Charles Sturt University

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The Data-Schema Bottleneck: Benchmarking Sixteen Deep Learning Architectures for Real-Time Starlink LEO Telemetry Management

Tanmoy Debnath (tdebnath@csu.edu.au)
Sourabhi Debnath (sdebnath@csu.edu.au)
Miroslaw Narbutt (miroslaw.narbutt@tudblin.ie)
Maumita Bhattacharya (mbhattacharya@csu.edu.au)

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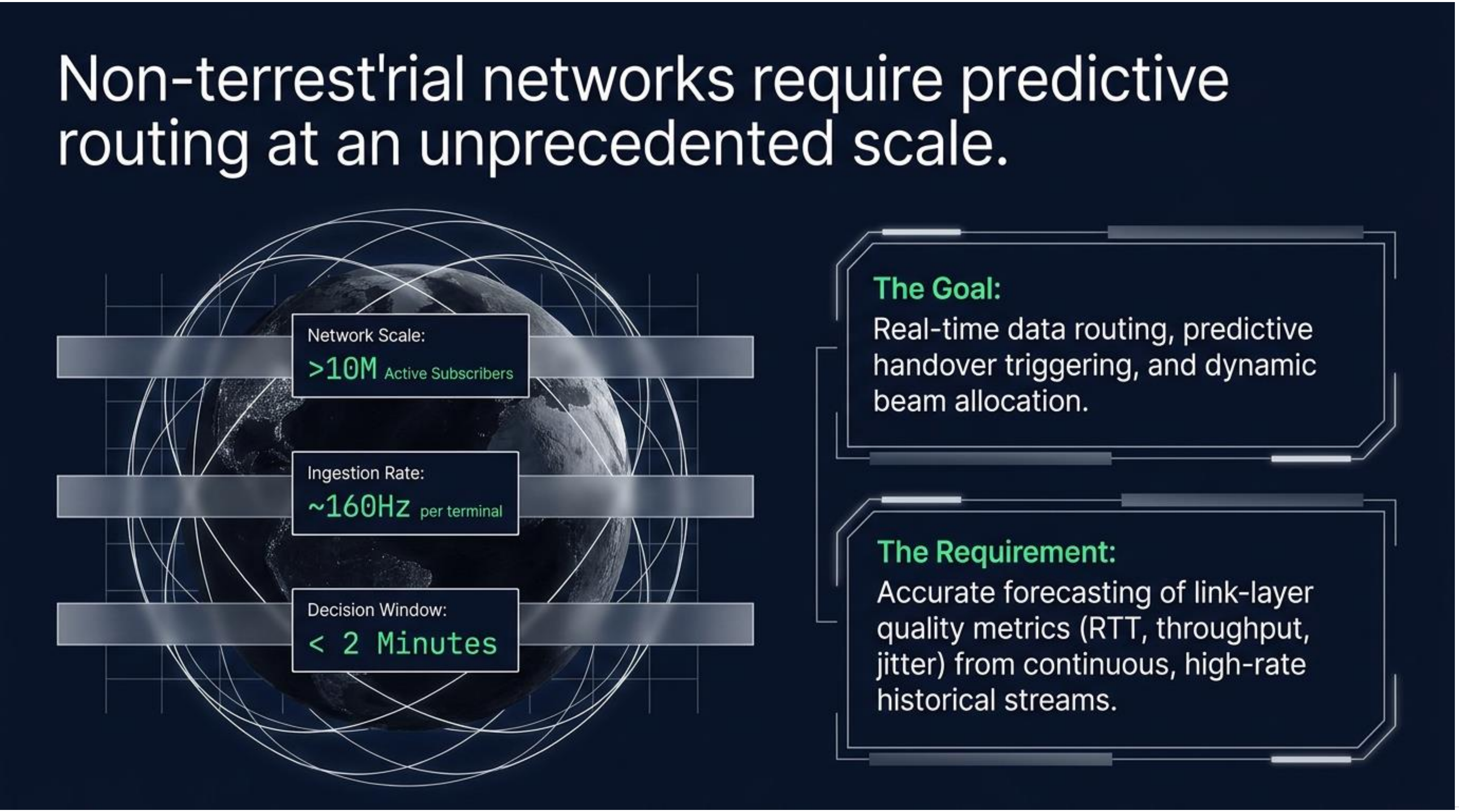
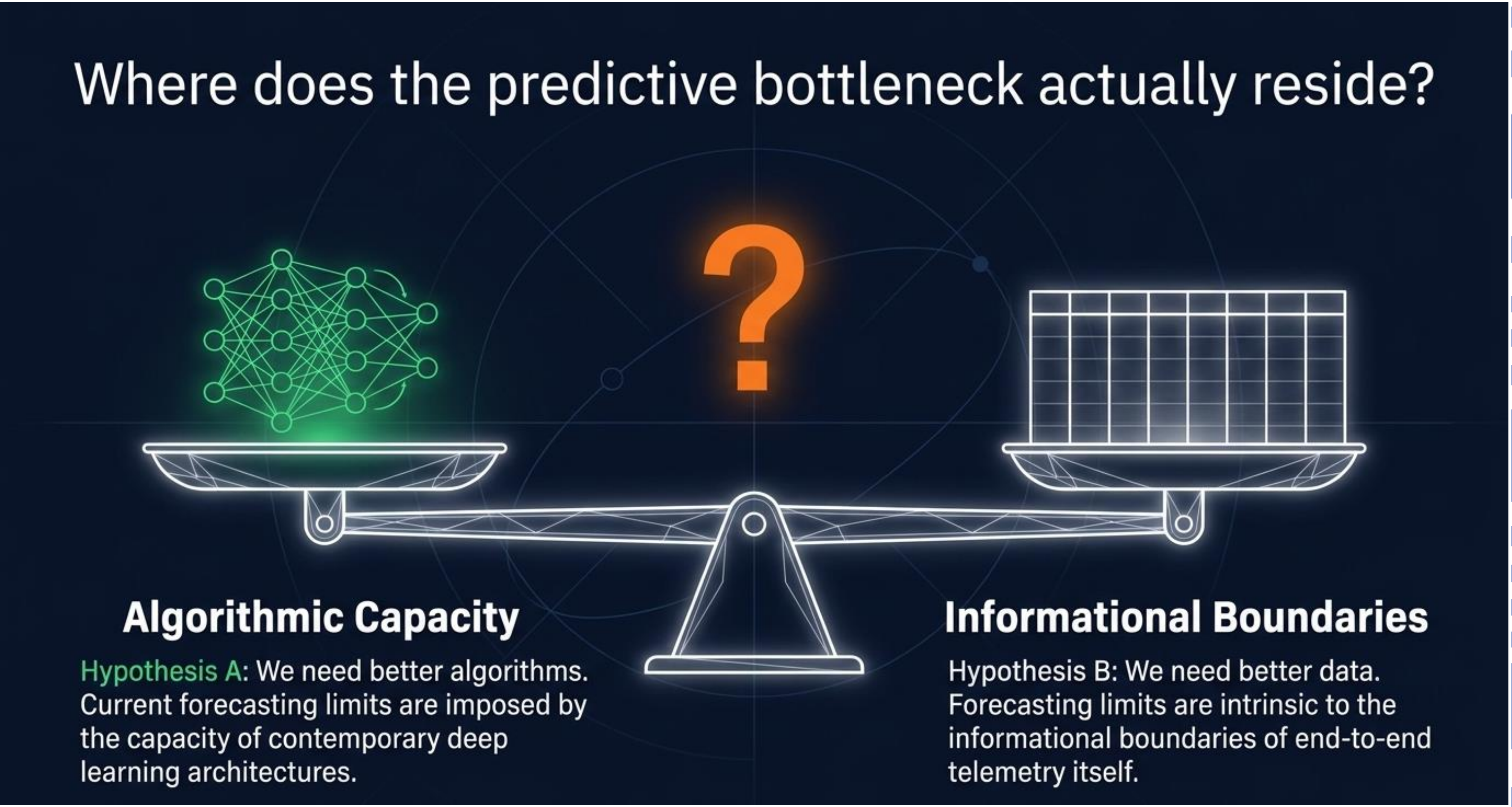
Presentation Outline

- Introduction
- Methodology
- Results
- Limitations and Future Directions
- Conclusion

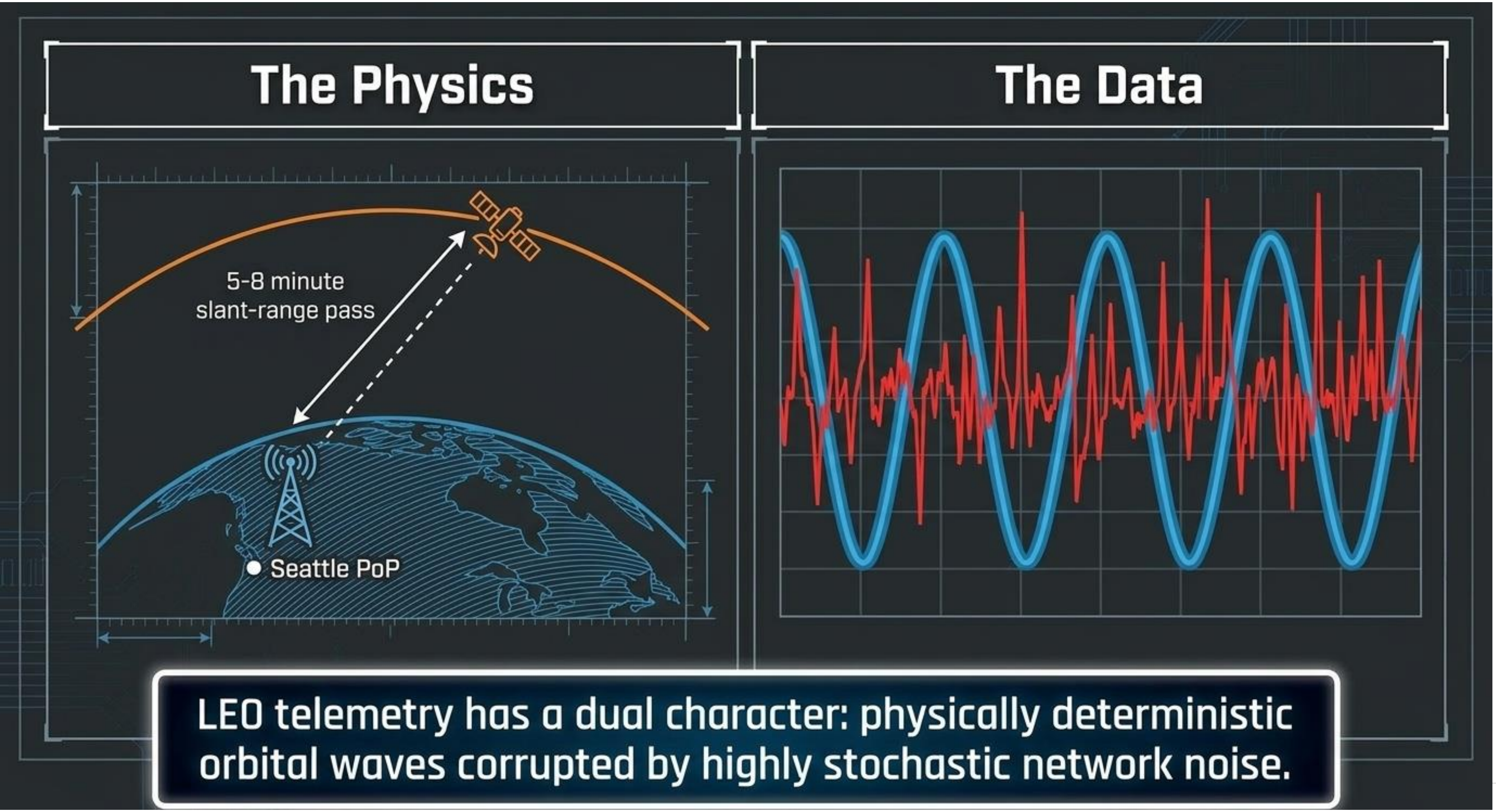
Introduction: The Rise of LEO Satellite Networks



Introduction: Orbital Mechanics & Telemetry Dynamics

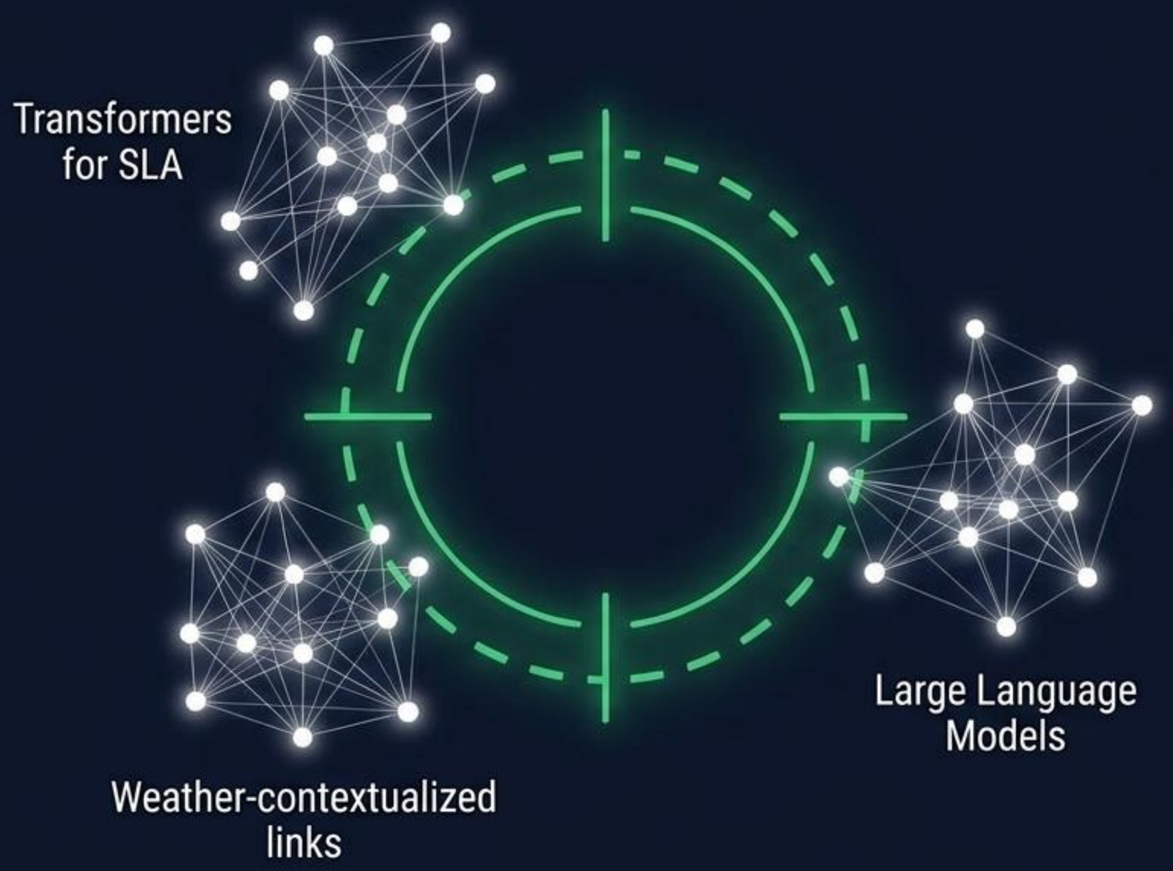


Introduction: Orbital Mechanics & Telemetry Dynamics



Introduction: Gaps in Current Research

Previous deep learning studies lack controlled, architecture-spanning benchmarks.



Fragmented Evaluations

Prior work evaluates narrow subsets of models under heterogeneous dataset splits.

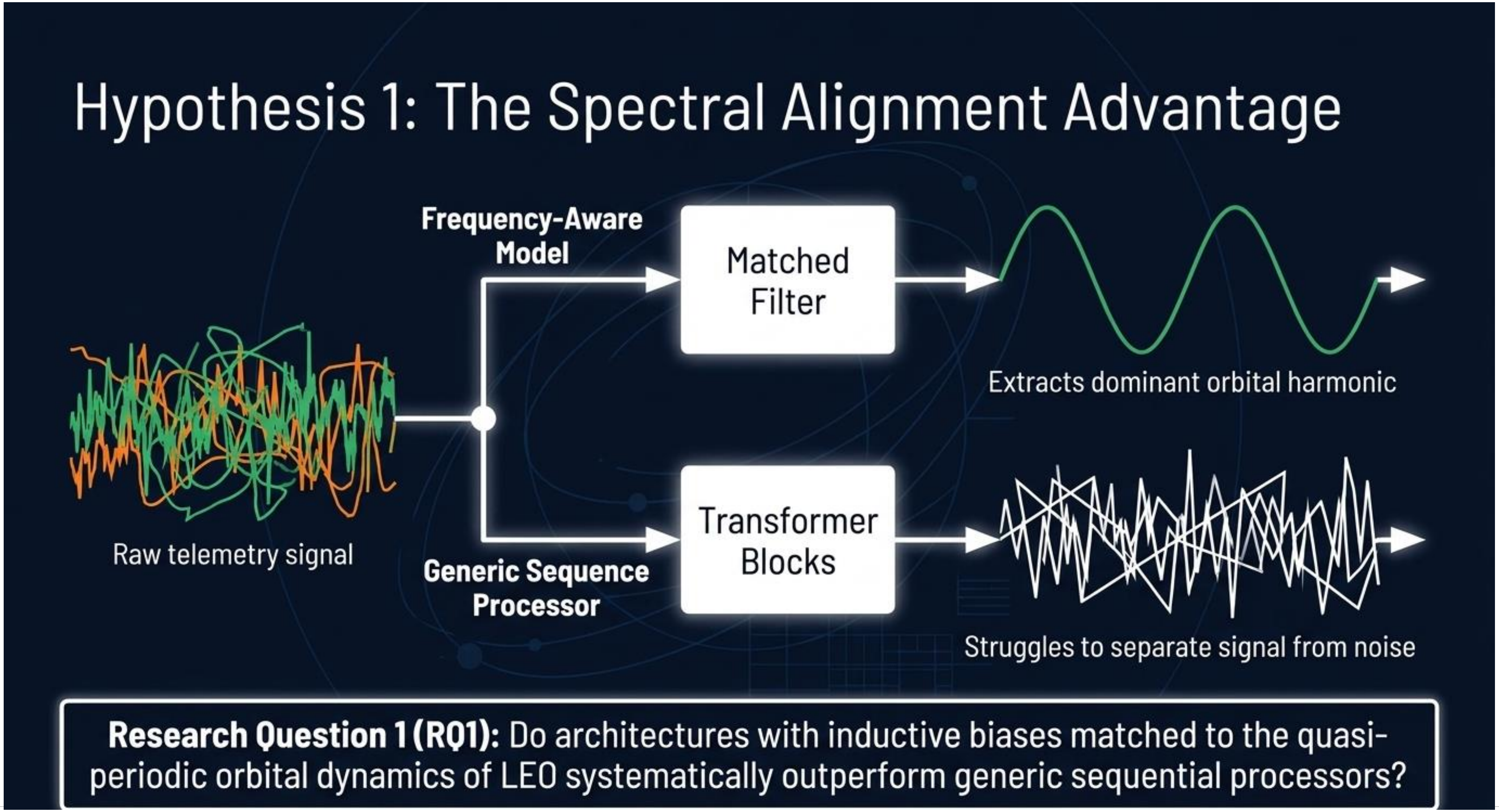
The Missing Link

No existing study explicitly defines the empirical predictability ceiling for end-to-end LEO telemetry.

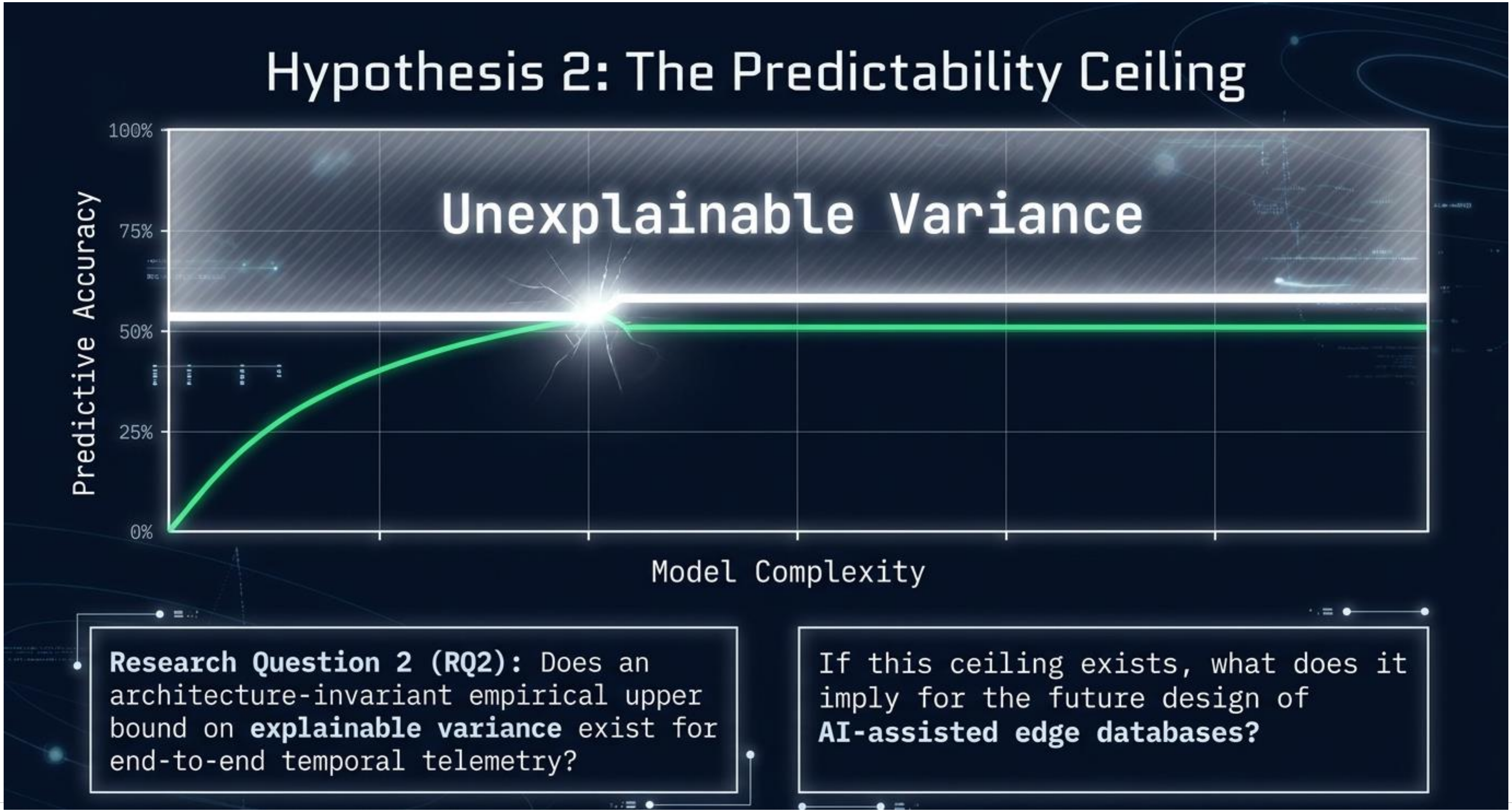
The Operational Risk

Operations teams are investing in larger AI models without knowing if a hard informational ceiling exists.

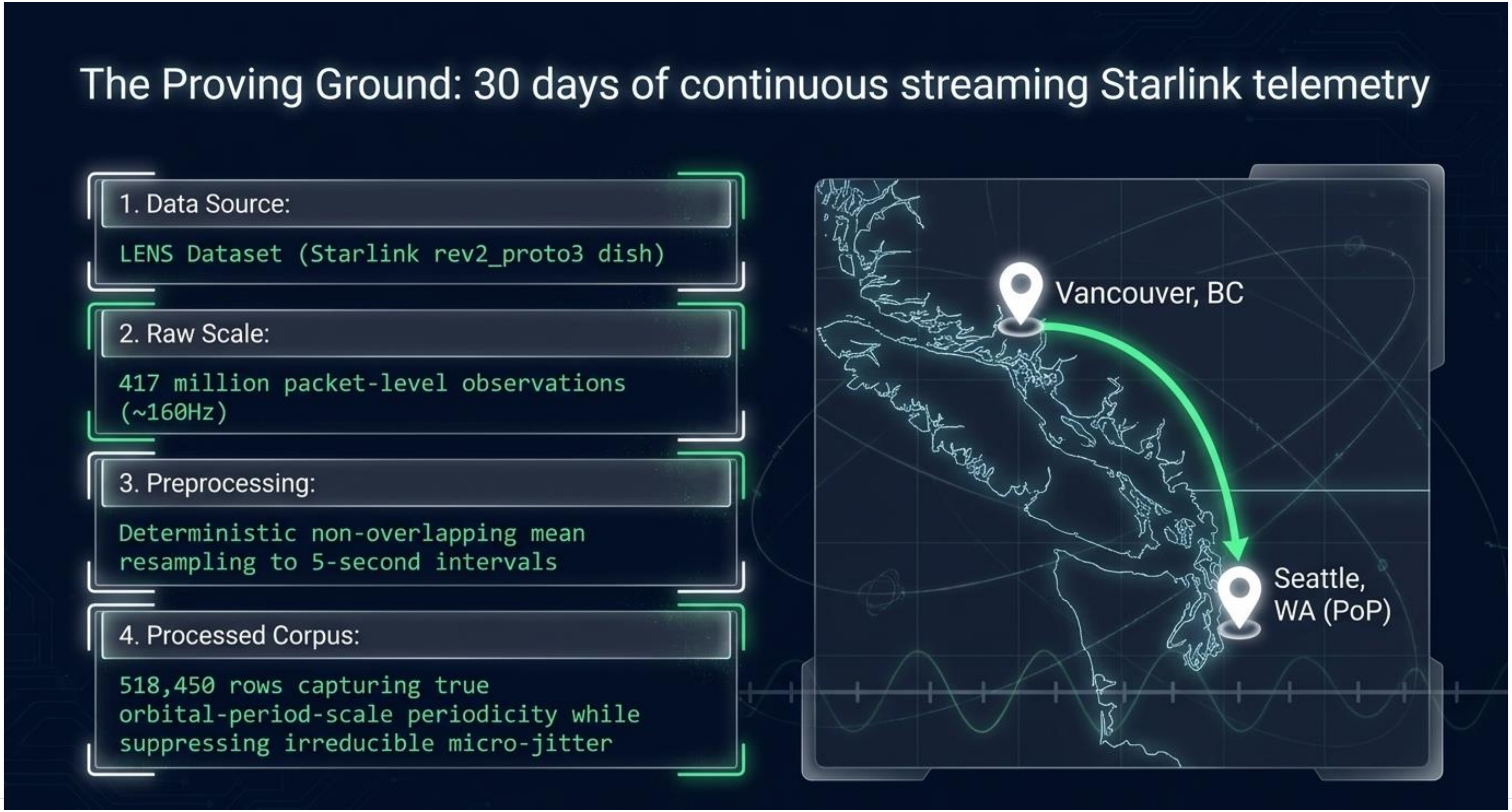
Introduction: Two Core Hypotheses



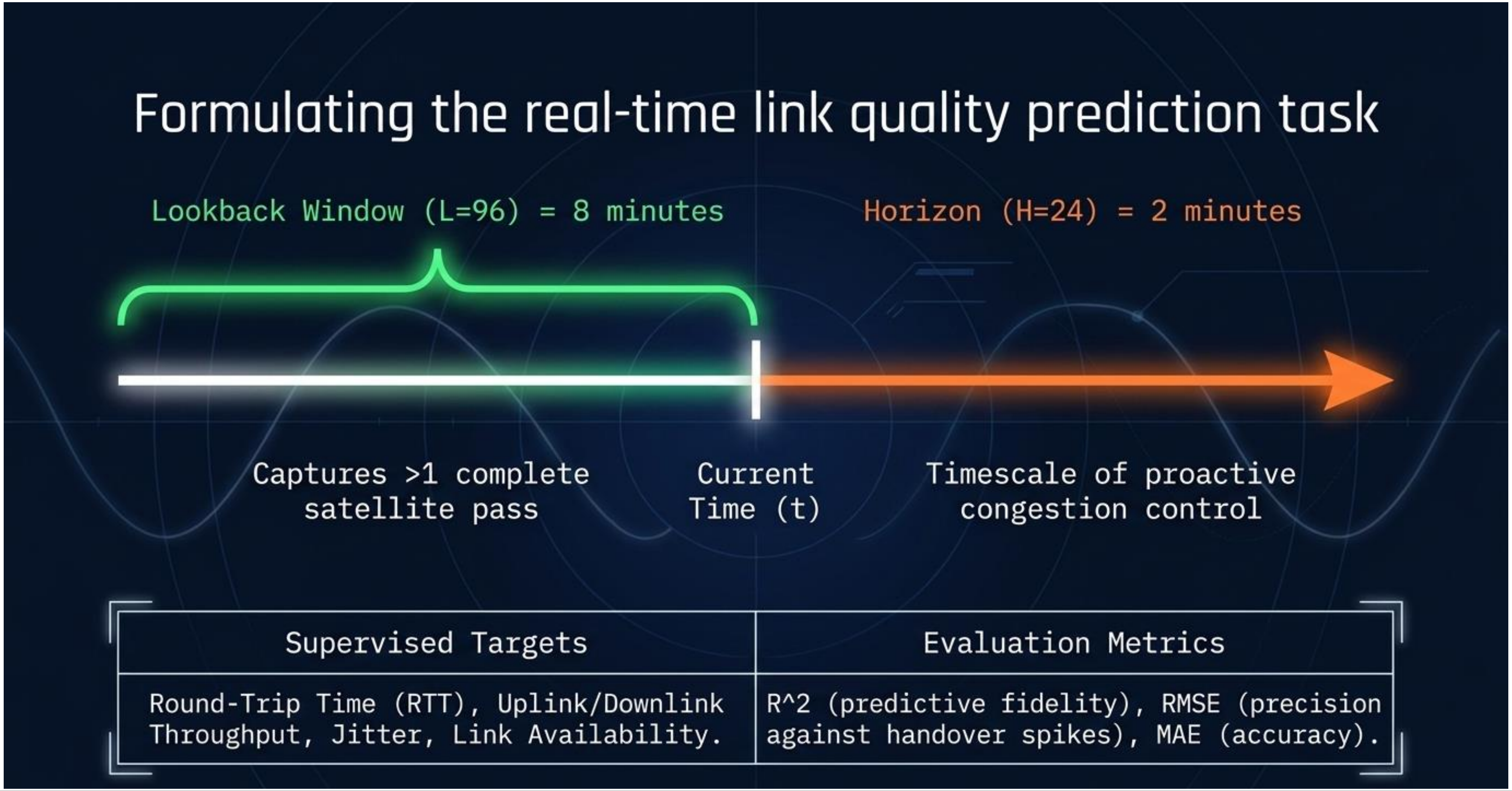
Introduction: Two Core Hypotheses *contd.*



Methodology: The LENS Dataset



Methodology: Feature Engineering & Preprocessing



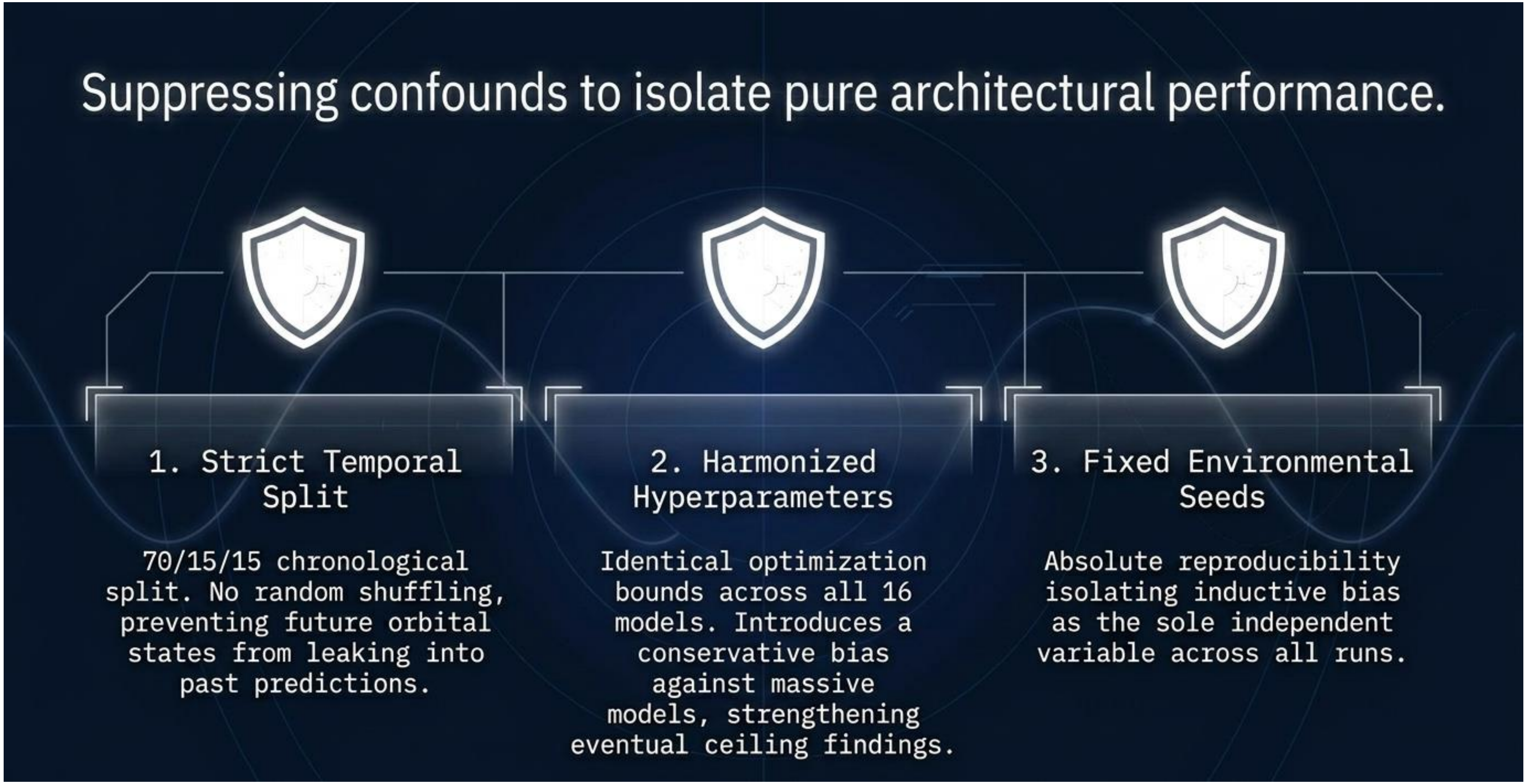
Methodology: Model Taxonomy (The 16 Competitors)

The LENS Dataset: 30 days of real Vancouver Starlink telemetry,
417 Million observations, strictly chronological split.

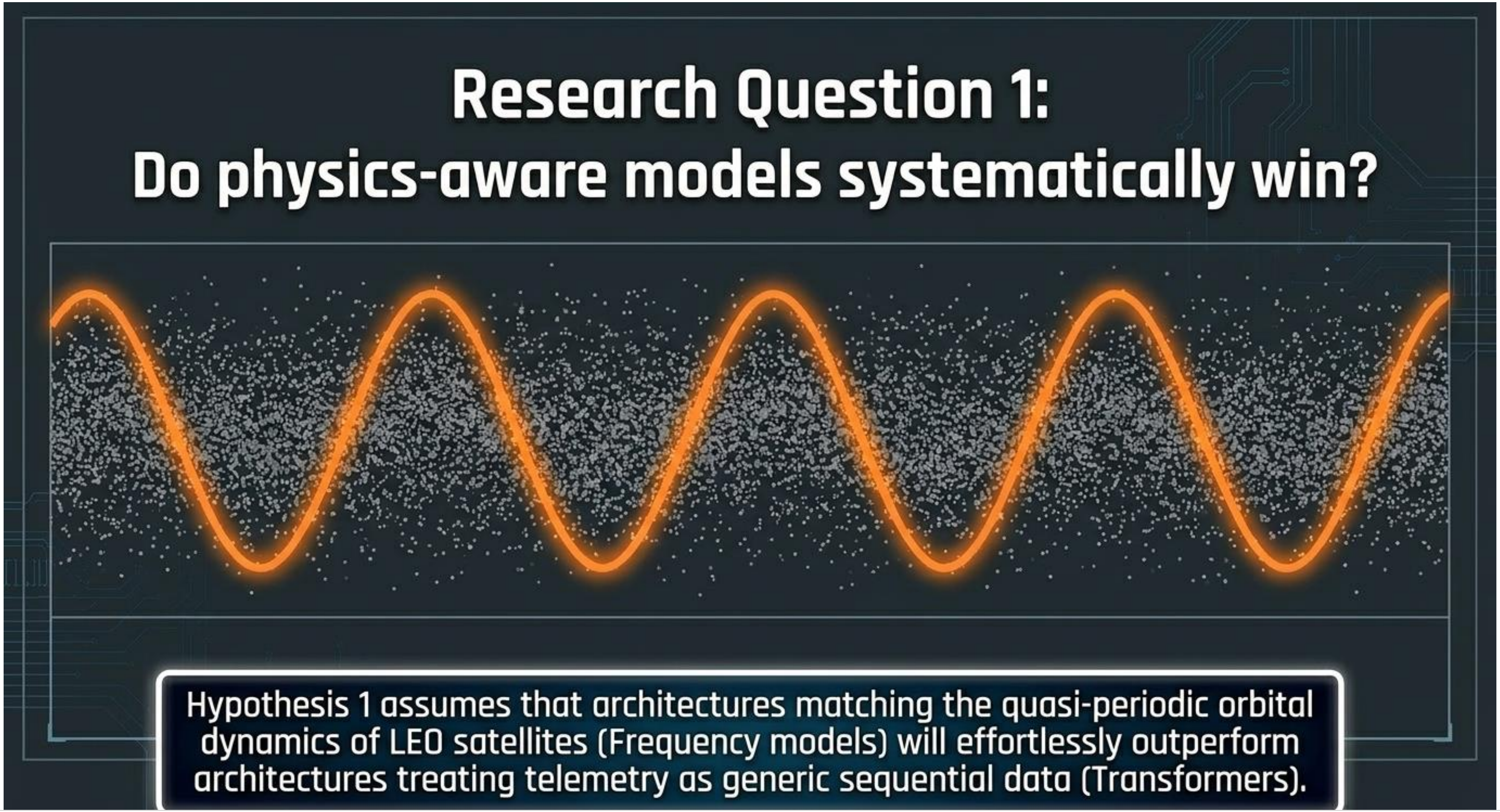
The Suspect Board: 16 AI Models

Frequency / Multi-scale	Transformers	Linear / MLP	State-Space / Foundation
A Priori Alignment: Strong	A Priori Alignment: Moderate	A Priori Alignment: Poor	A Priori Alignment: Weak
Explicitly designed to decompose periodic waves.	Heavyweight attention mechanisms looking for sequence patterns.	Basic trend decomposition.	Smooth state evolution and generic pre-training.
MSGNet, TimeMixer, TimesNet, TimeFilter, WPMixer, MultiPatchIF.	iTransformer, TimeXer, PatchTST, PAttn, Autoformer, Informer.	Koopa, DLinear.	Mamba, Sundial.

Methodology: Experimental Protocol



Results : Research Question 1



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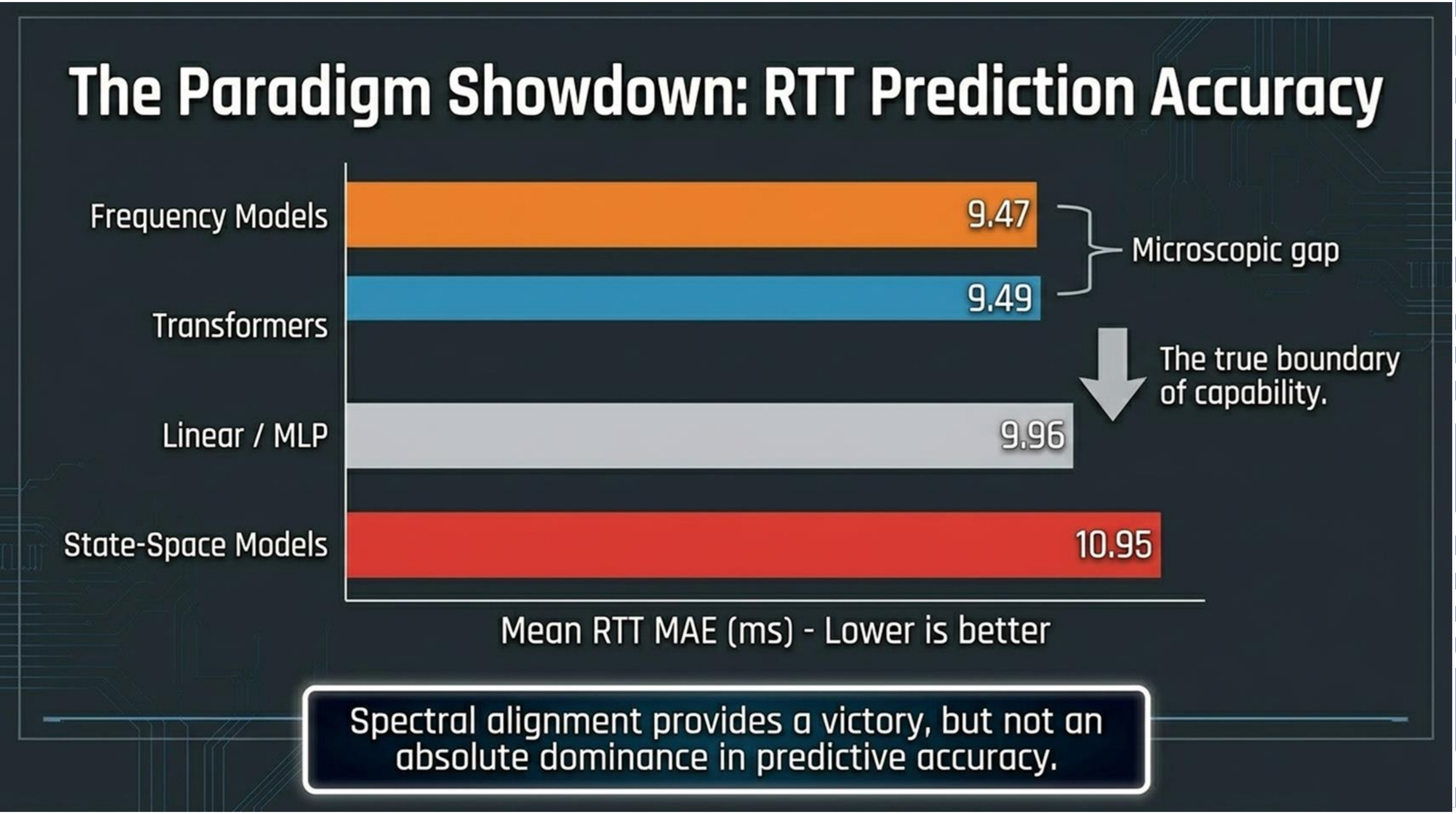

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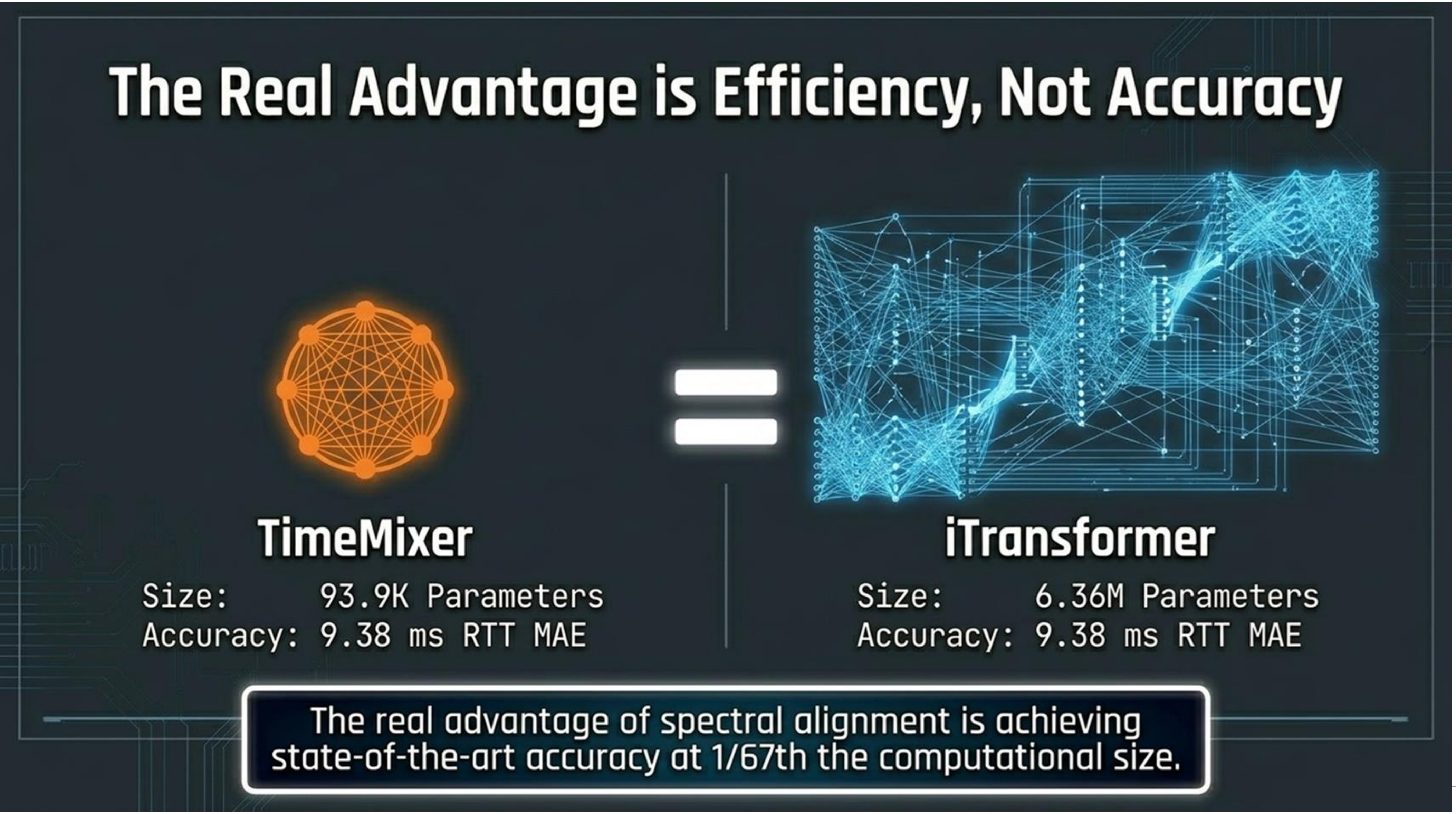
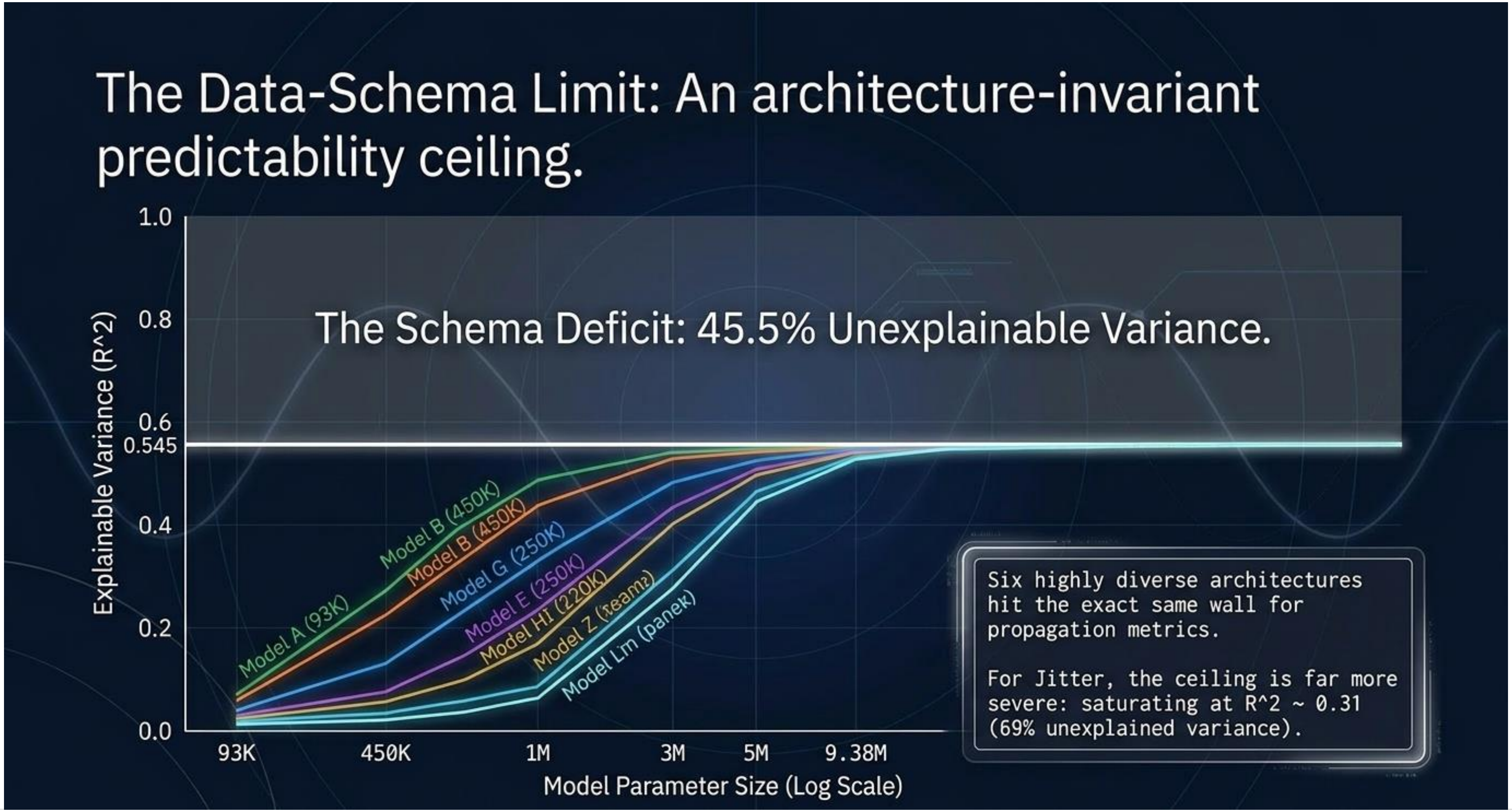
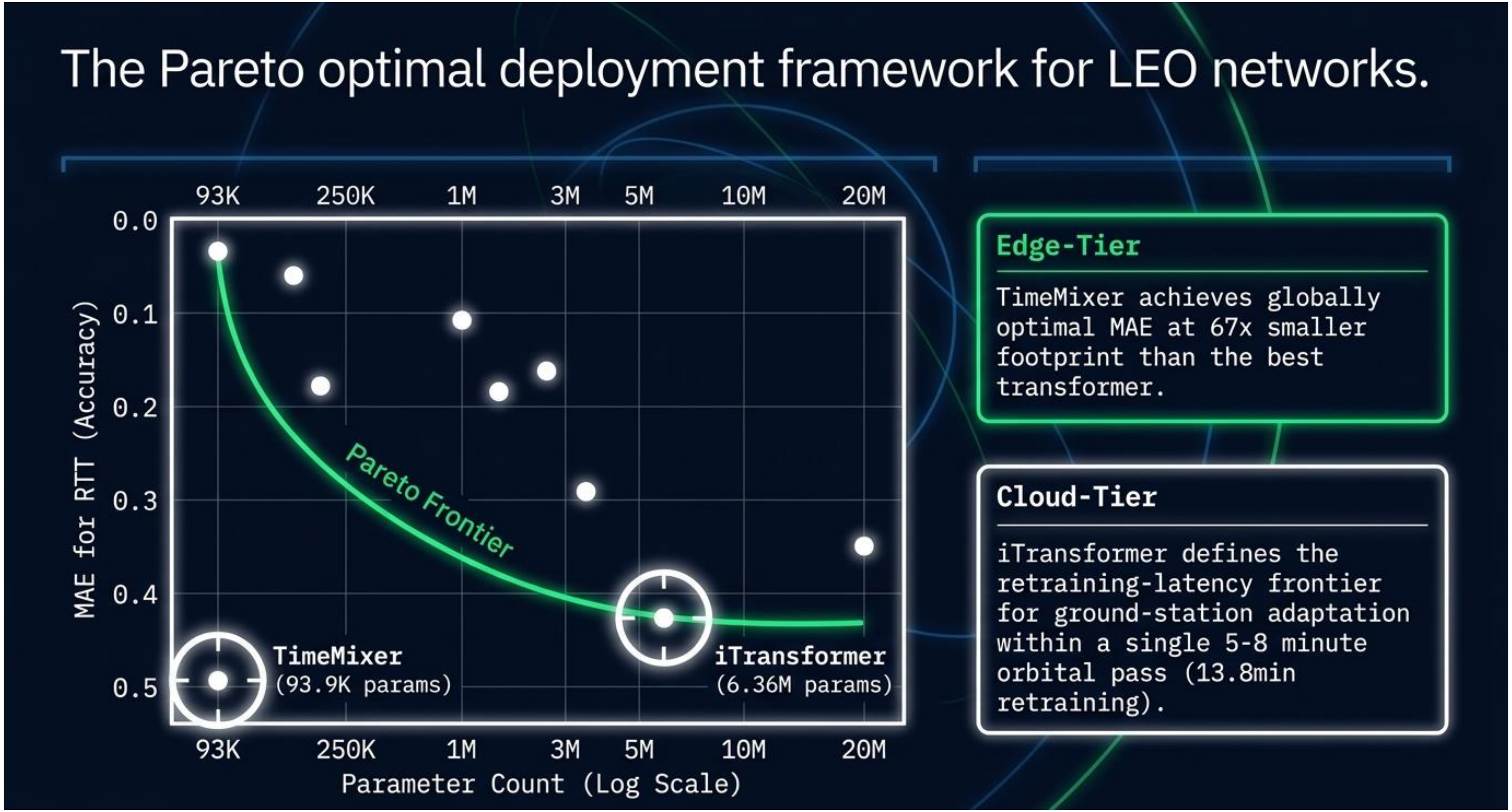


Results : Research Question 1

Results: Research Question 2

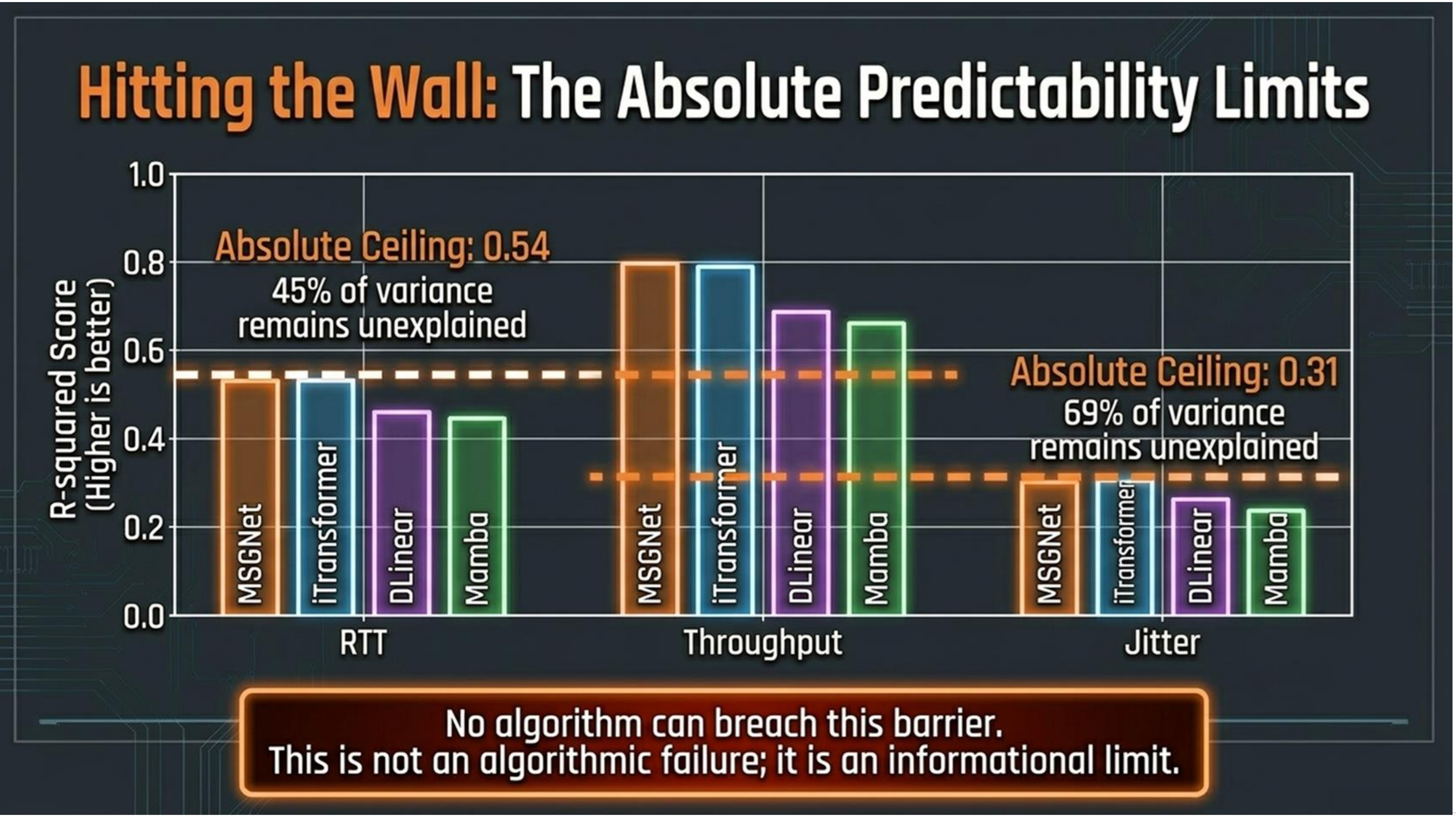


Results

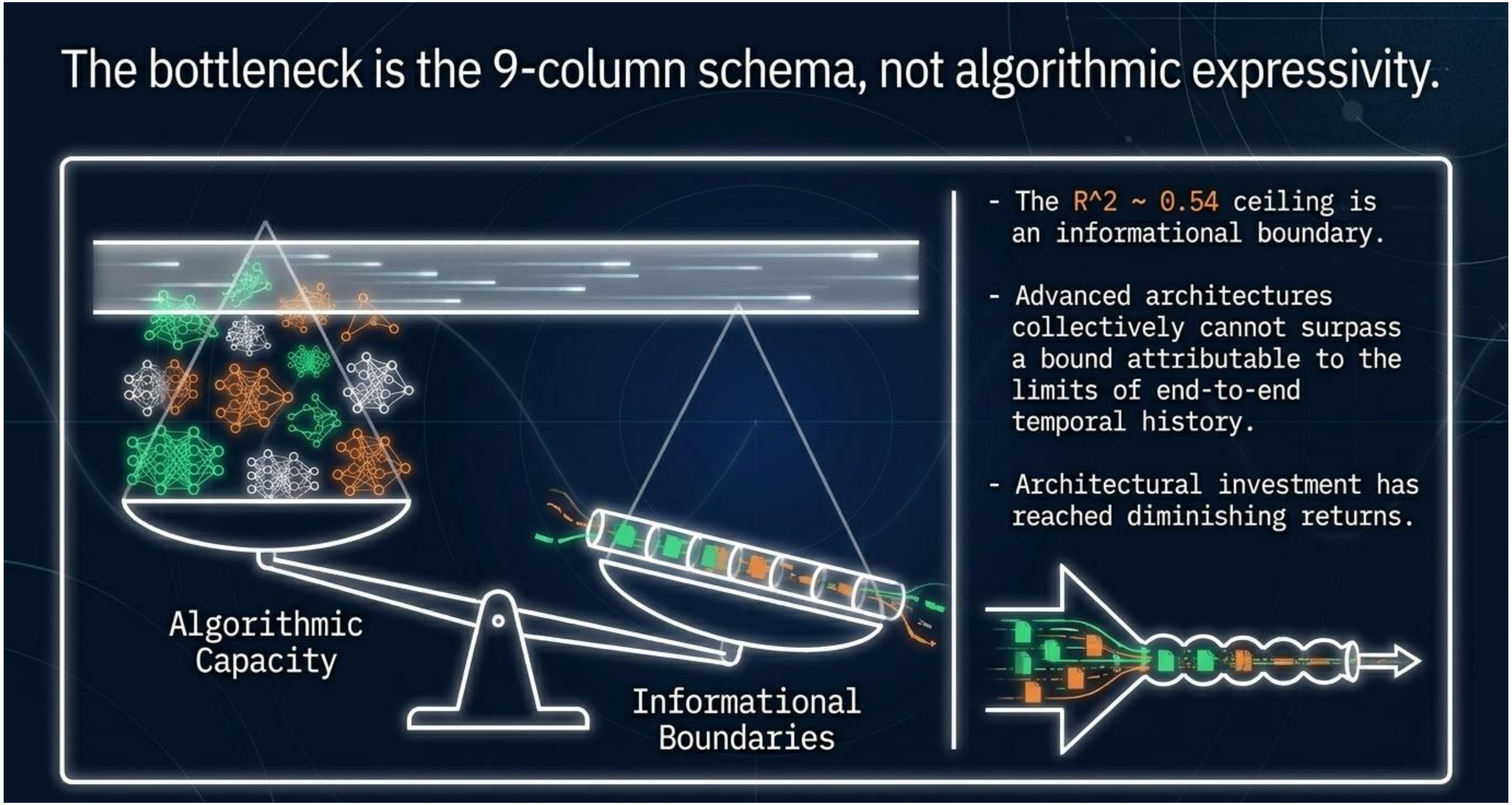


The Pareto optimal deployment framework for LEO networks.
93K
250K
1M
3M
5M
10M
20M
0.0
0.1
0.2
0.3
0.4
0.5
MAE for RTT (Accuracy)
Pareto Frontier
TimeMixer
(93.9K params)
iTransformer
(6.36M params)
Parameter Count (Log Scale)
Edge-Tier
TimeMixer achieves globally optimal MAE at 67x smaller footprint than the best transformer.
Cloud-Tier
iTransformer defines the retraining-latency frontier for ground-station adaptation within a single 5-8 minute orbital pass (13.8min retraining).

Results


Hitting the Wall: The Absolute Predictability Limits
R-squared Score (Higher is better)
1.0
0.8
0.6
0.4
0.2
0.0
Absolute Ceiling: 0.54
45% of variance remains unexplained
Absolute Ceiling: 0.31
69% of variance remains unexplained
MSGNet
iTransformer
DLinear
Mamba
RTT
Throughput
Jitter
No algorithm can breach this barrier.
This is not an algorithmic failure; it is an informational limit.

Results: The Necessity of Schema Augmentation

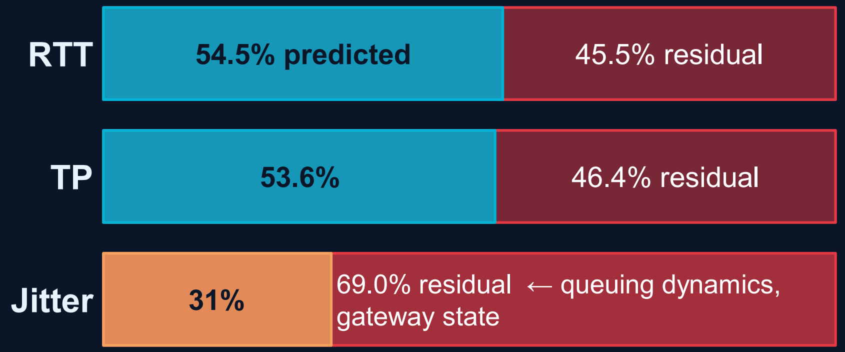


The Data-Schema Bottleneck: A Fundamental Information Limit

What the 9-column schema cannot capture:

- ⚠ Physical-layer SINR / beam ID
- ⚠ Gateway congestion state
- ⚠ Satellite ephemeris
- ⚠ Cross-user traffic interference
- ⚠ Atmospheric / weather context

Explained vs. Unexplained Variance



Architecture-Invariant Ceiling

Top-6 cluster: $\Delta R^2 = 0.011$ (4 freq. + 2 Transformer models)

Convergence evidences information limit, not architectural failure

System design implication:

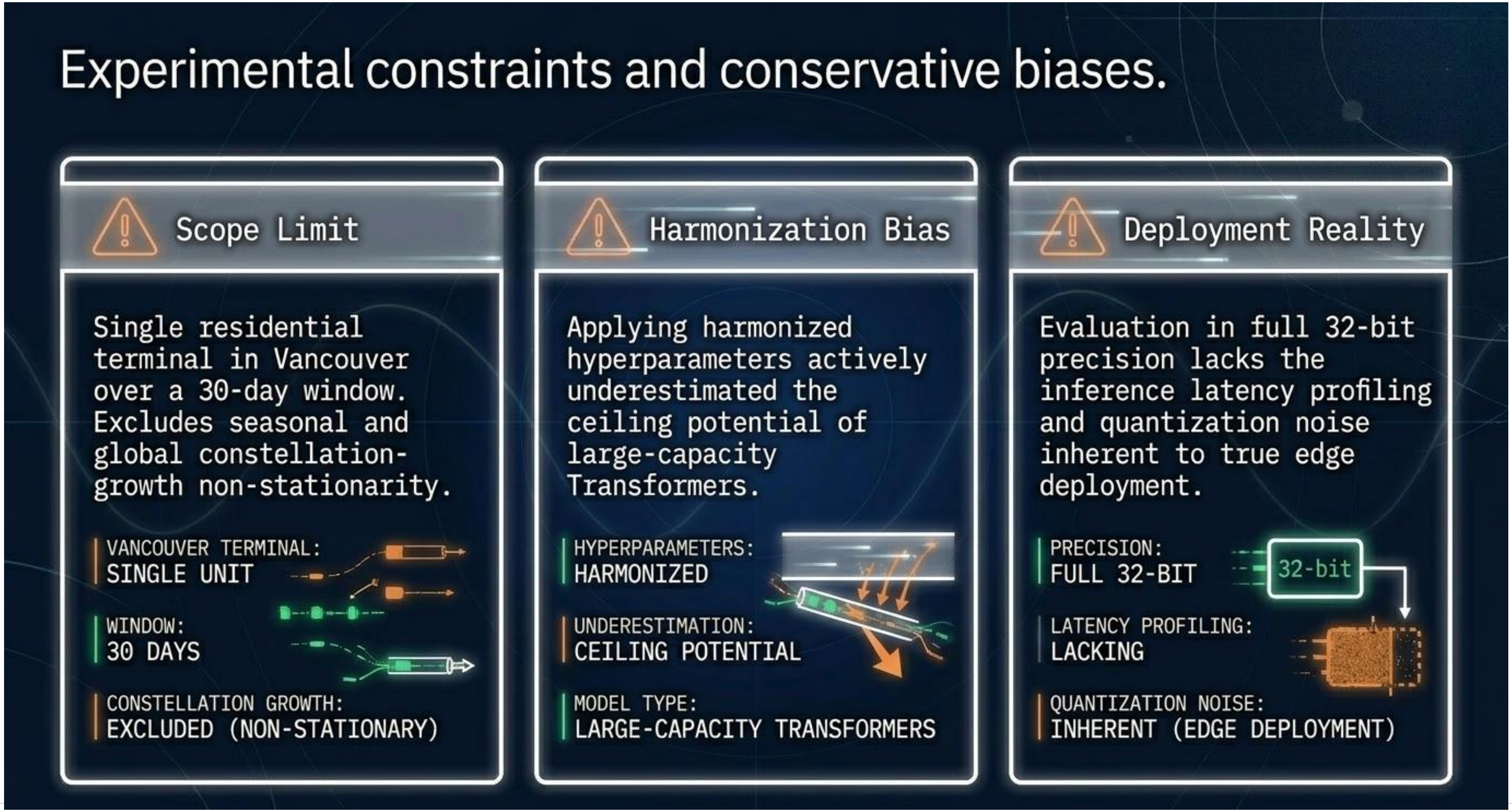
No further architectural refinement operating on this 9-column schema will breach:

- RTT ceiling at $R^2 \approx 0.545$
- Jitter ceiling at $R^2 \approx 0.310$

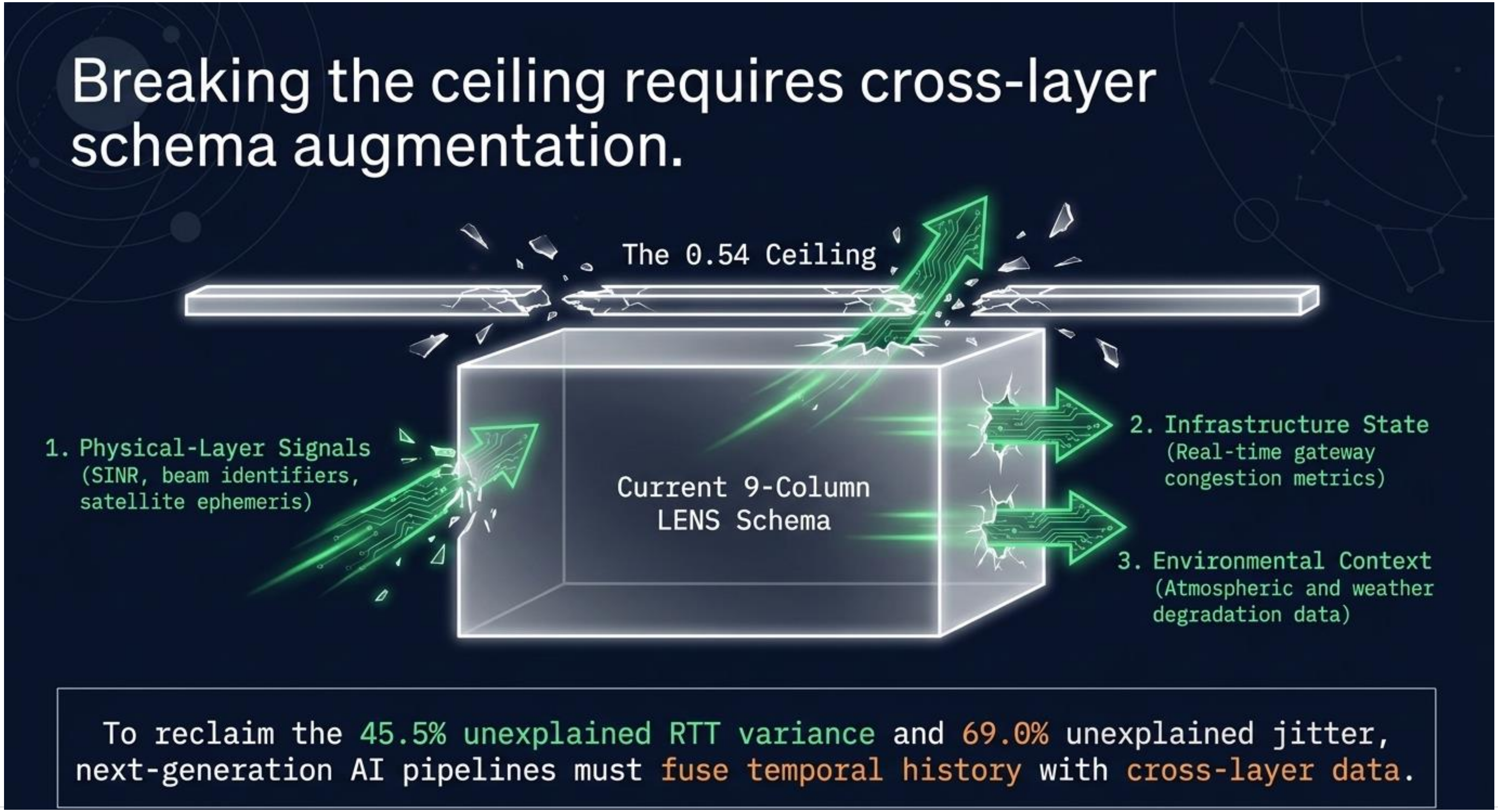
The decisive next intervention is schema augmentation, not a better model.

"This plateau represents a fundamental informational limit of the data schema itself, not an algorithmic deficiency."

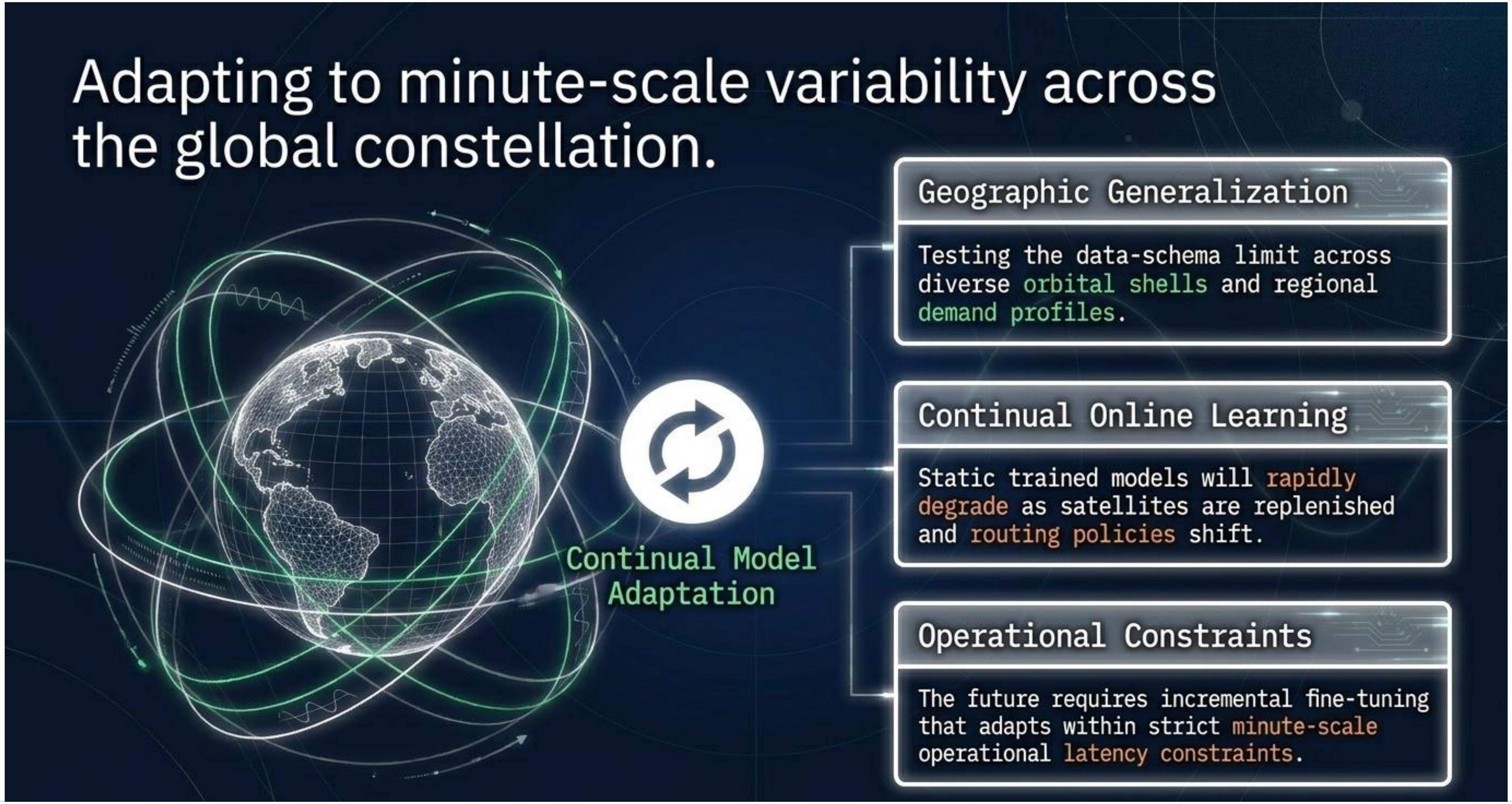
Experimental Limitations



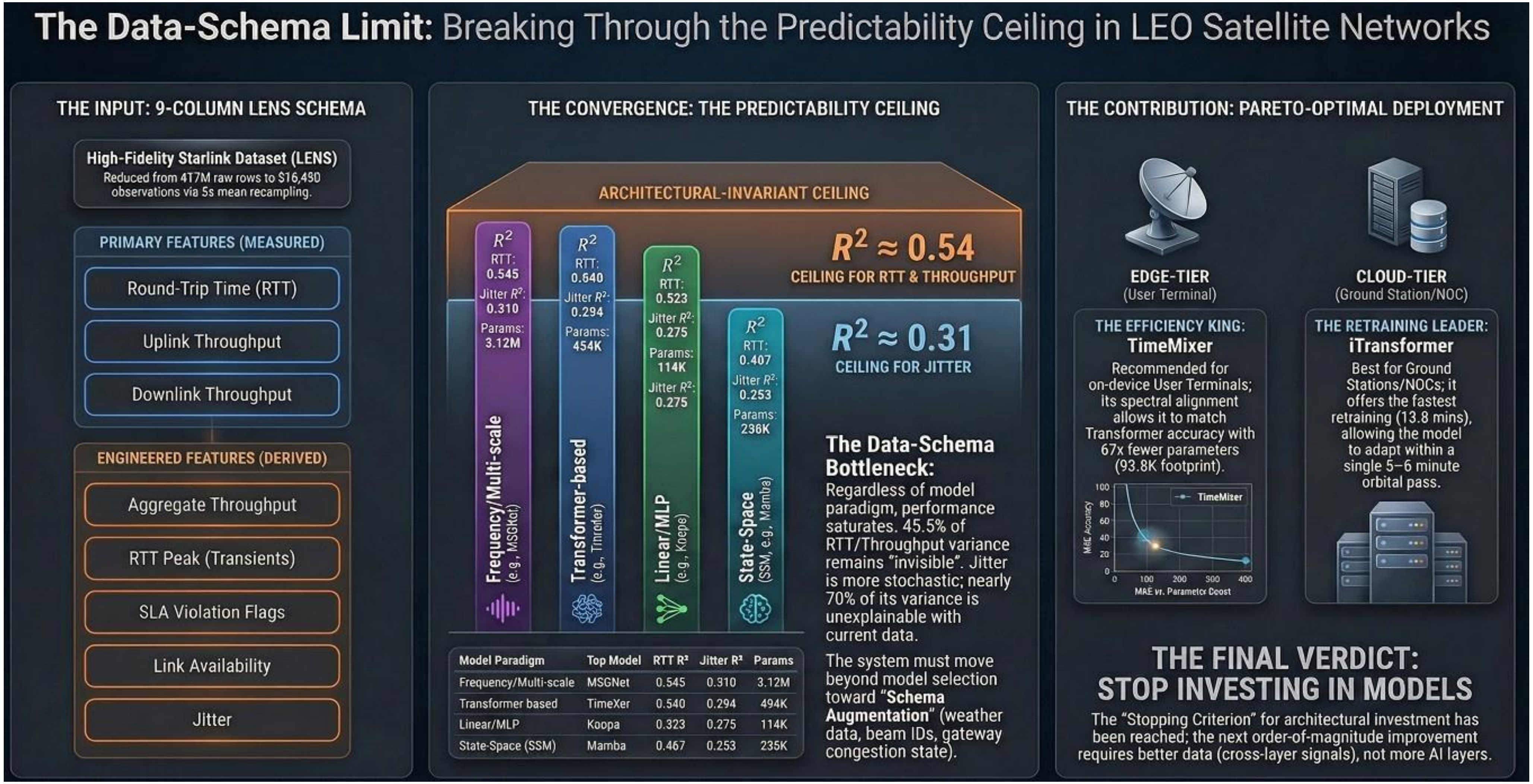
Future Work — Multi-Modal Feature Fusion



Future Work: Continuous Learning



Conclusion & Core Takeaways



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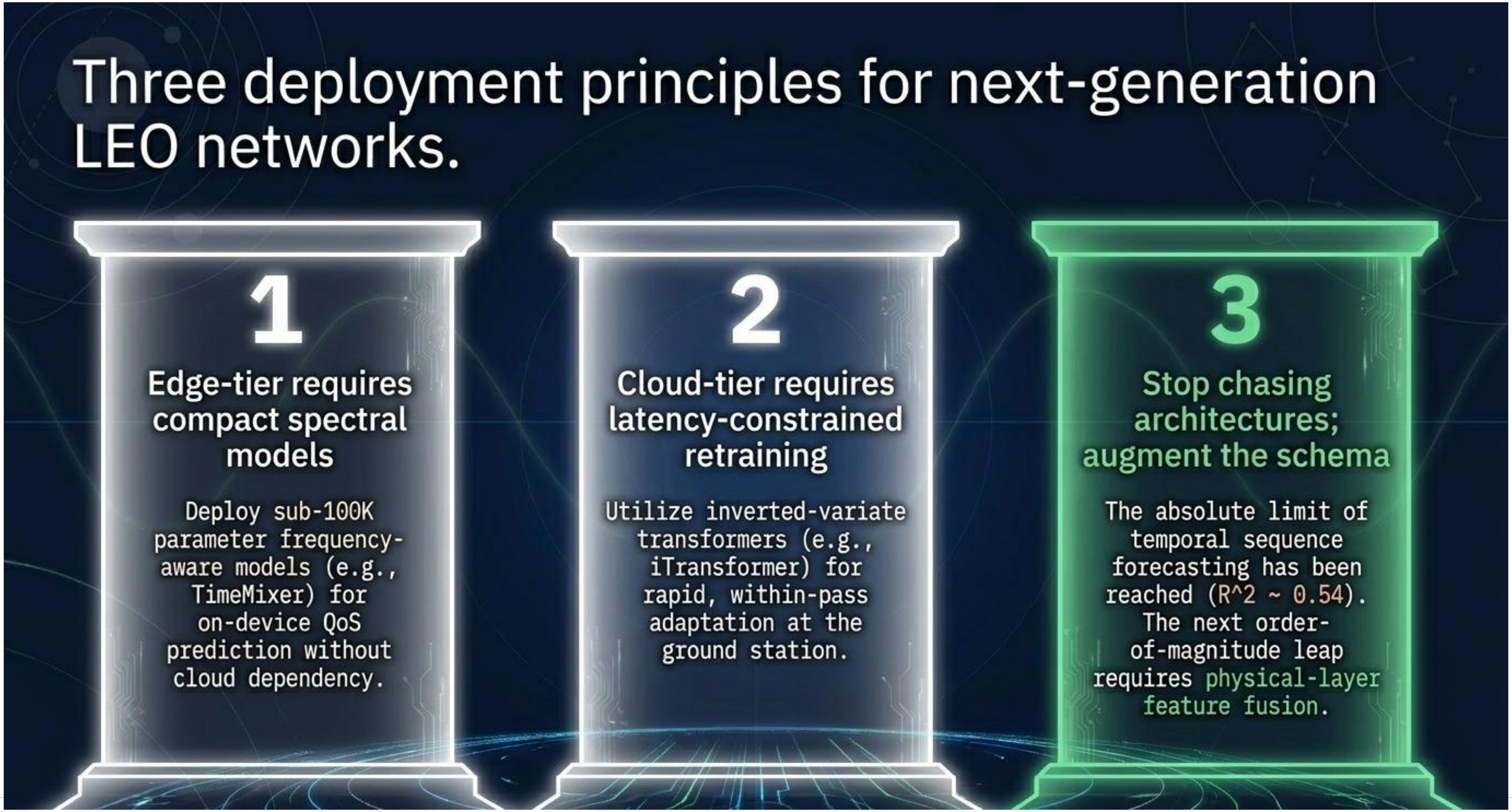

Thank you for your time and attention.

Any questions/comments?