Novel TAVR-AI algorithm for Valve Selection

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I, Femi Philip, MD DO NOT have any financial relationships to disclose.

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Background

- TAVR valve choice prioritized procedural safety but life-time management is important.
- Clinical need: Balance safety with long-term outcomes – minimize patient prosthesis mismatch (PPM) and TAV-in-TAV feasibility.
- Can AI driven algorithm valve selection balance procedural safety with lifetime management.
- Our approach: AI algorithmic valve selection validated against the MDT team and 30-day echo outcomes.

Study Objectives

Develop and Validate - CT driven TAVR valve selection algorithm using AI

Compare - Algorithm recommendations vs. MDT team

Assess - Concordance, PPM prevention and TAV-in-TAV feasibility

Human-AI Collaborative Framework

- Framework: Human-in-the-loop system
- AI module autonomously processes pre-procedural MDCT
- AI recommendations are reviewed by the MDT
- Modifications are annotated with structured rationale
- Closed-loop retraining pipeline for model refinement
- Outputs are version-controlled and time-stamped

Methods

Study Design:

Prospective cohort of ~200 patients with CT + TTE + procedural data;

Algorithm tested retrospectively on ~700 patients against two independent vendors' stereotyped CT analyses (external validation, confirming alignment);

Prospectively applied to 200 patients and compared to MDT.

Validation Details:

Internal: 5-fold cross-validation on 700 retrospective cases (92% accuracy for PPM prediction, AUC 0.95; 88% for TTF simulation).

External: Vendor benchmarking for CT-derived inputs; Temporal (prospective 200 vs. MDT) for real-world applicability

Methods

- Primary Endpoints

Concordance with the MDT team decisions (Valve type/ access)

- Secondary Endpoints

PPM avoidance (projected EOA used all discordant cases)

TAV-in-TAV feasibility (proprietary algorithm from the training data set)

Methods

Statistical Analysis

Descriptive stats (means ± SD, frequencies)

Chi-square/Fisher's exact for associations

Cramer's V for effect size

Relative risk reductions with 95% CI

Power: 80% power, $\alpha=0.05$ to detect ≥7% absolute PPM reduction

Tools: Python 3.9 (SciPy, StatsModels)

Algorithm Paradigms

Sizing: S3UR by annular area/diameter; Evolut by perimeter/diameter

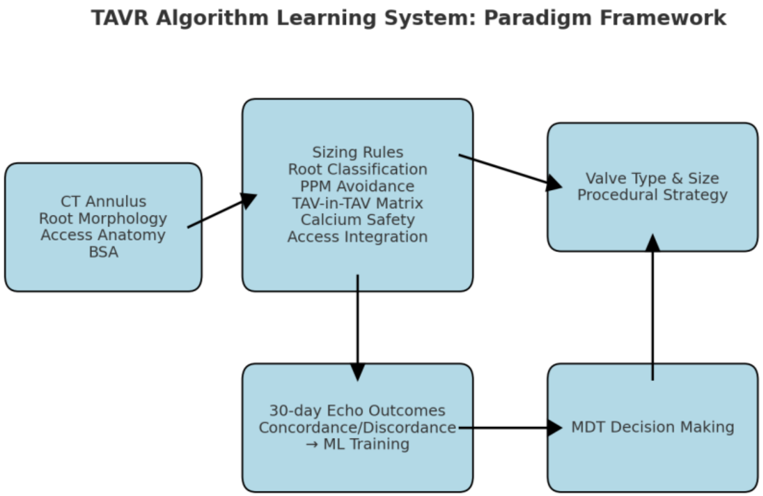
Root morphology: classification (Type I, II, III)

PPM thresholds: (EOAi <0.70 moderate, <0.55 severe)

TAV-in-TAV feasibility: VTC, VTSTJ, VTA using coronary height, sinus, STJ clearance

Calcium safety: downsizing or overfill limits if severe

Access integration: iliofemoral diameter and tortuosity



Model Architecture

Model: Feed-forward supervised neural network (MLP)

Inputs: CT + clinical features

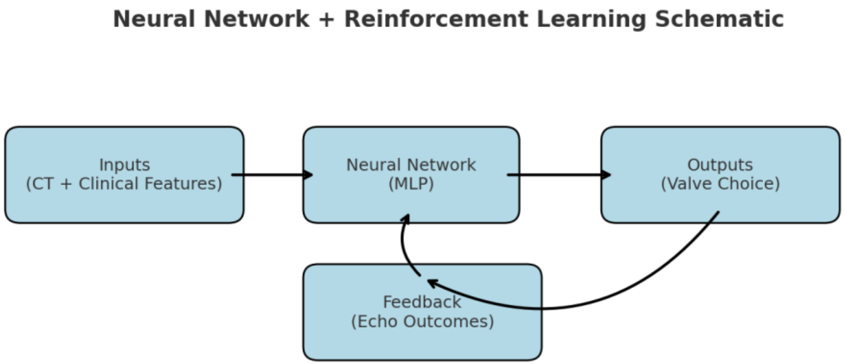
Outputs: Valve type, valve size, procedural strategy

Reinforcement Learning Feedback:

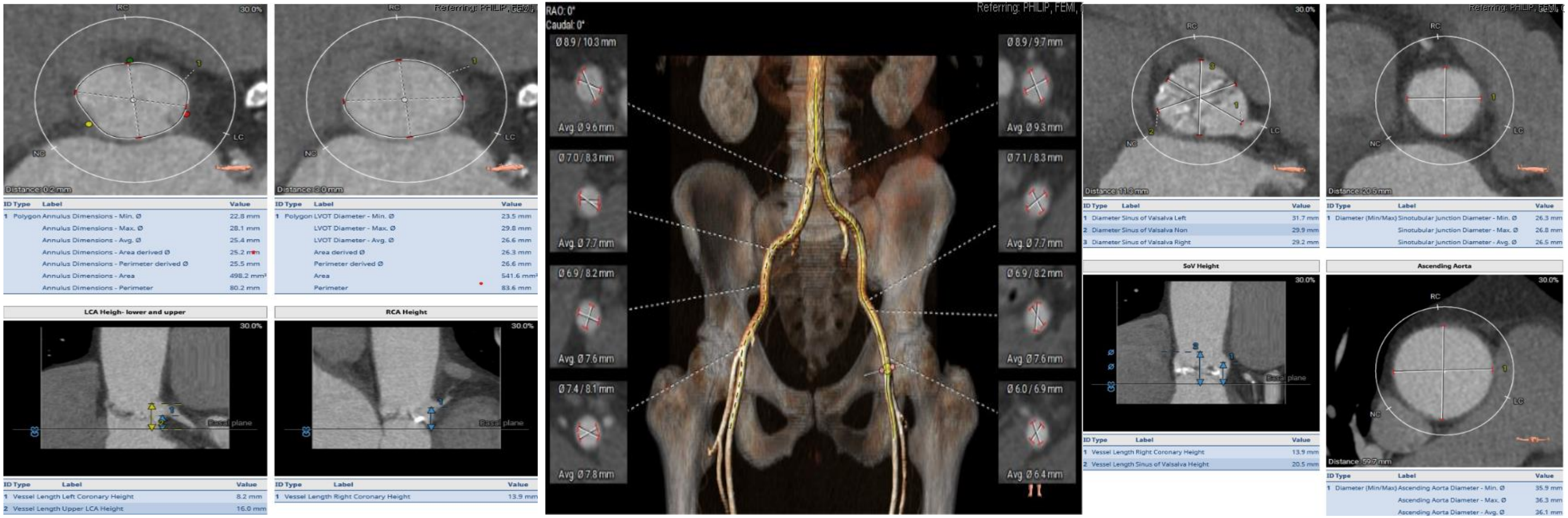
Reward = concordance + optimal echo (no PPM, low MG, no AR)

Penalty = mismatch or poor outcomes

Model updates weights to maximize long-term reward



TAVI AI: Model 1



TAVI AI: DEMO Model:1

Results- Baseline Characteristics

Characteristic	Value
Number of Patients	200
Age (mean ± SD)	72 ± 9 years
Female (%)	47
BSA (mean ± SD)	1.85 ± 0.25 m^2
STS Risk Score (mean ± SD)	4.2 ± 2.1%
Hypertension (%)	82
Diabetes (%)	35
Coronary Artery Disease (%)	48
LVEF (mean ± SD)	55 ± 12%
Annular Area (mean ± SD)	450 ± 120 mm^2
Annular Perimeter (mean ± SD)	75 ± 10 mm
Coronary Heights Left (mean ± SD)	14 ± 3 mm
Coronary Heights Right (mean ± SD)	16 ± 5 mm
Calcification (Agatston mean ± SD)	2200 ± 1500 AU
Mean gradient	42 ± 8 mm Hg

Results – Baseline Characteristics

Valve types: 60% S3UR, 40% Evolut FX+

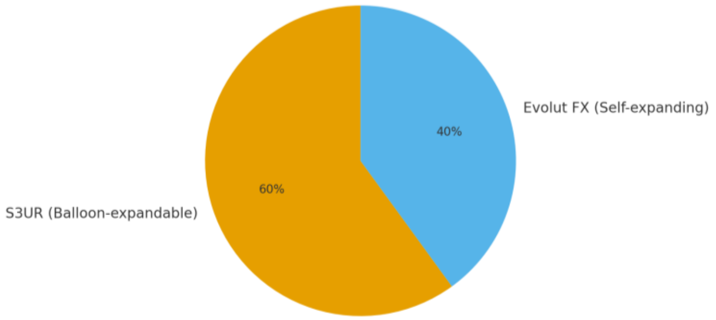
Root morphologies: Type I (40%), Type II (25%), Type III (35%)

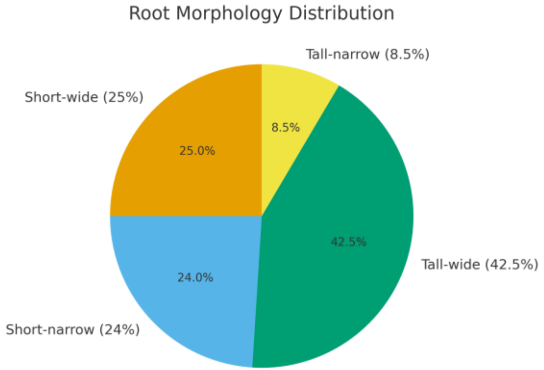
BSA mean 1.9 m² (range 1.27–2.5)

Coronary heights: LCA mean 13.5 mm; 20% <12 mm

Calcium: Moderate 45%, Severe 30%

Access: >90% transfemoral feasible; 10% borderline





Results: 30-day Outcomes

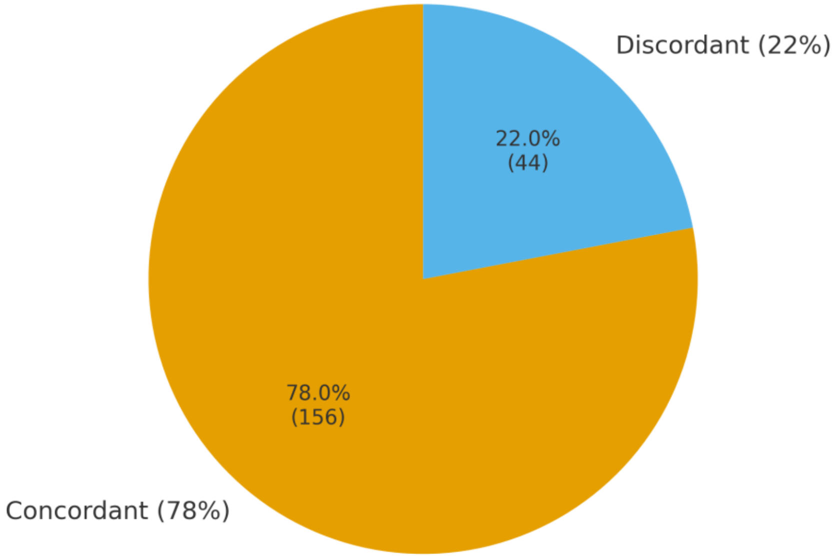
- Procedural Success: 98%
- All cause mortality: 1.5%
- Disabling stroke: 1.5%
- Major vascular complications: 5%
- Permanent Pacemaker: 8%
- Mean gradient: 9.6 ± 3.8 mmHg

Results

Primary Endpoint

- Overall concordance 78% Cramer's V=0.26, $p<0.001$;
- AI superiority in discordant cases 63.6% ($\chi^2=90.75$, $p=1.63e-21$, $V=0.67$)

Algorithm vs Valve Team Concordance (N=200)



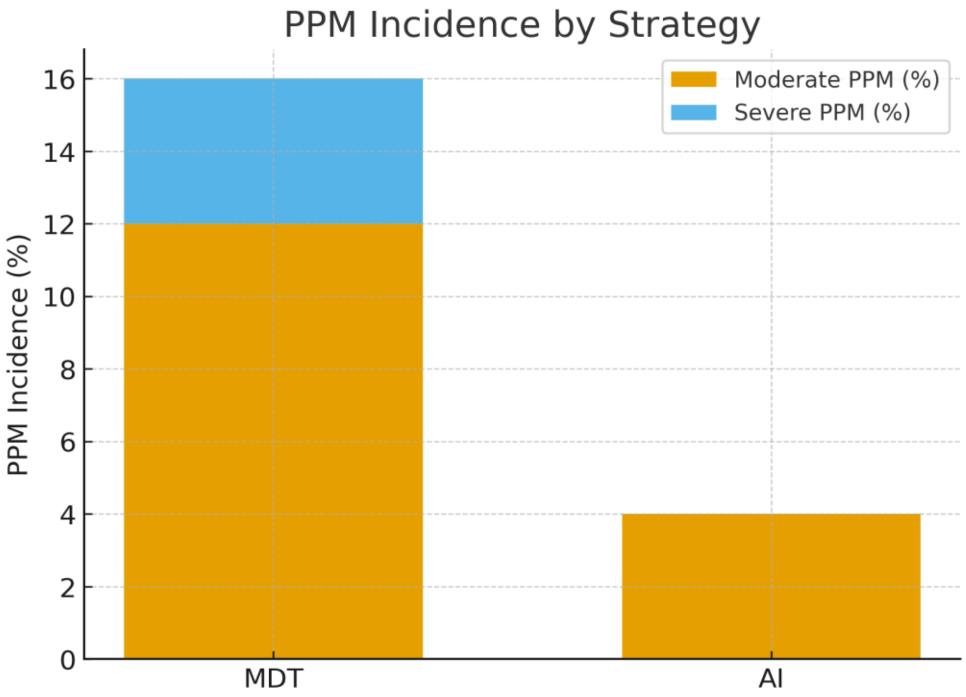
Results

PPM

Absolute reduction: 12% (95% CI 6.5-18%);

Relative reduction: 75% (95% CI 50-91.2%, p=9.23e-10

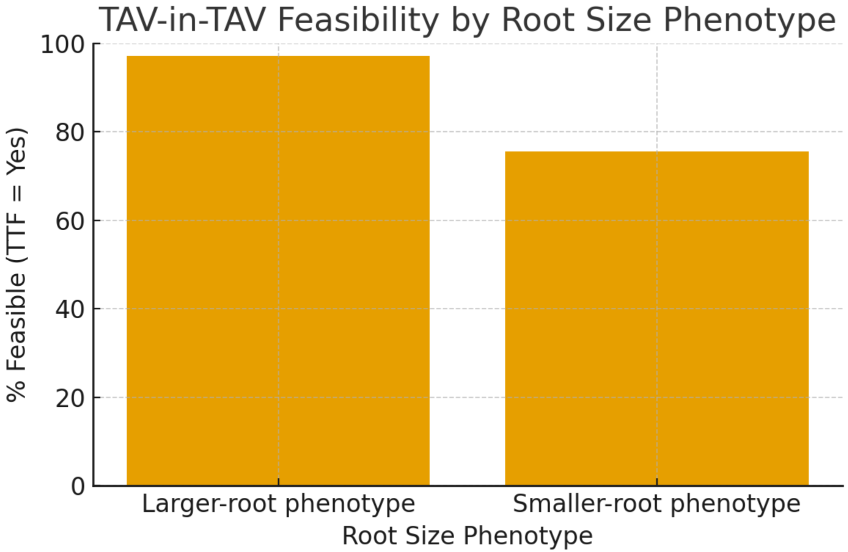
Group	Moderate PPM (%)	Severe PPM (%)	Total PPM (%)
MDT (32/200)	12	4	16
AI (8/200)	4	0	4



Results

TAV-in-TAV

•Overall feasibility: 90%
•Larger-root phenotype: 97.2% feasible
•Smaller-root phenotype: 75.5% feasible
• Most “spacious” group is highest (~100%), and the most “compact” group is lowest (~66.7%).



Limitations

- Single, small study.
- 30-day follow-up included but longer follow-up is needed.
- AI trained on historical data risks overfitting.
- PPM measured and compared to predicted EOA.

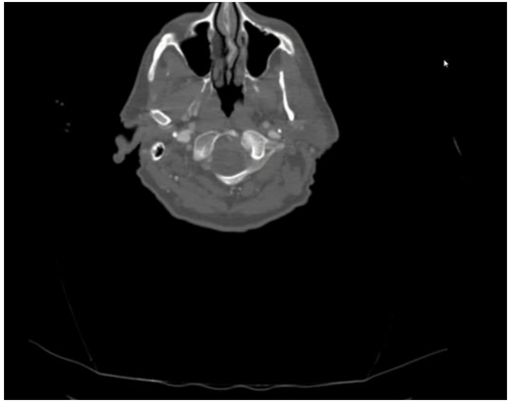
- Validation of decision fidelity

- Cost/ Integration barriers not assessed.

Conclusion

- Algorithm shows high concordance with the MDT team
- Reduced the PPM incidence
- Determine TAV-In-TAV feasibility
- Provides standardized, reproducible decision support
- Potential to augment and not replace clinical judgement

Appendix- Model 2.0



Appendix: Algorithm Backend (Pseudocode)

- Inputs: CT annulus, perimeter, LVOT, coronaries, SOV/STJ, BSA, calcium, access
- If short-wide root or low LCA → favor S3UR
- If tubular root + large BSA → favor Evolut
- Check calcium → limit oversizing if S3UR
- Choose size from manufacturer sizing tables
- Predict EOAi → classify PPM risk
- Output: Valve system, size, procedural notes
- Feedback: Compare to Valve Team choice + 30-day echo
- Reward = concordance + optimal hemodynamics
- Reinforcement loop updates weights to favor high reward patterns