

# SUPPLEMENTARY APPENDIX: ADC Schema Examples for the DigiMind Cognitive ADC Architecture

**Abstract**—This appendix provides detailed schema examples illustrating the architecture’s core feature of Vertical Flexibility and Granular Evolution, demonstrating how the system adapts its structural depth and bit-resolution based on domain complexity quantified by Knowledge Entropy ( $\mathcal{H}_K$ ).

## I. ADC SCHEMA EXAMPLES: FIXED, FLEXIBLE, AND GRANULAR

These tables illustrate the structure of the DigiMind architecture: the foundation schema, two examples of vertical flexibility, and the granular evolution mechanisms.

### A. Example A1: Foundational 4-Layer Fixed Bit-Depth ( $2^{40}$ Uneven Base)

This shows the initial, yet non-uniform, base architecture ( $D = 4$ ), prioritizing the upper layers for domain differentiation, Table:(I).

TABLE I: Foundational Schema: Fixed 40-Bit Allocation ( $16 + 12 + 8 + 4$ )

Layer	Function	Bit-Depth ( $B_{j,l}$ )	Node Count ( $2^{B_{j,l}}$ )	Resource Usage
$L_1$	<b>Major Domain</b>	16	65,536	Large LLM
$L_2$	<b>Sub-Domain</b>	12	4,096	Medium LLM
$L_3$	<b>Conceptual Node</b>	8	256	Light LLM
$L_4$	<b>Feature/Fact Node</b>	4	16	Feature Weight

Total Bits:  $16 + 12 + 8 + 4 = 40$  bits. Total Layers: 4.

### B. Example A2: Vertical Flexibility (Shallow Depth - 3 Layers)

This example demonstrates a shallow schema architecture where the total knowledge complexity ( $\mathcal{H}_K$ ) is concentrated at the upper layers, resulting in a path depth of  $D = 3$ . This is efficient for highly structured, less granular data, Table:(II).

### C. Example A3: Vertical Flexibility (Deep Depth - 7 Layers)

This example demonstrates a deep architecture required for domains with high, complex, and evolving knowledge entropy, such as Theoretical Physics. The path depth is expanded to  $D = 7$  layers, showcasing the maximum structural plasticity, Table:(III).

This supplementary material accompanies the manuscript "DigiMind: A Cognitive ADC Architecture for Continual Learning and Factual Coherence."

TABLE II: Vertical Flexibility Schema: Shallow Geography Example ( $M_{\text{Geography}}$ )

Layer	Function	Bit-Depth ( $B_{j,l}$ )	Node Count ( $2^{B_{j,l}}$ )	Resource Usage
$L_1$	<b>Major Schema: Country</b>	16	65,536	Large LLM
$L_2$	<b>Sub-Schema: City/Region</b>	8	256	Medium LLM
$L_3$	<b>Feature: Capital of City</b>	4	16	Feature Weight

Total Bits:  $16 + 8 + 4 = 28$  bits. Total Layers: 3. (Optimized for low-depth factual structure.)

TABLE III: Vertical Flexibility Schema: Deep Physics Example ( $M_{\text{Physics}}$ )

Layer	Function	Bit-Depth ( $B_{j,l}$ )	Node Count ( $2^{B_{j,l}}$ )	Resource Usage
$L_1$	<b>Major Field (e.g., Quantum)</b>	16	65,536	Large LLM
$L_2$	<b>Core Theory (e.g., QFT)</b>	12	4,096	Medium LLM
$L_3$	<b>Model Class (e.g., Standard Model)</b>	8	256	Medium LLM
$L_4$	<b>Sub-Model/Symmetry Group</b>	4	16	Light LLM
$L_5$	<b>Specific Parameter/Equation Set</b>	8	256	Light LLM
$L_6$	<b>Experimental Context/Setup</b>	8	256	Feature Weight
$L_7$	<b>Specific Datum/Reference Fact</b>	8	256	Feature Weight

Total Bits:  $16 + 12 + 8 + 4 + 8 + 8 + 8 = 64$  bits. Total Layers: 7. (Optimized for deep, multi-layered concepts.)

*D. Example A4: Granular Evolution: Localized Horizontal Bit-Depth Upgrade: 4 bits to 8 bits*

This demonstrates the **horizontal bit-depth upgrade**. A terminal module ( $M_{L4}$ ) is upgraded from 4 bits (16 slots) to 8 bits (256 slots) due to a surge in fine-grained information within its domain, Table:(IV).

TABLE IV: Simulated Granular Evolution: Horizontal Bit-Depth Upgrade

Component /Phase	Pre-Upgrade State	Upgrade Trigger & Action	Post-Upgrade State & Result
Target Module $M_{L4}$	Adaptive Algos (Feature LLM), Bit-Depth: 4 bits. Capacity: 16 feature slots.	High $\mathcal{H}_K$ detected; module capacity exceeds 80%.	Bit-Depth is increased to 8 bits. Capacity: 256 feature slots.
Upgrade Method	N/A	<b>Localized PEFT</b> applied only to the $M_{L4}$ weight matrix and its routing layer weights.	<b>Cost Efficacy:</b> Only the smallest relevant part of the network is trained.
Peer Module $M_{L4}'$	Second-Order Methods (Feature LLM). Bit-Depth: 4 bits.	<b>No Action.</b> Module is stable (low $\mathcal{H}_K$ ).	<b>Zero Interference:</b> $M_{L4}'$ is entirely protected and unaffected by the upgrade.

*E. Example A5: Granular Evolution: Vertical Layer Expansion (Split Operation)*

This demonstrates the **vertical layer expansion**, where a high-entropy terminal node ( $M_{L4}$ ) is replaced by a new routing layer and two new sub-modules, increasing the path depth from 4 layers to 5, Table:(V).

TABLE V: Simulated Granular Evolution: Vertical Layer Expansion (Split Operation)

Component /Phase	Pre-Expansion State	Expansion Trigger & Action	Post-Expansion State & Result
Target Path Depth	$D = 4$ : Path ends at $L4$ .	N/A	$D = 5$ : New path segment $L4 \rightarrow L5$ .
Target Module $M_{L4}$	Single, high-entropy module for $M_{Transporters}$ .	High $\mathcal{H}_K$ in $M_{L4}$ . Knowledge becomes conceptually separable ( <i>Passive</i> vs. <i>Active</i> Transport).	$M_{L4}$ is converted into a <b>Router Node</b> ( $L4$ -Router).
New Structure	N/A	$M_{Transporters}$ weights are cloned and initialized with antisymmetric perturbation ( $W_{old} \pm \epsilon$ ).	New <b>Layer 5</b> created: $M_{L5\_Passive}$ and $M_{L5\_Active}$ .