# NUMINA Simulation Supplement

## Overview

This supplement outlines the simulation methodology and results validating the core hypothesis of the NUMINA framework. Two conceptual AI models were compared:  
- Structure-First: Trained on pattern recognition, logic, and causality prior to any symbolic naming.  
- Language-First: Trained first on symbolic associations and linguistic input, followed by structure.  
Each model was evaluated in clean and adversarial conditions to assess robustness under symbolic distortion.

## Simulation Task

A number-sequencing task was used. Both models were asked to identify and continue simple numerical patterns under two conditions:  
- Clean Labeling: Standard symbolic mappings  
- Distorted Labeling: Labels were randomly shifted or swapped

## Key Results

Trial data across four runs produced the following outcomes:  
1. Structure-First (Clean): Fast convergence, minimal error.  
2. Structure-First (Distorted): Maintained stability and performance.  
3. Language-First (Clean): Moderate learning speed, more variability.  
4. Language-First (Distorted): Severe performance degradation—high error rates and loss spikes.

## Interpretation

These findings support the NUMINA thesis: grounding cognition in structural understanding before symbolic naming improves generalization, flexibility, and epistemic integrity.  
Structure-first agents learned abstract regularities and maintained performance even when labels changed. Language-first agents relied on fixed labels and broke under symbolic disruption.

## Conclusion

This conceptual experiment mirrors observed trends in both human development and AI architecture. Structure-first sequencing yields systems more resilient to linguistic manipulation and better aligned with reality—validating NUMINA’s proposed reordering of symbolic learning.