A Review of the Latest Research Achievements in the Basic Theory of Generative AI and Artificial General Intelligence (AGI)

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August 2, 2024

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Abstract: This paper focuses on generative AI, a typical representative of contemporary artificial intelligence (AI) and artificial general intelligence (AGI), aiming to delve into the latest research progress in its basic theory. The research method involves a comparative analysis of the differences in underlying logic and formal understanding between traditional AI and Current AI, further exploring the distinctions between the three core viewpoints of traditional AI (symbolism, connectionism, behaviorism) and the three major schools of Current AI (generative AI/AGI based on large language models (LLMs) such as ChatGPT; new quality productive force AGI characterized by small models, such as I3DNA; and twin Turing machines based on dual formal understanding models that are compatible with both large and small models). The research reveals the core components of the basic theory of AI and AGI: bit-list logic, linkage functions, followed by generalized bilingualism or generalized translation based on digital and intelligent text with the three fundamental laws. The significance of this research lies in not only enhancing the interpretability of generative AI/AGI based on LLMs represented by ChatGPT but also providing generalized translations for the new quality productive force AGI characterized by small models and its complex theories of cosmic intelligence and the universal model series. At the same time, it demonstrates the potential of twin Turing machines as inclusive intelligent agents in integrating data, knowledge, computing power, algorithms, and human-computer mutual assistance in the new era of cognitive paradigms, laying the foundation for constructing super intelligent systems.

Keywords: Generative AI, Artificial General Intelligence (AGI), Underlying Logic, Formal Understanding, Symbolism, Connectionism, Behaviorism, Large Language Models (LLMs), New Productive Force AGI, Twin Turing Machines, bit-list Logic, Linkage Functions, Generalized Bilingualism, Generalized Translation

I. Introduction

With the rapid advancement of artificial intelligence technology, generative AI, as a significant branch of contemporary AI and AGI, has demonstrated unprecedented innovative potential and application value. This research is dedicated to exploring the latest achievements in fundamental theories within the generative AI and its broader AGI domain, aiming to provide theoretical support for the further development of this field. [1][2] In recent years, artificial intelligence technology has made remarkable progress. Among these advancements, generative AI, as a crucial branch of current AI and the more extensive Artificial General Intelligence (AGI) domain, has exhibited substantial innovative potential and wide-ranging application value. Simply put, generative AI is capable of creating new content, such as text, images, or music, which holds revolutionary application prospects in numerous sectors, including but not limited to creative industries, healthcare, education, and scientific research.

The ability of generative AI to learn from vast datasets and generate novel, coherent, and contextually relevant outputs positions it as a transformative technology. Its potential to augment human creativity, enhance decision-making processes, and automate tasks that previously required human ingenuity is unparalleled. However, the full exploitation of this potential necessitates a solid theoretical foundation that can guide its development and application. Therefore, the primary objective of this study is to delve into the latest theoretical advancements in the generative AI and its affiliated AGI field. By conducting a comprehensive analysis of the current theoretical frameworks, we aspire to identify the gaps and limitations that hinder the progress of generative AI. Furthermore, we aim to propose novel theoretical perspectives that can address these challenges and pave the way for more sophisticated and efficient generative AI models.

Through such research, we envision not only offering robust theoretical backing but also fostering interdisciplinary collaborations that can accelerate the integration of generative AI into various sectors. Ultimately, our goal is to contribute to the realization of an AI-augmented future where generative AI plays a pivotal role in driving innovation, enhancing productivity, and improving the quality of life for individuals and society at large.

II. Underlying Logical Differences Between Traditional AI and Current AI

Traditional AI is primarily grounded in symbol manipulation, pattern recognition, and algorithm optimization, with its core philosophies rooted in symbolism, connectionism, and behaviorism. In contrast, contemporary AI, particularly generative AI, has shifted its focus to data-driven deep learning models, especially the application of Large Language Models (LLMs), marking a fundamental transition from rule-driven to data-driven approaches. [3][4][5]

Table 1. presents a multi-factor parallel comparison between traditional AI and generative AI.

Factor	**Traditional AI**	**Current AI (Especially Generative AI)**
Core Philosophy	Symbolism, Connectionism, Behaviorism	Data-driven Deep Learning
Main Methods	Symbol Manipulation, Pattern Recognition, Algorithm Optimization	Deep Learning Models, Especially LLMs
Logical Foundation	Rule-driven	Data-driven
Processing Approach	Reasoning and Judgment Based on Preset Rules and Patterns	Learning and Self-optimization Through Extensive Data
Application Scenarios	Expert Systems, Pattern Recognition, Algorithm Optimization	Natural Language Processing, Image Recognition, Intelligent Recommendations
Advantages	Excels in Specific Domains and Tasks with Clear Rules	Demonstrates Stronger Adaptability and Learning Capability in Complex, Variable Tasks
Challenges	Difficulty in Handling Large-scale Data and Complex Tasks	Requires Extensive Data and Computational Resources; Suffers from Poor Interpretability

As evident from Table 1:

a. **Core Philosophy and Methods**:

Traditional AI is primarily based on symbolism, connectionism, and behaviorism, employing methods such as symbol manipulation, pattern recognition, and algorithm optimization. In contrast, contemporary AI, especially generative AI, emphasizes data-driven deep learning models, particularly the application of Large Language Models (LLMs).

b. **Logical Foundation and Processing Approach**:

Traditional AI is rule-driven, relying on preset rules and patterns for reasoning and judgment. Current AI, on the other hand, is data-driven, learning and self-optimizing through extensive data to adapt to different tasks and environments.

c. **Application Scenarios and Advantages**:

Traditional AI finds wide application in expert systems, pattern recognition, and algorithm optimization, excelling in specific domains and tasks with clear rules. Current AI, however, demonstrates remarkable capabilities in natural language processing, image recognition, intelligent recommendations, and particularly exhibits stronger adaptability and learning capability when dealing with complex, variable tasks.

d. **Challenges and Prospects**:

Traditional AI faces challenges in handling large-scale data and complex tasks. Current AI, while requiring extensive data and computational resources and suffering from poor interpretability, holds immense potential and value for future development.

Furthermore, it is crucial to underscore that the shift from traditional AI to contemporary AI, particularly generative AI, signifies a paradigm shift in how AI systems are designed, trained, and deployed. Traditional AI often relied on explicit programming and manual feature engineering, limiting its applicability to domains where rules could be clearly defined. In contrast, current AI leverages deep learning algorithms that can automatically extract features and learn complex patterns from vast amounts of data, enabling it to tackle problems that were previously considered intractable.

Moreover, the advent of generative AI has not only revolutionized the field of natural language processing but has also shown promise in other domains such as healthcare, finance, and education. For instance, in healthcare, generative AI can assist in drug discovery by simulating molecular structures and predicting their efficacy. In finance, it can be used for fraud detection by generating synthetic transaction data to train detection models. In education, generative AI can personalize learning experiences by creating tailored educational content.

In conclusion, the underlying logical differences between traditional AI and contemporary AI are profound. Traditional AI, rooted in symbol processing and rule-driven approaches, contrasts sharply with contemporary AI, which is characterized by data-driven deep learning models. This transformation has endowed contemporary AI, particularly generative AI, with enhanced adaptability and learning capabilities when addressing complex, variable tasks. However, this progression also presents new challenges and considerations, including the need for extensive data, computational resources, and addressing issues related to interpretability. Despite these challenges, the potential and value of contemporary AI, particularly generative AI, for future advancements are immense.

III Differences Formally between Traditional AI and Current AI

At the level of formal understanding, traditional AI tends to construct explicit rule systems and solve problems through symbol manipulation and logical reasoning. In contrast, modern AI achieves implicit understanding and generation of complex patterns through deep learning. This transition not only enhances the ability to handle complex problems but also poses new challenges in interpretability [6][7].

Table 2. Distinctions between traditional AI and Current AI in terms of formal understanding.

Aspects and Capabilities	Traditional AI	Current AI
Core Methodology	Construction of explicit rule systems	Implicit understanding and generation through deep learning
Implementation Approach	Symbol manipulation and logical reasoning	Neural network models
Problem Solving	Reliant on predefined rules and logic	Autonomous learning of complex patterns in data
Ability to Handle Complex Problems	Limited, struggles with unstructured data	Elevated, adept at processing large-scale unstructured data

As evident from Table 2, traditional AI adopts structures akin to decision trees or flowcharts, indicating its reliance on explicit rules and logic for problem-solving. Conversely, modern AI employs simplified neural network structures, representing its utilization of deep learning models to autonomously learn complex patterns within data. These distinctions highlight the fundamental differences between traditional AI and modern AI in formal understanding, encompassing their core methodologies, implementation approaches, problem-solving capabilities, and abilities to handle complex problems.

Furthermore, traditional AI systems often struggle with ambiguity and context, as they rely heavily on predefined rules that may not account for all possible scenarios. This rigidity limits their adaptability and effectiveness in dynamic or diverse environments. In contrast, modern AI systems, particularly those leveraging deep learning, exhibit a remarkable capacity to handle ambiguity and context by learning from vast amounts of data. They can capture intricate relationships and dependencies that may be difficult to encode explicitly, enabling them to perform well in complex, real-world scenarios.

Moreover, the interpretability of traditional AI systems is generally higher, as the underlying rules and logic are transparent and can be easily traced. However, this transparency can also be a double-edged sword, as it may expose vulnerabilities and limit the system's ability to learn and adapt. On the other hand, modern AI systems, especially deep neural networks, often lack interpretability due to their complex, layered architectures. This lack of transparency can hinder trust and adoption in certain domains where interpretability is crucial, such as healthcare or finance.

In summary, the shift from traditional AI to modern AI in formal understanding represents a significant advancement in handling complex problems and learning from data. However, it also presents new challenges, particularly in interpretability and trust, which must be addressed to fully harness the potential of modern AI across various domains.

IV.Comparison of Traditional AI Perspectives with Contemporary AI Paradigms

Traditional AI perspectives, namely symbolism, connectionism, and behaviorism, emphasize the importance of symbol manipulation, network connections, and behavior simulation, respectively. In contrast, contemporary AI paradigms exhibit a more diversified and profound exploration of technology and practice:

- **Generative AI/AGI based on LLMs**, represented by ChatGPT, leverages large-scale corpus training to achieve natural language generation and understanding capabilities.
- **New Productivity AGI featuring small models**, such as I3DNA, focuses on model efficiency and practicality, demonstrating robust application capabilities in specific domains.

- **Twin Turing Machine**, compatible with both large and small models, achieves deep integration and intelligent processing of data and knowledge through a dual formalized understanding model. [8][9][10]

Table 3. Distinctions between ChatGPT, I3DNA, and Twin Turing Machine

	Generative AI/AGI (e.g., ChatGPT)	**New Productivity AGI (e.g., I3DNA)**
Core Characteristics	Based on LLM training for natural language generation and understanding	Small model, efficient and practical, specific domain applications
Model Scale	Large	Small
Computational Resource Consumption	High	Low
Versatility	High (in NLP domain)	Low (specific, especially new productivity domains)
Compatible with both large and small models AGI (e.g., Twin Turing Machine)		

As evident from Table 3, ChatGPT adopts a neural network-like architecture, indicating its reliance on large-scale corpus training for natural language generation and understanding. New Productivity AGI (e.g., I3DNA) employs a streamlined model structure, emphasizing efficiency and practicality, particularly demonstrating robust application capabilities in specific new productivity domains. The Twin Turing Machine adopts a dual-model structure, indicating its ability to achieve deep integration and intelligent processing of data and knowledge through dual formalized understanding models. Table 3 illustrates the distinctions between ChatGPT, New Productivity AGI (e.g., I3DNA), and Twin Turing Machine in terms of core characteristics, model scale, computational resource consumption, versatility, and application domains.

Comparative Analysis:

ChatGPT, as a representative of generative AI/AGI based on LLMs, is characterized by its ability to generate and understand natural language through large-scale corpus training. Its advantages lie in its wide application in the natural language processing domain, such as dialogue systems, text generation, and language translation. However, its limitations include potentially weaker deep understanding and application in specific domains, as well as high model complexity and computational resource consumption.

New Productivity AGI featuring small models, such as I3DNA, prioritizes model efficiency and practicality, demonstrating robust application capabilities in specific domains. Its advantages include a smaller model scale, lower computational resource consumption, and ease of rapid deployment and application in specific domains. Nevertheless, its limitations may include a lack of versatility and potentially weaker performance in cross-domain task processing.

The Twin Turing Machine, compatible with both large and small models, is distinguished by its ability to achieve deep integration and intelligent processing of data and knowledge through dual formalized understanding models. Its advantages encompass the versatility of large models and the efficiency of small models, enabling robust processing capabilities across different domains and tasks. However, its limitations include the relatively complex background knowledge of the model structure, requiring high theoretical and technical proficiency as well as computational resources for training and optimization.

Extended Analysis:

From an expert perspective in the AI field, it is imperative to underscore the nuances and implications of these paradigms. Generative AI/AGI, exemplified by ChatGPT, has revolutionized NLP by offering unprecedented naturalness in language generation and understanding. Its ability to learn from vast corpora enables it to mimic human language patterns effectively, making it invaluable for applications like chatbots, content creation, and language translation systems. However, its reliance on extensive training data and high computational demands poses challenges for widespread adoption and optimization in resource-constrained environments.

On the other hand, the emergence of New Productivity AGI, such as I3DNA, signifies a shift towards practicality and efficiency. These models, despite their smaller size, demonstrate remarkable performance in specialized tasks, making them ideal for deployment in niche applications where computational resources are limited. Their focused approach allows for quicker training times and easier integration into existing systems, fostering innovation in sectors like healthcare, finance, and manufacturing. Yet, their specialized nature restricts their versatility, necessitating the development of multiple models for diverse applications.

Lastly, the Twin Turing Machine represents an innovative attempt to bridge the gap between large and small models. By incorporating a dual-model architecture, it aims to retain the versatility of large models while enhancing efficiency through smaller sub-models. This hybrid approach presents a promising direction for achieving AI that is both intelligent and practical, capable of adapting to a wide array of tasks and domains. However, the complexity of designing and optimizing such a system underscores the need for continued research and development in theoretical AI and advanced computational techniques.

In conclusion, the evolution of AI paradigms from traditional symbolism, connectionism, and behaviorism to contemporary generative AI, new productivity AGI, and hybrid models like the Twin Turing Machine reflects a deepening understanding of AI's potential and limitations. Each paradigm offers unique advantages and challenges, necessitating a nuanced approach to their development, deployment, and optimization. As AI continues to advance, the exploration of diverse paradigms will remain crucial for driving innovation and addressing real-world challenges.

V.Theoretical Foundations of AI and AGI: Digital-Intellectual Text

Research has uncovered sequential logic and interaction function as core elements in the theoretical foundations of AI and AGI. Sequential logic focuses on the sequence and position relationships in information processing by intelligent agents, while the interaction function describes the interplay and influence among various components within an intelligent agent. Furthermore, the three fundamental laws governing generalized bilingualism and generalized translation based on digital-intellectual text provide an important theoretical basis for deepening our understanding and advancing generative AI and AGI. [11][12]

This section comprehensively elaborates on digital-intellectual text and its characteristics through text, formulas, graphics, and tables.

Overview of Digital-Intellectual Text:

Digital-intellectual text is a rigorously defined text type through dual formalization methods and dual computational models of both numbers and words. It follows specific rules of dual numeration systems, with digital IDs adhering to a P-based numeration system and Chinese characters (single-syllable "yan") and word groups (multi-syllable "yu") adhering to a Z-based numeration system. Digitalization is achieved through the Twin Turing Machine, and intelligentization is achieved through a series of Feng's machines, leveraging three types of formalized understanding models. This framework defines generalized bilingualism and generalized language (encompassing characters, forms, graphs, tables, audio, images, 3D models, and interactive elements) and their dual formalized digital-intellectual text. Its characteristics are that both basic elements (object language) and derived tuples at various levels (formalized combinations progressively deriving explanatory language, aka metalanguage) satisfy the three fundamental laws: (1) unique conservation of heterogeneous order (referred to as "order"), (2) corresponding conversion of homologous juxtaposition, and (3) corresponding conversion of consentaneous juxtaposition. Among these, law (1) is the sequential logic law, law (2) is the interaction function law, and law (3) is the generalized translation law. Here, "order" refers to the meaning of a term.

The following is a simplified graphic representation illustrating the relationship between basic elements and derived tuples in digital-intellectual text and how they adhere to the three fundamental laws:

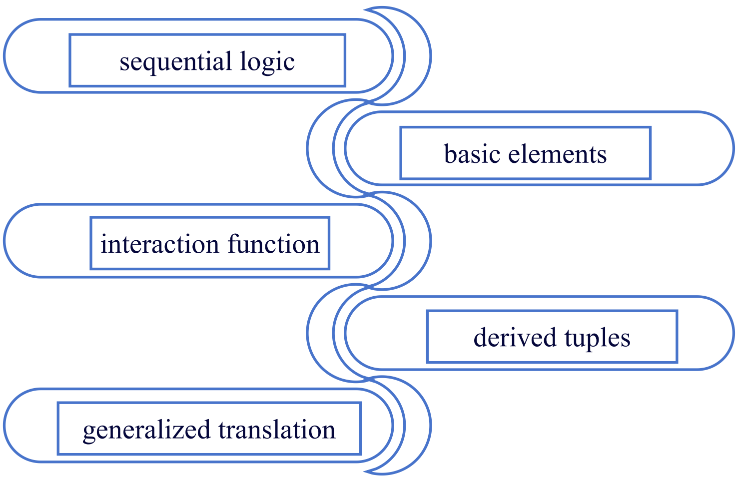

Figure 1. Relationship between basic elements and derived tuples in digital-intellectual text and their adherence to the three fundamental laws.

As depicted in Figure 1, it visually showcases the relationship between basic elements and derived tuples in digital-intellectual text and how they are constrained by the three fundamental laws. This approach facilitates understanding the complexity of digital-intellectual text and its underlying theoretical framework.

Digital-intellectual text is defined in a generalized bilingual context within the relationship database of "yan" and "yu," further extending to generalized language. Its basic elements (object language) and derived tuples (explanatory language and metalanguage) all satisfy the three fundamental laws: (1) unique conservation of heterogeneous order (sequential logic law), formulated as for any two terms a and b, their order positions p(a) and p(b) are unique and distinct identifiers. If $a=b$, then $p(a)=p(b)$, which leads to (2) corresponding conversion of homologous juxtaposition (interaction function law), formulated as for any two identical terms a and a', they can have different representations r and r' and undergo corresponding conversions between them. If $a \approx a'$, then there exists a conversion function f such that $f(a,r)=(a',r')$. This further leads to (3) corresponding conversion of consentaneous juxtaposition (generalized translation law), formulated similarly to (2) but with additional emphasis on conversion between different contexts or representations and further clarification of the selective intent of different agents and proxies (intelligent agents), which can be both agreed upon and stipulated. That is, if a and a' express the same or similar meaning in different contexts, then there exists a conversion function g such that $g(a,c)=(a',c')$, where c and c' represent specific selective intents in different contexts.

Table 4. The Three Fundamental Laws Followed by General AGI (Twin Turing Machine)

Fundamental Law	**Informal Overview, Description, or Identifier**	**Formulaic Explanation**
Sequential Logic	Each term has a unique and conserved order position in arrangement.	$P(a) = p(b)$ if $a = b$
Interaction Function	Identical terms undergo corresponding conversion between different text representations.	$F(a,r) = (a',r')$ if $a \approx a'$
Generalized Translation	Identical intent undergoes corresponding conversion between different contexts or representations.	$g(a,c) = (a',c')$ if a and a' are identical in different contexts
General AGI (Twin Turing Machine compatible with both large and small models) adheres to the above three fundamental laws.		

As evident from Table 4, the informal overviews and formulaic explanations of the three fundamental laws are provided. The following section further elaborates on two of these laws using formulas, tables, and graphics.

This research reveals sequential logic and interaction function as core elements in the theoretical foundations of AI and AGI. Specifically, sequential logic (Sequential Logic or The Logic of Sequence and Position or Bit-List Logic) focuses on the logical relationship of sequence and position in information processing by intelligent agents, describing how intelligent agents make decisions and inferences based on the sequence and position of information. The interaction function (Interaction Function) depicts the interplay and influence among various components within an intelligent agent, revealing the complex relationships and dynamic interactions between different parts of the agent. To gain a deeper understanding of these concepts, the following formulas can be used for representation:

Sequential Logic Formula: $SL = f(S, P)$

Where SL represents sequential logic, S represents the sequence of information, and P represents the position of information.

Interaction Function Formula: $IF = g(C_1, C_2, \ldots, C_n)$

Where IF represents the interaction function, and $C_1, C_2, \ldots, C_n$ represent the various components within the intelligent agent.

Table 5. *Summary of the Importance of Sequential Logic and Interaction Function in AI and AGI Development*

Fundamental Law	Informal Overview, Description, or Identifier	Formulaic Explanation
Sequential Logic	Describes the sequence and position relationship in information processing by intelligent agents.	Vital for understanding decision-making and inference processes of intelligent agents.
Interaction Function	Depicts the interplay and influence among various components within an intelligent agent.	Critical for revealing internal relationships and dynamic interactions of intelligent agents.

The three fundamental laws governing generalized bilingualism and generalized translation based on digital-intellectual text provide an important theoretical basis for deepening our understanding and advancing generative AI and AGI. These three fundamental laws can be represented using Figure 1.

In conclusion, sequential logic, interaction function, and the three fundamental laws governing generalized bilingualism and generalized translation based on digital-intellectual text collectively constitute a significant theoretical foundation for the development of AI and AGI. Through deep exploration of these concepts and laws, we can better understand and advance the development of generative AI and AGI.

VI. Research Significance and Future Prospects

This study not only enhances the interpretability of generative AI but also facilitates the broad translation of the emerging AGI (Artificial General Intelligence) theory, further demonstrating the potential of the Twin Turing Machine in integrating diverse intelligent elements and constructing superintelligent systems. Future research will delve deeper into the transformation pathways of these fundamental theories into practical applications, aiming to propel comprehensive advancements in AI technology. [13][14]

The significance of this research is profound. It not only enables us to better comprehend the working mechanisms of generative AI, thereby enhancing its interpretability, but also propels the generalized translation of AGI theory, fostering more profound exploration in this field. More importantly, the study reveals the substantial potential of the Twin Turing Machine in amalgamating various intelligent components and constructing superintelligent systems. [15][16] In essence, this research contributes to a deeper understanding of generative AI and AGI, while also providing a theoretical foundation for building more intelligent systems in the near future. It is poised to drive the practical application of AI technology across multiple domains, ushering in comprehensive technological progress. [17][18]

Looking ahead, we will continue to explore the transformation pathways of these fundamental theories into practical applications, striving to convert cutting-edge technology into actual productive forces and promote comprehensive advancements in AI technology. The ultimate goal is to harness these intelligent technologies to better serve society and bring more convenience and surprises into people's lives. [19][20]

Acknowledgments

I extend my gratitude to the interdisciplinary knowledge modeling research group at Peking University and the global explorers at the forefront of general AI technology. Their relentless pursuit of innovation and excellence has paved the way for groundbreaking discoveries in the field.

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