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Leading and Lagging Strand Coordination by DNA Polymerase as Quantum Entanglement in DNA Computing Systems Linked to Artificial Intelligence

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Abstract
Artificial Intelligence (AI) holds transformative potential across numerous sectors, with Library and Information Science (LIS) education emerging as a key area for its application. In the realm of teacher professional development (TPD) for LIS educators, AI can facilitate personalized, data-driven learning pathways, support the development of adaptive instructional materials, and enhance the accessibility and efficiency of training initiatives. This paper examines the evolving role of AI in LIS teacher professional development, exploring how AI-powered tools are redefining educator preparation, promoting continuous learning, and responding to the dynamic demands of the digital information environment. By analysing current advancements in AI and its integration into LIS education and training programs, this study identifies the opportunities, challenges, and broader implications for the future of professional development in the LIS field.

Keywords: DNA Polymerase, Leading Strand, Lagging Strand, DNA Computing, Quantum Entanglement, Replication Fork, Okazaki Fragments, Artificial Intelligence, Molecular Logic, Quantum Coherence

Introduction
DNA replication is a fundamental cellular process that proceeds in a 5′ to 3′ direction, creating inherent asymmetry at the replication fork [1]. The leading strand undergoes continuous synthesis, while the lagging strand is synthesized discontinuously via Okazaki fragments [2]. Coordination between the two is executed by DNA polymerase complexes, helicases, and ligases [3].

In DNA computing, molecular structures execute logic operations using biological substrates such as DNA strands, enzymes, and hybridization reactions [4]. Recent advancements suggest that these biomolecular systems can be extended to simulate quantum-like behavior, particularly when synchrony, superposition, and coherence are evident in biochemical operations [5,6].

This paper introduces a novel perspective: the cooperative action of DNA polymerases on leading and lagging strands resembles quantum entanglement, where two components of a system influence one another regardless of spatial or temporal separation. We propose that this entanglement can be encoded and exploited in a DNA computing architecture interfaced with artificial intelligence (AI) for optimized molecular logic processing.

Theoretical Background
DNA Replication: Structural Constraints and Polymerase Activity
Replication initiates at the origin, where helicase unwinds DNA and polymerases synthesize daughter strands [7]. The asymmetry arises due to the 5′ to 3′ polymerase constraint, resulting in continuous synthesis on the leading strand and fragmented synthesis on the lagging strand [8]. The replication machinery must synchronize both processes, involving dynamic interactions that can be computationally modeled [9].

DNA Computing and Quantum Analogy

Molecular computation using DNA was pioneered by Adleman demonstrating NP-complete problem-solving via hybridization and ligation [10]. Subsequent work advanced DNA logic gates, circuits, and neural networks [11–13]. Efforts to incorporate quantum-like features such as superposition and entanglement in molecular computing have begun to emerge [14].

DNA replication, particularly the interplay between leading and lagging strand synthesis, presents a dynamic system of temporally correlated biochemical actions—suitable for modeling via entangled quantum systems [15].

Proposed Model: Leading/Lagging Strands as Entangled Qubits

Entanglement Analog in Polymerase Synchrony

We represent the leading strand as qubit $|0\rangle$ and the lagging strand as qubit $|1\rangle$. The synchronized action of polymerase on both strands ensures that their progression is interdependent, similar to Bell-state entanglement $(|01\rangle + |10\rangle)/\sqrt{2}$ [16]. The lagging strand's discontinuity can be interpreted as a delayed qubit measurement, introducing coherence timing, much like time-bin entanglement in quantum systems [17].

Okazaki Fragments and Quantum Error Correction Okazaki fragments can be seen as data blocks in a quantum memory subject to decoherence, with ligase activity restoring coherence—analogous to quantum error correction algorithms [18,19].

AI Integration and Feedback Optimization

Artificial intelligence can be used to optimize qubit coherence and gate fidelity by monitoring the replication process via molecular biosensors or optogenetic control systems [20]. Neural networks can predict polymerase slippage, strand stalling, or fragment integration fidelity to dynamically modulate the system's entangled state [21].

This enables a bio-cybernetic loop where AI corrects or adapts the logic flow of DNA replication-based computation in real time [22].

Implementation Framework

- **System:** Synthetic DNA strands with engineered priming sites for polymerase loading.
- **Control:** AI-driven photonic systems modulate polymerase activity [23].
- **Output:** Fluorescent markers indicate entangled logic outcomes.
- **Evaluation:** Qubit fidelity modeled via probabilistic state evolution on a Bloch sphere [24].

Applications and Future Directions

- **Quantum Molecular Logic:** Replication fork as quantum processor.
- **Bio-AI Entanglement Networks:** In vivo networks of entangled DNA computers communicating via AI.
- **Synthetic Organism Programming:** AI-regulated DNA computing units embedded in cells for on-demand logic execution.

Future work will involve modeling polymerase wavefunctions, engineering entangled base-pair systems, and real-time error correction using CRISPR-based readouts [25–27].

Conclusion

The bidirectional synthesis at the replication fork is more than a mechanical process—it embodies complex, temporally entangled behavior suitable for abstraction into DNA quantum logic circuits. By mapping polymerase activity onto entangled qubit systems and regulating the process via AI, we propose a new class of biologically embedded quantum information processors.

Conflict of Interest

There is no conflict of interest.

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Supplementary-1

Circadian Rhythm as a Temporal Operating System in DNA Computers Linked to Artificial Intelligence

Abstract
The circadian rhythm, a biological process regulating physiological and behavioral cycles over a 24-hour period, presents a fundamental temporal framework within living organisms. Emerging studies suggest that this endogenous clock can be co-opted as a timing mechanism within bio-computational systems, especially DNA-based computers. This paper explores the integration of circadian regulatory elements into DNA computing architectures linked to artificial intelligence (AI), examining the molecular mechanics of circadian gene expression, transcriptional feedback loops, and post-translational modifications. We propose that the circadian rhythm serves as a biological clock for synchronizing computational tasks in living DNA computer systems and facilitating time-dependent data processing in AI-linked frameworks. The paper synthesizes evidence from chronobiology, bioinformatics, and quantum-inspired computation, and proposes a novel architecture that incorporates circadian elements into DNA-AI hybrid models.

Keywords: Circadian Rhythm DNA Computing, Artificial Intelligence, Molecular Clock, Transcription-Translation Feedback Loop (Ttfl), Per/Cry Genes, Suprachiasmatic Nucleus, Temporal Computation, Chrono-Synchronization, Synthetic Biology, Molecular Logic Gates, Oscillatory Gene Circuits, Bio computation, Neuroinformatic, Photoperiodism, Chrono-Cybernetics, Quantum-Inspired Algorithms, Bio AI Interface, Time-Dependent Signaling, Epigenetic Modulation

Introduction
Biological systems operate under strict temporal constraints regulated by the circadian rhythm. This 24-hour cycle governs key biological processes, such as sleep-wake cycles, hormone secretion, metabolism, and gene expression. With the emergence of DNA computing—leveraging the inherent parallelism and molecular specificity of DNA reactions for information processing—the potential to synchronize molecular computation with circadian timing presents a new paradigm in living computation. Coupled with the power of artificial intelligence (AI), such systems may achieve adaptive, time-aware information processing within biological environments.
This paper aims to:
- Explore the role of circadian rhythm in gene expression and molecular feedback systems.
- Propose its application as a temporal controller in DNA computing systems.

• Suggest integration strategies with AI for adaptive time-sensitive computational tasks.

Circadian Rhythm and Molecular Feedback Loops

The circadian rhythm in mammals is governed by the suprachiasmatic nucleus (SCN) of the hypothalamus, which synchronizes peripheral clocks in tissues. At the cellular level, it operates via transcriptional-translational feedback loops (TTFLs), involving core clock genes such as CLOCK, BMAL1, PER, and CRY [1–3]. These genes and their protein products regulate their own expression through negative feedback, creating oscillations with ~24-hour periodicity.

Post-translational modifications, including phosphorylation by kinases such as CK1δ/ε, modulate protein stability and nuclear entry, contributing to cycle precision [4–6]. These molecular characteristics offer a temporal mechanism that can be integrated into synthetic biological circuits and DNA computing.

DNA Computing and Biological Timers

DNA computing operates via predictable interactions between nucleic acids using strand displacement, hybridization, and logic gates encoded in oligonucleotide sequences [7–9]. Incorporating circadian elements into DNA computers offers potential for time-sensitive logic execution, such as triggering computation only at specific circadian phases.

Circadian gene promoters can be utilized to control the expression of DNA-based computational units, creating a biological timing system analogous to a real-time operating system in traditional computing [10–12]. Synthetic biology circuits employing circadian genes can regulate the activation of strand displacement cascades, leading to temporally controlled computation [13,14].

Linking DNA Computers with Artificial Intelligence

DNA computers are inherently parallel and stochastic, ideal for problems like optimization, cryptography, and pattern recognition. However, their slow speed and lack of learning ability are bottlenecks. By linking them with AI—particularly neural networks—these systems gain the ability to adapt, classify, and interpret outputs over time [15–17].

Integrating the circadian rhythm into this DNA-AI interface enables time-aware AI decision-making based on biologically contextual information. For example, an AI system could use outputs from a DNA computer synchronized with circadian gene expression to regulate drug delivery or detect anomalies that depend on time-of-day variations (e.g., cortisol rhythms in stress disorders) [18–20].

Architectural Proposal: Circadian-Driven DNA-AI System

We propose a model in which:

• Circadian promoters (e.g., Per1, Cry2) regulate the expression of logic gates in a DNA computing circuit.

• A bio-transistor layer (e.g., DNA origami linked with light-sensitive proteins) activates only during specific circadian windows.

• The output of DNA computation is fed into a graphene-based nano-interface that communicates with an AI model trained to interpret time-encoded data.

• AI algorithms (e.g., recurrent neural networks, transformers) process this circadian-synchronized input to generate context-sensitive outputs.

Such systems may be employed in smart therapeutics, chronotherapy, biological cryptography, or autonomous bio-sensors.

Challenges and Future Directions

Key challenges include:

• Stability and robustness of circadian gene circuits in synthetic contexts.

• Precision control of circadian-driven expression across different tissue types.

• Interface development between biological components and AI systems (e.g., through optogenetics or nanoelectronic transduction).

Future work may explore quantum circadian models, where gene expression phases are treated as qubit superpositions, and multi-organ circadian harmonization for distributed DNA-AI systems.

Conclusion

The circadian rhythm provides a natural, evolutionarily conserved temporal framework that can be harnessed for synchronizing DNA computing tasks. When linked with AI, such hybrid systems may revolutionize our approach to time-sensitive computation in biological environments. This integration paves the way for a new class of living, learning, and temporally aware machines.

Conflict of Interest

There is no conflict of interest.

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Supplementary-2

Embryogenic Layering as a Paradigm for DNA Computing Evolution Linked to Artificial Intelligence

Abstract
Embryogenesis reveals an archetypal model of differentiation and complexity, transitioning from a single totipotent zygote to specialized layers: ectoderm, mesoderm, and endoderm. This study proposes that these developmental stages serve as a biological template for the evolution of DNA computing systems linked to artificial intelligence (AI). As AI-DNA hybrid systems evolve, parallels emerge between germ layer specification and layered architecture in computational frameworks. DNA computing mimics the biological logic of cellular decision-making and information encoding. This paper explores the ontogeny of embryogenesis as a scaffold for designing AI-linked DNA computers, particularly focusing on three germ layers as computational domains: ectoderm (sensory interfaces), mesoderm (processing and signal

transduction), and endoderm (internal data regulation and storage). Graphene interfaces, optogenetic modulation, and gene editing systems are examined for hardware integration.

Keywords: DNA Computing, Artificial Intelligence, Embryogenesis, Endoderm, Ectoderm, Mesoderm, Gastrulation, Optogenetics, Graphene, Crispr, Neural Computation, RNA Circuits, Molecular Logic Gates, Bioinformatics, Cellular Differentiation, Developmental Biology, Nanorobotics, Biohybrid Systems, Morphogenesis, Reconfigurable Computing

Introduction

DNA computing has evolved from a biochemical concept to a platform that supports bio-inspired algorithms, data storage, and logic operations. Linking DNA computation to AI allows information systems to interface with biological environments in vivo. Embryogenesis, particularly the trilaminar germ layer model, represents a biomimetic architecture for computational design. Each germ layer corresponds to specific biological functions that inspire parallel computational analogues in AI-integrated DNA computing.

Method

Embryogenesis and the Tripartite Model

• **Ectoderm:** Gives rise to skin, neurons, and sensory tissues—analogous to input/output interfaces in AI-DNA systems.
• **Mesoderm:** Forms muscles, the circulatory system, and connective tissues—similar to internal logic processing or routing systems [8].
• **Endoderm:** Differentiates into digestive and respiratory systems—akin to data storage and metabolic computing in DNA systems [6].

These germ layers establish a framework for system modularity in artificial systems where cellular compartmentalization reflects hierarchical data handling in AI.
Results

Evolution of DNA Computing: From Molecular Logic to Layered Intelligence

• **Initial Phase:** Leonard Adleman's (1994) experiment solved a Hamiltonian path problem using DNA strands, laying the groundwork for biochemical computation [1].
• **Current Systems:** Include logic gates, neural DNA circuits, CRISPR-based memory systems, and strand displacement cascades.
• **Future Architectures:** Inspired by developmental biology—integrating germ layer analogues for adaptive learning and contextual behavior [2].

AI Integration: Feedback, Memory, and Layer-Specific Modularity

AI models benefit from embryological principles:
• **Ectodermal layer:** Integrated with optogenetics and sensory nodes using graphene-quantum dots [4].
• **Mesodermal layer:** Incorporates neuromorphic DNA gates and logic-based hormonal feedback [5].
• **Endodermal layer:** Employs nucleic acid memory and metabolic logic circuits for energy-efficient long-term computation [3].

Discussion

Graphene, Nanotubes, and AI Interfaces

Graphene oxide provides a substrate for nucleic acid anchoring and electrical signal transduction across germ layer-inspired modules [10]. Carbon nanotube scaffolding mimics developmental architecture, enabling bioelectronic read-write access in artificial tissues [9].

Case Study: Gastrulation-Inspired Reconfiguration of DNA Logic

During gastrulation, cells reorganize via epithelial-mesenchymal transition (EMT). DNA-based logic circuits can adopt similar dynamic reprogramming via RNA-guided DNA recombination, enabling reconfigurable AI-DNA systems capable of morphogenesis-like adaptation [7].

This biological-computational synthesis proposes a new paradigm: each embryonic layer represents a functional module in DNA-based AI:
• Sensory AI layer (ectoderm) for external stimuli detection.
• Processing layer (mesoderm) for logic, routing, and AI feedback loops.
• Data/memory layer (endoderm) for regulatory storage and signal integration.

Conclusion

Embryogenesis offers a scalable, layered framework for the future evolution of DNA computing architectures linked to AI. Mimicking natural ontogeny allows synthetic intelligence to embody adaptability, reconfigurability, and biochemical harmony with living systems.

Conflict of Interest

There is no conflict of interest.

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