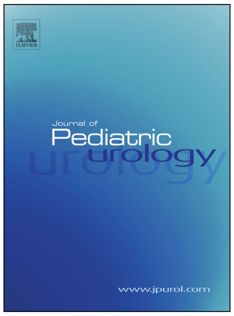

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The Future of Pediatric Vesicoureteral Reflux Management

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Abstract

Background and objective: Vesicoureteral reflux (VUR) is a common condition in pediatric urology, yet important uncertainties persist regarding risk stratification, imaging strategies, and prevention of long-term renal damage. Emerging technologies may help address these challenges. This review provides a forward-looking overview of recent advances in artificial intelligence (AI) and immunomodulation that may influence future management of pediatric VUR.

Methods: A forward-looking literature review was performed using the PubMed database (January 2000–March 2025), focusing on studies addressing IA, immunomodulation, or vaccination in the context of VUR and urinary tract infections. Criteria of inclusion were the relevance to pediatric VUR, the novelty of the proposed concept, the potential clinical implications and, for the IA literature, the existence of a clinical evaluation of the algorithm on a dataset from patients.

Key findings and limitations: AI-based models show promising performance in supporting clinical decision-making, including prediction of the need for voiding cystourethrography, automated grading of VUR, estimation of recurrent urinary tract infection risk and prediction of chemoprophylaxis. These tools may facilitate more individualized diagnostic and therapeutic strategies, although current evidence is largely retrospective and requires prospective validation. Immunization and immunomodulatory approaches aim to reduce infection burden and modulate inflammatory pathways associated with renal scarring. While early experimental and adult clinical data are encouraging, pediatric-specific evidence remains limited, and clinical applicability in children with VUR is not yet established.

Conclusion: Artificial intelligence and immunologically targeted strategies represent complementary, emerging approaches that may contribute to more personalized management of pediatric VUR. At present, both should be regarded as exploratory tools whose clinical impact will depend on further validation and appropriately designed pediatric studies.

Introduction

Vesicoureteral Reflux (VUR) is undoubtedly among the major pathologies in pediatric urology. Even if the gaps in our understanding of this disease have been reduced in the last years, many diagnostic and therapeutic questions remain unanswered. Data remain particularly limited regarding the natural history and rates of spontaneous resolution of VUR, the genetic contribution to its occurrence and its long-term impact on renal function, the precise role of bladder and bowel dysfunction, and the variability in renal scarring risk independent of VUR grade. All these missing data lead to intense current debates in imaging strategies and therapeutic approaches, especially for Voiding Cystourethrography (VCUG) and antibiotic prophylaxis [1]. These uncertainties are mostly explained by the lack of studies with solid methodology, lack of long-term follow-up, and the disease complexity. Retrospective studies do not provide definitive answers. Prospective randomized trials [2] are time-consuming, costly and generally test only a single variable, whereas VUR is a multifactorial disease whose outcome is influenced by is influenced by many known (e.g. age, sex, VUR grade, lower urinary tract status, genetic background, response to inflammation, antibiotic use, microbiota) and also still unknown factors.

These unresolved challenges provide the clinical rationale for exploring novel approaches that share a common clinical objective: preventing renal function degradation in children with VUR. Among these complementary strategies are artificial intelligence, which integrates multiple clinical variables to enhance diagnostic accuracy and enable multidimensional decision-making [3, 4]; and immunomodulatory strategies, which develop novel therapeutic tools to prevent VUR-related complications, particularly recurrent UTIs [5].

Rather than presenting practice-changing evidence, this review aims to provide a forward-looking overview of emerging concepts that may shape future research and clinical decision-making in pediatric VUR. Given the heterogeneity and early developmental stage of much of the available evidence—particularly in artificial intelligence and immunomodulation—these approaches should currently be regarded as exploratory and hypothesis-generating rather than immediately translatable to routine clinical practice.

Methods

This article was designed as a forward-looking review focusing on emerging concepts that may influence the future management of pediatric vesicoureteral reflux (VUR), rather than as a systematic review intended to generate practice recommendations.

A literature search was performed using the PubMed database, covering publications from January 2000 to March 2025. PubMed was selected as the sole database because it provides the most comprehensive index of peer-reviewed biomedical literature in this subspecialty domain and is well suited to forward-looking, hypothesis-generating reviews of this kind, in contrast to systematic reviews requiring multi-database strategies. Search terms included combinations of “vesicoureteral reflux” with “artificial intelligence”, “machine learning”, “deep learning”, “immunomodulation”, and “vaccine”. For the immunomodulation and vaccine searches, the same VUR-based terms were used without a pediatric filter, given the scarcity of pediatric-specific data in this domain. Forty-eight papers were identified for the AI search. The term “children” was used as an additional filter and reduced the number to 7 for the AI domain. Selected adult and experimental studies were subsequently included when their mechanistic or clinical findings were judged potentially transferable to pediatric populations, based on the following criteria: (1) the biological mechanism targeted was not inherently age-dependent, (2) the study population included patients with recurrent UTI or conditions analogous to VUR-associated renal vulnerability, and (3) the findings had direct implications for either infection prevention or modulation of post-infectious renal scarring.

Given the limited number, heterogeneity, and rapidly evolving nature of the available literature—particularly in the field of artificial intelligence—no meta-analytic approach was applied. Nevertheless, criteria of inclusion were the relevance to pediatric VUR, the novelty of the proposed concept, the potential clinical implications and, for the AI literature, the existence of a clinical evaluation of the algorithm on a dataset from patients. This review does not aim to provide a reproducible quantitative synthesis, but rather to contextualize emerging technologies within established principles of VUR pathophysiology and management.

Results

Artificial intelligence

The PubMed search on AI and VUR yielded 48 papers initially; after applying the "children" filter, 7 remained. The overall volume of published work is small, reflecting the novelty of this field. Studies vary considerably in design: most are retrospective, single-center, and based on modest sample sizes (typically 85–500 patients), and none has yet been validated in a prospective multicenter setting. The available evidence is nonetheless consistent in demonstrating proof-of-concept performance across three clinical domains: diagnosis, treatment selection, and parental counseling.

AI is the umbrella term to describe all computer systems capable of performing tasks that involve a human-like way of thinking, such as problem-solving, pattern recognition, learning and decision-making [6]. Statistical models can be deterministic, relying on suspected or established risk factors as predefined input variables such as grade of VUR, sex, history of UTIs. In this configuration, the use of AI typically results in structured, interpretable models, where prediction pathways can be explicitly traced. However, such models may have limitations in capturing complex, non-linear interactions or high-dimensional patterns within the data, especially for VUR since it is highly multifactorial. To deal with this situation AI can also operate through data-driven models, such as Machine Learning (ML) which improves with experience [7] or deep learning that includes Artificial Neural Network (ANN), which may achieve higher predictive performance [8]. The value of each of these AI subsets in the context of VUR is highlighted in Table 1.

As VUR outcome can be influenced by many different known and unknown variables, AI can help in management decision-making. Clinicians take into account many variables when assessing a patient such as age, sex, dilatation, grade of reflux, history of UTIs and bowel bladder dysfunction [9]. However, they often do not consider many other variables, such as familial, genetic, bacteriological and environmental factors. AI applications can contribute to make more efficient individualized decisions by including these numerous variables. Currently, there are two main ways to use AI in VUR. First, a single clinician or an institution can collect and run their input data on a model that could become an 'alike-mind' to help patient assessment and diagnosis (i.e., in house models). Second, AI can help design high-quality studies based on feedback of the current literature and ultimately help clinicians in treatment decision-making.

At the time the review was written, less than 30 articles are available on PubMed on AI and VUR. The progress in the AI field is so rapid that between the writing of this chapter and its publication, this number will certainly increase. Before using AI for clinical purposes, it is crucial to understand the importance of the quality and quantity of the input data that feed the system and the algorithm. Large amounts of robust input data will give better outcomes. If the input data come from a small cohort, overfitting remains a risk. In VUR, AI can be used in many areas that can be divided into three sections: diagnosis, treatment, and counseling.

AI and VUR diagnosis

First, AI can be used to predict the need of a VCUG. At Boston Children's Hospital, Scott Wang et al. tested an ML model to predict VUR in children with antenatal urinary tract dilation with the aim of reducing unnecessary VCUGs [10]. Their algorithm could classify children into two groups (low and high risk) and the area under the curve (AUC) for VUR prediction was 0.81. The high-risk group included 88% of children with VUR, and the low-risk group included only 3-9% of children with VUR. This algorithm is available as an application (PredictVUR). In addition, this method remains simple, and unlike some prediction algorithms with a black box (where it is not clear exactly what the algorithm is doing), users can interact with the proposed scheme to understand and confirm the ML predictions or add new variables. Ultrasonography data may also be used by AI to predict the presence/absence of Congenital Abnormalities of the Kidney and Urinary Tract (CAKUT). As a simple two-dimensional ultrasound image can give a distorted view of the dilation, the AI model should be able to analyze all the slices to understand the three-dimensional anatomy of the kidney. To address this challenge, Yin et al. used a multiple-instance learning method to integrate the analysis of all slices, correct for the volume effect, and determine which areas to study. Associated with a neural network, this method displayed a diagnostic accuracy > 91% when used for CAKUT detection in 182 children. In their next study (n=86 children with CAKUT and n=71 controls), the AUC was > 0.95 [11]. Although this study does not specifically address VUR, it illustrates the potential of advanced AI-based ultrasound interpretation to extract clinically meaningful three-dimensional information from standard imaging modalities, a concept that may be transferable to VUR-related diagnostic workflows.

Second, AI can be used for VUR grading. Khondker et al. [12] developed a ML-based quantitative approach for VUR grading from VCUG data to address the low inter-rater reliability of traditional VUR grading methods. They created an image analysis software to find, standardize, and calculate the essential parameters for VUR grading using a random forest classifier. They concluded that ureter tortuosity, maximum ureter width, ureterovesical junction width and ureteropelvic junction width are the most important features to predict and distinguish between high-grade and low-grade VUR. Then, in a multi-institutional validation study [13], the ML method displayed an accuracy of 62% and an AUC of 0.84. Moreover, inter-rater reliability was improved by 3.6-fold, moving from fair to substantial agreement, compared with the usual grading method. This tool can be accessed at https://sickkidsurology.shinyapps.io/qVUR.

Similarly, Kabir et al. tested six supervised ML models to improve VUR grading based on VCUG images [14]. They asked seven experts (four pediatric radiologists and three pediatric urologists) to assess 113 VCUG images to establish the ground truth. They found that the pelvicalyceal outline length and ureter curvature can be used as adjunctive features in addition those found by Khondker et al. [13]. The authors showed that ML outperformed four of the seven human graders in terms of F1 score (a performance metric used in ML to evaluate the performance accuracy of a classification model especially when class distribution is imbalanced) and achieved results comparable to those of the best-performing clinical specialists.

Lastly, Chen et al. proposed an enhanced multi-head convolutional neural network for VUR grading automatically from VCUG images [15]. Based on a set of 1,529 pediatric patients, the model incorporated a deep supervision dual-stream architecture for better feature learning and classification accuracy. In the validation step (n = 300 patients), the network achieved an average patient-level accuracy of 84% and AUC of 0.82, which surpassed the existing state-of-the-art approaches. The model could distinguish between clinically important VUR grades and provide a robust instrument for clinical decision-making.

Since contemporary management of VUR recognizes that reflux grade represents only one of several factors influencing clinical decision-making, alongside numerous previously mentioned parameters, AI-based grading tools should be interpreted as components of broader decision-support systems rather than standalone determinants of treatment.

DMSA scan and AI

While DMSA renal scintigraphy is the gold standard for detecting renal scarring in children with vesicoureteral reflux (VUR) and recurrent UTIs, its limitations—such as radiation exposure and significant interobserver variability—necessitate a more targeted approach. Rather than replacing DMSA, AI-based predictive models can serve as complementary tools by integrating clinical and biological variables to stratify risk [16]. By leveraging deep learning algorithms for automated image analysis and machine learning for pre-scan risk assessment, clinicians can standardize the detection of cortical defects while identifying low-risk patients for whom imaging can be safely omitted [17]. This synergy may allow for more selective imaging and individualized follow-up, ultimately minimizing renal damage while reducing unnecessary investigations.

AI and VUR treatment

An important question is how to select patients with VUR who may benefit from medical or surgical treatment. For this, it would first be relevant to predict which children are at risk of recurrent UTIs. The Advanced Analytics Group of Pediatric Urology [18] used data from 500 children from the Randomized Intervention for Children with Vesicoureteral Reflux (RIVUR) and Careful Urinary Tract Infection Evaluation (CUTIE) cohorts to develop a model to predict the risk of UTI recurrence and VUR in children with a first UTI. The authors included age, sex, race, weight, systolic blood pressure, dysuria, albumin/creatinine ratio, previous antibiotic use, and current pharmacological treatments for training a gradient boosting model to predict UTI recurrence associated with VUR. Using an independent test set, this model predicted UTI recurrence associated with VUR with an AUC of 0.76. This demonstrates the strong potential of AI to streamline diagnostic workflows, to reduce invasive testing in children with febrile UTI (VCUG reduction by 34%) and to identify patients at risk of recurrent UTI when robust data are used as input.

Once the right patient is selected, AI can also help to determine the best treatment. For non-surgical treatment, Bertsimas et al. [19] used gradient boosting models to determine the individual risk of UTI recurrence with continuous antibiotic prophylaxis and with placebo based on data from the RIVUR trial (n = 607 children). In their model that was built using a huge set of variables and different infection risk cut-offs, the algorithms could select the 40% of patients to be placed on antibiotic prophylaxis to have the same protection for the entire cohort as when treating all patients. In other words, AI identified the only patients who needed to be treated, avoiding 60% of unnecessary prescriptions without increasing the UTI risk in the cohort. In Iran, Tafazoli et al. [20] employed ML models, particularly random forest algorithms, to identify predictors of treatment outcomes in 225 infants (younger than 2 years) with VUR receiving continuous antibiotic prophylaxis. The authors analyzed clinical factors, such as renal scarring, bladder dysfunction, VUR grade and bilateral involvement. The models effectively predicted persistent VUR and febrile UTI. Renal scarring and bladder dysfunction emerged as significant independent predictors of the treatment outcome. Despite the limitations (small sample size and retrospective design), this study highlights ML capability to guide personalized management strategies for children with VUR.

Regarding surgical treatments, one of the first application of AI in VUR was to create an ANN to assist in predicting the endoscopic treatment results. Serrano-Durbá et al [21] used the results of 145 patients and 261 ureteral units with VUR to compare logistic regression and ANN. They considered a series of factors, such as VUR cause and grade, age, sex, type and amount of injected material, number of treatments, affected ureter, endoscopic findings and cystography type. The found that in both training (n=174) and validation (n=87) groups, ANN success rate surpassed logistic regression (88.6% and 78.9% vs. 61.4% and 53.9%, respectively). A couple years later, Seckiner et al. developed an ANN to support treatment decision-making [22]. They exploited data of 96 children with VUR with 145 ureteric units (n=100 units for the training step, n=23 for the validation step and n=22 for the test step). They used supervised learning for outcome prediction and reported a success rate of 98% for the cured units (66/67), 100% for improved units (5/5), and 92% for failed units (25/27). These two studies are important examples of in-house AI tools.

AI and parental counseling

In an attempt to use large language models for patient counseling, Akyol Onder et al. evaluated how ChatGPT could help parents of children with VUR to get reliable and readable information about their child condition [23]. Twenty of the most frequently asked English-language questions about VUR in children were selected. Two independent pediatric nephrologists assessed ChatGPT answers and reliability using various scoring systems and indexes. Most of the responses of ChatGPT have moderate / good reliability to high quality according to the score used to evaluate the answers. The level of reading difficulty nevertheless appeared to be high, preventing its wide use as the solely source of information, requiring either assistance or a more user-friendly readability for a broader audience.

Barriers to clinical implementation of AI in pediatric VUR

Despite encouraging preliminary results, the integration of AI-based tools into routine pediatric urology practice remains limited. Key barriers include the retrospective and single-center nature of most available studies, lack of external validation across diverse populations, variability in data quality, and limited standardization of clinical input variables. Additional challenges include regulatory approval processes, medico-legal considerations, and clinician trust in algorithm-driven decision support. Addressing these barriers will require prospective multicenter studies, transparent model development, and close collaboration between clinicians, data scientists, and regulatory bodies.

Immunization and immunomodulation for urinary tract infections

The body of literature on immunization and immunomodulation for UTI is substantially larger than that on AI, spanning several decades of experimental and clinical work. However, the vast majority of clinical studies have been conducted in adult women with recurrent UTI; pediatric data, particularly those specific to VUR, are sparse. Study populations in the clinical trials described below are predominantly adult, and none of the pivotal randomized controlled trials focused specifically on children with VUR. The evidence grades accordingly: experimental and mechanistic data for immunomodulators are largely derived from animal models; clinical vaccine data represent moderate-quality RCT evidence in adults; pediatric applicability remains extrapolated and unvalidated. The most clinically advanced interventions are presented first, in order of available evidence.

Antibiotics remain the cornerstone of UTI treatment. In some countries, approximately 25% of antibiotic prescriptions are for urological reasons [24]. This brings the question of prevention and therefore, of vaccines, the most successful preventive measure in human history. The aim of vaccines against UTIs is to reduce the use of antibiotics to limit costs, the risk of resistance and side effects associated with antibiotic therapy, and to modulate the post-infectious inflammatory process that causes renal scarring [5]. Currently, there are two promising approaches: immunization against germ-specific virulence factors (adhesion fimbriae, toxins) and immunomodulation.

<u>*Substances*</u>

For immunization, the available vaccines to prevent UTI include Uro-Vaxom/OM-89 [25], the first vaccine authorized in Europe and ExPEC4V [26]. Urovaxome is developped from lysates of uropathogenic *Escherichia coli* strains and is administered orally. ExPEC4V contains O-antigens from four *E. coli* serotypes and is administered by intramuscular injection. There are also vaccines developed using different bacterial species that cause UTIs, such as Solco-Urovac [27] (*E. coli*, *Proteus mirabilis*, *Proteus morganii*, *Enterococcus faecalis*, and *Klebsiella. pneumoniae*) and Uromune/MV140 [28] (*E. coli*, *K. pneumoniae*, *E. faecalis*, and *Proteus vulgaris*).

Regarding immunomodulation, the principle is that the immune system response is protective and blocks the pathogen, but it can also cause excessive inflammation leading to renal scarring. Immunomodulation precisely aims to maintain the protective antimicrobial effect on one hand, and to attenuate the harmful effects of uncontrolled inflammation on the other hand [29]. Applied to UTI, immunomodulation should increase the Th1 response (to boost killing/resistance to infectious agents) and reduce the Th2 response (to limit the harmful effects of inflammation) [30]. Three immunomodulators are of particular interest. The first one is interleukin 1 receptor antagonist (IL-1RA). It helps to control inflammation in animal models and patients [31]. The second ones are Si-RNAs against interferon regulatory factor 7 [29]. Small interfering RNA are fragments of RNA that binds to DNA to prevent translation. Applied to UTIs, they interfere with the translation of genes that are deleterious in the inflammation cascade. The last type of immunomodulators are natural antimicrobial peptides such as cathelicidin and ribonuclease 7. These peptides are naturally produced by immune cells and epithelial cells. They participate in the innate immune response, accelerate bacterial clearance and modulate, to a lower extent, the immune response.

<u>*Preliminary outcomes*</u>

A meta-analysis of the four vaccines (Uromune/MV140, OM-89/Uro-Vaxom, Solco-Urovac, ExPEC4 V) found an almost 5-fold reduction in the risk of UTI recurrence at 3 months (odds ratio of 0.17) [32]. At 9–12 months, the reduction in UTI risk persisted (odds ratio of 0.20). Solco-Urovac efficacy seems to be higher after a booster dose. ExPECV4 is currently assessed in phase 3 trials and appears to be particularly effective in preventing *E. coli* septicemia. Moreover, in a randomized, double-blind, placebo-controlled trial, Uromune/MV140 halved the risk of UTI recurrence at 200 days compared to placebo [33]. For all these vaccines, severe side effects have not been reported so far (n = 17 studies involving 3,228 patients) [32].

Immunomodulation provides also exciting preliminary results. Exogenous cathelicidin administration reduces bacteriuria and bacterial colonization of kidneys in murine models [5]. It also limits biofilm formation on the uroepithelium and prevents bacterial ascension to the kidneys in *in vivo* studies. Treated animals show reduced kidney tissue damage and abscess formation, and lower urinary cytokine levels (IL-6, TNF-α) [34]. The cathelicidin and antibiotic combination enhances bacterial clearance compared to antibiotics alone. Human studies found elevated urinary cathelicidin concentrations during acute UTI that correlated with bacterial clearance and resolution. Conversely, low cathelicidin concentrations may be associated with recurrent UTI. Moreover, patients with interstitial cystitis/bladder pain syndrome have responded favorably to off-label treatment with IL-1RA [5] but these results still have to transposed to the kidney.

Limitations of current evidence and barriers to translation

Most clinical studies evaluating vaccines and immunomodulatory strategies for the prevention of urinary tract infections have been conducted in adult populations, predominantly women with recurrent UTIs [35]. At present, there are no large-scale, VUR-specific pediatric clinical trials assessing UTI vaccines. This represents a major translational gap between promising experimental or adult clinical data and routine pediatric application. Nevertheless, the underlying immunological mechanisms targeted by these approaches—such as enhancement of bacterial clearance and modulation of excessive inflammatory responses—are not inherently age-dependent and may therefore be biologically relevant in children with VUR.

Regarding safety, currently available data suggest a favorable safety profile of UTI vaccines, with no severe adverse events reported across published clinical studies to date. However, pediatric-specific safety and efficacy data remain limited, and extrapolation from adult populations should be approached with caution. Well-designed pediatric trials, particularly in infants and children at high risk of recurrent febrile UTIs and renal damage, are required before these strategies can be recommended for routine pediatric practice.

At present, these immunologically targeted strategies should be regarded as experimental approaches with potential future relevance to pediatric VUR rather than established clinical interventions. Their true clinical impact will depend on the results of appropriately designed pediatric trials focusing on high-risk populations, on clear regulatory requirements, on data standardization and on clinician trust that further represent significant barriers to widespread clinical adoption [36].

Taken together, the evidence reviewed here illustrates both the promise and the current limits of AI and immunologically targeted strategies in pediatric VUR. AI-based tools have demonstrated proof-of-concept performance across diagnosis, treatment selection, and counseling, with AUCs generally ranging from 0.76 to 0.95 in single-center studies—results that are encouraging but not yet sufficient for clinical adoption without prospective multicenter validation. For immunization and immunomodulation, the most mature clinical data concern adult populations with recurrent UTI; the meta-analytic evidence for vaccine efficacy (OR 0.17–0.20 for UTI recurrence at 3–12 months) is compelling in this group, but directly applicable pediatric data remain absent. Immunomodulatory agents such as cathelicidin, IL-1RA, and siRNA targeting IRF7 show mechanistic plausibility and favorable results in animal models, yet none has entered pediatric clinical trials. Both fields share a common bottleneck: the absence of large-scale, prospective, VUR-specific pediatric studies

Conclusion

VUR management has long been constrained by single-variable decision-making; these emerging approaches offer a path toward genuinely individualized care. Their clinical value will depend on prospective validation and pediatric-specific trial design. At present, both AI and immunological strategies should be regarded as exploratory—promising enough to warrant rigorous investigation, but not yet ready for routine practice.

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Table 1. AI in Pediatric Urology – Algorithm Stratification Table

Level	Model / Algorithm	Type	Example Applications in Pediatric Urology
ML (Supervised)	Decision Tree (DT)	Classification, Interpretable	Classifying urinary tract infection (UTI) risk; simple diagnostic rule models
	Support Vector Machine (SVM)	Classification	Differentiating types of urinary anomalies from ultrasound or MRI data
	Naïve Bayes (NB)	Probabilistic classification	Predicting likelihood of vesicoureteral reflux (VUR) based on clinical features
	K-Nearest Neighbors (KNN)	Instance-based classification	Classifying bladder dysfunctions using urodynamic profiles
	Random Forest (RF)	Ensemble (bagging)	Predicting post-surgical complications, feature importance analysis
	Gradient Boosting (e.g., XGBoost)	Ensemble (boosting)	Risk prediction of urinary obstruction, UTI or hydronephrosis progression
ML (Unsupervised)	K-Means Clustering	Clustering	Grouping patients by symptom patterns or bladder diary data
	Hierarchical Clustering	Clustering	Phenotyping congenital urinary tract anomalies
	PCA (Principal Component Analysis)	Dimensionality Reduction	Reducing complex urodynamic datasets to key components
DL	ANN (Artificial Neural Network)	Feedforward Neural Network	Predicting surgical outcomes based on patient history and lab data
	MLP (Multilayer Perceptron)	Deep ANN	Multivariable analysis of voiding dysfunction
	CNN (Convolutional Neural Network)	Image-based Deep Learning	Detecting anatomical anomalies from renal/bladder ultrasound images
	RNN (Recurrent Neural Network)	Sequence Modeling	Tracking longitudinal urinary tract function trends in children
	LSTM (Long Short-Term Memory)	Advanced RNN	Forecasting urinary symptom recurrence over time
	Transformers (e.g., BioBERT)	Attention-based NLP	Analyzing clinical notes for pediatric urologic symptoms, NLP-based triage
RL	Q-Learning	Value-based Reinforcement Learning	Optimizing individualized treatment schedules (e.g., timed voiding or medication)
	DQN (Deep Q-Network)	Deep RL	Selecting optimal interventions for bladder training or VUR in neuropathic bladder

AI is top level concept for enabling intelligent systems for diagnosis, decision-making, and workflow support. ML: machine learning, DL: deep learning, RL: reinforced learning