precise boundary segmentation. The U-Net3+ model was chosen as it effectively captures both global and local regions in detail, making it the most suitable not only for achieving accurate segmentation results but also for enhancing pelvimetry calculation performance. Using this architecture, five separate models were trained to segment three bones and three tissues. Each model used the Adam optimizer with a learning rate of 0.0001, weight decay of 0.9, batch size of 4, and 200 epochs. The training was conducted using two RTX 2080 GPUs, and a single model training took approximately two hours to complete.

Post-segmentation algorithm

The post-segmentation algorithm is proposed to measure 15 pelvimetric parameters using the segmentation results. This algorithm enables the pelvimetric parameters to be measured and calculated automatically from MRI slices. From the sagittal results that segmented the coccyx and pubic symphysis, the top and bottom endpoints of the coccyx and pubic symphysis are detected from the contours of each area that are created from the resulting mask images. Six lengths and four angles are measured from this image using the detected points: pelvic inlet, pelvic outlet, pubic height, sacral length, pelvic depth, sacral depth, angle α , angle β , angle γ , and angle δ . Similarly, from the axial results that segmented the rectum and mesorectum, areas of each tissue are calculated using the contours and the mesorectal fat area is determined by subtracting the area of the rectum from the area of the mesorectum. Finally, from the axial results that segmented a pair of ischial spines and ischial tuberosities, the bottom endpoints of each segmented area are determined, and the interspinous distance and intertuberos distance are calculated respectively by connecting the two endpoints. All pixels were converted into centimeters prior to the calculation for improved convenience.

Statistical analysis

For the evaluation of the trained segmentation models, pixel-wise performance was assessed on the independent test cohort (n=105) using confusion-matrix-based metrics: accuracy, sensitivity, specificity, and the Dice similarity coefficient (DSC). To evaluate the agreement between manual and automated pelvimetry measurements, three complementary methods were

applied: 1) correlation analysis using Pearson's r with 95% confidence intervals (CIs) (with Spearman's ρ additionally checked when normality was questionable); 2) Bland-Altman analysis, reporting the mean bias and 95% limits of agreement ($LoA = \text{bias} \pm 1.96 \times SD$ of differences) and testing proportional bias by regressing differences on means; and 3) intraclass correlation coefficients (ICC) using a two-way random-effects, absolute-agreement, single-measurement model ICC(2,1) with 95% CIs derived from the F-distribution. Axial and sagittal measurements were analyzed separately. Two-sided $p \leq 0.05$ was considered statistically significant.

Clinical data were collected retrospectively based on electronic clinical records. The clinical data included in the investigation were as follows: age, sex, BMI, surgical procedure, operation time, PDT, estimated blood loss (EBL), tumor size, tumor location from anal verge (AV), conversion to open procedure, duration of hospital stay after surgery and anastomotic leakage. All clinical and imaging variables included in the analysis were defined at baseline prior to surgery. In particular, "hospital stay (days)" refers to the number of inpatient days after surgery until discharge, excluding any preoperative hospitalization, and was used for descriptive analysis only, not included as a predictive variable in the model. As PDT is reported to more directly reflect the surgical difficulty than the total operation time, we used PDT as an indicator of surgical difficulty; <45 minutes as easy procedure and ≥ 45 minutes as difficult. This was determined based on the clinical experience of the surgeon.³⁶ PDT was defined as the time from the beginning of the pelvic dissection at the level of the sacral promontory to the distal rectal margin resection for TME. For the other variables, several variables such as tumor location (<6 cm from AV) were categorized based on widely accepted clinical criteria.^{37,38} For others such as tumor size or blood loss, appropriate cutoffs were determined based on data distribution and clinical interpretability.^{39,40}

Univariable analyses of preoperative clinical and pelvimetric parameters were conducted to identify predictors significantly associated with surgical difficulty. Categorical variables were analyzed using the Pearson chi-square test or Fisher's ex-

act test as appropriate, and continuous variables were compared using Student's t -test. Variables with a p -value ≤ 0.05 were considered statistically significant and subsequently included in a multivariable logistic regression model to identify independent predictors of surgical difficulty. Using the selected predictors, a nomogram was generated to predict the probability of difficult surgery. Nomogram is a graphical depiction that helps users to easily compute output probabilities by displaying all variables in scaled lines. We created a nomogram of a multivariable logistic regression prediction model. All continuous variables included in the multivariable logistic regression model were dichotomized using cutoff values determined through univariable analysis in relation to surgical difficulty, defined as PDT. All variables were defined at baseline prior to surgery. The generated nomogram was evaluated using a C-index and a calibration curve. Calibration was assessed using quantile binning (5 bins), plotting the observed event rate against the mean predicted probability in each bin. The 95% confidence bands were obtained by 1000-resample non-parametric bootstraps. The Brier score and the Hosmer-Lemeshow goodness-of-fit test were used to calculate the quantitative aspect of the calibration curve. Two-sided tests were used.

RESULTS

Segmentation of pelvimetry parameters

To evaluate the performance of the segmentation models, MRI images of 105 patients were used as the test data. One sagittal model (coccygeal tip, pubic symphysis) and four axial models (mesorectum, rectum, ischial spines, and ischial tuberosities) were evaluated using pixelwise confusion matrices to compute accuracy, sensitivity, specificity, and the DSC.

Table 1 displays the results of the performance evaluation of five segmentation models. The sagittal view segmentation model exhibited a DSC score of 95.8%, and the DSC scores of axial view segmentation models were 95.7%, 95.3%, 92.7%, and 93.2%, respectively. All models showed high DSC scores which

Table 1. Patient Dynamics and Results of the Segmentation Models

	Train	Validation	Test
Sagittal view	297 (682)	297 (170)	105 (105)
Axial view-rectal area	297 (712)	297 (177)	105 (105)
Axial view-ischial spine	297 (665)	297 (166)	105 (105)
Axial view-ischial tuberosities	297 (648)	297 (162)	105 (105)
Sagittal view		Axial view	
	Mesorectum	Rectum	Ischial spine
Accuracy (%)	99.4	99.7	99.6
Sensitivity (%)	96.1	95.3	92.9
Specificity (%)	99.7	99.9	99.8
DSC (%)	95.8	95.3	92.7
			Ischial tuberosities
			93.2

DSC, Dice similarity coefficient.

Data are presented as number of subjects (number of datasets).

indicate that the trained models have the ability to correctly segment the desired areas.

Automatic pelvimetry was applied to the segmented images to obtain lengths, angles, and areas. To compare AI-based and manual measurements, we first assessed correlation (all $r=0.725\text{--}0.931$, all $p<0.0001$) (Table 2) and visualized Bland–Altman plots (Figs. 2 and 3), where the mean differences were 0.0–0.20 cm (length), 0.0–3.5° (angle), and 0.2–0.4 cm² (area). To further evaluate the agreement between the two methods, the ICC using a two-way random-effects, absolute-agreement, single-measurement model [ICC(2,1)] was also calculated. As shown in Table 3, the ICC values ranged from 0.65 to 0.93 for most structures (e.g., interspinous distance ICC=0.93, 95% CI 0.90–0.95; mesorectal fat area ICC=0.74, 95% CI 0.64–0.82), in-

Table 2. Correlation between Automatic and Manual Measurement Results

	Correlation coefficient (R)	95% CI	<i>p</i>
Pelvic inlet	0.88	0.83–0.92	<0.0001
Pelvic outlet	0.86	0.80–0.90	<0.0001
Pubic height	0.75	0.65–0.82	<0.0001
Sacral length	0.86	0.81–0.91	<0.0001
Pelvic depth	0.88	0.82–0.92	<0.0001
Sacral depth	0.87	0.82–0.91	<0.0001
Interspinous distance	0.93	0.90–0.95	<0.0001
Intertuberos distance	0.92	0.89–0.95	<0.0001
Angle α	0.84	0.78–0.89	<0.0001
Angle β	0.76	0.67–0.83	<0.0001
Angle γ	0.73	0.62–0.80	<0.0001
Angle δ	0.84	0.77–0.89	<0.0001
Mesorectum	0.80	0.72–0.86	<0.0001
Rectum	0.78	0.69–0.85	<0.0001
Mesorectal fat area	0.74	0.64–0.82	<0.0001

CI, confidence interval.

dicating good to excellent agreement. Sacral depth showed a relatively high correlation coefficient ($r=0.87$) but poor agreement (ICC=0.39, 95% CI 0.22–0.54), suggesting a consistent bias in scale despite similar trends between the two methods. These findings collectively support the reliability of the AI-based measurements and their potential applicability in clinical settings.

Prediction of surgical difficulty

Univariable analyses of preoperative clinical data and MRI pelvimetric parameters were performed to select the predictors that show significant relationships with PDT, which was set as an indicator of surgical difficulty. Patients were divided into two groups according to surgical difficulty, based on PDT (<45 min vs. ≥ 45 min). According to the results demonstrated in Table 4, younger age under 65 ($p=0.043$), male sex ($p=0.021$), uLAR surgery ($p=0.020$), and shorter tumor distance from the AV ($p=0.008$) had a significant correlation with the difficult group, whereas BMI, EBL, tumor size, hospital stay, and anastomotic leakage had no statistical significance in relation to surgical difficulty. Among the 15 pelvimetric parameters, interspinous distance, intertuberos distance, angle δ , and mesorectal fat area showed a significant difference between the two groups, with p values of 0.015, 0.026, 0.022, and 0.005, respectively. The other parameters showed no significant correlation with the surgical difficulty.

Multivariable logistic regression analysis was performed on seven factors that showed statistical significance with PDT. The results are displayed in Table 5. Although there were more patients who were male or had a short intertuberos distance in the difficult group, these two factors did not show statistically significant results according to multivariable analysis. On the other hand, age, tumor location, interspinous distance, angle δ , and mesorectal fat area were statistically significant with PDT. According to the results demonstrated in Table 5, age un-

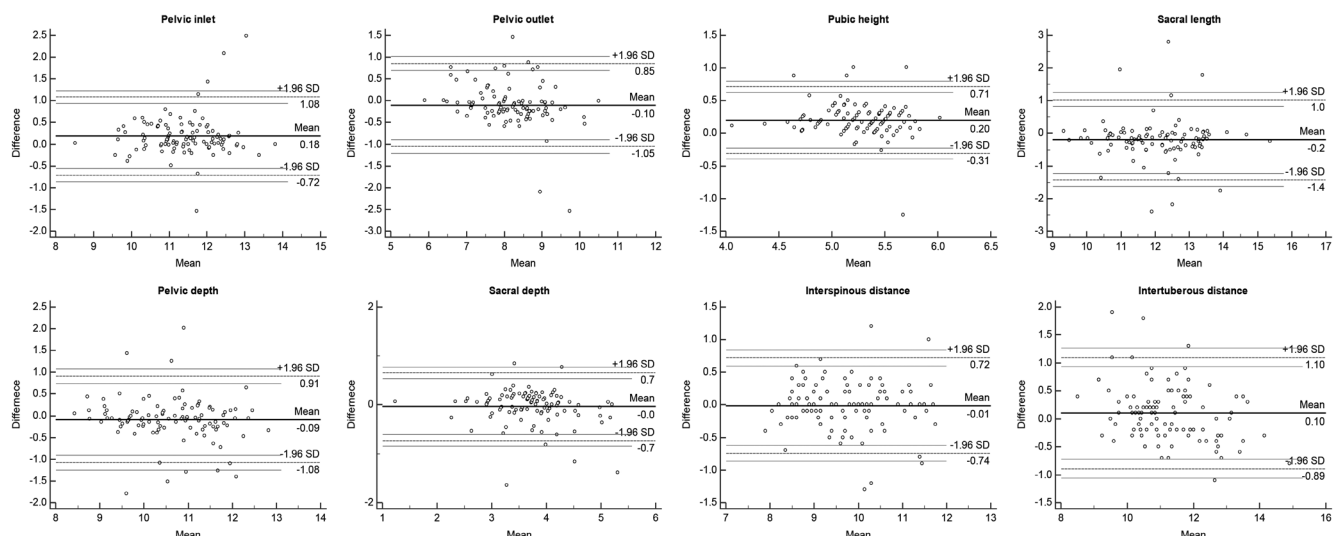


Fig. 2. Bland–Altman plot of length parameters comparing manual and automatic measurement results.

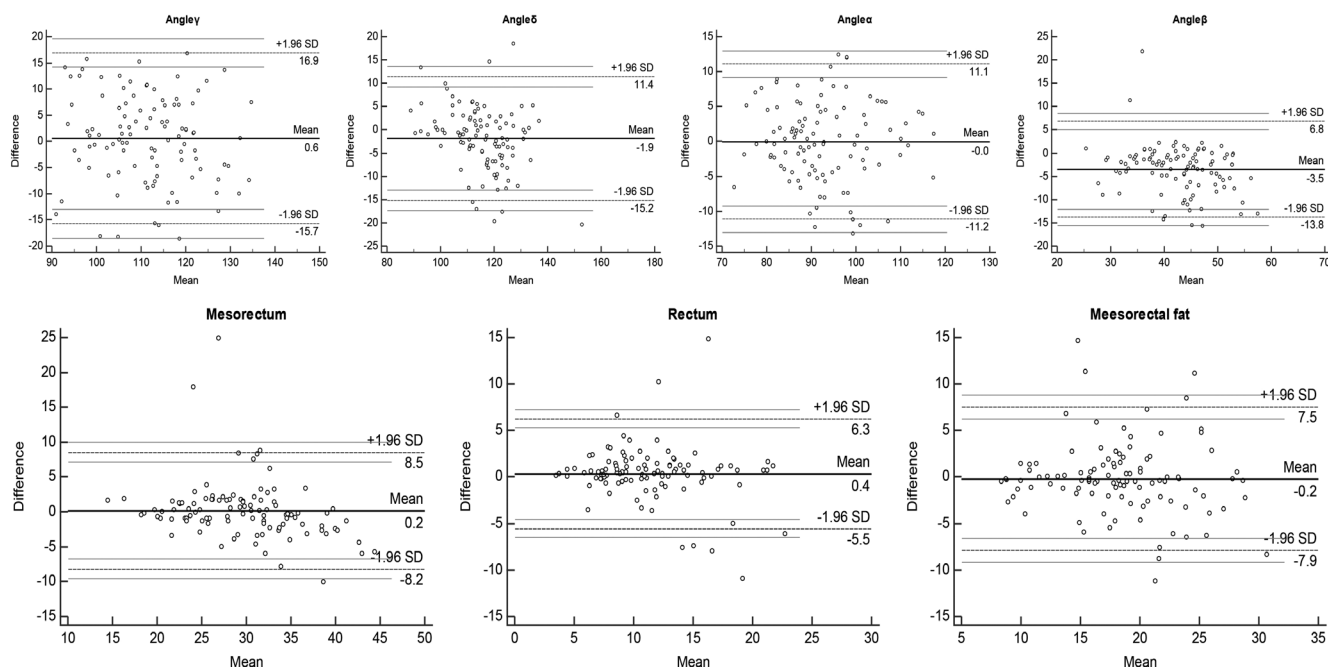


Fig. 3. Bland–Altman plot of angle and area parameters comparing manual and automatic measurement results.

Table 3. ICC between Automatic and Manual Measurement Results

	ICC	95% CI	<i>p</i>
Pelvic inlet	0.87	0.78–0.92	<0.0001
Pelvic outlet	0.85	0.78–0.89	<0.0001
Pubic height	0.65	0.25–0.82	<0.0001
Sacral length	0.85	0.78–0.90	<0.0001
Pelvic depth	0.87	0.82–0.91	<0.0001
Sacral depth	0.39	0.22–0.54	<0.0001
Interspinous distance	0.93	0.90–0.95	<0.0001
Intertuberous distance	0.91	0.87–0.94	<0.0001
Angle α	0.84	0.78–0.89	<0.0001
Angle β	0.68	0.37–0.82	<0.0001
Angle γ	0.72	0.62–0.80	<0.0001
Angle δ	0.81	0.73–0.87	<0.0001
Mesorectum	0.79	0.70–0.85	<0.0001
Rectum	0.78	0.69–0.84	<0.0001
Mesorectal fat area	0.74	0.64–0.82	<0.0001

ICC, Intraclass Correlation Coefficients; CI, confidence interval.

der 65 years ($p=0.022$), tumor location from the AV less than 6 cm ($p=0.001$), interspinous distance less than 10 cm ($p=0.007$), angle δ less than 127° ($p=0.016$), and mesorectal fat area 18 cm^2 or greater ($p=0.004$) appeared to be associated with a more difficult surgical procedure.

Finally, a nomogram was constructed from the multivariable logistic regression coefficients estimated in the training cohort; variables not retained in multivariable analysis were excluded. Its performance was evaluated in the independent test cohort ($n=105$). The nomogram is shown in Fig. 4A, and the corresponding calibration curve for the test cohort is shown in Fig.

4B. In the nomogram, each predictor variable is represented as a scaled line, and the value corresponding to a patient's characteristic is mapped vertically to the "points" scale at the top. The points for all predictors are then summed to yield a "total points" value. Finally, a vertical line is drawn from the total points scale down to the probability scale to determine the estimated likelihood of surgical difficulty. The calibration plot demonstrates the agreement between predicted probabilities and observed surgical difficulty outcomes, indicating good model calibration.

For example, if a patient has a total of 340 points on the nomogram, the predicted probability of a difficult surgery—defined as PDT ≥ 45 minutes—is approximately 80%. This probability reflects the likelihood that the case will be classified as surgically difficult based on the model. In the independent test cohort ($n=105$), the model achieved a C-index of 0.853 (95% CI 0.753–0.951). Fig. 4B depicts the calibration curve for the test set. Although the mid-probability bins (~ 0.2 – 0.4) appear irregular, the wide bootstrap bands indicate instability due to limited bin counts rather than systematic miscalibration. Global fit was acceptable (Brier score=0.1272; Hosmer-Lemeshow $\chi^2=4.44$, $df=8$, $p=0.8150$).

DISCUSSION

The purpose of this study was to develop a system that can automatically predict the difficulty of laparoscopic TME for rectal cancer using colorectal MRI data and clinical characteristics of the patients. The overall workflow was divided into three categories: investigation of patient demographics, auto-

Table 4. Univariable Analysis of Clinical and MRI Pelvimetry Parameters according to Surgical Difficulty Defined by PDT (<45 min vs. ≥45 min)

Characteristics and parameters	PDT (min)		<i>p</i>
	<45 (n=80)	≥45 (n=25)	
Sex			0.021
Male	51 (63.7)	22 (88.0)	
Female	29 (36.3)	3 (12.0)	
Age			0.043
<65 years	38 (47.5)	17 (68.0)	
≥65 years	42 (52.5)	8 (32.0)	
BMI (kg/m ²)	23.3±3.0	24.0±2.4	0.252
Tumor location from AV			0.008
<6 cm	10 (12.5)	9 (36.0)	
≥6 cm	70 (87.5)	16 (64.0)	
Tumor size			0.191
<3 cm	34 (42.5)	11 (44.0)	
≥3 cm	46 (57.5)	13 (52.0)	
Surgical method			0.020
LAR	61 (76.3)	13 (52.0)	
uLAR	19 (23.8)	12 (48.0)	
Conversion to open procedure	0 (0.0)	1 (1.0)	0.072
EBL			0.241
<100 mL	55 (68.8)	14 (56.0)	
≥100 mL	25 (31.3)	11 (44.0)	
Anastomotic leakage	2 (1.9)	1 (1.0)	0.694
Hospital stay (days)	9.0±2.7	10.4±5.5	0.240
Pelvic inlet length			0.982
<11 cm	29 (36.3)	9 (36.0)	
≥11 cm	51 (63.7)	16 (64.0)	
Pelvic outlet length			0.927
<8 cm	28 (35.0)	9 (36.0)	
≥8 cm	52 (65.0)	16 (64.0)	
Pubic tubercle height			0.758
<5 cm	25 (31.3)	7 (28.0)	
≥5 cm	55 (68.8)	18 (72.0)	
Sacral length			0.660
<12 cm	36 (45.0)	10 (40.0)	
≥12 cm	44 (55.0)	15 (60.0)	
Pelvic depth			0.344
<11 cm	47 (58.8)	12 (48.0)	
≥11 cm	33 (41.3)	13 (52.0)	
Sacral depth			0.822
<4 cm	50 (62.5)	15 (60.0)	
≥4 cm	30 (37.5)	10 (40.0)	
Interspinous distance			0.015
<10 cm	42 (52.5)	20 (80.0)	
≥10 cm	38 (47.5)	5 (20.0)	
Intertuberous distance			0.026
<12 cm	56 (70.0)	23 (92.0)	
≥12 cm	24 (30.0)	2 (8.0)	
Angle α			0.600
<92°	40 (50.0)	14 (56.0)	
≥92°	40 (50.0)	11 (44.0)	

Table 4. Univariable Analysis of Clinical and MRI Pelvimetry Parameters according to Surgical Difficulty Defined by PDT (<45 min vs. ≥45 min) (continued)

Characteristics and parameters	PDT (min)		<i>p</i>
	<45 (n=80)	≥45 (n=25)	
Angle β			0.382
<45°	40 (50.0)	10 (40.0)	
≥45°	40 (50.0)	15 (60.0)	
Angle γ			0.527
<112°	39 (48.8)	14 (56.0)	
≥112°	41 (51.2)	11 (44.0)	
Angle δ			0.022
<127°	60 (75.0)	24 (96.0)	
≥127°	20 (25.0)	1 (4.0)	
Mesorectal area			0.470
<30 cm ²	45 (56.3)	12 (48.0)	
≥30 cm ²	30 (43.8)	13 (52.0)	
Rectal area			0.126
<10 cm ²	34 (42.5)	15 (60.0)	
≥10 cm ²	46 (57.5)	10 (40.0)	
Mesorectal fat area			0.005
<18 cm ²	45 (56.3)	6 (24.0)	
≥18 cm ²	35 (43.8)	19 (76.0)	

MRI, magnetic resonance imaging; PDT, pelvic dissection time; BMI, body mass index; EBL, estimated blood loss; AV, anal verge.

Data are presented as mean±standard deviation or n (%).

matic pelvimetry measurement using DL segmentation, and statistical analyses for prediction of surgical difficulty. The DL models trained with the U-Net3+ architecture exhibited high performance in segmenting desired areas needed for pelvimetric measurement, yielding automatic measurement results that are generally consistent with the manual measurement results. Statistical analyses performed on patient clinical characteristics and pelvimetric parameters determined five predictors that affected surgical difficulty: age, tumor location, interspinous distance, angle δ, and mesorectal fat area. Using these indicators, a nomogram was generated that predicts the difficulty of laparoscopic TME in patients with rectal cancer. The nomogram can be examined by assessing each variable, drawing a vertical line to obtain the corresponding score, summing these values, and interpreting the total score to estimate surgical difficulty.

Prediction of surgical difficulty in laparoscopic TME is critical, especially when the surgeon plans TME for mid and low rectal cancer.^{21,41} Surgeons would be able to design an overall surgical plan based on predicted surgical difficulty, as it can provide them with guidance for various surgical approaches. If surgical difficulty could be examined and predicted preoperatively, it could help determine the range of TME and resection margin or anastomosis level. Furthermore, the prediction of surgical difficulty provides objective evidence for clinical decisions such as whether to choose laparoscopic or open sur-

gery, whether to perform anastomosis or choose alternatives such as temporary or permanent colostomy, and these decisions help patients receive optimal treatment that is personalized to each individual. For example, robotic surgery can be advantageous for patients with large mesorectum, narrow pelvis, and low rectal cancer because it allows a wider anatomical plane compared to laparoscopy, where the maximum angle the instrument can reach may be limited. The most appropriate surgical method based on this study may be suggested to ensure optimal results in these patients. Furthermore, the patients can be provided with more objective understanding of the overall surgical procedure and difficulty beforehand. For example, if the prediction result showed a high probability of difficult surgery, surgeons can give a more detailed explanation about their surgical decisions based on the presented numerical score to their patients. In the short term, it can improve postoperative prognosis, and ultimately, it could contribute to improved overall surgical outcomes such as reduced anasto-

motric leakage or postoperative complications. As examining pelvic structure and shape could largely affect the completeness of pelvic dissection that can directly influence surgical outcomes, prediction of surgical difficulty using colorectal MRI images and patients' clinical characteristics can be considered to have significant clinical relevance.

There were various attempts to examine the difficulty of laparoscopic TME using patient clinical data and pelvic structure, and there exist different opinions on which parameters should be considered as factors that influence surgical difficulty. Lorenzon, et al.⁴² reported that there is a difference in pelvic structure between male and female patients; thus, surgeons should take gender differences into account in surgical approaches, as female pelvises are relatively wider and shallower than those of males. In our study, no statistical significance in gender is reported ($p=0.2$), while age under 65 years was found to be significant ($p=0.022$). While sex differences in pelvic anatomy are well-documented, the analysis suggests that other factors, such as BMI, tumor size, and pelvimetry parameters, may have a more dominant influence on PDT than sex alone. The observed association in the univariable analysis likely reflects an indirect effect of sex through these other variables, which was attenuated when all relevant factors were considered together in the multivariable model. One possible explanation for younger patients exhibiting a more difficult surgical procedure is that younger patients tend to have tighter pelvic structures and denser connective tissues, which could increase surgical difficulty compared to older patients, who may exhibit more tissue laxity. Additionally, in younger individuals, less fatty infiltration in the pelvic area may reduce the available

Table 5. Multivariable Logistic Regression Analysis of Predictors of Pelvic Dissection Time

Factor		OR (95% CI)	<i>p</i>
Sex	Male	2.78 (0.420–18.381)	0.289
Age	<65 years	4.26 (1.240–14.694)	0.022
Tumor location from AV	<6 cm	12.61 (2.680–59.254)	0.001
Interspinous distance	<10 cm	6.67 (1.670–26.580)	0.007
Intertuberous distance	<12 cm	1.31 (0.145–11.820)	0.811
Angle δ	<127°	16.87 (1.685–168.791)	0.016
Mesorectal fat area	$\geq 18 \text{ cm}^2$	6.45 (1.836–22.685)	0.004

OR, odds ratio; CI, confidence interval; AV, anal verge.

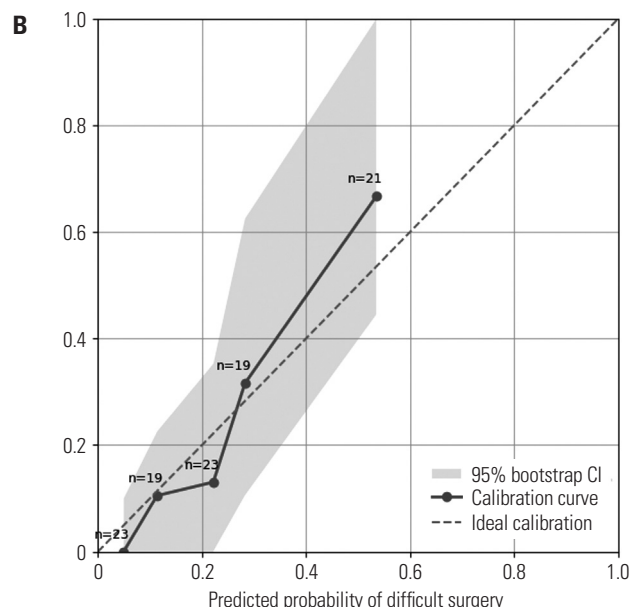
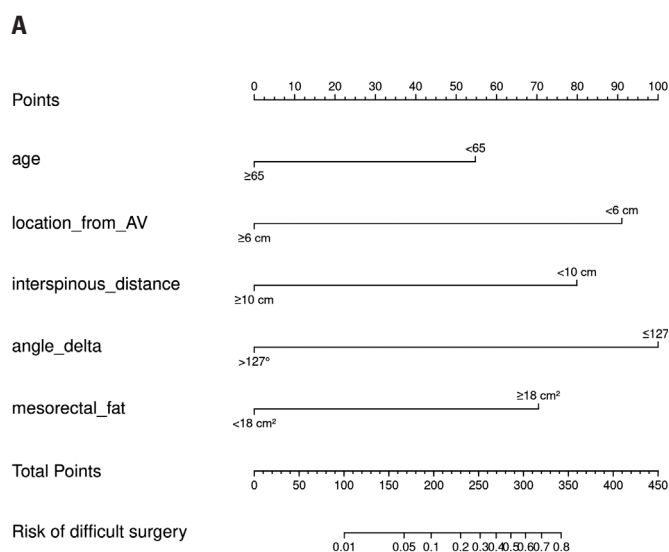


Fig. 4. Nomogram for predicting the risk of difficult surgery and its calibration performance. (A) Nomogram developed to predict the risk of high surgical difficulty based on logistic regression from the training cohort. (B) Calibration curve of the nomogram in the test cohort, showing the relationship between predicted probabilities and actual outcomes. The shaded area denotes 95% bootstrap confidence bands (1000 resamples); labels indicate bin counts (n). AV, anal verge; CI, confidence interval.

surgical planes, making dissection more technically demanding. Another possible factor is the presence of more advanced tumor stages or unfavorable tumor locations in younger patients. While the role of aging in surgical difficulty remains underexplored, our findings suggest that anatomical and oncological factors associated with younger age may contribute to increased PDT. Chen, et al.⁶ found that surgical difficulty varied depending on tumor location, tumor size, and pelvic structure. They reported that the lower the tumor location and the smaller the interspinous distance, the higher the surgical difficulty, which is in accordance with our findings. However, they included angle α in the group of important factors for surgical difficulty determination, which disagrees with our study results. Another study categorized the surgical difficulty through scoring of various factors instead of focusing on one factor. Yamamoto, et al.⁴¹ used a score table to determine surgical difficulty of a patient and concluded that BMI and pelvic outlet length are predictors of surgical difficulty, which showed statistical significance. Yuan, et al.⁴³ conducted similar research emphasizing pelvimetry as a crucial factor in predicting surgical difficulties. However, there is a lack of studies utilizing AI for this procedure.

The reason for the identification of different predictors is thought to be due to differences in experimental procedure, such as the patients' preoperative status or selection of parameters. For example, Chen, et al.⁶ investigated the patients who received TME after neoadjuvant chemoradiotherapy, and Yamamoto, et al.⁴¹ did not take pelvic angle into account when evaluating surgical difficulty. Furthermore, the methodology of surgical difficulty determination was different for each investigation.

It is noteworthy that this study focused on PDT as the indicator of surgical difficulty. Since TME is a key for the success of rectal cancer surgery, it is important to measure PDT to evaluate the surgical difficulty.¹⁸ The results of our study suggest that the factors that could increase the probability of surgical difficulty are younger age, lower tumor location which is closer to the AV, and pelvic structure. According to the analysis, the surgical difficulty was higher when the patient was younger. We can infer that this is because the younger the patient is, the more aggressive the tumor could be.⁴⁴ Furthermore, the results indicated that the surgical difficulty is more likely to be higher when the tumor is located in the lower rectal area. The possible explanation for this finding is that when the tumor is located nearer to the AV, the anastomotic site should also be lower, leading to a wider range of TME, which makes the whole procedure more difficult, demanding a longer operation time.

In pelvic structure, shorter interspinous distance, smaller angle δ , and larger mesorectal fat area were specifically found to be important factors when surgical difficulty was predicted to be higher. The short interspinous distance and the small angle δ indicate narrow pelvic width and high sacral curvature. The wider mesorectal fat area indicates that the mesorectum is rel-

atively larger than the average size. Thus, it is likely that if the patient has a larger mesorectum with a narrow and deep pelvic space, the surgical procedure is likely to be more difficult. From these findings, we could deduce that the pelvic structure is highly important in determining the surgical difficulty.

Another implication of this study is that we attempted to perform the pelvimetric measurements automatically. Existing studies are generally limited to investigating the relationships between pelvic structure and surgical difficulty, without suggesting the application method of their findings in clinical settings. The procedure of measuring pelvic parameters manually is a time-consuming process. Hence, the level of application of these factors in clinical settings is still insignificant. As far as we are aware, research on automatically measuring pelvimetry using AI is still limited. Our study proposed an automatic process of pelvimetry measurements, applying AI and DL, decreasing the time taken for measuring the parameters and thus simplifying the overall process. To achieve this, we identified key anatomical landmarks in pelvic MRI using both axial and sagittal images. Some regions of interest (ROIs) exhibited partial overlap, which posed challenges for standard semantic segmentation models, particularly when overlapping structures were assigned the same class label. Although it is technically possible to assign each ROI a unique class within a single model, we found that training independent models for each ROI led to better segmentation performance by enabling task-specific optimization. Instance segmentation models were also considered as potential alternatives. However, training multiple U-Net-based models with identical architecture provided greater flexibility for fine-tuning each segmentation task while ensuring consistency across ROIs. Semantic segmentation, which performs pixel-wise classification, remained an appropriate choice for our task by supporting precise boundary delineation—critical for accurate pelvimetry measurements. As a result, the automatic and manual measurements were highly correlated, as presented in Table 2 and Figs. 2 and 3, indicating that the automatic measurements are as accurate as manual measurements. In our follow-up studies, we could develop these ideas to create a user interface using the automated system and nomograms to output the level of predicted surgical difficulty so that surgeons could use the system in clinical settings to provide objective predictions and explanations to patients who require laparoscopic TME.

At present, there are several aspects of the study that need to be further improved in our follow-up studies. This study is a single-center retrospective analysis with a limited sample size, which likely contributed to the observed variability in the C-index and the calibration curve. Owing to the small cohort, we did not model additional preoperative factors—most notably neoadjuvant treatment—despite its high prevalence. In future work, we will 1) increase the dataset size to improve both DL segmentation and nomogram performance, 2) explicitly analyze the impact of neoadjuvant therapy on operative duration,

3) conduct multi-institutional studies to enhance generalizability, 4) include multiple surgeons to account for operator effects, and 5) fully automate MRI slice selection so the pipeline is end-to-end.

In conclusion, we present an AI-driven pelvimetry system and nomogram that predict surgical difficulty with a C-index of 0.853 and acceptable calibration in an independent cohort. The method may aid preoperative planning, but confirmation in larger, multi-center datasets and full pipeline automation are required before routine adoption.

ACKNOWLEDGEMENTS

This research was supported by a grant of the Korea Health Technology R&D Project through the Korea Health Industry Development Institute (KHIDI), funded by the Ministry of Health & Welfare, Republic of Korea (grant number : HI16C2319), and by the Gachon Gil Medical Center (FRD2020-19).

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