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A Comparative Review of Entropy-Based Models in Physics and Artificial Intelligence

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ABSTRACT

This study aims to compare entropy-based models in physics and artificial intelligence (AI), highlighting their theoretical foundations, mathematical structures, and domains of application. Method: A systematic literature review (SLR) was conducted using 11 selected Q1 journal articles published between 2020 and 2023. Articles were classified and analyzed based on domain, entropy formulation, purpose, strengths, and limitations. Results: Findings show that physics-based models emphasize analytic rigor through concepts such as Boltzmann entropy, partition functions, and maximum entropy principles. In contrast, AI-based models apply entropy in decision-making, classification, and information fusion using fuzzy logic, divergence measures, and quantum evidence theory. Despite different traditions, both domains use entropy to quantify uncertainty and optimize systems, revealing potential for convergence. Novelty: This review offers a cross-disciplinary synthesis that maps entropy as both a physical and computational concept. It provides a comparative framework that bridges formal physics and practical AI, proposing hybrid entropy models as a promising direction for future research.

INTRODUCTION

In the development of modern science, entropy has become a key cross-disciplinary concept that promises a universal understanding of complex systems. In physics, entropy plays a role as a measure of microscopic disorder in statistical mechanics and thermodynamics (Babajanyan et al., 2020). On the other hand, in artificial intelligence (AI), entropy is used to measure information uncertainty, guide data classification processes, and optimize multi-source fusion (Xiao, 2023; Xiao, Wen, & Pedrycz, 2022). Great hopes arise that entropy can be a theoretical bridge between physical systems and adaptive intelligent systems. Unfortunately, the use of entropy in physics and AI is still separate. Physics maintains a formal mathematical approach rooted in the basic principles of nature, while AI tends to utilize entropy heuristically for algorithmic efficiency (Fan & Xiao, 2022). Approaches such as graph visibility-based probability transformation (Chen, Deng, & Cheong, 2021) or quantum-based evidence theory (Xiao, 2023) show great potential, but the philosophical meaning of physical entropy is rarely explicitly integrated into intelligent systems.

Due to this fragmentation, there is no comprehensive mapping that explains how entropy models from these two domains can complement each other. Models in physics such as the integration of game theory and statistical mechanics (Babajanyan et al., 2020) have high relevance for the dynamics of information systems in AI. In contrast, information divergence models developed for pattern classification and decision making in AI (Xiao & Pedrycz, 2022; Fan & Xiao, 2022) have the potential to enrich the analysis of physical systems.

Several approaches have tried to bridge this gap. For example, the use of fractal dimensions to measure the complex structure of information networks (Wen & Cheong, 2021), or fractal information from mass functions in belief theory (Qiang, Deng, & Cheong, 2022). Entropy measurement models based on Pythagorean fuzzy (Wang, Xiao, & Cao, 2022) and divergence generalization (Xiao, Wen, & Pedrycz, 2022) also demonstrate the flexibility of entropy in the context of AI, especially to handle high uncertainty in multi-source data.

However, these approaches still face limitations. Many models rely on the assumption of independence of information sources and ignore the complex dynamics that occur in the real world. Models such as the maximum entropy of a permutation set (Deng & Deng, 2022) are theoretically interesting, but their applicability to multi-scale systems is still limited. In addition, the absence of a synthesis between the physical and technical meanings of entropy leads to the loss of integrative potential that is much needed in today's interdisciplinary era. Therefore, this article is here to comparatively review various approaches to entropy modeling in physics and AI. By examining the principles, applications, and limitations of each approach, this article aims to build an integrative framework that unifies entropy as a physical and technical concept. The novelty of this article lies in the attempt to juxtapose models such as game theory-based entropy (Babajanyan et al., 2020), quantum evidence theory (Xiao, 2023), and fuzzy divergence (Fan & Xiao, 2022), to reveal the potential of entropy in managing the complexity of information systems and physical systems simultaneously.

RESEARCH METHOD

Type and Design

This study uses a qualitative-descriptive research design, employing a Systematic Literature Review (SLR) approach. The design is aimed at identifying, selecting, evaluating, and synthesizing relevant studies that propose, utilize, or review entropy-based models in both physics and artificial intelligence.

Sample of Research

The sample in this study consists of 11 primary articles, including one main reference (Babajanyan et al., 2020) and ten supporting articles from reputable journals indexed in Scopus Q1, published between 2020–2023, and selected based on relevance, citation impact, and methodological clarity. The main themes of the articles include entropy, statistical mechanics, quantum and fuzzy information fusion, network complexity, and decision-making. These sources were extracted from academic databases such as Scopus, IEEE Xplore, SpringerLink, and Elsevier ScienceDirect.

Inclusion criteria were:

(1) articles written in English,

(2) published in peer-reviewed Q1 journals,

(3) directly related to entropy-based modeling in either physics or AI,

(4) have received at least 10 citations (for impact consideration), and

(5) offer a conceptual or mathematical contribution.

Instruments and Procedures

The primary research instrument in this study is a literature classification matrix, which was used to categorize and compare the studies based on key elements such as:
(a) theoretical foundation of entropy used,
(b) domain of application (physics or AI),
(c) mathematical structure or algorithm,
(d) strengths and limitations, and
(e) type of data or system modeled.

Procedures of data collection involved four stages:
1. Identification – using keyword combinations (e.g., "entropy AND statistical mechanics," "entropy AND AI," "fuzzy entropy," "quantum mass function," etc.)
2. Screening – removing duplicates and irrelevant titles/abstracts.
3. Eligibility – evaluating full-text based on inclusion criteria.
4. Data Extraction – summarizing core content into the classification matrix for comparison.

Data Analysis
The data analysis in this review follows a comparative qualitative approach. Each selected article was analyzed using thematic coding, focusing on the purpose, entropy formulation, methodology, and implications. From this, themes were developed and clustered into two main categories: (1) physics-based entropy models, and (2) AI-based entropy models.
A cross-case synthesis technique was employed to identify similarities, contrasts, and opportunities for theoretical convergence between the two categories. Tables and figures were also generated to visually represent structural relationships between models, conceptual overlaps, and application domains.
This methodology ensures replicability and transparency in the review process while allowing critical insight into the evolution, usage, and potential of entropy as a unifying framework.

Figure 1. Research flowchart

Literature Classification Matrix
To structure the results of the literature review, the following literature classification matrix was used, which contains core information from each article regarding the

entropy approach used, its application domain, and its respective strengths and weaknesses in Table 1.

Table 1. Literature classification matrix

	Author(s) & Year	Domain	Entropy Approach	Methodological Focus	Strength	Limitation
1	Babajanyan et al. (2020)	Physics	Statistical entropy & Game Theory	Bridge between game-theoretic decisions and statistical mechanics	Theoretical synthesis, rigorous mathematical derivation	No direct AI application
2	Xiao (2023)	AI	Quantum Evidence Theory	Fusion of contradictory information sources using entropy	High adaptability in AI uncertainty modeling	Still abstract for physical modeling
3	Xiao & Pedrycz (2022)	AI	Generalized divergence	Pattern classification under multiple source uncertainty	Improved classification accuracy	Parameter tuning sensitive
4	Wang et al. (2022)	AI	Pythagorean fuzzy entropy	Multi-criteria decision making	Effective in handling vague/uncertain data	Complex fuzzy logic computation
5	Deng & Deng (2022)	Physics	Maximum entropy on permutation sets	Combinatorial entropy modeling	Strong in randomness estimation	Limited real-world applications
6	Qiang et al. (2022)	AI/ Physics	Information fractal entropy	Representation of belief structure via fractal dimension	Bridges entropy and complexity	Hard to interpret for non-mathematicians
7	Wen & Cheong (2021)	AI/ Physics	Fractal dimension	Quantifying network complexity	General framework for network entropy	Abstract; needs further practical link
8	Chen et al. (2021)	AI	Probability transformation via visibility graph	Mapping mass function to network structures	Creative entropy mapping to networks	Application-specific assumptions
9	Fan & Xiao (2022)	AI	Complex Jensen–Shannon divergence	Multi-source info fusion	High robustness against source conflict	May require complex prior structuring

10	Xiao et al. (2022)	AI	Generalized divergence	Decision under pattern ambiguity	Mathematically elegant, flexible	Heavy computational load
11	Xiao & Pedrycz (2022)	AI	Divergence theory	Pattern classification	Efficient entropy-based decision	Needs more comparative benchmarking

Conceptual Mapping of Entropy Models

To visualize the relationship between entropy models in physics and AI, here is a conceptual diagram in Figure 2.

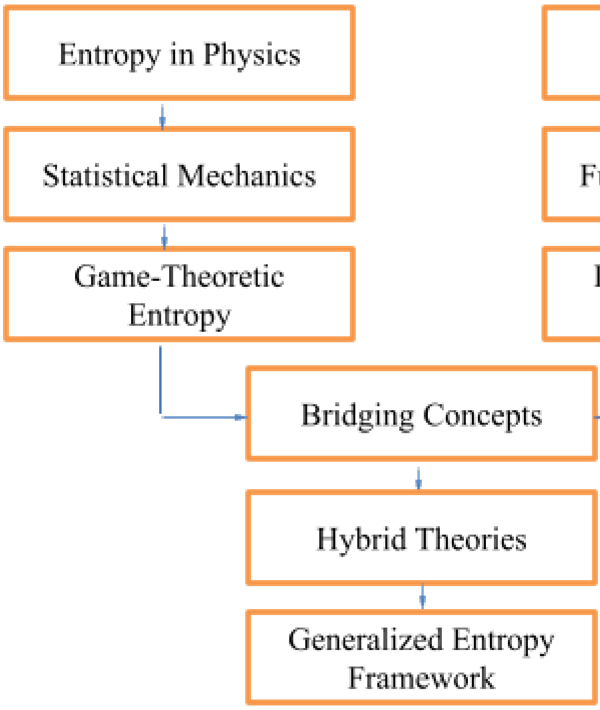

Figure 2. Conceptual mapping of entropy models

Explanation:

Bridging Concepts: includes fractal dimensions, visual probability theory, quantum proof theory, and fuzzy divergence. It is the meeting point between physical models and modern information systems.

Hybrid Theories: are the result of integration, such as the generalized entropy framework, which can be used in both domains.

RESULTS AND DISCUSSION

Classification of Entropy Models

The reviewed literature reveals that entropy-based models can be broadly classified into two major categories based on their disciplinary orientation: physics-based models and artificial intelligence (AI)-based models. Each category reflects distinct theoretical foundations, mathematical structures, and application domains, yet shares the common objective of addressing uncertainty and complexity in systems. In the physics-oriented category, entropy is often grounded in classical or statistical mechanics and serves as a theoretical tool for understanding the behavior of physical systems. Babajanyan, et al., (2020) proposed an integrative model that links game theory with statistical mechanics, offering insights into agent-based interactions in thermodynamic systems. Meanwhile, Deng & Deng (2022) introduced a model based on maximum entropy of random permutation sets, which explores combinatorial entropy in probabilistic ensembles. Additionally, Qiang, Deng, & Cheong (2022) applied information fractal dimension to mass functions in order to quantify the complexity and distribution of belief structures, bridging physical and informational representations of entropy.

In contrast, the AI-based category adopts entropy as a computational and decision-support tool for dealing with imprecise, ambiguous, or multi-source data. Wang, Xiao, & Cao (2022) employed entropy measures in Pythagorean fuzzy sets for multi-criteria decision-making (MCDM), enhancing the ability of systems to handle uncertainty in linguistic and numeric preferences. Xiao (2023) extended the theoretical landscape by formulating a generalized quantum evidence theory, enabling the fusion of conflicting or uncertain sources through quantum-inspired entropy mechanisms. Moreover, Xiao & Pedrycz (2022) developed a generalized divergence-based model which utilizes entropy divergence to support classification tasks under incomplete or conflicting data. This classification highlights the dual nature of entropy: as a foundational theoretical concept in physics and as a functional computational tool in AI. While the former emphasizes analytic rigor and physical law conformity, the latter focuses on adaptability, decision-making accuracy, and system performance under uncertainty.

Mathematical and Theoretical Framework

Entropy-based models exhibit diverse mathematical formulations depending on the disciplinary lens through which they are developed. In general, the physics-based models rely on classical principles of statistical mechanics and thermodynamics, emphasizing rigorously defined analytic structures. In contrast, AI-based models tend to employ flexible, computational frameworks such as fuzzy logic, divergence measures, and probabilistic mass functions, often tailored to handle uncertainty in real-world decision systems. Within the physics domain, foundational models of entropy often invoke the partition function to describe the probabilistic distribution of microstates in a system. The Boltzmann entropy formula,

$$S = kBln\Omega$$

where Ω is the number of accessible microstates, represents the core idea behind entropy as a measure of microscopic disorder. Additionally, the principle of maximum entropy is frequently used to infer the most unbiased probability distribution under given constraints. This principle, widely used in statistical inference and thermodynamic modeling, is particularly evident in models such as those developed by Babajanyan et al. (2020) and Deng & Deng (2022), where game-theoretic interactions and combinatorial arrangements are analyzed through entropy maximization.

Conversely, AI-based entropy models are constructed to support tasks such as classification, information fusion, and multi-criteria decision making. One common formulation is the Jensen–Shannon divergence, a symmetrized and smoothed variant of the Kullback–Leibler divergence, used to quantify the dissimilarity between probability distributions. This divergence-based approach is central to the work of Xiao & Pedrycz (2022), where it is extended into generalized divergence frameworks capable of managing multi-source uncertainty. Fuzzy entropy models, such as those applied in Pythagorean fuzzy sets (Wang et al., 2022), are characterized by entropy functions that operate over degrees of membership and non-membership. These models relax the crisp assumptions of classical logic, making them suitable for complex decision-making contexts where vagueness is inherent.

A particularly advanced and integrative formulation is offered by generalized quantum evidence theory (Xiao, 2023), which blends quantum probability amplitudes with mass function theory. This framework introduces quantum interference and superposition into the realm of belief functions, allowing for a more nuanced representation of uncertainty and conflict in multi-source environments. Mathematically, it builds upon both Hilbert space representations and Dempster–Shafer theory, positioning itself at the intersection of physics and AI.

Overall, the diversity of mathematical structures across these models reflects not only the domain-specific requirements but also the evolving role of entropy as both a descriptive quantity and an inferential tool. While physics provides robust theoretical underpinnings, AI enriches the operational flexibility and applicability of entropy, especially in complex, ambiguous, and data-driven environments.

Domains of Application

The application domains of entropy-based models vary significantly between the fields of physics and artificial intelligence (AI), reflecting their respective epistemological goals and system characteristics. In physics, entropy models are predominantly applied to closed systems or agent-based simulations where the dynamics follow well-defined physical laws and can be modeled through probabilistic ensembles or thermodynamic principles.

For instance, Babajanyan et al. (2020) applied game-theoretic entropy to model interactive systems governed by statistical mechanics, illustrating how entropy can regulate equilibrium states within thermodynamic-like games. Similarly, Deng & Deng (2022) utilized maximum entropy principles to characterize the distribution of random permutation sets—relevant in modeling physical states where combinatorial configurations represent different energetic possibilities. Qiang et al. (2022) further extended the domain by employing fractal entropy to understand the structural complexity of mass functions, a concept with implications in the physics of irregular systems.

In contrast, AI-based entropy models are typically applied in dynamic, data-rich environments, especially where uncertainty, vagueness, and conflict among data sources are prevalent. One prominent application is pattern classification, as demonstrated by Xiao, Wen, & Pedrycz (2022), who used generalized divergence measures to classify data under uncertain and ambiguous conditions. Their approach showed how entropy can be adapted to improve accuracy in decision-making processes that involve noisy or incomplete information.

Another critical domain is multi-criteria decision-making (MCDM), where fuzzy entropy plays a central role. Wang, Xiao, & Cao (2022) employed Pythagorean fuzzy entropy to support MCDM in situations involving linguistic variables and subjective judgments, such as resource allocation, policy evaluation, or expert systems. These models allow for more nuanced evaluations by incorporating degrees of membership, non-membership, and hesitation in the decision matrix.

Additionally, information fusion from conflicting sources is a key area where entropy models have shown significant utility. Fan & Xiao (2022) proposed the use of complex Jensen–Shannon divergence within complex evidence theory to manage and reconcile inconsistent or contradictory data streams. This is particularly relevant in fields like sensor networks, security systems, and medical diagnostics, where multiple observations must be aggregated into a single coherent interpretation.

Overall, the contrast in application domains illustrates how entropy, as a concept, is both domain-sensitive and methodologically flexible. In physics, it provides deep explanatory power for natural systems, while in AI, it serves as a practical tool for managing decision-making under uncertainty. The convergence of these two application domains presents opportunities for developing hybrid entropy models that are both theoretically grounded and operationally robust.

Comparative Table Output

To facilitate a clearer understanding of the distinct characteristics and potential complementarities between entropy-based models in physics and artificial intelligence (AI), a comparative table was constructed. This table summarizes the key features of each model, focusing on the domain of application, theoretical basis, mathematical formulation, practical utility, strengths, and limitations.

The comparison reveals that physics-based models prioritize mathematical rigor and alignment with fundamental natural laws, whereas AI-based models emphasize adaptability, decision support, and resilience to uncertainty. Despite their different origins, both share a common reliance on entropy as a means to quantify complexity and optimize system behavior.

Table 2. Comparative analysis of entropy-based models in physics and ai

Aspect	Physics-Based Models	AI-Based Models
Primary Purpose	Modeling thermodynamic systems, equilibrium, microscopic order	Handling uncertainty, improving decision-making, classification
Key Theories	Statistical mechanics, maximum entropy, Boltzmann entropy	Fuzzy logic, evidence theory, divergence-based entropy
Mathematical Basis	Partition function, entropy maximization, fractal geometry	Jensen–Shannon divergence, fuzzy sets, quantum mass functions
Representative Models	Game-theoretic entropy (Babajanyan et al., 2020); maximum entropy permutations (Deng & Deng, 2022); fractal entropy (Qiang et al., 2022)	Generalized quantum evidence (Xiao, 2023); Pythagorean fuzzy entropy (Wang et al., 2022); divergence entropy (Xiao & Pedrycz, 2022)
Application Scope	Closed physical systems, agent-based simulations	Pattern recognition, MCDM, multi-source information fusion
Strengths	Strong theoretical foundation, grounded in natural laws	High flexibility, effective in uncertain and dynamic environments

Limitations	Limited applicability to real-world data complexity	Less emphasis on physical interpretation, sometimes computationally intensive

This comparative output not only highlights the differences between domains but also opens up possibilities for cross-fertilization. For instance, the analytical depth of physics-based models could enhance the robustness of AI systems, while the adaptive techniques from AI could be used to enrich physical modeling in complex, real-world systems.

The comparative analysis of entropy-based models across physics and artificial intelligence (AI) domains reveals a dynamic interplay between theoretical depth and practical adaptability. While the origins and formulations of entropy in these two domains differ, both utilize entropy to address one central problem: the quantification and management of uncertainty and complexity in systems.

One prominent observation is the epistemological fragmentation between the domains. In physics, entropy is tightly linked to thermodynamic laws, equilibrium states, and microscopic configurations. For instance, Babajanyan et al. (2020) use entropy to model equilibrium behavior through game-theoretic lenses, emphasizing formal derivation from fundamental physical principles. Similarly, Deng and Deng (2022) apply entropy to permutation sets, underlining its combinatorial and statistical nature. These models possess strong analytical rigor but are often limited in applicability to more dynamic or ill-structured environments.

In contrast, entropy models in AI exhibit greater flexibility and contextual responsiveness. As demonstrated by Wang et al. (2022), entropy within Pythagorean fuzzy sets is adept at capturing ambiguity in multi-criteria decision-making. Likewise, Xiao and Pedrycz (2022) apply generalized divergence-based entropy to enhance pattern classification in uncertain and multisource contexts. Although these models may lack grounding in physical law, their computational efficiency and robustness in real-world applications make them invaluable in modern data-driven systems.

The discussion also uncovers an emerging convergence zone a theoretical middle ground where both domains begin to overlap. This is particularly evident in models that incorporate fractal structures, quantum reasoning, or generalized divergence formulations. For instance, the generalized quantum evidence theory proposed by Xiao (2023) merges probabilistic logic with quantum information processing, enabling rich representation of contradictory evidence. Similarly, Qiang et al. (2022) utilize information fractal dimension to bridge entropy with complexity analysis in both physical and informational structures. These models embody the potential for cross-disciplinary synthesis, harnessing strengths from both physics (structure, law-based reasoning) and AI (adaptability, uncertainty management).

Another key point is the shared use of entropy as an optimization criterion. In both domains, entropy is often maximized or minimized to reach desirable system states be it thermodynamic equilibrium in physics or optimal classification/fusion decisions in AI. This suggests that despite surface-level differences, the functional role of entropy is conceptually aligned, making it a viable candidate for unified modeling frameworks.

Nevertheless, the integration of these approaches faces several challenges. Physics-based models may lack scalability and struggle with context-rich, high-dimensional data. Conversely, AI models, while powerful in application, sometimes lack interpretability and theoretical grounding. To address this, future research should explore hybrid models that combine the structural rigor of physics with the operational flexibility of AI. For example, embedding fuzzy or quantum-based entropy measures within agent-based physical simulations could yield more realistic representations of complex environments.

In conclusion, the discussion highlights that entropy is not merely a domain-specific tool but a universal language of complexity. Its ability to quantify uncertainty, structure, and informational disorder makes it uniquely positioned to support interdisciplinary knowledge integration. The insights derived from this review serve as a foundation for future theoretical development and applied innovations in both the natural and computational sciences.

CONCLUSION

This review found that entropy plays a dual role: as a rigorous theoretical construct in physics and as a flexible computational tool in AI. Despite differing formulations, both domains use entropy to manage uncertainty and system complexity. A convergence potential exists through hybrid models combining physical structure and intelligent adaptability. Integrating entropy models across domains can enhance decision-making systems with theoretical depth and extend physical modeling with greater adaptability. This interdisciplinary synthesis opens new paths for both scientific understanding and applied innovation. This review is limited to 11 articles from Q1 journals published between 2020–2023. It focuses on conceptual and mathematical comparison, without testing models in real-world case studies. Future studies should develop and empirically evaluate hybrid entropy models that blend physical laws with AI techniques, especially in complex systems like climate modeling, intelligent robotics, or socio-technical networks.

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