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Generating a Model of Computational Correlation Between Lithiasis and Diet: Insights into Anthropometric Predictors and the Exploratory Role of AI

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Abstract: *The relationship between lithiasis (kidney stone disease) and dietary habits has been widely debated but remains incompletely clarified. This study used a computational framework that combined statistical testing with AI-based exploratory modelling to assess the relative contributions of dietary and anthropometric parameters on lithiasis recurrence and stone type. Data from 144 patients with documented kidney stones were analysed. AI algorithms were not intended as predictive tools due to the small and imbalanced dataset; they served to identify the most influential variables. Classical statistical methods revealed no significant associations between relapse and isolated dietary factors such as fast-food or carbonated drinks, though higher water intake showed a protective trend ($p \approx 0.09$). Anthropometric features, particularly ideal weight, were significantly associated with both relapse ($p \approx 0.006$) and stone type (corrected $p \approx 0.046$). Machine learning models (multinomial logistic regression, Random Forest, and XGBoost) demonstrated modest predictive performance (accuracy ≈ 55–63%), with variable importance analyses highlighting weight, ideal weight, and water intake as stronger predictors than single dietary variables. The findings suggest that anthropometric parameters, rather than isolated dietary habits, show stronger associations with stone type and recurrence, and that AI models hold promise but require larger datasets and biochemical variables to achieve clinical utility.*

Keywords: *lithiasis; kidney stones; diet; computational model; artificial intelligence; anthropometry; relapse; stone type; water intake; obesity.*

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1. Introduction

Kidney stone disease is a multifactorial condition influenced by metabolic, environmental, and lifestyle factors (Khan et al., 2017; Curhan, 2007). Dietary habits are frequently cited as potential risk factors, yet their precise contribution remains unclear (Ferraro et al., 2020; Siener, 2021). The acknowledged contributions of hydration and obesity are recognised, yet the independent influence of particular food components is still debated (Littlejohns et al., 2020; Lin et al., 2023; Ma et al., 2024). Prior studies report mixed associations for meat, fast food, and carbonated beverages, whereas water intake consistently shows protective effects (Chewcharat et al., 2022; Sorensen et al., 2012; Shabani et al., 2023). Traditional statistical approaches often yield inconclusive or contradictory results (Taylor et al., 2004; Worcester & Coe, 2010). Nephrolithiasis constitutes a considerable global health challenge, with prevalence rates between 5-12% in developed countries, which have been progressively rising over recent decades (Curhan, 2007; Zeng et al., 2017). Beyond its acute clinical manifestations - such as renal colic, haematuria, and risk of infection - kidney stones are associated with high recurrence rates, reduced quality of life, and substantial healthcare costs (Khan et al., 2017; Worcester & Coe, 2010). The aetiology of stone disease is multifactorial, reflecting complex interactions between genetic predisposition, metabolic and biochemical imbalances, environmental exposures, and lifestyle factors (Ferraro et al., 2020; Siener, 2021).

Among these determinants, diet has received significant attention. High intake of animal protein, sodium, and refined sugars has been implicated in stone formation, while fluid intake and certain dietary patterns such as the DASH diet have been shown to reduce recurrence (Taylor et al., 2004; Sorensen et al., 2012; Ferraro et al., 2020). However, evidence regarding the role of specific food categories–such as fast food, carbonated beverages, or meat consumption–remains inconsistent, with some studies reporting modest effects and others showing no significant associations (Chewcharat et al., 2022; Shabani et al., 2023). This variability may reflect heterogeneity in populations studied, differences in dietary assessment methods, and the multifactorial nature of stone pathophysiology.

At the same time, anthropometric and body composition factors, including obesity, body mass index (BMI), and waist circumference, have emerged as stronger and more consistent predictors of stone risk, particularly for uric acid stones (Taylor et al., 2004; Lin et al., 2023). These observations underscore the importance of considering diet in the broader context of metabolic health. Hydration, meanwhile, is one of the most universally recognised protective factors, with randomised and observational studies consistently showing that higher water intake reduces recurrence risk (Sorensen et al., 2012; Worcester & Coe, 2010; Littlejohns et al., 2020). These findings underscore the importance of integrating dietary and metabolic factors into comprehensive risk models.

Traditional statistical studies have made valuable contributions but often yield conflicting results when applied to small or heterogeneous datasets (Taylor et al., 2004; Sorensen et al., 2012). Recent advances in computational methods and artificial intelligence (AI) offer new opportunities to uncover subtle patterns and interactions among dietary, anthropometric, and clinical variables (Anastasiadis et al., 2023; Mao et al., 2025). AI approaches, including machine learning algorithms, have shown promise in improving risk prediction in nephrolithiasis, especially when biochemical and imaging data are integrated (Caudarella et al., 2011; Abraham et al., 2022; Shee et al., 2024; Yanase et al., 2025). However, their value in datasets emphasising diet and anthropometry remains less explored (Doyle et al., 2023; Sánchez et al., 2024).

The present study does not aim to introduce novel AI algorithms, but rather to evaluate how established machine learning tools can enhance the interpretability of clinical and anthropometric data. By applying these methods to a nephrological context, the analysis contributes to the growing discourse on data-driven medical intelligence, a domain that shares methodological foundations with neuroinformatics and cognitive modeling in its focus on pattern recognition, feature salience, and decision-support systems.

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Against this background, the present study applies a computational framework combining classical statistics and AI modelling to a clinical cohort of 144 patients with kidney stone disease. Our primary aim was to assess the relative contribution of dietary factors and anthropometric parameters to stone recurrence and type, given prior evidence linking diet and obesity to nephrolithiasis (Ferraro et al., 2020; Lin et al., 2023; Shabani et al., 2023). Specifically, this study investigates whether AI-assisted feature importance analysis can provide complementary insights to traditional statistics, rather than serve as a predictive model, thereby clarifying which parameters hold the greatest clinical relevance.

2. Methods

A dataset containing 157 variables from 144 patients with documented lithiasis, collected between 2022 and 2024 at the 'Mihaela Nikolić' Clinical Nutrition and Dietetics Office, was analysed. Although the total cohort included 144 patients, relapse status was available for only 143; one patient was excluded from this analysis due to missing relapse-status data.The study considered a comprehensive set of variables. The study included a range of dietary, anthropometric, physiological, and clinical variables. The data were obtained as part of routine nutritional and clinical assessment, where 24-hour biochemical urine analyses are not standard, explaining the absence of biochemical parameters such as urinary calcium, oxalate, citrate, or uric acid.

Dietary variables comprised fast-food consumption, carbonated drinks, meat intake per meal, daily water intake, coffee and tea consumption, alcohol intake, fruit and vegetable intake, and dairy product consumption. Anthropometric and physiological variables included weight, *ideal weight*, body mass index (BMI), abdominal circumference, body water percentage, fat percentage, and urinary pH. *Ideal weight* was calculated using the Lorentz formula: for males, ideal weight = height (cm) − 100 − [(height − 150)/4], and for females, ideal weight = height (cm) − 100 − [(height − 150)/2.5]. This variable was included to capture the proportionality between body mass and height, serving as an anthropometric normalisation factor.

For statistical analysis, descriptive statistics were first calculated to summarise the dataset. Associations between categorical dietary variables and clinical outcomes were examined using chi-square tests, or Fisher's exact test when expected cell counts were small, to ensure robust inference from categorical data. Continuous variables were assessed using parametric tests (t-tests) when normally distributed, and nonparametric tests (Mann–Whitney U and Kruskal–Wallis) when distributions deviated from normality. This approach allowed appropriate handling of both symmetric and skewed data. To enhance interpretability, results were reported with corresponding effect sizes and 95% confidence intervals in addition to p-values. A sequential testing strategy was applied, with analysis halted once statistically significant associations were identified (Fink et al., 2013).

3. AI Modelling

To explore predictive modelling beyond standard regression, we implemented a supervised machine learning pipeline in R version 4.4.2. The cleaned dataset was exported to CSV and analysed using the packages *caret*, *nnet*, *ranger*, and *xgboost*. Preprocessing steps included one-hot encoding for categorical variables, *z-score* centring and scaling for numerical predictors, and median imputation for missing continuous data. These procedures were carried out using the *caret* package in R.

The outcome variable was stone type (oxalate, uric acid, other). Predictors included anthropometric variables (weight, ideal weight, BMI, age, sex), and dietary variables (fast-food, carbonated drinks, meat per meal, daily water intake, vegetable consumption).

The analytical pipeline was structured into two sequential stages (Figure 1). First, data preprocessing was performed, which involved categorical encoding, centring and scaling of numeric variables, as well as imputation of missing values. Second, model training was conducted using three approaches: a baseline multinomial logistic regression, a Random Forest model, and an XGBoost multiclass model.

Machine-learning models were utilised using default settings and without comprehensive hyperparameter optimization, due to the restricted sample size (n = 144) and class imbalance. K-fold cross-validation and external validation were not conducted, as the models were utilised exclusively for the exploratory evaluation of feature significance rather than for creating a clinically relevant predictive tool.

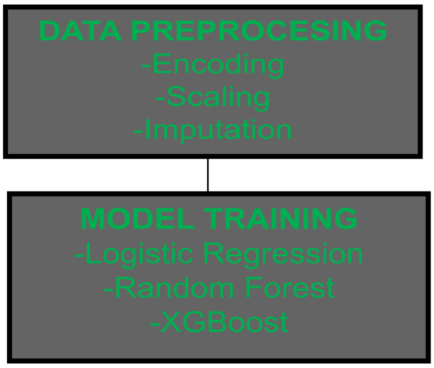

Figure 1. Flowchart of the computational pipeline for stone type prediction

4. Results

The analysis revealed several noteworthy patterns. Regarding relapses and diet, no significant associations were found with fast-food consumption, carbonated drinks, meat intake, or coffee/tea. Water intake, however, showed a protective trend, with higher average daily intake observed among non-relapsers, although the difference did not reach statistical significance (*p ≈ 0.09*).

Table 1. Dietary Factors, Relapse Rates, and Patient Characteristics by Stone Type

Parameter / Factor	Group (mean)/ Stone Type	Value	Observations
Relapse Rates by Dietary Factors	Fast-food	60.0 % Consumers	*Relapse percentages and mean values are rounded; no differences reached statistical significance*
		58.9 % Non-consumers	
	Carbonated Drinks	59.6 % Consumers	
		58.9 % Non-Consumers	
	Meat Intake	210.8 g/day Relapse group	
		192.3 g/day Non-relapsed	
	Water Intake	1.7 L/day Relapse group	
		2.1 L/day Non-relapsed	
	Vegetable Intake	180 g/day Relapse group	
		210 g/day Non-relapsed	
Patient Characteristics by Stone Type	Oxalate	Weight: 92.6 kg	
		Ideal Weight: 64.8 kg	
		Water Intake: 2.0 L/day	
	Uric Acid	Weight: 103.3 kg	*Uric acid stone patients had higher weight and ideal weight, lower water intake*
		Ideal Weight: 73.3 kg	
		Water Intake: 1.6 L/day	
	Other	Weight: 83.9 kg	
		Ideal Weight: 64.5 kg	
		Water Intake: 1.9 L/day	

When examining stone type and diet, no statistically significant differences were detected across stone types in relation to fast-food or carbonated drink consumption (Table 1). Nonetheless, patients with uric acid stones reported slightly lower vegetable intake and higher alcohol use compared with oxalate stone patients, though these differences fell short of conventional significance thresholds.

No significant associations were observed between relapse and fast-food consumption, carbonated drinks, meat intake, coffee, or tea. Water intake was higher among non-relapsers (median 2.1 L/day) compared to relapsers (median 1.7 L/day), showing a borderline protective trend ($p \approx 0.09$). These findings are consistent with prior evidence supporting hydration as a key protective factor.

Anthropometric measures showed stronger signals. Weight exhibited borderline significance in relation to stone type, with uric acid stone patients presenting higher median weight than those with oxalate or other stones. Ideal weight was significantly associated with both relapse ($p \approx 0.006$) and stone type (oxalate vs. uric acid, $p \approx 0.015$; corrected $p \approx 0.046$), (Table 2). Specifically, patients with relapse tended to have lower calculated 'ideal weight,' while uric acid stone patients displayed higher ideal weight compared to oxalate stone patients.

Although the total cohort included 144 patients, relapse status was available for only 143; one patient was excluded from this analysis due to missing relapse-status data. As shown in Table 2, patients with relapse (n = 85) had significantly lower ideal weight values (median = 62.4 kg) compared to non-relapse patients (median = 72.3 kg; Mann–Whitney U, $p = 0.006$). Weight itself was slightly lower in the relapse group (median = 92.1 kg) compared to non-relapse (median = 96.5 kg), but this did not reach statistical significance ($p = 0.053$).

Uric acid stone patients (n = 22) were heavier (median weight 103.3 kg) and had higher ideal weight (median 73.8 kg) compared to oxalate stone patients (median weight 92.6 kg, ideal weight 64.8 kg). Kruskal–Wallis tests confirmed that both weight ($p = 0.011$) and ideal weight ($p = 0.025$) were significantly different across stone types (Table 2).

Overall, ideal weight emerged as the most consistent anthropometric predictor, significantly associated with both relapse and stone type. Hydration showed a protective trend, though not statistically definitive in this dataset.

Table 2 Weight and Ideal Weight by Relapse Status and Stone Type

Parameter / Group	N	Ideal Weight (Median / Mean ± SD), (kg)	Weight (Median / Mean ± SD), (kg)	Observations
Relapse Status				*Mann–Whitney U test: Ideal weight p = 0.006 (significant), Weight p = 0.053 (borderline)*
Relapse	85	62.4 / 66.6 ± 8.9	92.1 / 92.4 ± 13.7	
Non-relapse	58	72.3 / 70.7 ± 9.1	96.5 / 98.8 ± 17.5	
Stone Type				*Kruskal–Wallis test: Ideal weight p = 0.025, Weight p = 0.011 (both significant)*
Oxalate	114	64.8 / 67.7 ± 9.2	92.6	
Uric acid	22	73.8 / 72.2 ± 8.1	103.3	
Other	6	60.5 / 64.8 ± 11.3	81.8	

Finally, the AI analysis provided additional insights. Trend-level connections revealed that anthropometric parameters and hydration patterns may be more important than individual dietary factors; nevertheless, these findings were not statistically significant and should be regarded as exploratory.

5. Discussion

This study explored dietary and anthropometric factors associated with kidney stone recurrence and type using both statistical and AI-assisted analyses. Among all anthropometric indicators, *ideal weight* showed the strongest association with both relapse and stone type. Interestingly, patients with recurrence exhibited lower calculated ideal weight values, while uric acid stone formers showed higher *ideal weight* compared to oxalate stone formers. This finding, although statistically significant, should be interpreted cautiously. Since *ideal weight* is derived from height rather than measured body composition, it may act as a proxy for stature or frame size rather than metabolic status. Alternatively, this relationship may reflect differences in lean body mass or total body water, factors previously linked to urinary solute concentration and stone risk (Taylor et al., 2005). Another possibility is that the association arises as a statistical artefact, given the modest sample size and potential confounding by sex or age distribution. Future studies integrating direct body composition analysis are warranted to clarify whether *ideal weight* represents a physiologically meaningful predictor.

Dietary factors such as fast-food, carbonated drinks, coffee, and alcohol did not demonstrate significant associations with relapse or stone type in this dataset. Water consumption and vegetable intake, however, showed trends of protective associations, suggesting a potential role in reducing relapse or shifting stone type prevalence, though the results were not statistically definitive. This observation raises the possibility that metabolic and body composition factors may be stronger determinants of stone recurrence and type than isolated dietary choices.

Our results are broadly consistent with the literature. Hydration has been consistently shown to reduce recurrence risk in randomised trials and cohort studies, aligning with the protective water-intake trend observed here (Worcester & Coe, 2010; Littlejohns et al., 2020). Obesity and higher BMI are well-established risk factors for uric acid stones, consistent with our finding of higher weight and ideal weight among uric acid stone patients (Taylor et al., 2004; Lin et al., 2023). By contrast, the role of meat and fast-food consumption is less clear, with meta-analyses reporting mixed or modest effects (Chewcharat et al., 2022; Shabani et al., 2023). Our null findings for these single dietary variables are consistent with the growing consensus that overall dietary patterns, such as a DASH-style diet, may be more relevant than isolated components (Ferraro et al., 2020; Dai & Pearle, 2022).

This study has several important limitations. First, the sample size (n = 144) limits statistical power and may have contributed to borderline findings, such as the association between water intake and relapse. Second, dietary intake data were self-reported, making them subject to recall bias and under- or overestimation. Third, the stone type distribution was imbalanced, with oxalate stones predominating, potentially reducing the reliability of comparisons with less frequent stone types (uric acid, other). Fourth , the single-centre nature of the cohort may limit generalisability to other populations. Finally, the AI models tested (multinomial regression, Random Forest, XGBoost) were constrained by the modest dataset size, which reduced predictive accuracy and increased the risk of overfitting.

The key limitation of this study is the absence of biochemical data, including urinary calcium, oxalate, citrate, and uric acid levels, which are established predictors of lithiasis risk. These data were unavailable because of the patient cohort, where 24-hour urine analyses are not part of the standard intake protocol. Consequently, our models relied exclusively on anthropometric and self-reported dietary variables, limiting the ability to assess metabolic risk factors. Future research should incorporate biochemical and urinary parameters to improve the accuracy and clinical applicability of predictive models.

Due to the small sample size and inadequate clinical covariate data, no multivariate correction for age, gender, or comorbidities was conducted. The absence of hyperparameter tuning or cross-validation reflects a deliberate methodological choice to minimise overfitting risk in a small dataset. Consequently, model performance metrics should be interpreted as internal exploratory indicators rather than predictive benchmarks. This methodological transparency aligns with similar studies (Abraham et al., 2022; Shee et al., 2024; Yanase et al., 2025) that have applied AI models to clinical nephrolithiasis datasets primarily for pattern recognition and hypothesis generation, rather than clinical prediction.

While the current framework is primarily exploratory, it illustrates the potential of interpretable AI approaches to uncover latent patterns in small clinical datasets. Such methodologies, although applied here to urolithiasis, are conceptually transferable to other biomedical domains, including neurocognitive data analysis, where transparent, feature-level modelling is crucial. Thus, our work contributes to the methodological conversation on how AI can responsibly augment hypothesis generation in biomedical science.

6. Conclusions

These findings reinforce the importance of body composition and hydration in stone pathophysiology, aligning with prior evidence that obesity increases uric acid stone risk and adequate water intake reduces recurrence. However, several limitations must be acknowledged. The modest sample size and reliance on self-reported dietary data restrict statistical power and generalisability. Moreover, the absence of urinary biochemical markers-unavailable due to the dataset's origin in a clinical nutrition setting-limits physiological interpretation.

These results underscore that datasets based solely on anthropometric and dietary factors are insufficient for accurate predictive modelling. Instead, our findings highlight the value of AI as an exploratory tool for ranking variable importance and guiding hypothesis generation.

Future research should therefore expand to larger, multicentre cohorts, incorporate urinary and metabolic biomarkers, and adopt advanced, explainable AI techniques to refine prediction and guide personalised prevention strategies. By integrating clinical, dietary, anthropometric, and biochemical data, next-generation models may offer robust, clinically useful tools for risk stratification and recurrence prevention in kidney stone disease.

References

Abraham, A., Kavoussi, N. L., Sui, W., Bejan, C., Capra, J. A., & Hsi, R. (2022). Machine learning prediction of kidney stone composition using electronic health record-derived features. *Journal of Endourology, 36*(2), 243–250. https://doi.org/10.1089/end.2021.0211

Anastasiadis, A., Koudonas, A., Langas, G., Tsiakaras, S., Memmos, D., Mykoniatis, I., Symeonidis, E. N., Tsiptsios, D., Savvides, E., Vakalopoulos, I., Dimitriadis, G., & de la Rosette, J. (2023). Transforming urinary stone disease management by artificial intelligence-based methods: A comprehensive review. *Asian Journal of Urology, 10*(3), 258–274. https://doi.org/10.1016/j.ajur.2023.02.002

Caudarella, R., Tonello, L., Rizzoli, E., & Vescini, F. (2011). Predicting five-year recurrence rates of kidney stones: An artificial neural network model. *Archivio Italiano di Urologia e Andrologia, 83*(1), 14–19.

Chewcharat, A., Thongprayoon, C., Vaughan, L. E., Mehta, R. A., Schulte, P. J., O'Connor, H. M., Lieske, J. C., Taylor, E. N., & Rule, A. D. (2022). Dietary risk factors for incident and recurrent symptomatic kidney stones. *Mayo Clinic Proceedings, 97*(8), 1437–1448. https://doi.org/10.1016/j.mayocp.2022.04.016

Curhan, G. C. (2007). Epidemiology of stone disease. *Urologic Clinics of North America, 34*(3), 287–293. https://doi.org/10.1016/j.ucl.2007.04.003

Dai, J. C., & Pearle, M. S. (2022). Diet and stone disease in 2022. *Journal of Clinical Medicine, 11*(16), 4740. https://doi.org/10.3390/jcm11164740

Doyle, P., Gong, W., Hsi, R., & Kavoussi, N. (2023). Machine learning models to predict kidney stone recurrence using 24-hour urine testing and electronic health record-derived features. *Research Square*, rs.3.rs-3107998. https://doi.org/10.21203/rs.3.rs-3107998/v1

Ferraro, P. M., Bargagli, M., Trinchieri, A., & Gambaro, G. (2020). Risk of kidney stones: Influence of dietary factors, dietary patterns, and vegetarian-vegan diets. *Nutrients, 12*(3), 779. https://doi.org/10.3390/nu12030779

Fink, H. A., Wilt, T. J., Eidman, K. E., Garimella, P. S., MacDonald, R., Rutks, I. R., Brasure, M., Kane, R. L., Ouellette, J., & Monga, M. (2013). Medical management to prevent recurrent nephrolithiasis in adults: A systematic review for an American College of Physicians Clinical Guideline. *Annals of Internal Medicine, 158*(7), 535–543. https://doi.org/10.7326/0003-4819-158-7-201304020-00005

Khan, S. R., Pearle, M. S., Robertson, W. G., Gambaro, G., Canales, B. K., Doizi, S., Traxer, O., & Tiselius, H. G. (2016). Kidney stones. *Nature Reviews Disease Primers, 2*, 16008. https://doi.org/10.1038/nrdp.2016.8

Lin, G., Zhan, F., Ren, W., Pan, Y., & Wei, W. (2023). Association between novel anthropometric indices and prevalence of kidney stones in US adults. *World Journal of Urology, 41*(11), 3105–3111. https://doi.org/10.1007/s00345-023-04582-x

Littlejohns, T. J., Neal, N. L., Bradbury, K. E., Heers, H., Allen, N. E., & Turney, B. W. (2020). Fluid intake and dietary factors and the risk of incident kidney stones in UK Biobank: A population-based prospective cohort study. *European Urology Focus, 6*(4), 752–761. https://doi.org/10.1016/j.euf.2019.05.002

Ma, Y., Cheng, C., Jian, Z., Wen, J., Xiang, L., Li, H., Wang, K., & Jin, X. (2024). Risk factors for nephrolithiasis formation: An umbrella review. *International Journal of Surgery, 110*(9), 5733–5744. https://doi.org/10.1097/JS9.0000000000001719

Mao, C., Li, J., Pang, P. C., Zhu, Q., & Chen, R. (2025). Identifying kidney stone risk factors through patient experiences with a large language model: Text analysis and empirical study. *Journal of Medical Internet Research, 27*, e66365. https://doi.org/10.2196/66365

Sánchez, C., Larenas, F., Arroyave, J. S., Connors, C., Giménez, B., Palese, M. A., & Fulla, J. (2024). Artificial intelligence in urology: Application of a machine learning model to predict the risk of urolithiasis in a general population. *Journal of Endourology, 38*(8), 712–718. https://doi.org/10.1089/end.2023.0702

Shabani, E., Khorshidi, A., Sayehmiri, K., Moradi, K., & Abdolyousefi, N. E. (2023). The effect of nutritional factors on urolithiasis: A case-control study. *Journal of Medicine and Life, 16*(7), 1062–1069. https://doi.org/10.25122/jml-2022-0321

Shee, K., Liu, A. W., Chan, C., Yang, H., Sui, W., Desai, M., Ho, S., Chi, T., & Stoller, M. L. (2024). A novel machine-learning algorithm to predict stone recurrence with 24-hour urine data. *Journal of Endourology, 38*(8), 809–816. https://doi.org/10.1089/end.2023.0457

Siener, R. (2021). Nutrition and kidney stone disease. *Nutrients, 13*(6), 1917. https://doi.org/10.3390/nu13061917

Sorensen, M. D., Kahn, A. J., Reiner, A. P., Tseng, T. Y., Shikany, J. M., Wallace, R. B., Chi, T., Wactawski-Wende, J., Jackson, R. D., O'Sullivan, M. J., Sadetsky, N., & Stoller, M. L. (2012). Impact of nutritional factors on incident kidney stone formation: A report from the WHI OS. *Journal of Urology, 187*(5), 1645–1650. https://doi.org/10.1016/j.juro.2011.12.077

Taylor, E. N., Stampfer, M. J., & Curhan, G. C. (2004). Dietary factors and the risk of incident kidney stones in men: New insights after 14 years of follow-up. *Journal of the American Society of Nephrology, 15*(12), 3225–3232. https://doi.org/10.1097/01.ASN.0000146012.44570.20

Taylor, E. N., Stampfer, M. J., & Curhan, G. C. (2005). Obesity, weight gain, and the risk of kidney stones. *JAMA, 293*(4), 455–462. https://doi.org/10.1001/jama.293.4.455

Worcester, E. M., & Coe, F. L. (2010). Clinical practice. Calcium kidney stones. *New England Journal of Medicine, 363*(10), 954–963. https://doi.org/10.1056/NEJMcp1001011

Yanase, T., Unno, R., Tokas, T., Gauhar, V., Sasaki, Y., Kawase, K., Chaya, R., Hamamoto, S., Maruyama, M., Yasui, T., & Taguchi, K. (2025). AI-driven prediction of renal stone recurrence following ECIRS: A machine learning approach to postoperative risk stratification incorporating 24-hour urine data. *Journal of Clinical Medicine, 14*(12), 4037. https://doi.org/10.3390/jcm14124037

Zeng, G., Mai, Z., Xia, S., Wang, Z., Zhang, K., Wang, L., Long, Y., Ma, J., Li, Y., Wan, S. P., Wu, W., Liu, Y., Cui, Z., Zhao, Z., Qin, J., Zeng, T., Liu, Y., Duan, X., Mai, X., Yang, Z., Kong, Z., Zhang, T., Cai, C., Shao, Y., Yue, Z., Li, S., Ding, J., Tang, S., & Ye, Z. (2017). Prevalence of kidney stones in China: An ultrasonography-based cross-sectional study. *BJU International, 120*(1), 109–116. https://doi.org/10.1111/bju.13828