# Computational Decision Support Model in Clinical Analysis of Female Urinary Incontinence Surgery: A Methodological Approach

Uribe O<sup>1</sup>, Sánchez J<sup>2</sup>, Cortés D<sup>2</sup>, Feijóo-García M<sup>3</sup>

1. Universidad El Bosque, 2. Univeridad Nacional de Colombia, 3. Purdue University Abstract #365

#### Introduction

Female urinary incontinence affects 40% of patients over the age of 40. Among these patients, 50% require surgical intervention, with a variety of surgical techniques available. This diversity in treatment options makes the choice of the most appropriate surgical procedure challenging.

# **Hypothesis**

Informed by global guidelines, expert input, and prior case experience, a computational prediction model can streamline surgical decision-making for female urinary incontinence.

#### **Materials**

**SFUI Guidelines**: National and international guidelines for management rules.

**Expert Interviews**: Input from three urogynecology experts.

**Clinical Data**: Anonymized records (2014-2019) for identifying 53 clinical variables.

Microsoft Excel: For descriptive analysis and patient simulation.

**AppSheet Tool**: For expert input on surgical recommendations.

**Python**: For data generation and machine learning model development.

Monte Carlo Method: To generate synthetic clinical data.

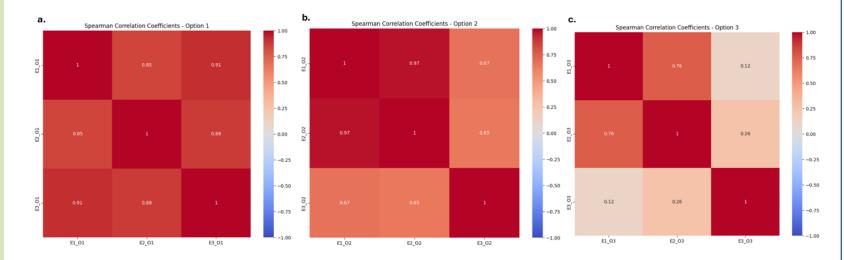
Validation Dataset: 100 synthetic patients for model validation.

**Dashboard Tool**: For displaying and updating model performance metrics.

Fig 1 View for the expert to assign treatment



Fig 2 Spearman correlation between the three experts in the decision making of the seed sample (160 patients)



# Methodology

- 1. **Define Rules:** Reviewed guidelines and conducted expert interviews to establish decision rules.
- **2. Define Inputs:** Identified risk factors and selected 53 clinical variables from patient data (2014-2019).
- **3. Define Outputs:** Chose one surgery recommendation from eight options (TVT, TOT, Mini Sling, Burch, Bulking, Autologous TVT, Adjustable TVT, Artificial Sphincter).
- **4. Simulate Patients:** Generated a seed sample of 160 patients; experts assigned treatments.
- **5. Assign Treatments:** Developed an app for expert surgical recommendations, prioritized using the Borda method.
- **6. Expand Data:** Synthetically generated 3,000 patients, partitioned into training and validation sets.
- **7. Validate Treatments:** Experts reassigned treatments to 100 synthetic patients for validation.
- **8. Data Analysis:** Conducted analysis to identify patient characteristics and trends.
- **9. Develop Models:** Evaluated machine learning algorithms to determine the best approach.
- **10. Integrate Model:** Incorporated the model into a clinical application for use.
- **11. Evaluate Performance:** Created a dashboard to display performance metrics, updated with new data.

#### Results

**Monte Carlo Simulation**: Generated a seed sample of 123 patients with treatments assigned by experts; results were clinically feasible and similar to the previous sample.

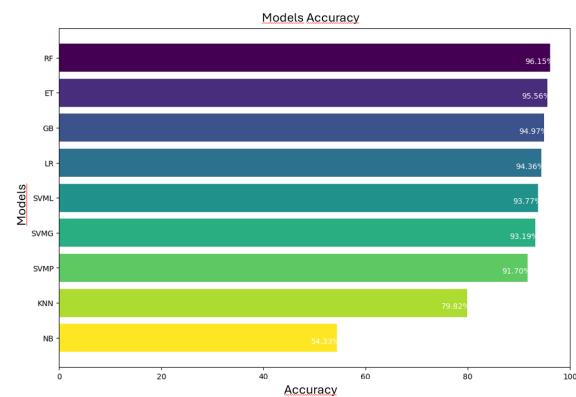
**AppSheet Tool**: Simplified expert treatment assignment, integrating with the machine learning model.

**Machine Learning Models**: Developed using Python; precision ranged from 54,33% to 96,15%.

**Logistic Regression Model**: Achieved 83% precision, with higher precision models needing bias assessment.

**Current Phase**: Nearing completion of the decision support system design; further refinement and validation required before clinical use.

Fig 3 Precision of the nine different models obtained



### Discussion

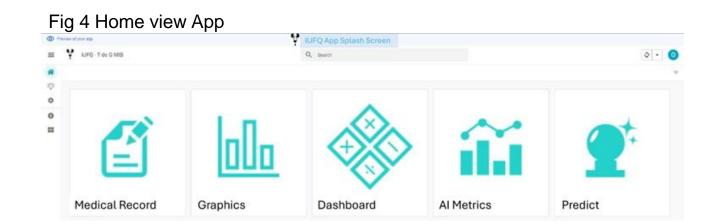
The successful simulation of a patient sample and development of machine learning models mark significant progress toward a decision support system for surgical management for female urinary incontinence. Key points include:

**Model Precision Variability**: Variability in precision across models highlights the complexity of predicting optimal treatments for SFUI patients. Further refinement and investigation of underlying factors and biases are necessary to enhance accuracy.

**AppSheet Tool Utilization**: The AppSheet tool simplified treatment assignment by clinicians. However, integrating it with machine learning models needs careful consideration to ensure seamless operation in clinical practice.

Importance of External Validation: Promising simulated results lack external validation with real-world data. Rigorous external validation studies are essential before clinical implementation to assess performance, generalizability, and reliability. Ongoing validation is crucial for maintaining system accuracy.

**Potential Clinical Impact**: A robust decision support system can significantly improve clinical practice by providing evidence-based, personalized recommendations, aiding clinicians in making informed decisions, optimizing treatment outcomes, and improving UI patient care. Integration of this technology may also enhance workflow efficiency and advance personalized medicine in urogynecology.



# **Conclusions**

the development of a computational model incorporating simulation, expert input, and historical clinical data represents a significant advancement in improving decision-making for surgical management of urinary incontinence patients. By leveraging these tools, clinicians can make more informed decisions tailored to individual patient needs, ultimately leading to enhanced patient care and improved surgical outcomes.

Further research and validation are needed to ensure clinical viability. Interdisciplinary collaboration and addressing limitations are crucial for realizing this innovative approach.

## References

Imamura M, Hudson J, Wallace SA, MacLennan G, Shimonovich M, Omar MI, Javanbakht M, Moloney E, Becker F, Ternent L, Montgomery I, Mackie P, Saraswat L, Monga A, Vale L, Craig D, Brazzelli M. Surgical interventions for women with stress urinary incontinence: systematic review and network meta-analysis of randomised controlled trials. BMJ. 2019 Jun 5;365:I1842. DOI: 10.1136/bmj.I1842. PMID: 31167796; PMCID: PMC6549286.

Swaminathan S, Qirko K, Smith T, Corcoran E, Wysham NG, Bazaz G, Kappel G, Gerber AN. A machine learning approach to triaging patients with chronic obstructive pulmonary disease. PLoS One. 2017 Nov 22;12(11):e0188532. DOI: 10.1371/journal.pone.0188532 PMID: 29166411; PMCID: PMC5699810.

Kobashi KC, Albo ME, Dmochowski RR, Ginsberg DA, Goldman HB, Gomelsky A, Kraus SR, Sandhu JS, Shepler T, Treadwell JR, Vasavada S, Lemack GE. Surgical Treatment of Female Stress Urinary Incontinence: AUA/SUFU Guideline. J Urol. 2017 Oct;198(4):875-883. DOI: 10.1016/j.juro.2017.06.061 Epub 2017 Jun 15. PMID: 28625508.