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Thermodynamics and Quantum Computing in AI and Climate Change Financial Decisions

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Abstract

We explore the connection between complex systems and theories of physics, information fields and energy matrices, with an emphasis on the anti-dichotomy of the natural and social worlds. This research includes chaos, nonlinearity, evolution and artificial intelligence, with the aim of resolving uncertainty in complex systems through optimization methods, modelling and numerical simulations. Key application areas include climate change and financial decision-making in stock markets, where thermodynamics, fractal artificial intelligence and quantum computing are key in the research. In addition, the Earth's rotation and the Fermi resonance significantly affect ecological and economic models.

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Introduction

“Nothing has such power to expand the mind as the ability to systematically and truly investigate everything that happens in life.”
Marcus Aurelius

We analyse the complex interrelationships between systems, theories of physics, information fields, and energy matrices, challenging traditional boundaries between the natural and social sciences, focusing on the complexity, chaos, nonlinearity, fractality, and dynamics of these systems, and their applications in financial decision-making, stock markets, and climate change.

Establishing a theoretical scientific approach establishes fundamental principles, predicts outcomes with mathematical rigor, and guides experimental validation. Theoretical frameworks enable advances in computing, energy systems, and modelling, addressing limitations such as thermodynamic efficiency in quantum processes. Thermodynamics informs thermal management in quantum computing and supports sustainable practices, optimizing climate simulations for emissions predictions. Quantum theory enhances artificial intelligence algorithms through superposition and entanglement, improving the speed of machine learning and the accuracy of climate predictions. These theoretical models facilitate simulations of molecular interactions and govern chaotic systems, ultimately providing reliable scenarios for policy-making and optimizing investments in sustainability.

Complex systems are characterized by chaotic, nonlinear, and fractal properties, requiring modern modeling and interdisciplinary knowledge for effective solutions to natural and social problems. Artificial intelligence, especially through deep learning and neural networks, is advancing the study of quantum dynamics and thermodynamic systems, leading to the development of fractal AI, which uses stochastic calculus to generate complex patterns. The lack of a universally accepted definition of complexity highlights the need for concepts of robustness and modularity. Decision theory helps to make optimal choices under uncertainty, which is relevant to AI applications. The development of theoretical frameworks, including string theory and thermodynamic AI, reflects the continuous progress in understanding complexity and integrating knowledge across disciplines.

The potential of large language models (LLMs) in research on thermodynamics, quantum computing, and climate systems is explored. The analysis highlights their computational capabilities and alignment with information physics, suggesting that a unified mathematical framework could integrate thermodynamic artificial intelligence, fractal artificial intelligence, quantum-assisted climate science, and financial decision-making, including factors such as Earth's rotation and Fermi resonances.

Our paper represents an attempt at pioneering work that integrates physics-inspired AI theory with advanced computational paradigms, addressing real-world challenges such as climate dynamics and market volatility. It introduces neural thermodynamic laws for LLM dynamics and fractal AI for scalable, self-similar structures. The paper applies thermodynamic principles to the efficiency of LLM training, uses fractal geometry to improve AI performance in complex simulations, and uses quantum algorithms for climate modelling. It also improves financial forecasting by combining LLM and quantum optimization with hybrid methodologies for high-precision decision making in chaotic markets.

“A new scientific truth does not triumph by convincing its opponents and making them see the light, but rather because its opponents eventually die, and a new generation grows up that is familiar with it.”

Scientific Meaning of The Laws of Physics in Complex Systems

All concepts related to monetary and new financial systems, thermodynamics of artificial intelligence, fractal artificial intelligence, climate change, financial markets, intelligent financial systems and structural economic functions are examined as complex systems. These systems are characterized by nonlinear interactions between different agents, emergent behaviours, feedback loops and path dependence. Financial markets exhibit phenomena such as clustering of volatility and contagion, while climate change arises from the intertwined dynamics of the ocean, atmosphere and land. In financial systems, complexity arises from adaptive agents and systemic risks. Thermodynamics of artificial intelligence deals with energy dissipation, and fractal artificial intelligence uses models for chaotic processes. Climate is viewed as a complex system with human influences, and economic functions are explored through sequential machines and qualitative analysis.

The convergence of thermodynamics, artificial intelligence (AI), quantum computing, and complex systems theory represents a paradigm shift in how we model nonlinear phenomena, from planetary climate dynamics to the stochastic nature of financial markets. At the heart of this synthesis is the realization that information processing, energy dissipation, and entropy production are fundamentally linked. By applying the principles of statistical mechanics to AI architectures, researchers are beginning to understand the "thermodynamic cost" of computation, where Landauer's principle states that erasing information necessarily increases the entropy of the environment.

Thermodynamic AI explores the energy efficiency of neural networks. As models grow in complexity, the heat dissipation associated with synaptic weight updates becomes a limiting factor. Fractal AI, which uses self-similar, multiscale architectures, mimics the efficient energy distribution found in biological systems. By applying fractal geometry, these systems can optimize the flow of information through hierarchical layers, effectively minimizing the rate of entropy production (σ) defined by Prigogine's principle of minimum entropy production in non-equilibrium states: $\sigma=\sum_i J_i X_i \geq 0$ (J_i represents thermodynamic fluxes, and X_i represents the corresponding forces).

In research, analyses of climate change, Earth's rotation, and atmospheric resonances—such as the Fermi resonance—are creating nonlinear systems that defy classical linear modeling. Quantum computing offers a transformative approach by simulating the Hilbert space of complex climate variables, which is exponentially larger than classical machines. Quantum algorithms can better resolve the coupling between rotational dynamics and atmospheric oscillations, providing greater fidelity in predicting long-term climate change. The integration of quantum-enhanced artificial intelligence enables the identification of hidden patterns in chaotic climate data, effectively acting as a "Maxwell's demon" that sorts information to reduce uncertainty in climate projections.

Financial markets are complex systems characterized by a "fat tail" and emergent behaviour. The application of thermodynamic analogies—often called "econophysics"—treats market participants as particles in a potential field. Fractal AI models are capable of capturing the "memory" of market time series, identifying long-term correlations that standard Gaussian models overlook. Using quantum-inspired optimization, financial institutions can navigate high-dimensional decision spaces to mitigate risk in volatile environments, treating market crashes as phase transitions in a complex thermodynamic system.

The scientific significance of this interdisciplinary field lies in its ability to unify different domains under the umbrella of information theory and energy conservation. Whether analysing the rotational stability of the Earth or the volatility of a stock market index, the underlying mathematics of complex systems—governed by non-equilibrium thermodynamics—remains consistent. This holistic approach provides a robust framework for addressing global challenges, ensuring that technological advances in AI and quantum computing are grounded in the physical boundaries of the universe.

In short, the interdisciplinary research of thermodynamics, artificial intelligence, and complex systems is essentially the science of how information and energy move through chaotic environments. Whether we look at the Earth’s climate or the stock market, these systems are “complex” because they involve millions of moving parts that interact in unpredictable ways. By using the laws of physics—specifically thermodynamics—we can treat these systems as energy-processing machines to better predict their behaviour.

The scientific significance of combining these fields is that they provide a universal “language” for understanding change. Rather than studying climate, economics, and artificial intelligence as separate subjects, this approach treats them all as systems that must obey the laws of energy and information. This allows us to harness the power of quantum computing and advanced artificial intelligence to solve real-world problems, such as predicting financial instability or managing the impacts of a changing climate, by understanding the physical constraints of the systems themselves.

Monetary and New Financial System

Theoretical monetary systems, like the "Joule Standard," tie money to thermodynamic principles, viewing it as an information protocol that optimizes entropy production in energy-dissipative economies. In frameworks blending thermodynamics of AI, fractal AI, and quantum computing, these systems gain importance by aligning financial flows with physical laws of complexity and energy rate density (Φm), preventing "viscosity gaps" that cause economic friction or collapse.

The integration of theoretical monetary systems into the framework of artificial intelligence (AI), fractal intelligence, and quantum computing represents a paradigm shift in the way we model complex systems, including climate change and global financial markets. At the heart of this synthesis is the application of statistical mechanics to information theory, where money functions as a proxy for the "negentropy" or ordered energy within a system. In the context of climate change, the rotation of the Earth and phenomena such as Fermi resonance - where energy transfer occurs between vibrational modes - serve as physical analogs for the way information propagates through financial networks. Just as climate systems exhibit chaotic behaviour governed by nonlinear dynamics, financial markets exhibit fractal properties where price fluctuations follow power distributions rather than Gaussian curves.

The importance of a new financial system within this framework lies in its ability to take into account the "thermodynamic cost" of computation. As AI systems become increasingly complex, the energy required to process information becomes a limiting factor, mirroring the way planetary rotation and atmospheric heat exchange constrain climate stability. Using quantum computing, these complex systems can be simulated with greater fidelity, as quantum bits (qubits) allow for the representation of superposition states that better capture the probabilistic nature of market crashes and climate tipping points. The mathematical representation of these systems often includes an entropy production rate, defined as: $\sigma=dSdt\geq 0$ where S is the entropy of the system. In financial decision-making, the "new" monetary system must take into account the dissipation of information, treating market transactions as thermodynamic processes where the "work" performed is the allocation of capital based on predictive AI models.

Fractal AI is well suited to analysing Earth's climate because it recognizes self-similarity at different scales - from micro-turbulence to macro-planar rotation. When applied to financial markets, fractal analysis helps identify the "memory" of a system, where past events influence future states through long-term correlations. This is fundamental to understanding the Fermi resonance in climate systems, where periodic forcing (such as the Earth's rotation) interacts with internal oscillations to create unpredictable changes in global temperatures. A financial system that integrates these physical realities can better protect itself from systemic risks, because it treats the market not as an isolated entity, but as a subsystem of the global thermodynamic environment.

Quantum computing introduces the possibility of solving optimization problems that are currently intractable for classical computers, such as the multivariable analysis required for climate modeling and high-frequency trading. By exploiting quantum entanglement, financial algorithms can process huge data sets to identify patterns in market sentiment that correlate with environmental indicators. This creates a feedback loop in which the "monetary value" of a resource dynamically adjusts based on its thermodynamic impact, effectively accounting for the long-term costs of climate change. In short, we are moving toward a future where financial decisions are underpinned by the same laws of physics that govern the stars and climate, using artificial intelligence as the “brain” to process that complexity.

Scientific Understanding of Artificial Intelligence Thermodynamics of Complex Systems

The intersection of thermodynamics, artificial intelligence (AI), and complex systems represents a frontier of modern physics and computational theory. At its core, computational thermodynamics, as explored by Rolf Landauer, posits that information erasure is a dissipative process that generates heat. As AI systems scale, the energy requirements for training large models—governed by Landauer's principle—become a critical constraint. This principle states that the minimum energy required to erase a single bit of information is $E=kBTln\boxed{f0}2$ where kB is Boltzmann's constant and T is the absolute temperature. In the context of complex systems, such as global climate models or financial markets, artificial intelligence acts as an information processing mechanism that must manage the trade-off between entropy and information.

Fractal AI applies self-similar, recursive algorithms to model complex, scale-invariant systems, such as the Earth's climate and financial markets. Fractal dimensions help to approximate nonlinear dynamics such as the Fermi resonance in climate and to identify hidden patterns in financial data, which often exhibit chaotic, fat-tailed distributions that defy traditional models. Quantum computing improves simulations of complex systems by exploiting the superposition and entanglement of qubits to solve high-dimensional equations (e.g., climate dynamics) more efficiently than classical methods. Quantum-inspired artificial intelligence also optimizes financial portfolios by navigating through vast state spaces. Financial markets, viewed as dissipative structures, operate via non-equilibrium thermodynamics, where decisions driven by AI reduce the system’s entropy at a thermodynamic cost, which reflects the energy required to process market information.

The interplay of thermodynamics, artificial intelligence (AI), and complex systems focuses on their theoretical foundations, applications, and interpretability challenges. We highlight the principles of thermodynamics as they apply to neural networks, emphasizing concepts such as energy minimization, entropy maximization, and their role in preventing overfitting. AI models, often viewed as black boxes, present interpretability challenges, which are addressed by inherently interpretable models and post-hoc explanatory techniques, such as linear surrogates and permutation-based methods. Despite these advances, interpretability remains limited, especially in complex feature spaces. We discuss the ability of AI to model complex systems across disciplines, noting the emergent properties of such systems and the importance of interdisciplinary approaches. Future directions include understanding the neural code and the potential for AI to mimic aspects of human consciousness, while continuing to address the trade-off between model accuracy and interpretability.

Synthesis thermodynamic principles underpin AI training and the analysis of complex systems, highlighting the importance of interpretability in black-box AI models. The role of AI in understanding complex, dynamic systems across disciplines provides insights into future breakthroughs in unravelling the neural code of the brain, which could usher in a new era of superhuman AI.

Complex Systems through the Lens of Fractal AI

Fractal AI includes AI frameworks that use fractal mathematics—specifically self-similarity, scaling laws, and recursive structures—in learning and decision-making algorithms. This approach treats intelligence as a multiscale, self-organizing process, capable of adapting to uncertainty and complexity, similar to fractal systems in nature. Fractals are attuned to complex systems such as ecosystems and financial markets, effectively capturing their nonlinear dynamics through fractal geometry. Fractal AI improves the accuracy of modelling and prediction for phenomena such as climate variability and social network dynamics, promoting adaptive systems that can handle complexity without assuming uniformity. Ultimately, fractal AI brings together mathematics, computer science, and natural philosophy, providing new insights into adaptive systems and broader scientific research.

Climate Change (Fermi Resonance)

“Look after the land and the land will look after you, destroy the land and it will destroy you.” Aboriginal Proverb

The climate system is a complex, dynamic network composed of multiple interacting subsystems, including the atmosphere, ocean, cryosphere, land, biosphere, and anthroposphere. These components interact in nonlinear ways, making understanding climate and climate change a significant scientific challenge that relies on data, experimentation, and advanced modelling tools, such as quantum computing, which uses quantum mechanics to solve complex problems that are beyond the capabilities of classical computers.

Human activity is the main cause of climate change, outweighing natural variation. Uncertainties persist due to limited understanding of Earth systems, model deficiencies, measurement problems, and unpredictable societal factors that influence future emissions. These uncertainties can be categorized into four levels, which complicates climate risk management and policy formulation. In addition, Fermi resonance, a quantum phenomenon in CO2 where two vibrational states interact, enhances its absorption of infrared radiation across a wider spectrum, making it significantly more effective as a greenhouse gas. This resonance accounts for half of the warming effect of CO2, linking it to anthropogenic global warming and influencing climate models.

The Impact of Climate Change on The Rotation of The Planet Earth (With AI Methods)

Artificial intelligence is becoming a key tool for analysing the impact of climate change on Earth’s rotation, as measured by changes in its rotational speed and axis position. Melting ice sheets cause mass to shift to lower latitudes, slowing rotation and lengthening the length of the day. New models such as physically based neural networks (PINNs) allow researchers to analyse complex data and project possible scenarios for changing day length and pole shifts. These changes, although small, have important implications for universal weather patterns and indicate the profound consequences of human activities on planetary dynamics. AI is essential for understanding and monitoring these complex interactions.

Financial Markets/Stock Exchanges, Complex Decision-Making Systems/Theories in The Context of Climate Change

Financial markets and stock exchanges are key to combating climate change by pricing risk and facilitating the transition to low-carbon economies. They model interactions taking into account uncertainties such as policy changes and physical risks, including extreme weather events and carbon prices, that affect asset values. Stock exchanges encourage orderly trading by disclosing information on climate risks, helping investors assess them – even increasing risks in financial networks by 40-54% in eurozone data. The evolution towards complex adaptive systems poses challenges in integrating climate considerations. Alternatives such as long-termism, interconnectedness, dynamic carbon pricing and active ownership are key to the transition to a low-carbon economy. Policymakers rely on the Financial Stability Board (FSB) guidance to manage risks, while investors integrate climate science into their portfolios, ensuring transition plans to address stranded assets and systemic impacts.

Intelligent Systems of Finance/Integration of Quantum Field Theory and Finance

The concept of “Intelligent Financial Systems / Integration of Quantum Field Theory and Finance” encompasses two main ideas: intelligent financial systems driven by artificial intelligence and the application of quantum finance models to asset pricing and risk modelling. Intelligent financial systems use artificial intelligence and machine learning to automate financial intermediation and improve functions such as credit scoring, customer service, and algorithmic trading. Central banks now consider these systems to be crucial for financial stability. Quantum finance uses the framework of quantum field theory (QFT) to better model financial phenomena. It introduces concepts such as quantum price fields and uses mathematical methods from physics, enabling richer models for understanding market behaviour. Recent integrations of QFT with artificial intelligence have led to predictive trading systems that capitalize on correlations and non-local market shocks. However, the mathematical complexity of these systems can pose challenges in interpretation and regulatory oversight compared to traditional models.

Structural Economic Functions - Climate Change

Structural economic functions related to climate change encompass the evolution of sectors, technologies, labour markets and institutions of the economy in response to climate impacts and policies. This transformation affects production, trade, investment, employment and growth. Climate change and carbon pricing are shifting resources from higher-risk sectors, such as agriculture, to low-carbon sectors, such as renewable energy and energy-efficient industries. Accelerated action on climate change is shifting economic activity towards sectors with lower energy content, driven by advances in low-carbon technologies. Structural changes require a reallocation of capital and labour, particularly as climate impacts differ across sectors. Institutions play a key role in facilitating the transition to low-carbon activities, while existing economic dependencies on fossil fuels can affect the costs and disruptions that occur during this transition.

Materials and Methods

We emphasize that there is currently no standardized framework that integrates AI thermodynamics, fractal AI, and quantum computing in climate modelling and financial decision-making. AI thermodynamics focuses on energy efficiency and entropy in neural networks, while fractal AI uses self-similar patterns to learn from complex data. Quantum computing facilitates climate simulations related to CO2 dynamics and improves financial modelling. There are proposals for hybrid approaches, such as fractal information dynamics combined with quantum mechanics. However, different fields lack unified methodologies or experimental protocols, especially in areas such as the Fermi resonance affecting CO2 absorption and Earth rotation models, which rely on traditional fluid dynamics rather than fractal-thermo AI methods.

LLM models and associated mathematical frameworks can be formally described as "materials and methods" within the overarching framework of thermodynamics of AI + fractal AI + quantum computing applied to complex systems, climate science, and financial decision-making, but only in the metaphorical and formal sense of modelling, not as literal physical materials. LLMs and mathematical frameworks serve as "materials and methods" in interdisciplinary studies, modelling thermodynamic, fractal, and quantum aspects of AI within complex systems such as climate dynamics and financial markets. In scientific papers, LLMs provide scalable inference mechanisms for the thermodynamics of AI, while frameworks such as entropy equations guide principles such as neural thermodynamic laws (NTL). The dynamics of LLM training illustrate thermodynamic principles, helping to analyse the effectiveness of AI. Fractal AI uses self-similar structures to model emergent intelligence, and quantum machine learning (QML) improves climate modeling and stock forecasting. Fermi resonance affects climate by influencing absorption spectra, and quantum neural networks improve financial decision-making by efficiently capturing market correlations.

The mathematical framework integrates stochastic and quantum thermodynamics, scale-invariant dynamics, and quantum-inspired state evolution as a unified framework. It conceptualizes systems (AI, climate, markets) as non-equilibrium stochastic processes, using thermodynamic uncertainty relations to bridge precision and information between the classical and quantum realms. The framework emphasizes fractal equations for modelling complex systems, normalizing dimensionality through effective fractal dimensions. In addition, it applies the principles of quantum mechanics to various abstract states, connecting quantum Hamiltonians to macroscopic thermodynamic variables. The integration of AI and finance is explored, categorizing AI agents as information-driven engines and applying fractal dynamics under thermodynamic constraints. Finally, it advocates the use of quantum algorithms to solve climate and financial modelling, framing financial markets in thermodynamic terms to derive new financial laws.

Quantum-inspired state evolution extends the generalized Schrödinger equation of the type $i\hbar\partial t|\psi\rangle=H|\psi\rangle$ $i\hbar\partial t|\psi\rangle=H|\psi\rangle$ to various domains, including molecular dynamics and abstract states such as climate models and AI belief states. It involves coupling quantum Hamiltonians with macroscopic thermodynamic variables via open quantum systems. Fractal AI can be modeled using recursive neural dynamics under stochastic constraints, balancing scale invariance and optimizing information. In climate and finance, quantum algorithms help solve fluid dynamics equations by integrating thermodynamic structures. Financial markets are viewed as thermodynamic ensembles, with the concepts of "market temperature" and "price impact", leading to new financial laws and arbitrage constraints.

A unified framework is proposed across domains, characterized by a state space Ω, a probability density $\rho(t)$ and an entropy $S(t)$ defined as $S(t) = -Tr[\rho(t) \log\rho(t))$. The information flow $I(t)$ between subsystems, including AI, climate and finance, is described. The evolution of $\rho(t)$ is influenced by factors such as AI, climate and finance, where L includes quantum Hamiltonian elements and dissipative terms that model entropy and friction in the market. The framework requires the establishment of a common ontology across domains and an understanding of the impact of Earth's rotation and Fermi resonances on climate and AI and financial systems. It emphasizes the development of a coherent mathematical formalism that harmonizes various structural theorems into a single overarching principle, recognizing the feasibility of this extensive research program.

Our research and analysis suggest favouring models with proven consistency over those that merely adjust to the data, especially when it comes to generalizing under conditions of distributional change such as extreme climate events or market crashes. Thermodynamically inspired models tend to generalize better due to their alignment with fundamental physics. Energy efficiency is key; models that reduce parameters and use quantum gates, such as fractal and thermodynamically regularized models, outperform raw LLMs. For climate and financial compliance, hybrid models with explainable frameworks are recommended over black-box approaches. QR-GANs or quantum-classical hybrids need to be evaluated for robustness against noise. The simplest model that meets physical, risk, and explainability standards should be chosen, and advanced methods are integrated only when necessary (scientists in this field include colleagues in thermodynamic artificial intelligence and hybrid neuro fractal research.

Research contributions in AI, thermodynamics, and finance highlight significant collaborations. Notable researchers include Denis Melanson and Patrick J. Coles from Normal Computing, and Daniel Speckhard from the University of Wisconsin-Madison, who focused on adapting AI models to predict crystal structure relaxation using thermodynamics. Steve Yang from Stevens Institute of Technology explores generative AI in financial risk modelling. Key developments involve Molecular Dynamics Language Models for generating molecular trajectories, AI optimizing organoid quality assessments, and the use of LLMs like Kepler Agent to discover physical equations via symbolic regression. Additionally, LLMs like Fin BERT are used for market sentiment analysis.

QR-GANs (quantum reservoir generative adversarial networks) leverage quantum reservoir computers for generating realistic outputs, excelling in complex data distributions relevant to finance and climate. They outperform large language models (LLMs) in generating high-dimensional stochastic data but are limited in symbolic reasoning. Hybrid mathematical models that integrate AI with classical physics equations enhance precision in solving complex problems. The analysis advocates for thermodynamically inspired models, supporting robustness and energy efficiency for better generalization under variable conditions. Research efforts in AI, thermodynamics, and finance emphasize collaborative advancements, focusing on predictive modelling and risk assessment.

Conclusion

Artificial intelligence thermodynamics focuses on energy efficiency and entropy in neural networks, while fractal AI employs self-similar patterns for scalable architectures. Quantum computing enhances climate simulations, including Earth's dynamics, and these concepts converge in financial modelling for stock predictions. AI models require significant energy, leading to advancements in thermodynamic frameworks, such as machine learning force fields (MLFF) and physics-informed neural networks (PINNs), which uphold thermodynamic principles. Fractal geometries improve pattern recognition in neural networks, supporting complex data processing in various fields. Quantum algorithms address climate modelling and enhance ensemble predictions, with applications in exoplanet climates. In stock analysis, these innovations predict market entropy, identify chaotic patterns, and utilize quantum simulations for risk assessment in uncertain conditions [1-89].

Discussion

AI integrates thermodynamics, fractals, quantum computing, and complex systems in areas like climate modelling and financial markets through energy-efficient methods and simulations. Training AI like GPT-4 requires significant energy, generating heat and increasing entropy, with GPT-4's training consuming about 50 GWh. Researchers like Jörg Behler and Michele Parrinello have contributed to the development of high-dimensional neural network potentials for cost-effective molecular simulations, while Jim McCarthy's work at Thermal Shift AI focuses on stochastic thermodynamics for enhancing energy efficiency in AI.

Fractal AI models intelligence with self-similar, cellular automata, enabling efficient reinforcement learning - outperforming Monte Carlo Tree Search on Atari games with 1,000 times fewer samples. This theory is applied to non-equilibrium thermodynamics, quantum physics and economics by handling complex, scale-invariant data. Researchers at Fractal.ai, such as Kunal Singh and Abhijit Guha, are developing fractal-inspired multimodal models for real-world pattern recognition.

Quantum computers simulate molecular chemistry for carbon capture and climate models, solving partial differential equations exponentially faster. The Fermi resonance in CO2—the quantum interaction between vibrational modes—broadens the absorption bands, doubling its greenhouse effect and linking it to Earth's rotation through atmospheric dynamics. Leaders like Jeremy O'Brien (CEO of Psi Quantum) are targeting climate change mitigation, while Richard Toohey is applying quantum technology to energy and climate sustainability.

Quantum algorithms optimize portfolios, risk analysis, and high-frequency trading by processing market correlations beyond classical limits. Marco Pistoia of JPMorgan leads quantum risk modeling, and companies like Applied Quantum Software (Tom Finke) are integrating it for stock predictions. Alireza Khodaei is developing quantum finance solutions using financial quantum particles to predict market behaviour.

Integrated Discussion

McCarthy: "Thermodynamics limits AI scalability; fractals could minimize entropy in quantum climate simulations."

O'Brien: "Quantum edges classical in CO2 Fermi resonance modelling for precise rotation and climate forecasts."

Pistoia:"Quantum fractals improve stock volatility predictions, linking thermodynamic efficiency to trades."

This framework reveals synergies: fractal patterns model climate fractals (e.g. turbulence), quantum accelerates both climate and finance, all limited by the thermodynamic costs of AI.

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Author Contributions

Scientific contributions across thermodynamics AI, fractal AI, quantum computing, complex systems, and financial decision-making exemplify a new interdisciplinary approach. This framework integrates physics, artificial intelligence, and scalable modelling, utilizing thermodynamic principles, fractal structures, and quantum methods to address complex real-world challenges.

Conflict of Interest

The author declares that there is no conflict of interest.

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