Ontogenetic AGI Frameworks: Developmental Pathways toward General Machine Intelligence

L. Verma[1], S. D. R. K. Sharma[2], P. Patil[3], M. Joshi[4]
Associate Professor[1], Students[2, 3, 4]
Department of Computer Science Engineering
Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering & Technology
Corresponding Author Email: *Rksharma50@gmail.com[2]*

ABSTRACT

Artificial General Intelligence (AGI) is expected to perform wide variety of intellectual tasks similar to human intelligence. Traditional AI systems mostly rely on large datasets and static training methods, but human intelligence grows gradually through developmental stages from infancy to adulthood. This concept of gradual learning is known as ontogeny in biological sciences. Ontogenetic AGI frameworks propose that machine intelligence should also follow developmental trajectory, where learning happens progressively through stages, guided by environment interaction, self-exploration, memory growth, and cognitive maturation. This paper reviews the concept of ontogenetic AGI, its theoretical foundations, cognitive inspirations, architectural designs, and practical implementations. Different developmental stages of machine intelligence, role of curiosity, embodiment, memory evolution, and learning scaffolds are discussed. The study also presents architectural diagrams and comparative tables to illustrate differences between static AI models and ontogenetic AGI frameworks. Finally, challenges and future research directions are highlighted for building self-developing intelligent systems.

KEYWORDS: *AGI, Ontogeny, Developmental Learning, Cognitive Architecture, Self-learning Systems, Curiosity-driven Learning, Embodied Intelligence*

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

INTRODUCTION

Most present AI systems are trained once and deployed. They do not *grow* intellectually. Humans, however, develop intelligence through stages such as sensory learning, motor control, language learning, reasoning, and abstract thinking. This progressive development is called **ontogeny**.

Ontogenetic AGI frameworks aim to design machines that start with minimal knowledge and develop intelligence over time by interacting with environment. Instead of feeding massive datasets at once, the system learns gradually, similar to a child. This approach promises adaptability, generalization, and robust reasoning.

This paper explores how ontogenetic principles can be applied to AGI architectures and how developmental stages can be embedded into machine intelligence.

1. Concept Of Ontogeny In Intelligence

Ontogeny is the biological term used to describe how an individual organism develops from early stage to maturity. In humans, intelligence is not present in full form at birth. It gradually emerges through continuous interaction with surroundings, body movements, sensory experiences, language exposure, social learning, and memory formation. This developmental pathway is structured, stage-wise, and highly dependent on experience.

When this idea is applied to Artificial General Intelligence, it suggests that a machine should **not be pre-loaded with complete knowledge**, but should **grow its intelligence progressively**, just like a child grows into an adult thinker.
Human cognitive development gives very important clues for designing such systems.

a) Sequential Emergence of Cognitive Abilities

A newborn baby does not understand objects, language, or logic. First it learns to see patterns, recognize faces, and distinguish sounds. Later it learns to move, grasp, crawl, and walk. After that comes object understanding, language learning, reasoning, and abstract thinking.

This sequential growth is very important. Each stage builds foundation for the next one.

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

Table: 1

Human Development Stage	Cognitive Ability Formed	Equivalent Stage in AGI
Sensory exploration	Recognizing light, sound, touch	Raw sensor data processing
Motor control	Hand-eye coordination	Actuator learning, robotics movement
Object permanence	Understanding objects exist	Object representation models
Language learning	Symbol grounding	NLP with perceptual grounding
Logical thinking	Cause-effect reasoning	Planning and reasoning engines
Abstract thinking	Imagination, ethics	Meta-learning and self-modeling

This table shows that intelligence is **constructed**, not pre-programmed.

b) Experience before Knowledge

In humans, experience comes before formal knowledge. A child touches fire and learns it is hot before learning the word "heat". The brain first forms sensory-motor experiences and later attaches symbols and concepts to them.

Ontogenetic AGI follows this rule:

Perception → Interaction → Experience → Concept → Symbol → Reasoning

Traditional AI reverses this by starting from symbols and data. Ontogenetic AGI starts from experience.

c) Role of Environment in Cognitive Growth

Human intelligence depends strongly on environment. Children raised in different environments develop different skills. Similarly, AGI systems should learn based on environment exposure rather than fixed datasets.

This means:

- Learning from simulation or real world
- Adapting to changing conditions
- Building internal world model from interaction

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

d) Gradual Complexity Increase

Another key feature of ontogeny is that complexity increases slowly. Children are not taught calculus before they understand numbers. Learning tasks are naturally ordered.

In AGI, this is called **developmental curriculum**:

1. Pattern recognition
2. Movement learning
3. Object interaction
4. Language grounding
5. Logical reasoning
6. Social learning

Skipping stages may lead to unstable intelligence.

e) Memory Development Over Time

Human memory is not fixed. It grows, reorganizes, and strengthens. Early memories are episodic, later they become semantic knowledge.

Ontogenetic AGI must therefore include:

- Growing memory storage
- Conversion of experiences into knowledge
- Reuse of past experiences for new tasks

f) Self-Discovery and Curiosity

Children learn not only because they are told to learn, but because they are curious. They explore, experiment, and sometimes make mistakes. This intrinsic motivation plays huge role in intelligence development.

In AGI, curiosity modules replicate this by rewarding novelty and prediction errors.

g) Importance of Embodiment

Human cognition is deeply connected to the body. Understanding of space, distance, gravity, and object properties comes from physical interaction.

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

Therefore, ontogenetic AGI often uses:

- Robots
- Virtual agents
- Simulated physical environments
- To allow learning through action.

2. Motivation For Ontogenetic Agi

The main motivation behind Ontogenetic AGI comes from observing the gap between today's Artificial Intelligence systems and natural human intelligence. Modern AI models are powerful in narrow tasks, but they still lack adaptability, understanding, and developmental growth that humans show from childhood to adulthood. These limitations clearly indicate that a different approach is required—one that focuses on **development over time**, rather than only large-scale training.

Ontogenetic AGI is motivated by the idea that intelligence should **emerge gradually** through interaction, experience, and memory evolution.

a) Dependence on Large Labeled Datasets

Most AI systems today depend on huge labeled datasets. Image recognition models require millions of labeled images. Language models require massive text corpora. This approach has two problems:

- Labeling data is costly and time consuming
- Learning is passive, not experiential

Humans do not require millions of labeled examples to recognize objects. A child may see a dog few times and still identify dogs everywhere. This happens because learning is based on **interaction and experience**, not labels.

Motivation: Ontogenetic AGI aims to reduce dependence on labeled datasets by enabling systems to learn from environment interaction and self-supervised exploration.

b) Poor Adaptability to New Environments

Traditional AI models perform well only in environments similar to their training data. When

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

conditions change, performance drops drastically. This is called the **generalization problem**. Humans easily adapt to new homes, new cities, and new tools because intelligence is not tied to fixed data but to **understanding of the world**.

Motivation: Ontogenetic AGI encourages the formation of internal world models through exploration, allowing better adaptability to unseen situations.

c) Lack of Long-Term Memory Growth

Most AI models have fixed parameters after training. They do not continuously grow their memory. There is no structured episodic memory or semantic knowledge formation like in humans.

Humans remember experiences, learn from them, and reuse them in future decisions. Memory is dynamic and expanding.

Motivation: Ontogenetic AGI proposes memory architectures that grow over time:

- Episodic memory for experiences
- Semantic memory for knowledge
- Working memory for reasoning

This allows lifelong learning.

d) Absence of Self-Motivated Learning

AI systems usually learn only when given a task and reward. They do not explore on their own. In contrast, children explore their surroundings out of curiosity, not because they are told to. Curiosity leads to discovery and deeper understanding.

Motivation: Ontogenetic AGI integrates curiosity-driven learning where agents seek novelty and learn even without external rewards.

e) Learning from Interaction, Not Only Data

Traditional AI learns from static datasets. Ontogenetic AGI learns from **active interaction** with environment. This includes:

- Touching objects

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

- Moving in space
- Observing consequences of actions

Such interaction leads to deeper understanding of cause-effect relationships.

f) Progressive Development of Memory

Instead of storing all knowledge at once, ontogenetic systems build memory gradually. Early experiences shape later learning. Knowledge is layered and organized over time.

This mirrors human cognitive growth where early sensory memories form basis for later reasoning abilities.

g) Use of Curiosity and Reward Signals

Curiosity is implemented through prediction errors or novelty measures. When system encounters unexpected outcomes, it tries to learn more.

Mathematically:

Curiosity Reward $\propto$ Prediction Error

This drives autonomous learning without constant supervision.

h) Formation of Internal World Models

Perhaps the strongest motivation is to enable AGI to form **internal representations of the world**. Instead of memorizing patterns, the system understands:

- Object permanence
- Spatial relations
- Physical rules
- Social patterns

This internal model allows reasoning, planning, and imagination.

3. Cognitive Inspiration from Human Brain (Elaborated)

One of the strongest foundations for Ontogenetic AGI comes from studying how the human brain is organized. The brain is **not a single uniform processor**. It is composed of multiple specialized subsystems, each responsible for different cognitive functions, and intelligence emerges from their interaction.

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

Modern AI often relies on a single large neural network trained end-to-end. In contrast, the brain follows a **mechanism-based organization**, where perception, action, memory, reasoning, and motivation are handled by different yet interconnected regions. Ontogenetic AGI borrows this idea and designs architectures composed of interacting cognitive mechanisms.

a) Sensory Cortex – Perception and Pattern Recognition

The sensory cortex processes inputs from eyes, ears, skin, nose, and tongue. It converts raw sensory signals into meaningful patterns such as shapes, sounds, textures, and motion.

In Ontogenetic AGI:

- This corresponds to perception modules handling vision, audio, tactile, and other sensors.
- Early developmental stage focuses heavily on this module.
- Uses self-supervised learning to detect patterns without labels.

Role: Transform raw data into structured representations for higher cognition.

b) Motor Cortex – Action and Interaction

The motor cortex controls body movements and coordination. Learning to crawl, walk, grasp, and manipulate objects depends on motor learning.

In Ontogenetic AGI:

- Maps to actuation and control systems in robots or simulated agents.
- Learns cause–effect relationships through movement.
- Essential for embodied learning and environment interaction.

Role: Enable the agent to experiment with the world and learn through action.

c) Hippocampus – Memory Formation

The hippocampus is responsible for forming and retrieving memories, especially episodic memories. It links experiences across time and helps in learning from past events.

In Ontogenetic AGI:

- Implemented as episodic and semantic memory stores.
- Experiences are stored and later generalized into knowledge.

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

- Supports lifelong learning and recall for reasoning.

Role: Convert experiences into reusable knowledge.

d) Prefrontal Cortex – Reasoning and Planning

The prefrontal cortex handles decision making, logical reasoning, planning, and problem solving. It uses information from memory and perception to choose actions.

In Ontogenetic AGI:

- Corresponds to reasoning engines, planners, and symbolic processors.
- Develops later in the ontogenetic timeline after perception and memory mature.
- Enables goal-directed behavior.

Role: High-level cognition and intelligent decision making.

e) Limbic System – Emotion and Motivation

The limbic system controls emotions, rewards, fear, and motivation. It is deeply connected to learning because motivation drives exploration.

In Ontogenetic AGI:

- Modeled as curiosity modules, reward systems, and safety controls.
- Encourages exploration of novel states.
- Regulates risk during learning.

Role: Provide intrinsic motivation and regulate behavior.

4. Developmental Stages in Ontogenetic AGI

a) Sensory Learning Phase

System learns to recognize patterns from raw sensor inputs without labels.

b) Motor Interaction Phase

Agent interacts with environment, learning cause-effect relations.

c) Object and Concept Formation

Agent groups experiences into objects and basic concepts.

d) Language and Symbol Learning

Symbols are mapped to experiences, grounding language.

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

e) Reasoning and Planning

Agent uses stored memory and models for decision making.

f) Meta-cognition Stage

Agent reflects on its own knowledge and improves learning strategies.

5. Architectural Components Of Ontogenetic AGI



Figure 1: Ontogenetic AGI Architecture

Key modules:

- Perception unit
- Memory hierarchy
- Curiosity module
- Reasoning engines
- Action system

6. Role Of Curiosity And Intrinsic Motivation

Curiosity-driven learning helps the system explore unknown states. Instead of external rewards only, system seeks novelty.

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

Mathematically, curiosity reward can be based on prediction error:

Curiosity = |Predicted State – Actual State|

7. Memory Growth And Knowledge Representation

Ontogenetic AGI uses layered memory:

Table: 2

Memory Type	Function
Sensory memory	Short duration inputs
Working memory	Temporary reasoning space
Episodic memory	Past experiences
Semantic memory	General knowledge

Memory grows with time instead of being fixed.

8. Learning Mechanisms Used

- Reinforcement learning
- Self-supervised learning
- Imitation learning
- Meta-learning
- Continual learning

These are applied at different developmental stages.

9. Embodiment In Ontogenetic AGI

Physical or simulated embodiment allows:

- Understanding of space and physics
- Learning through action
- Better concept formation

Robotics platforms and virtual agents are commonly used.

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

10. Comparison with Traditional AI

Table: 3

Aspect	Traditional AI	Ontogenetic AGI
Training	One-time large dataset	Gradual learning
Memory	Static	Growing
Motivation	Task reward	Intrinsic curiosity
Adaptability	Low	High
Architecture	Monolithic	Modular developmental

11. Practical Implementations

Examples include:

- Developmental robotics
- Open-ended learning agents
- Child-like language learners
- Simulation-based growing agents

12. Challenges in Ontogenetic AGI

- Long training time
- Memory management
- Safety during exploration
- Computational resources
- Designing developmental curriculum

13. Future Research Directions

- Lifelong learning frameworks
- Neural-symbolic developmental systems
- Ethical reasoning emergence
- Self-repairing cognitive architectures
- Cross-domain knowledge transfer

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

Case Study: Developmental Robot



Figure 2: Developmental Learning Cycle

14. Importance of Developmental Curriculum

Just like schooling, AGI requires structured exposure:

- Sensory tasks
- Motor tasks
- Language tasks
- Logical tasks
- Social tasks

15. Ontogenetic AGI And Meta-Learning

Meta-learning allows system to learn *how to learn*, an important late stage development.

16. Ethical And Safe Development

Developmental control is needed to avoid unsafe behaviors during exploration.

17. Applications Of Ontogenetic AGI

- Autonomous robots
- Personal assistants
- Adaptive education systems
- Scientific discovery agents

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved

CONCLUSION

Ontogenetic AGI frameworks provide a promising path toward true general intelligence by mimicking developmental growth of human cognition. Instead of static training, machines should grow intellectually through interaction, memory expansion, and curiosity-driven exploration. Though challenges exist, this approach can lead to robust, adaptable, and self-improving intelligent systems. Future research must focus on structured developmental stages, safe exploration, and scalable memory architectures to realize full potential of ontogenetic AGI.

REFERENCES

1. Oudeyer, P. Y., & Kaplan, F. (2007). What is intrinsic motivation? A typology of computational approaches.
2. Schmidhuber, J. (2010). Formal theory of creativity, fun, and intrinsic motivation.
3. Tani, J. (2016). Exploring robotic minds: Actions, symbols, and consciousness.
4. Lake, B. et al. (2017). Building machines that learn and think like people.
5. Hassabis, D. et al. (2017). Neuroscience-inspired artificial intelligence.
6. Bengio, Y. (2013). Representation learning: A review and new perspectives.
7. Silver, D. et al. (2016). Mastering the game of Go with deep neural networks.
8. Botvinick, M. et al. (2019). Reinforcement learning, fast and slow.
9. Thrun, S., & Mitchell, T. (1995). Lifelong robot learning.
10. Parisi, G. I. et al. (2019). Continual lifelong learning with neural networks.

Page 28-41 © MANTECH PUBLICATIONS 2026. All Rights Reserved