World Journal of Urology (2025) 43:396
https://doi.org/10.1007/s00345-025-05771-6

RESEARCH

From laser-on time to lithotripsy duration: improving the prediction of lithotripsy duration with 'Kidney Stone Calculator' using artificial intelligence

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Received: 16 February 2025 / Accepted: 14 June 2025
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Abstract

Introduction "Kidney Stone Calculator" (KSC) helps to plan flexible ureteroscopy, providing the stone volume (SV) and an estimated duration of laser lithotripsy (eLD). eLD is calculated from in vitro ablation rates and SV. KSC's accuracy has been demonstrated with a mean difference between eLD and effective LD (EfLD) of 18.8%. We aimed to reduce the eLD–efLD difference using Machine Learning (ML).

Methods From the prospective multicenter KSC database, demographic and peri-operative data were anonymously extracted: SV, stone location, maximum density, anatomy, surgical expertise, ureteral access sheath, basket use, laser source, fiber diameter and settings, eLD and efLD. After normalization and splitting (training (80%), test (20%)), significant variables influencing the difference between eLD and efLD were selected through multiple linear regression (MLR). Six types of ML models were subsequently evaluated to minimize the mean absolute error (MAE) between eLD and efLD on the test group.

Results 125 patients were included. After normalization and MLR, MAE were significantly influenced by 14 variables (including diverticulum location, surgical expertise, laser sources, laser fiber diameters, 5 Hz frequency, 1.5 J pulse energy and eLD). eLD had the greatest positive impact on the eLD–efLD difference (2.45 (2.16–2.73), $p<0.0001$)). Above the various tested ML models, the Bayesian "Automatic-Relevance-Determination" and Dense Neural Networks respectively presented the lowest and highest MAE on the test group (3.9% and 6.8%). Results did not differ among models overall ($p=0.93$) and two by two.

Conclusion The difference between KSC's eLD and efLD can be five-fold reduced using ML and Artificial Intelligence, including clinically impactful factors such as the surgical technique or expertise. A clinical inference could help to externally validate our findings.

Keywords Pulsed-Thulium:YAG · Holmium:YAG · Thulium Fiber Laser · Kidney Stone Calculator · Flexible ureteroscopy · Laser · Lithotripsy · Surgical planning

Introduction

Kidney Stone Disease (KSD) is common, with an increasing prevalence (almost 12%) due to global warming, lifestyle and dietary changes [1]. According to international guidelines, Extracorporeal Shockwave Lithotripsy (ESWL), Ureteroscopy (URS) and Percutaneous Nephrolithotomy (PCNL) are the three options to surgically treat upper tract urinary stones [2]. Over the last decades, Flexible URS (FURS)'s popularity has grown, especially for stones with a 10–20 mm maximum stone diameter (MSD) [2]. Advances in laser technology can explain the growing role of FURS,

Extended author information available on the last page of the article with great versatility and better dusting abilities [3]. Indeed, the Holmium:Ytrium-Aluminium-Garnet (Ho:YAG) laser was the gold-standard pulsed laser source since the 90s [4, 5]. Recently, the Thulium Fiber Laser (TFL) demonstrated better dusting abilities than Ho:YAG, both laser sources being recommended for endoscopic lithotripsy [2, 6]. Even more recently, the pulsed-Thulium:YAG (p-Tm:YAG) was proposed for stone treatment, but with limited available evidence [7, 8].

However, FURS remains limited in time and consequently stone burden, due to the risk of sepsis [9]. If suction devices could help to overcome this limitation, a better surgical planning seems primordial, including stone burden assessment using stone volume (SV) and subsequent operative duration estimation, especially for young or in-training urologists [10–12]. As a first step, predicting the laser lithotripsy duration (LLD) seems of upmost importance. Thus, a prolonged surgical duration (over 90 min) increases the risk of postoperative sepsis [9]. Therefore, estimating the LLD seems primordial for safety and efficiency matters. Furthermore, no current guidelines for aspiration devices utilization are available. In this context, "Kidney Stone Calculator" (KSC) has been developed as a free software for FURS surgical planning. Using in vitro laser ablation volumes and a 3D stone segmentation, KSC provides a LLD estimation with Ho:YAG, TFL and p-Tm:YAG [13]. Previous studies confirmed its reliability in both SV measurement and accuracy to predict LLD with all available pulsed laser sources [11, 13–15]. However, Chicaud et al. reported that estimated and effective LLD (eLD and efLD) were not identical (27.37 vs 28.36 min, $p=0.43$, mean absolute difference:18.8%), identifying potential factors that could explain the difference: SV, stone location, laser settings and technique.

Artificial Intelligence and machine learning (ML) are now revolutionizing urological care in several aspects, including surgical planning [16]. Trained models are now able to precisely predict operative outcomes, using classification and regression methods (categorical and continuous variables, respectively). Therefore, we aimed to reduce the eLD–efLD difference, using ML processes, including clinically impactful factors. Secondarily, we aimed to analyze KSC's ability to predict LLD according to laser sources (Ho:YAG, TFL and p-Tm:YAG).

Methods

Kidney Stone Calculator

KSC is an open-source add-on of 3DSlicer, that measures the stone volume (SV) using Hounsfield Units-based threshold segmentation on Non-Constrast Computed Tomography (NCCT), and provides eLD according to laser source and laser settings [11]. A dedicated tutorial is available (https://www.youtube.com/watch?v=pZLXHdfJtP0&t=5s). KSC multicenter database prospectively included 125 patients who undergone FURS with laser lithotripsy [11, 13, 15]. Approvals from Ethics Committee were obtained (CERU_2020/003, CERU_2023-18B, CNIL_2216615V0, CNIL_2230198V0).

Machine learning environment and data analysis

From KSC database, patients with available input variables were included. Selected input variables were: those used to estimate KSC's eLD (SV, stone density, laser source, fiber diameter and settings (energy (J) and frequency (Hz)), eLD, preoperative variables regarding the surgeon and his technique (ureteral access sheath (UAS), basket, experience (expert (>100 FURS per year), senior (<100 FURS per year), junior (trainee)), and the presence of an anatomical variation on the preoperative NCCT.

The ML environment included Anaconda Navigator (Austin, USA) and Jupyter Notebook (v6.5.4) with Python 3.11.4, with the appropriate libraries (sklearn, pandas, numpy, matplotlib, statmodels, seaborn, keras 2.13.1 and Tensorflow 2.13.0). Data preprocessing included normalization using "OneHotEncoder" module for categorical variables and "StandardScaler" for continuous ones. Then, a data splitting was realized (training 80%, test 20%) with "RandomPermutation" to avoid selection bias.

ML models included multiple linear regression (MLR), support vector machine (SVM, with "radial basis function"), Random Forrest (RF), Bayesian models (Ridge Regression and Automatic Relevance Determination (ARD). Deep Learning models were also evaluated: dense and convolutional neural networks). After training, models were evaluated on the test cohort, unknown during the training phase.

Outcomes and metrics

To compare the performance of our models, the mean absolute error (MAE) between eLD and efLD was evaluated on the test cohort. Secondarily, we compared MAEs among models. Finally, a comparative analysis of the eLD–efLD among laser sources in KSC's database is presented (quantitative (significant difference between eLD and efLD) and qualitative (correlation).

Statistics

MAEs are presented in percentages and compared by ANOVA with Tukey post-hoc analysis. eLD–efLD differences were reported as absolute values and percentages, compared by Student's t-test and overall, by ANOVA with Tukey post-hoc analysis. eLD–efLD Pearson correlation coefficients were calculated and compared using Ficher test.

Statistical analysis of this section was carried out using Python 3.11.4 via the Jupyter Notebook interface (Anaconda©, Austin, USA). The significance level was set at 0.05.

Results

Cohort demographics

125 patients were included, 43, 46 and 36 in the Ho:YAG, TFL and p-Tm:YAG groups, respectively (Table 1a–c). Groups presented similar patients characteristics, except for BMI ($p=0.001$), history of urolithiasis disease (63% vs. 31% vs. 12% in TFL, p-Tm:YAG and Ho:YAG groups respectively, $p<0.0001$) and anatomical variation (33% vs. 8% vs. 7% in TFL, p-Tm:YAG and Ho:YAG groups respectively, $p<0.0002$). We reported higher rates of complex stones in TFL and p-Tm:YAG groups, compared to Ho:YAG($p=0.002$), and differences in location ($p=0.0001$) but median MSD and SV were similar among groups ($p=0.07$ and 0.1) (Table 1b). The surgical technique differed among groups with higher rates of inserted UAS, basketing and relocation for Ho:YAG (Table 1c), but laser settings were similar (J/Hz/W), as well as operative and laser-on times ($p=0.17$ and 0.25, respectively). p-Tm:YAG presented 3-fold and 1.5-fold higher ablation rates than Ho:YAG and TFL, respectively (0.91 vs. 0.66 vs. 0.36 mm^3/s, $p=0.0002$). Energy consumption was slightly higher with TFL compared to p-Tm:YAG (15 vs. 14 J/mm^3, $p=0.006$). Stone-free (69% vs. 72% vs. 75% for Ho:YAG, TFL and p-Tm:YAG) and complications rates were similar among groups ($p=0.57$ and 0.77, respectively).

Prediction of the lithotripsy duration

Overall, eLD and efLD did not significantly differ ($p=0.52$), but the eLD–efLD absolute difference was 7.8 min (18.8%), with a high correlation coefficient ($r=0.87$, $p<0.0001$) (Supplementary Table 1). KSC performances in LD estimation differed according to laser sources ($p=0.01$). The lowest eLD–efLD absolute difference was reported for TFL 5.15 min (14%), outperforming Ho:YAG ($p=0.04$) and p-Tm:YAG ($p=0.02$). Similarly, TFL was associated with the highest eLD–efLD correlation coefficient ($r=0.94$, $p<0.00001$), outperforming Ho:YAG ($p=0.01$) and p-Tm:YAG ($p=0.03$).

Machine learning reduction of the eLD–efLD difference

After one hot encoding, the number of variables increased from 13 to 47. After MLR, fourteen factors significantly impacted efLD (Table 2): diverticular location of the stone ($p<0.0001$), levels of experience (expert ($p<0.0001$)–senior ($p<0.0001$)–junior ($p<0.0001$)), laser source (Ho:YAG ($p<0.0001$)–TFL ($p=0.035$)–p-Tm:YAG ($p<0.0001$)) and fiber diameter (150 µm ($p=0.002$)–200 µm ($p<0.0001$)–270 µm ($p=0.01$)–365 µm ($p=0.005$)), frequency (5 Hz, $p=0.05$), energy (0.5 J ($p=0.02$) and 1.5 J ($p=0.04$)), and eLD ($p<0.0001$). eLD was the most impactful factor (coefficient value 2.4467).

After training, the Automatic Relevance Determination (ARD) model presented the lowest eLD–efLD MAE on the test cohort (3.9%), while the Dense Neural Network performed worse (6.8%) (Table 3). Overall and two by two, MAEs among models did not differ ($p=0.93$).

Discussion

From laboratory to clinical practice: the "operative uncertainty" concept

The present study demonstrates that predicting LLD during FURS is feasible but emphasizes that numerous pre- and intra-operative factors influence LLD. Indeed, integrating fourteen of them in Machine Learning models reduced the eLD–efLD absolute difference almost fivefold (from 18.8 to 3.9%). Nevertheless, planning a surgical procedure can limit the "operative uncertainty" but could not predict the unforeseeable. Somehow, surgery could be still considered as a manual craft profession, even if new technologies trend to transform it into that of a mixed surgeon–engineer profession. FURS has gained popularity thanks many technological improvements such as laser technologies, disposable scopes and recently aspirating solutions (flexible and navigable suction UAS(FANS), direct in-scope suction (DISS)) [10, 17–19]. Therefore, integrating Artificial Intelligence and trained algorithms in Endourology seems paramount to pursue innovation.

Our study highlights the differences between laboratory and in vivo conditions. This difference is of upmost importance, as many endourological studies are conducted in vitro with perfect, reproducible and safe conditions. As previously mentioned, surgeons face the "operative uncertainty" during the procedure, that requires reasonable utilizations of surgical devices and adaptability. Drawing a parallel with car racing and in-town racetrack, professional drivers may not drive as fast in or out of the race. Indeed, surgeons

Table 1 "Kidney Stone Calculator" database including Holmium:YAG (Ho:YAG), Thulium Fiber (TFL) and pulsed thulium:YAG (p-Tm:YAG) lasers

Variables	Ho:YAG	TFL	*p*-Tm:YAG	*p*-value*	HoYAG vs. TFL *p*-value**	HoYAG vs. *p*-TmYAG *p*-value**	*p*-Tm:YAG vs. TFL *p*-value**
(a) *Patients' characteristics*							
Patients (n)	43	46	36				
Age (IQR)	55 (38–66)	46 (36–61)	57(43–75)	0.57	0.65	0.35	0.52
Gender							
Female (%)	47%	31%	31%	0.06	0.7	**0.02**	0.06
Male (%)	53%	69%	69%				
ASA score	2	2	2	0.26	0.4	0.42	0.09
BMI (IQR)	25.7 (23.4–30.8)	26(21.4–30)	25.5(22.8–28)	**0.001**	0.73	**0.008**	**0.001**
Comorbidities							
High blood pressure (%)	17 (40%)	11 (24%)	19(53%)	0.07	0.11	0.52	**0.02**
Obesity (%)	12 (28%)	13 (28%)	6(17%)	0.16	0.8	0.11	0.07
Diabetes (%)	4 (9.3%)	4 (8.7%)	7(19%)	0.5	1	0.34	0.34
Urolithiasis disease (%)	5 (12%)	29 (63%)	11(31%)	**<0.0001**	**<0.0001**	0.1	**<0.0001**
Anatomical variation (%)	3 (7.0%)	15 (33%)	3(8%)	**0.0002**	**0.001**	1	**0.001**
(b) *Stone characteristics*							
Present stone							
Upper pole	2 (4.7%)	7 (15%)	8 (22%)	**0.0001**	**0.003**	**<0.0001**	**0.01**
Interpole	2 (4.7%)	3 (6.5%)	3 (8%)				
Lower pole	26 (60%)	8 (17%)	9 (25%)				
Renal pelvis	7 (16%)	5 (11%)	8 (22%)				
Complex	3 (7.0%)	9 (20%)	8 (22%)				
Ureter	3 (7.0%)	13 (28%)	1 (4%)				
Side							
Left (%)	23 (53%)	20 (56%)	20 (56%)	**0.04**	**0.002**	0.9	**0.009**
Right (%)	20 (47%)	16 (44%)	16 (44%)				
Bilateral (%)	0 (0%)	2 (6%)	2 (6%)				
Number							
1 (%)	35 (81%)	28 (61%)	18 (50%)	**0.0002**	**0.007**	0.21	**0.0002**
>1 (%)	8 (19%)	18 (39%)	10 (28%)				
Complexe	3 (7.0%)	9 (20%)	8 (22%)				
Median density(HU)(IQR)	1231 (953–1565)	969 (694–1200)	974 (600–1200)	**0.0001**	**0.04**	**0.0001**	**0.01**
Median maximum stone diameter (mm)	10 (8–15)	14.3 (8-18.5)	17.5 (11–30)	0.07	0.09	**0.03**	0.36
Median stone volume (mm^3)	479 (222–934)	617 (303–2005)	1514 (428–3000)	0.1	0.3	0.07	0.42
(c) *Intra-operative outcomes*							
Operative duration (min)	68 (53–80)	69 (55–99)	69.4 (45–90)	0.17	0.12	0.99	0.15
Lithotripsy duration (min)	27.2 (11–52)	29.4 (8.3–40)	30.2 (11–52)	0.25	0.41	0.36	0.12
Ureteral access sheath	42 (98%)	15 (33%)	20 (55%)	**<0.0001**	**<0.0001**	0.06	**<0.0001**
Basket use	34 (79%)	6 (13%)	8 (22%)	**<0.0001**	**<0.0001**	**<0.0001**	0.2
Stone relocation	8 (19%)	1 (2.2%)	0 (0%)	**0.0003**	**0.007**	**0.001**	0.31
Laser fiber diameter							
150 µm	0 (0%)	18 (39%)	0 (0%)	**<0.0001**	**<0.0001**	0.7	**<0.0001**
200 µm	1 (3%)	27 (59%)	0 (0%)				
270 µm	39 (90%)	1 (2%)	36 (100%)				
365 µm	3 (7%)	0 (0%)	0 (0%)				
Laser settings							
Energy (J)	0.8 (0.5–0.8)	0.6 (0.5–0.8)	0.6 (0.6–0.8)	0.15	0.1	0.3	0.27
Frequency (Hz)	15 (12–25)	15 (10–20)	15 (13.75-20)	0.26	0.46	0.09	0.16
Average power (W)	12.5 (8.5–15)	10 (7-13.5)	12 (9–16)	0.2	0.4	0.1	0.3

Table 1 (continued)

Variables	Ho:YAG	TFL	*p*-Tm:YAG	*p*-value*	HoYAG vs. TFL *p*-value**	HoYAG vs. *p*-TmYAG *p*-value**	*p*-Tm:YAG vs. TFL *p*-value**
Pulse modulation	Long pulse (100%)	High peak power (100%)	Captive fragmenting (100%)				
Total energy (kJ)	11.6 (2.49-12)	17.4 (4.8–21)	23.5 (6.3–32.8)	**0.002**	0.08	**0.0002**	0.08
Energy consumption (J/mm^3)	14 (7–21)	15 (10–21)	14(10–19)	**0.02**	0.13	0.17	**0.006**
Ablation rate (mm^3/s)	0.36 (0.30–0.63)	0.66 (0.46–0.85)	0.91 (0.5–1.17)	**0.0002**	0.08	**0.0002**	0.08
Postoperative stenting	42 (98%)	45 (98%)	35 (97%)	0.76	0.96	0.54	0.56
Stone free rate (RF < 3 mm on NCCT)	30 (69,8%)	33 (72%)	27 (75%)	0.57	0.64	0.55	0.28
Complications							
Clavien-Dindo 1–2	0 (0%)	1 (2.2%)	1 (4%)	0.77	0.56	1	0.56
Clavien-Dindo 3–4	0 (0%)	0 (0%)	0 (0%)				

p values < 0.05 is in bold

Table 2 Multiple linear regression results on the difference between estimated and effective lithotripsy durations

	Coefficient	SE	t	p >|t|	[0.025	0.975]
Constant	− 0.5278	0.010	− 53.718	< 0,0001	− 0.547	− 0.508
Stone location : diverticulum	− 1.799e−15	1.02e−16	− 17.617	< 0,0001	− 2e−15	− 1.6e−15
Surgical expertise : Expert	− 0.1913	0.019	− 10.089	< 0,0001	− 0.229	− 0.154
Surgical expertise : Senior	− 0.1385	0.015	− 8.946	< 0,0001	− 0.169	− 0.108
Surgical expertise: Junior	− 0.1979	0.021	− 9.527	< 0,0001	− 0.239	− 0.157
Laser source: Holmium:YAG	− 0.1625	0.020	− 8.171	< 0,0001	− 0.202	− 0.123
Laser source: Thulium Fiber Laser	− 0.1559	0.028	− 5.530	< 0,0001	− 0.212	− 0.100
Laser source: pulsed-Thulium:YAG	− 0.2094	0.024	− 8.714	< 0,0001	− 0.257	− 0.162
Laser fiber diameter: 150 µm	− 0.1274	0.027	− 4.803	< 0,0001	− 0.180	− 0.075
Laser fiber diameter: 200 µm	− 0.1316	0.018	− 7.229	< 0,0001	− 0.168	− 0.095
Laser fiber diameter: 270 µm	− 0.1236	0.022	− 5.710	< 0,0001	− 0.167	− 0.080
Laser fiber diameter: 365 µm	− 0.1451	0.039	− 3.700	< 0,0001	− 0.223	− 0.067
Pulse frequency: 5 Hz	− 0.0891	0.050	− 1.793	0,05	− 0.188	− 0.010
Pulse energy: 1.5 J	− 0.2075	0.055	− 3.786	< 0,0001	− 0.317	− 0.098
Estimated lithotripsy duration	2.4467	0.143	17.075	< 0,0001	2.161	2.732

integrates all pre- and intra-operative factors to obtain the best surgical outcome, with the lowest complication risk. Using this concept, we included all factors that were available before FURS in our MLR model, in order to select the significant ones. We must acknowledge that other factors could have been integrated, and that exhaustively recording all factors is impossible, considering some of them could remain unknown. Therefore, our results relies on probability and interdependence hypotheses, ruled by Bayes' theorem [20]. Indeed, this aspect could explain why the Bayesian ARD model was associated with the lowest eLD–ef-LD MAE (3.9%), while the popular deterministic neural networks presented lower performances (6.8% and 4.9% for dense and convolutional neural networks, respectively). Moreover, the eLD from KSC was the most impactful variable, demonstrating that KSC methodology to estimate the LLD, i.e. using SV and in vitro ablation volumes, is accurate [12]. Regarding the other impactful factors, only the diverticular location of a stone was significant, possibly causing a reduced visibility with an early "snowstorm" effect during lithotripsy, and potential difficult access to the stone. Then, all levels of surgical experience significantly impacted the LLD estimation. Even an expert surgeon was not able to reach the perfect in vitro displacement of the laser fiber at the stone surface. Similarly, a junior surgeon could present higher eLD–efLD differences, compared to an expert, opening the educational applications of KSC and high-fidelity simulation [21]. Finally, laser sources, fiber diameter and extreme settings significantly impacted the eLD–efLD, emphasizing the importance of the surgical devices and the surgical technique driven by them. Indeed, using Ho:YAG was associated with production of larger fragments, requiring basketing and ureteral access sheath to limit the risk of multiple basketing sessions through the ureter. Similarly, using high pulse energy (1.5 J) could be associated with "fragmentation", while KSC estimates a

Table 3 Comparison of various machine learning and deep learning models to improve KSC's estimation of the lithotripsy duration

Model type	Training		Test		*p* value*
	Mean squared error	Mean absolute error (%)	Mean squared error	Mean absolute error (%)	
Multiple Linear Regression	0.005	5	0.005	4.3	0.93
Support Vector Machine	0.004	3.7	0.006	4.1	
Random Forest	0.001	2.3	0.009	6.4	
Automatic Relevance Determination	0.005	5	0.005	**3.9**	
Dense Neural Network	0.005	5.2	0.009	6.8	
Convolutional Neural Network	0.003	3.8	0.006	4.9	

Direct comparison (mean absolute error, test group)	*p* value*
Multiple Linear Regression vs. Support Vector Machine	0.27
Multiple Linear Regression vs. Random Forest	0.68
Multiple Linear Regression vs. Automatic Relevance Determination	0.29
Multiple Linear Regression vs. Dense Neural Network	0.84
Multiple Linear Regression vs. Convolutional Neural Network	0.96
Support Vector Machine vs. Random Forest	0.73
Support Vector Machine vs. Automatic Relevance Determination	0.93
Support Vector Machine vs. Dense Neural Network	0.58
Support Vector Machine vs. Convolutional Neural Network	0.31
Random Forest vs. Automatic Relevance Determination	0.77
Random Forest vs. Dense Neural Network	0.86
Random Forest vs. Convolutional Neural Network	0.71
Automatic Relevance Determination vs. Dense Neural Network	0.61
Automatic Relevance Determination vs. Convolutional Neural Network	0.34
Dense Neural Network vs. Convolutional Neural Network	0.87

*ANOVA

**Student t-test

"dusting" LLD. Moreover, the 5 Hz frequency level could be encountered in case of impacted ureteral stones, for which the surgeon pays a particular attention to limit the number of pulses delivered in the mucosa, in order to avoid thermal injuries [22]. Even if not entirely exhaustive, the trained ARD model performances are clinically relevant, a 3.9% MAE representing 3 min 30 s out of a 90 min LLD.

Artificial intelligence and stones: an example of medical innovation

As mentioned before, Artificial Intelligence's interest is growing among the research community [16]. Numerous medical fields will be impacted by Artificial Intelligence-driven devices, such as radiology [23, 24]. Indeed, KSC still requires a manual stone detection and volumetry. Future improvements will include automated stone detection and quantification, using segmentation algorithms [25]. On the other hand, we acknowledge that our method to estimate LD is based on in vitro experiments on stone phantoms [26]. Our stone model (Bego©, Germany), as well as our in vitro conditions, are not totally reflecting the in vivo conditions. Therefore, exploring the laser-to-stone interaction appears paramount, determining the specific importance of photo-thermal and photo-mechanical effects [27–29]. Knowing the thermal characteristics of human stones seems primordial before providing an innovative numerical simulation of the laser-to-stone interaction.

Finally, the LLD prediction represents a first step of estimating the operative duration, which represents the main objective of FURS surgical planning. Futures projects should focus on this specific criterion.

Strengths and limitations

The current study does have certain limitations, including the multicenter setting. All patients in the TFL and p-Tm:YAG groups were treated in the same tertiary reference center, and mostly by an endourology expert and senior respectively, whereas Ho:YAG patients were treated from different centers and operators with various expertise levels. This could have impacted demographics, and laser outcomes [30]. Regarding surgical devices, we acknowledge that suction devices were not used, limiting the clinical inference of our ML model. On the other hand, suction devices are not yet recommended by international societies (American Urological Association and European Association of Urology), as well as p-Tm:YAG. Suction ureteral access sheath or in-scope suction could modify the way dusting and retrieving fragments is conducted, potentially enlarging the fragments' size retrieved through the ureteral access sheath, using the Venturi's effect. Regarding our ML training, several differences in the model fitting have to be highlighted. First, our database enrolled 125 patients, which could be considered as limited, but our multicenter and prospective database ensures high data quality. Then, neural networks were fitted on the test cohort, while other ML models were unaware of the test cohort during training. Lastly, other ML models were evaluated including "Ensembles Method" but presented lower performances than the ARD model. Further research should train other ARD Bayesian models.

Nevertheless, the present study firstly implements Artificial Intelligence in LLD estimation, that needs to be confirmed by an external validation. Further clinical deployment using the same imaging platform (3DSlicer) or a standalone application (such as a streamlit-coded one) would facilitate its wide utilization.

Conclusion

Kidney Stone Calculator reliably predict the lithotripsy duration during flexible ureteroscopy with all available sources, but KSC's accuracy is even better when dusting is the preferred technique. The difference between KSC's eLD and efLD can be reduced five-fold using Machine Learning and Artificial Intelligence, including clinically impactful factors such as the surgical technique or expertise. A clinical inference could help to externally validate current findings.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00345-025-05771-6.

Acknowledgements The authors declare that they have no conflict of interest but: Frédéric Panthier has declared as consultant for DornierOlivier Traxer has declared as consultant for Karl Storz, Coloplast, IPG photonics, Ambu, Quanta System and Rocamed.Steeve Doizi has declared as consultant for Boston Scientific Corporation and Coloplast.

Author contributions Frederic Panthier had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.F PANTHIER Protocol/project development, Data collection or management, Data analysis, Manuscript writing/editingM CHICAUD Protocol/project development, Data collection or management, Data analysisS KUTCHUKIAN Data analysisS DOIZI Protocol/project development, Data collection or managementF AUDENET Protocol/project development, Data collection or management, Data analysisL BERTHE Protocol/project developmentL YONNEAU Data collection or managementT LEBRET Protocol/project development, Manuscript writing/editingMO TIMSIT Protocol/project development, Manuscript writing/editingA MEJEAN Protocol/project development, Manuscript writing/editingL CANDELA Manuscript writing/editingC SOLANO Manuscript writing/editingM CORRALES Data collection or managementC GHNATIOS Manuscript writing/editingF CHINESTA Manuscript writing/editingO TRAXER Protocol/project development, Data analysis, D SMITH Protocol/project development, Data collection or management, Data analysis, Manuscript writing/editing.All authors reviewed the manuscript.

Funding Frédéric Panthier received a "Association Française d'Urologie" research grant 2024 and a European Urological Scholarship Program grant in 2023.

Data availability No datasets were generated or analysed during the current study.

Declarations

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Ethical approval Approvals from Ethics Committee were obtained (CERU_2020/003, CERU_2023-18B, CNIL_2216615V0 CNIL_2230198V0).

Informed consent A written informed consent was obtained from all patients after explaining the study protocol and giving an information sheet.

Research involving human participants The present study included human participants, with an informed written consent. Data anonymization was assured by the principal investigator.

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