Review

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Managerial Infophysics Unveiled: A Systematic Literature Review on the Amalgamation of Business Process Management and Information Entropy Analysis

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Posted Date: 22 January 2025

doi: 10.20944/preprints202501.1628.v1

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Review

Managerial Infophysics Unveiled: A Systematic Literature Review on the Amalgamation of Business Process Management and Information Entropy Analysis

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Abstract: This systematic literature review introduces managerial infophysics, a novel framework and metaparadigm that integrates Business Process Management (BPM) principles with entropy-based metrics to address organizational uncertainty and enhance decision-making in complex environments. Employing the PRISMA methodology, the review spans research from 2018 to 2024, drawing on a comprehensive search across 21 databases, each selected for its focus on peer-reviewed content in BPM, econophysics, and informatics. The identification stage yielded 16,101 records, which were rigorously evaluated to ensure the inclusion of the most current and valid research on these topics. This review highlights the potential for entropy-based metrics to quantify process variability, offering a dynamic alternative to traditional KPIs. Through an interdisciplinary synthesis, managerial infophysics is proposed as a metaparadigm, presenting a unified approach to managing complexity and uncertainty within structured organizational processes. Findings suggest that entropy-enhanced BPM frameworks not only improve operational predictability and resource allocation but also extend BPM's applicability to sectors with high variability, such as healthcare and finance. Despite challenges in aligning BPM's efficiency orientation with entropy's probabilistic insights, the curated evidence supports this interdisciplinary framework's role in fostering organizational resilience and adaptability. This review establishes managerial infophysics as a promising conceptual model, inviting further empirical validation for broader application.

Keywords: managerial infophysics; business process management (BPM); econophysics; information entropy; entropy-based metrics; systematic literature review; complexity management; PRISMA methodology

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1. Introduction

BPM frameworks play an essential role in optimizing organizational workflows, reducing inefficiencies, and managing process complexity in modern business environments [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15]. As organizations face rising complexity and unpredictability, the integration of concepts from information theory, specifically entropy, has garnered attention for its potential to quantify uncertainty and improve decision-making across various fields, including finance, social sciences, and, more recently, managerial science [9], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33]. This paper proposes a novel framework and metaparadigm, termed managerial infophysics, that combines BPM principles with information entropy to provide a more comprehensive approach for managing uncertainty.

Developing a framework for assessing new modeling methods could bridge academia and industry by focusing on real-world relevance, comprehensive documentation, and collaborative research, ultimately enhancing BPM's practical applicability [1], [4], [6], [10], [11], [34], [35]. Research

 doi:10.20944/preprints202501.1628.v1

into entropy-based metrics promises a shift from traditional KPIs, enabling optimized resource allocation and more manageable, predictable models tailored to specific sectors [3], [6], [16], [29], [36], [37], [38]. However, BPM research currently lacks a systematic framework that incorporates these principles to address inherent process variability [3], [6], [11], [32], [33], [36], [39], [40]. The systematic literature review conducted here identifies this research gap, emphasizing the potential benefits of combining BPM's structured approach with entropy's focus on complexity and unpredictability, thus providing a solid foundation for managerial infophysics.

In academic discourse, entropy has demonstrated its utility across various fields, from quantifying market dynamics in finance to managing resource allocation in healthcare [9], [21], [26], [40], [41], [42]. Its interdisciplinary applications show how entropy, particularly Shannon entropy, can measure complexity, assess uncertainty, and optimize processes by reducing variability in different contexts [9], [17], [20], [21], [26], [29], [36], [43]. The use of entropy in BPM could offer similar benefits, allowing managers to identify inefficiencies and streamline operations. The versatility of entropy across fields reinforces its applicability in BPM, where variability often leads to inefficiencies that disrupt process flows and impact organizational outcomes [4], [9], [17], [20], [26], [29], [36], [43], [44].

However, integrating BPM and information entropy is not without challenges. Divergent focuses, BPM on operational efficiency and entropy on managing unpredictability, pose questions regarding their compatibility [2], [3], [6], [9], [17], [26], [29], [43], [45]. Moreover, applying theoretical entropy models in real-world business scenarios requires empirical validation to ensure that the framework effectively enhances decision-making without adding undue complexity [3], [9], [11], [17], [20], [26], [29], [45], [46]. Despite these challenges, interdisciplinary studies underscore the potential for entropy-based models to provide robust, actionable insights for business process optimization. For instance, studies in econophysics demonstrate how entropy-based methods enhance resource allocation, support strategic planning, and foster adaptability, qualities that could significantly benefit BPM frameworks [9], [16], [20], [23], [29], [36], [44], [47], [48], [49], [50].

The main aim of this paper is to develop and validate the managerial infophysics framework through a systematic literature review, employing the PRISMA framework [51] for a thorough analysis. This systematic review explores the integration of BPM, econophysics, and information theory, establishing a foundation for a unified framework. By synthesizing research from 2018 to 2024, it highlights how entropy-based metrics can enhance BPM models, helping decision-makers manage process uncertainty more effectively. The anticipated findings suggest that combining BPM's systematic methodologies with entropy's probabilistic approaches could lead to a more resilient, adaptable framework for process management [3], [6], [9], [32], [33], [44], [49].

The hypothesis posits that the integration of BPM principles with information entropy leads to the formation of a cohesive managerial framework which will enhance managerial decision-making by balancing process efficiency with informational complexity. The PRISMA-based literature review is expected to reveal instances where entropy-based metrics have successfully managed complexity in other fields, reinforcing the viability of this interdisciplinary approach for BPM. If supported, this hypothesis would substantiate managerial infophysics as a unified approach to organizational management, emphasizing adaptability and optimization in fluctuating environments. As such, an appropriate, qualitative lemma will be presented in the *Discussion* section, encapsulating the anticipated finding of the literature review serving as the core substantiation of the proposed hypothesis. The purpose of this systematic review is to synthesize the inductive reasoning drawn from the literature, indicating that the integration of BPM and information entropy is not only theoretically sound but also practically observable within the reviewed studies.

For falsifiability, the hypothesis would be rejected if theoretical models and empirical studies fail to demonstrate a conceptual overlap between BPM and entropy principles, or if entropy-based metrics do not show measurable improvements in BPM outcomes. Conversely, validation would occur if case studies indicated that organizations applying entropy-based BPM experience enhanced efficiency and adaptability, reflecting the framework's practical benefits. Evidence of

 doi:10.20944/preprints202501.1628.v1

interdisciplinary adoption would further support its applicability across different organizational settings, underscoring the framework's broad potential.

In conclusion, the introduction of information entropy into BPM represents a promising avenue for advancing organizational management, enhancing decision-making, and optimizing resource allocation. The managerial infophysics framework leverages entropy to quantify uncertainty and drive process efficiency, potentially setting a new standard for process management in complex, adaptive environments.

2. Materials and Methods

2.1. Research Design and PRISMA Framework

Systematic reviews are necessary in the synthesis of current knowledge, the prioritization of future research, the identification of primary research issues, and the evaluation of theories [52]. To render a systematic review beneficial to a wide range of users, authors should provide a comprehensive, detailed, and clear description of its objectives, methodologies, and findings. Researchers have the capacity to achieve this with the support of reporting guidelines [53].

The PRISMA statement establishes a structural framework for the aforementioned type of reporting guidelines; its principal objective is to enhance the standards for reporting systematic reviews [51]. The recent iteration of the statement has been extensively referenced in interdisciplinary literature; it has been cited in more than sixty thousand papers and has received recognition from two hundred journals and review organizations [51]. Based on observational research, the utilization of the statement results in improved reporting [54]. Since the previous iteration, systematic review practices have changed considerably. The statement's evolution was made possible and necessary by certain technological advancements. For instance, deep machine learning and natural language processing rendered it less difficult to identify and evaluate research systematically [55]. Certain approaches have been devised [56] to facilitate the synthesis and presentation of findings in situations where conducting a meta-analysis is problematic [57]. In addition, the understanding of bias sources has improved systematic review assessment methodologies [58]. Recent modifications in review systems have changed the emphasis from high quality evidence to reliable evidence [59].

The statement's latest version is termed PRISMA 2020[1]. The primary emphasis of PRISMA 2020 is on conducting systematic reviews of health practices. However, other fields may also utilize and benefit from its checklist. The most recent version of the statement is encompassing of meta-analyses and other synthesis methodologies, irrespective of the subject of study. This methodology can be utilized in mixed-methods reviews, although the presentation and analysis of qualitative data may need to adhere to supplementary criteria [51]. It is noteworthy to mention, however, that the statement is not necessary to serve as a guide for conducting systematic reviews, when such a task can be accomplished with the assistance of extensive, peer reviewed resources [61]. Figure 1 represents the general schematic of the PRISMA flow diagram which has been used as the basic literary tool for conducting this review.

[1] Additional information and editable extensions, such as flowcharts and checklists, may be retrieved at the official PRISMA [60] website: https://www.prisma-statement.org/.

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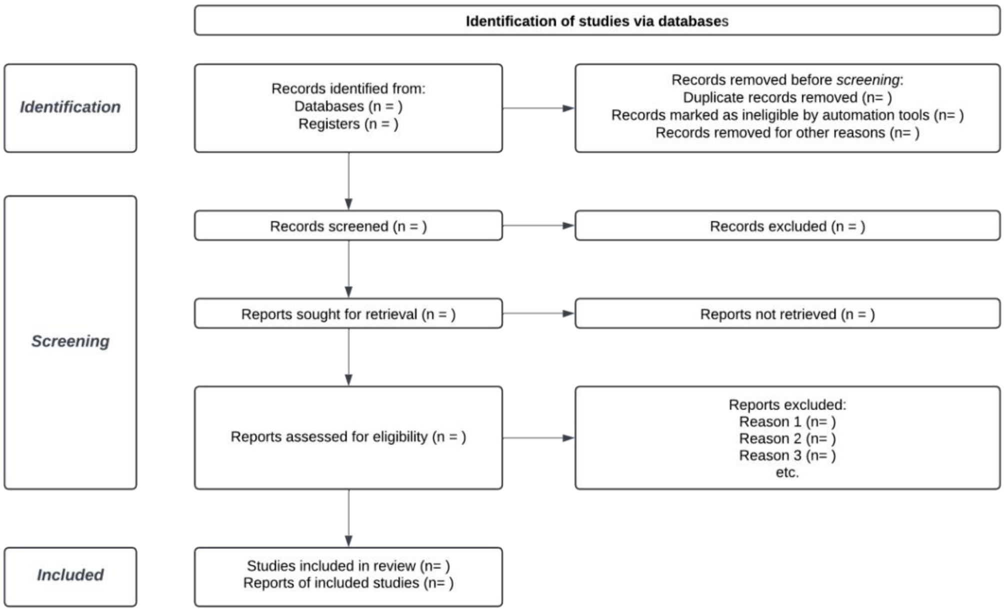

Figure 1. PRISMA 2020 Flow Diagram for Systematic Reviews Using Databases & Registers [51].

Even though its fundamental structure should remain unchanged, it can be altered in accordance with the pertinent details of the research at hand. However, the authors mention the following considerations:

1. If possible, the number of records found in each database or registration searched should be reported rather than the total;
2. The number of excluded records (either manually or automatically) should be indicated.

This systematic review follows the PRISMA framework to ensure a transparent and replicable review process. The study, conducted from 2018 to 2024, involved three research cycles, each focusing on distinct, overarching thematic units:

1. BPM: Focusing on optimization through modeling, quality standards, and data-driven decision-making;
2. Econophysics and Financial Networks: Integrating complex systems theory and machine learning within economic and ethical contexts;
3. Thermodynamics, Entropy, and Information Theory: Their applications in industrial settings, complex systems, and interdisciplinary scientific advancements.

Each research cycle was designed to assess whether a convergence of ideas could be identified across the literature, spanning multiple disciplines. To ensure thorough coverage of relevant literature, this review employed primary queries and sub-queries, with the primary queries targeting broad research themes and sub-queries allowing for a deeper investigation within those themes.

2.2. Database Selection and Search Strategy

A total of 21 databases were selected, each specializing in peer-reviewed content relevant to the thematic areas under investigation. The following key databases were utilized: ACS Publications: 2 times, AIP: 1 time, APS: 2 times, Annual Reviews: 1 time, Cambridge Core: 1 time, Emerald: 8 times, ICI: 1 time, IDEAS: 2 times, IEEE Xplore: 10 times, IOPscience: 2 times, JSTOR: 1 time, MDPI: 47 times, NIH: 9 times, Nature: 1 time, PLOS ONE: 1 time, PhilPapers: 1 time, Royal Society Publishing: 1 time, SAGE: 1 time, Science Direct: 47 times, Springer: 26 times, arXiv: 14 times.

The identification process began with the formulation of 179 primary queries and 62 sub-queries, resulting in 241 total queries across the three research cycles. These queries targeted a wide range of identification terms, 435 in total, which can be further categorized in the following segments. For a detailed thematic categorization of the identification terms used in this study, please refer to Table A1 in Appendix A.

2.3. Inclusion and Exclusion Criteria

At the identification stage, a total of 16,101 records were retrieved from the selected databases. These records were filtered based on specific criteria:

1. Inclusion Criteria: Records were considered if they were peer-reviewed articles, review papers, or studies that directly addressed the research themes, such as BPM optimization, entropy in complex systems, or econophysics;
2. Exclusion Criteria: Records were excluded if they did not contain relevant keywords, were non-English, were not suitable peer-reviewed types (e.g., conference abstracts or non-academic publications), were irrelevant to the core themes of the study, or were duplicates. Specifically, 1,221 records were excluded for missing relevant keywords when a narrowing down of the scope was necessary, 72 non-English records were removed to focus on English-language publications, 10,172 records were excluded for being inappropriate peer-reviewed types, and 3,708 records were excluded for irrelevance to the study's main themes. Additionally, 34 duplicate records were removed manually.

In total, 15,207 records were excluded before the screening stage, substantially reducing the initial pool of potential sources. Details on the exclusion and inclusion criteria can be found in Table A2 in Appendix A.

2.4. Screening Stage

During the screening phase, 894 records were examined based on their relevance to the thematic units and their contribution to the research objectives. Two sets of exclusion criteria were applied: 251 records were excluded for containing irrelevant information, and 417 records were excluded for containing redundant information already found in other sources. Thus, a total of 668 records were excluded during this phase, narrowing the literature to studies that met the thematic and methodological criteria.

During this stage, it was essential to delineate a clear division of citations, with twelve citations, specifically [32], [33], [40], [62], [63], [64], [65], [66], [67], [68], [69], and [70] excluded from the PRISMA framework because they did not meet the imposed research criteria. However, these citations were deemed valuable by the authors for providing foundational context and additional insights that supported the thematic units being studied. Furthermore, one cross-reference is used to highlight some key findings to ensure transparency in tracking the development of thematic concepts, namely, the concept explored in reference [71] which was cross-referenced through a newer paper (reference [71] on page thirteen of [72]), allowing readers to trace the development of this idea from its origins. This thorough process helped streamline the review and maintain focus on the most unique and relevant information for further assessment.

2.5. Eligibility Stage

During the eligibility phase, a closer examination was conducted on 226 records that had passed the initial screening. However, 11 records could not be retrieved due to issues with their Digital Object Identifiers (DOIs). Further exclusions were made based on specific criteria: 6 records were excluded due to retractions, 5 were excluded because of errata published after their initial release, and 13 were excluded for relying on small datasets that limited the generalizability of their conclusions. In total, 24 records were excluded, leaving 191 records eligible for the systematic review.

2.6. Data Extraction and Synthesis

Following the eligibility stage, data extraction was conducted on the remaining 191 records. Key information, including the relevant database, query and sub-query numbers, identification terms, total records found, database hits that aligned with the inclusion criteria or lacked exclusion criteria,

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and the number of records selected for screening, was extracted, and categorized according to the three primary thematic units mentioned in *2.1. Research Design and PRISMA Framework* on the data extraction and synthesis process are provided in Table A3 in Appendix A.

These records were deemed to be the most relevant and reliable, meeting all eligibility criteria established in the earlier stages. The PRISMA process ensured that the systematic review was grounded in a robust methodological approach, meticulously filtering records through various layers of scrutiny to achieve the highest standards of research quality.

2.7. Query Formulation

The search strategy used can be described as a segmentation strategy. The emphasis was on the use of well-defined identification terms and exclusion criteria to narrow down the search results, ensuring only relevant records are selected for further screening. This approach focuses on refining the search in two stages:

1. Pre-Screening: Removing records not meeting all of the inclusion criteria;
2. Detailed Screening: Removing records for meeting all the exclusion criteria for in-depth review.

Structured Boolean operators (AND, OR) were used in stages 1 and 2 for each query to ensure a thorough retrieval of relevant studies, as shown in Table A3. For instance, query 2 was conducted on Science Direct to explore use cases and process management in technology-assisted applications. The search string included the terms: industrial internet of things, IoT, integrating process management, system, architecture, event processing, use cases, integration, application scenarios, and BPM, yielding 20 records. By filtering for research papers, 4 were excluded, leaving 16. Since research papers were needed for their in-depth, peer-reviewed analyses, theoretical frameworks, and case studies—critical for understanding complex technical fields—the initial 16 publications were skimmed on a surface level. However, to focus more precisely on use cases and process management, a sub-query (2b) was performed, filtering for the term "*use cases*," which reduced the results to 1[2]. This remaining result passed the PRISMA process and was eventually included in the systematic review as the relevant citation [15].

The process starts with defining relevant the relevant identification terms (ID Terms) and running the query in a database. Even though the queries presented in Table A3 are in chronological order, searches on other databases for the same ID Terms which did not yield any useful results were not included in this table to avoid extensive tables which would confuse the reader. This process, overall, ensured that only highly relevant information would be presented in this review. Essentially, this review’s segmentation strategy involves breaking down search results by specific publication inclusion criteria such as filtering for relevance to certain academic disciplines (e.g., business, management, and accounting). This approach allowed for both extremely broad searches and specific, nuanced searches that captured detailed aspects of each theme. Furthermore, synonyms and variants were included throughout this process to ensure completeness (e.g., Artificial Intelligence vs. Machine Intelligence, AI).

2.8. Data Summary and PRISMA Flowchart Construction

To construct the PRISMA flowchart, it was essential to summarize the data in a clear and concise manner, as presented in Table 1. For clarity, the "*records found in databases*" refers to the total number of records retrieved after applying the exclusion criteria, encompassing all records that were not excluded as well as those that met the inclusion criteria.

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[2] Thus, query number 2 becomes 2a and the sub-query becomes 2b (1 primary query and 1 sub-query totaling to 2 queries).

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Table 1. PRISMA Data Summary.

PRISMA Data Summary		
Identification	Databases searched	21
	Records found in databases	16.101
	Records excluded due to missing keywords	1.221
	Non-English records excluded	72
	Records excluded (inappropriate publication type)	10.172
	Records excluded (irrelevant scope)	3.708
	Duplicates (removed manually)	34
	Total records removed before screening	**15.207**
Screening	Records screened	894
	Records excluded (irrelevant information)	251
	Records excluded (duplicate information)	417
	Total records excluded in screening	***668***
Eligibility	Records sought for retrieval	226
	Records not retrieved (DOI issues)	11
	Records assessed for eligibility	**215**
	Records excluded (retracted articles)	6
	Records excluded (errata published)	5
	Records excluded (small datasets)	13
	Total records excluded in eligibility	***24***
Included	**Records included in review**	**191**

Additionally, the categorization of records by database is detailed in Figure 2, which depicts the PRISMA flowchart used in this systematic review.

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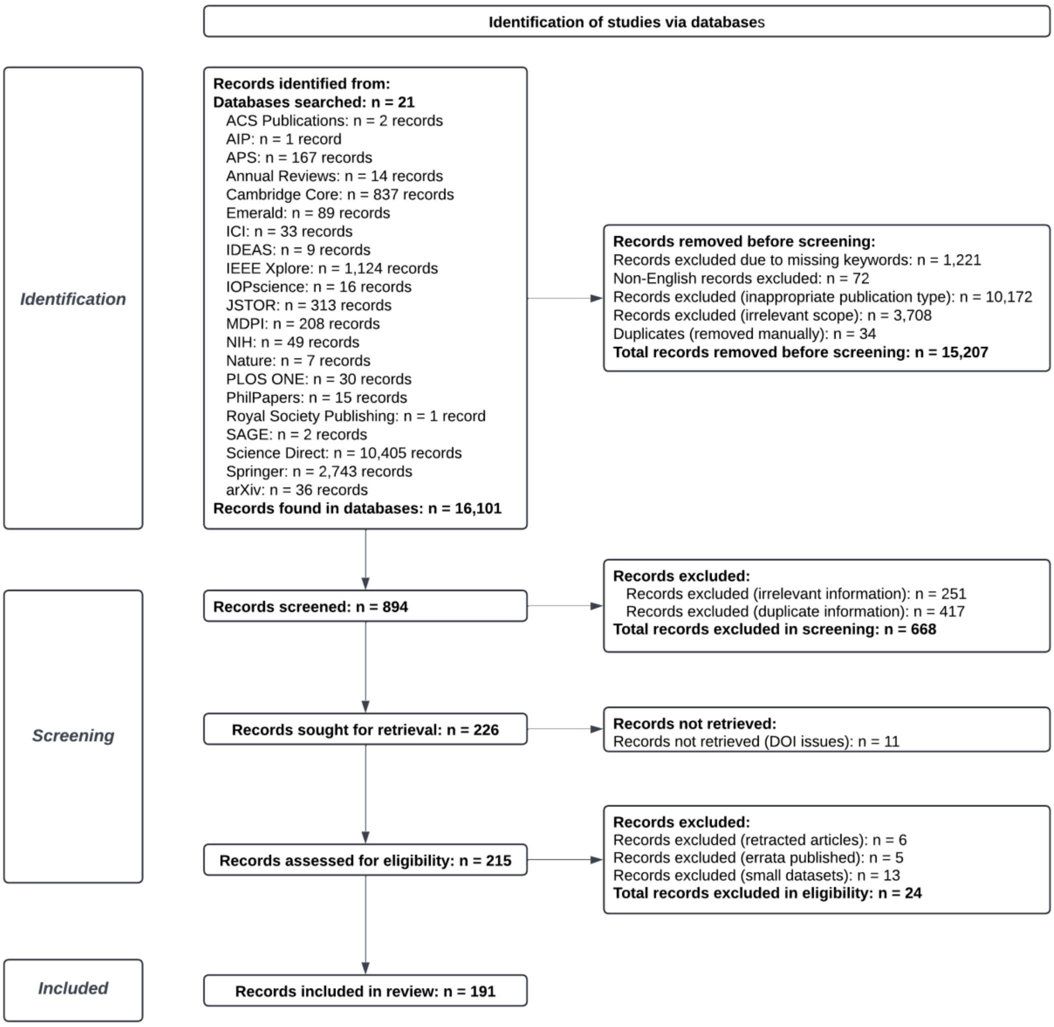

Figure 2. PRISMA 2020 Flow Diagram.

Detailed information on the frequency of each database's usage and the number of records retrieved for publications included in the review is provided in Table A4.

2.9. Data Availability and Ethical Considerations

All data associated with this systematic review, including the raw search queries, and data extraction forms have been deposited in a publicly available repository [*https://www.dropbox.com/scl/fi/66entykq9s1oas6ypsbmb/Prisma-Query-Tables.xlsx?rlkey=3n8e2md3xzf1euf5i3t38esb0&st=d7jbzh1t&dl=0*]. The accession numbers for the data will be available upon request to ensure full transparency and reproducibility of the review's findings. It should be noted that up until the publication of this review certain query results in the databases will yield more results since new papers are published daily. Lastly, this review did not involve any interventionary studies involving humans or animals; thus, ethical approval was not required.

2.10. Data Synthesis and Analysis

Given the nature of this systematic literature review, the analysis primarily focused on qualitative synthesis. Studies were grouped based on thematic units, including BPM, Econophysics, Theory of Complex Systems and Entropy and Information Theory. The goal was to identify recurring

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patterns, themes, gaps in the literature, and a potential convergence of diverse scientific fields pertinent to the scope of this review.

A meta-analysis was not conducted due to the diverse methodologies and outcomes across the selected studies. However, a structured narrative synthesis was used to summarize the key findings. No formal bibliometric or citation analysis was performed, as the scope of this review was to assess the content and findings of the included studies rather than their citation impact or publication trends.

By using a structured approach, the PRISMA framework enabled the systematic review to narrow down a vast amount of literature from various databases, arriving at a final body of research that was both comprehensive and relevant to the subject areas under investigation. The process, from identification through inclusion, ensured that the data supporting this review was carefully curated and highly reliable, contributing to a well-founded analysis of the selected topics.

3. Results

3.1. BPM Overview: Concepts and Evolution

3.1.1. BPM Ontology

BPM is a collection of activities taken by an organization to define, plan, implement, document, measure, monitor, control, and enhance its processes to achieve its goals [1]. It is essentially a series of actions that are coordinated to produce a desired outcome. BPM offers a framework for managing and transforming organizational processes [73]. According to the Supplier, Input, Process, Output, Customer (SIPOC) methodology, a process may be understood as a set of procedures that utilize inputs (resources) to create outputs (deliverables) [2].

Standardized process management frameworks provide consistency which is especially important in organizations that need strict adherence to standards like EFQM[3] or ISO Standards[4] [74]. A comprehensive BPM system is particularly significant for enterprises as it allows for clear and distinct processes, which promote uniformity and long-term customer loyalty [75].

3.1.2. BPM Life Cycle

A standard BPM life cycle consists primarily of the following stages: (re)design, implementation/configuration, operation, and control [3]. During the (re)design stage, a process model is developed, followed by the stage of implementation/configuration, where the model is integrated into a functional system. During the second stage, non-recurring performance issues may arise, which are often caused by design flaws, whereas recurring issues are frequently caused by execution errors. Addressing design flaws often requires thorough process reconstruction [4]. On the other hand, execution errors may contribute to extreme variations in specific operations due to a lack of end-to-end processes, especially in areas like product development and customer engagement [34]. Following appropriate BPM system interventions, results are analyzed, and the cycle iterates in accordance with the Plan, Do, Check, Act (PDCA) model. Well-designed business processes, ensuring interdependent procedures work seamlessly to achieve goals, are crucial for customer satisfaction, and operational efficiency [5], which are key factors for organizational sustainability.

[3] The European Foundation for Quality Management is a nonprofit membership organization established in nineteen eighty-nine. In its initial phase, the policy document for organizational excellence garnered the support of sixty-seven CEOs and presidents from prominent European companies, reaffirming their commitment to upholding EFQM's missions and values. EFQM partners with an extensive network of over fifty thousand enterprises across Europe and beyond, encompassing notable organizations such as BMW, Siemens, and Huawei [62].

4 The International Organization for Standardization is a globally recognized establishment responsible for the development of international standards, comprising delegates appointed by the national standards organizations, affiliated with members all over the world [63].

3.1.3. Process Classifications

Given the current integration of business processes and information [6], two scopes seem to be more suitable for the purposes of this review. It is important to note, however, that given the abundance of relevant literature on the topic, a different focus will result in a different set of taxa.

The first classification system originates from a classical BPM perspective. It considers the presence or absence of information regarding the execution or execution method prior to the operation [76]. This results in a classification of static, structured with ad hoc exceptions, unstructured with pre-defined fragments, semi-structured and unstructured processes. Static processes optimize their route before execution, while structured processes allow for ad hoc exceptions and accommodate one-time tasks. Semi-structured processes include structured processes with exceptions and unstructured processes with specific components. Unstructured processes can establish objectives, performance metrics, and execution constraints, but only provide comprehensive flow descriptions for specific segments and not an explicit articulation of a sequence of actions.

The second classification system concern Process Aware Information Systems (PAIS). In PAIS, business processes can be broadly categorized into three types: peer to peer, person to application, and application to application [71], [72]. Peer-to-peer processes involve extensive human interaction, with modern examples like Meta and X, necessitating BPM systems capable of integrating computer-mediated human interactions. Person to application processes combine human operations with autonomous applications, aiming for seamless user-application integration in information systems. Application to application processes involve actions performed by automated software systems. Strict boundaries between these classifications are unclear, with a spectrum of procedures, and methodologies spanning from peer-to-peer manual intervention to application-to-application automated operations.

3.1.4. BPM Principles

Multiple decisions in managing complicated processes can influence the evolution and outcome of its component procedures [77]. Even though an influential and empirically driven set of ten principles for a good BPM system exists [7], to perform an effective review that includes a wide variety of overarching topics, BPM's principles will be condensed into more precise and interrelated concepts, categorized as:

1. Value Creation: Organizations deploy various processes, from employee management to financial reporting, to create value for stakeholders [8]. Managing a collective of processes in a business setting should eventually promote the creation of value;
2. Process Optimization: Effective process design methodologies with integrated maturity assessment procedures are essential; leveraging new information technologies is advisable [78]. Without well-defined process designs, regardless of mode of representation, a system will experience a propensity towards destabilization, thus, hindering overall performance [9];
3. Process Standardization: Standardized processes enhance efficiency and consistency, yielding cost efficiency [74];
4. Effective Management: Having established a fundamental process conceptualization in [2], it may be deduced that managing processes is not feasible without managing procedures. BPM, encompassing processes such as risk management and strategic planning, is an essential component of governance, similar to Project Management [79]. For a BPM system to merely possess effective design or standards is not enough; thorough execution management is essential for achieving continuous improvement [80]. Overseeing each updated BPM cycle is crucial for maintaining performance as operational efficiency may decline over time due to changing conditions.

3.1.5. BPM Paradigms

By attempting to identify the most important BPM concepts, it is obvious that intensive BPM research has resulted in multiple methodologies, strategies, and approaches to facilitate the formulation, execution, supervision, and evaluation of business processes [81]. To precisely identify the most important milestones in the formation of BPM paradigms is challenging, if not arbitrary, due to the complexity, interconnectedness, and density of historical events, such as World War II. Nonetheless, literature formulates a basic outline based on distinct historical eras in which they took place.

First, F. W. Taylor developed the concept of scientific management, which was based on A. Smith's description of the benefits of breaking down work into tasks and emphasized efficiency and productivity [82].

Subsequently, W. A. Shewhart and W. E. Deming made significant contributions to statistical process control, emphasizing the importance of evaluating outcomes using statistical techniques to address performance issues [83].

Currently, contemporary BPM frameworks find common application within traditional information systems [6], indicating a maturation in BPM practices embraced by various professionals and scholars [84]. Integrating emerging technologies such as blockchain, artificial intelligence, and big data are anticipated to transform inter-organizational operations, but with hurdles and opportunities for integration and applicability outside the constraints of a given organization's process system [85], [86], [87]. These technologies are poised to transform transactional paradigms, prompting organizations to adapt their business processes accordingly.

Thus, by examining the evolution of BPM concepts in their historical context, this review identifies three main paradigms of BPM, fostered by tautologically equivalent intellectual streams: quality control, epistemic management, and information technology.

Quality Control

World War II acted as a catalyst for the quality control movement; following the war, the movement established the American Society for Quality (ASQ) to provide a platform for professionals and manufacturers to continue quality improvement methods developed during the war [10], with J. M. Juran becoming a leading figure [88]. Concurrently, Japanese organizations embraced the movement, influenced by Deming whose work inspired key figures such as S. Shingo and T. Ohno, the pioneers of lean philosophy and lean manufacturing [89]. Total Quality Management (TQM) dominated the seventies but gave way to Six Sigma (6σ) in the late eighties, popularized by Motorola [89]. ASQ established a 6σ system at the start of the twenty-first century, signaling a transition towards lean 6σ methodologies, epitomized nowadays by companies like Walmart, Amazon, and Costco [90]. Up until the nineties, the quality control movement continued to evolve by including specialized developments like the Capability Maturity Model (CMM), addressing software quality concerns [91].

Epistemic Management

As previously stated, epistemic management may be traced back to Taylor's conception of scientific management in the early twentieth century [82]. The sub-field of quality management may be traced to Juran who highlighted the stable post-World War II production capacity of the United States, attempted to track the main reasons for product inadequacies, and conceptualized the cost of quality [89].

In the eighties, M. Porter, a significant figure in management theory influencing and influenced by Japanese enterprises, characterized a corporation's strategic orientation and internal operations as value chains, demonstrating a departure from conventional strategy theories [92]. Porter's analyses are still relevant today, as evidenced by contemporary research [93], [94]. This highlights patterns and persistent themes, emphasizing the trend of emulating effective methods in the face of declining profit margins, the challenge of achieving long-term competitive advantage, and the importance of prioritizing a distinct strategic position over operational effectiveness.

A significant milestone in the early nineties was the paradigm shift towards adopting performance metrics that encompassed more than just financial information. This shift was embodied

 doi:10.20944/preprints202501.1628.v1

in the concept of the Balanced Scorecard (BSC), first introduced by D. Norton and R. Kaplan, which aligned operational metrics with organizational goals alongside financial performance [95]. BSC is still widely employed in management, with current literature indicating the interest on the subject increasing over the past ten years [95].

Information Technology

The third paradigm involves leveraging computerized systems to streamline operational processes, with the concept of Business Process Re-engineering (BPR), developed by M. Hammer and J. Champy, serving as the catalyst for integrating information technology applications extensively into BPM [11], [96]. In recent decades, BPR has emerged as a crucial tool for improving business productivity and enhancing economic sectors, challenging TQM since the early nineties, despite its high failure rate [97]. Presently, business executives and ERP developers focus on implementing effective business strategies and methodologies, facilitated by BPM platforms that address complexity issues by transforming ERP systems into process-based structures [98].

3.1.6. Business Process Modeling (BPMo)

When discussing process models, it is important to distinguish between the frameworks used to contextualize process systems and the methodologies employed to depict them. In the context of frameworks, the term signifies the alignment of a BPM system with the quality criteria of institutions like EFQM [99]. As a depiction methodology, BPMo employs standardized notations, such as Business Process Model and Notation (BPMN), to visually represent business processes, providing a clearer and more efficient understanding of process inputs, procedures, and outputs compared to text-based descriptions [12].

A key feature of the BPMo approach is its capacity to assess process systems. This assessment may encompass a variety of dimensions, including, but not limited to the efficiency and efficacy of business ventures in practice and in academia [100], the analysis and verification of time limitations [101] and run time constrictions [102], and the ability to generate data for assessing the relationship between business process performance and financial performance, as demonstrated in contemporary empirical research [13].

In this review, models and modeling refer to methodologies for representing processes. Their ability to structure process systems is crucial for the amalgamation discussed later.

3.1.7. Business Process Modeling Languages (BPMLs)

BPM systems have benefited from various process modeling methodologies since the advent of information systems. The first formal attempts at modeling using a generic notation system are attributed to A. Turing in 1949 [14].

By examining practical business use cases, BPM can evaluate and optimize processes with the assistance of modeling and analysis tools. Use cases demonstrate how process modeling integrates with event processing by outlining how to combine multiple scenarios into composite events that approximate actual BPMo applications, such as event data diagnostics and process execution assessments [15].

The contemporary BPM landscape features a diverse array of models that vary in complexity and understandability. Two of the most influential BPMLs, which can be easily integrated with Petri nets, Enterprise Resource Planning (ERP) applications, and other BPMLs, are the Event-driven Process Chains (EPC) [103] and, more notably, BPMN, as observed in [1], [3], [12], [101].

EPC is a classic BPML, well-known for its ability to integrate with the ARIS[5] platform and the SAP[6] reference model, making it widely used in practice. The ARIS platform and SAP process library

5 The Architecture of Integrated Information Systems (ARIS) platform is a BPM toolset, allowing organizations to model, analyze, and optimize their processes effectively [64].

6 The Systems, Applications, and Products in Data Processing (SAP) reference model is a collection of predefined processes and best practices designed to help organizations implement and manage their enterprise resource planning systems efficiently [65].

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include approximately six hundred EPC-based process models, emphasizing three key aspects: data, function, and organization [103].

BPMN is an effective visual tool for representing complex business processes. While the primary objective of BPMN is to facilitate business process modeling, the framework does include an extension mechanism that enables its application for other purposes as well [104].

The Object Management Group[7] has established the latest iteration of BPMN, namely, the BPMN 2.0 standard. Concurrent research [105] on automating the BPMN 2.0 guidelines verification process resulted in a comprehensive list of fifty guidelines based on relevant literature assessment and synthesis for specific modeling objectives such as process learning or information system development. In the same research paper, the authors developed an open-source tool called BEBoP (understandaBility vErifier for Business Process models) which is able to automatically verify thirty-four of the fifty guidelines, making it the first open-source tool to check a substantial set of modeling guidelines [105].

Contemporary evidence [106] highlights BPMN 2.0 as a leading BPML, favored for its extensive features essential for both practitioners and academics. It currently supports more than eighty percent of BPM features deemed important in the decision-making process for selecting an appropriate modeling language [106].

BPMo can often be challenging considering the growing number of BPMLs; the selection of the most appropriate language for a task can result in issues such as increased complexity and decreased understandability. This results in decision makers depending on familiarity rather than pertinent quality attributes [106].

Overall, the fundamental factor influencing the success of a BPM initiative is the underlying rationale for its implementation [107]. Establishing clear targets when modeling processes is essential, particularly in the context of identifying BPM life cycles via the contextualization of acknowledged BPM principles [7]. Nevertheless, many organizations fail to articulate distinct objectives. Defined goals enable organizations to evaluate process performance post-(re) design effectively [3]. Continuous process improvement is an ongoing endeavor, making performance measurement vital for sustainable enhancement. Although the concept of continuous improvement is familiar to most organizations, several challenges arise concerning continuous measurement. From a strategic perspective, one significant issue with BPM is the use of diverse tools by the BPM team to model processes for varying purposes [107].

3.1.8. Process Metrics

Various parameters, such as time, cost, and quality, are used to assess process or organizational effectiveness, each with distinct KPIs [16]. Time-related metrics include lead time, service time, waiting period, and synchronization time, which collectively offer insights into process efficiency. Costing frameworks like Activity-Based Costing (ABC) and Resource Consumption Accounting (RCA) help gauge expenses, considering resource allocation and task completion duration with feasible integration into BPMN 2.0 process systems [39]. Quality metrics focus on product delivery and require tailored evaluation criteria for knowledge-based procedures [108]. Although several businesses have quantitative criteria, KPIs may vary by industry, process, and occupation, highlighting the need for specific evaluation methods. Existing research [109] indicates that determining suitable KPIs is more intricate than simply selecting them. Once KPIs are defined, the next phase involves identifying strategies to enhance their effectiveness or making necessary adjustments to achieve established objectives. The optimal approach to organizational restructuring in a given setting may remain ambiguous. Therefore, future research should focus on improving the understanding of (re)design and implementation methodologies. For example, by leveraging novel AI tools alongside traditional BPMo and BPMLs, emphasis could be placed on process-oriented

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7 The Object Management Group (OMG) is an international, open membership, non-profit technology standards group that formed to develop standards for a variety of industries [66].

 doi:10.20944/preprints202501.1628.v1

approaches, where business processes are examined via the scope of information exchange and, ideally, enhanced in real-time.

With advancements in computational resources, it is possible to determine the level of uncertainty pertaining to the completion of procedural tasks in a given process. Uncertainty can be quantified as a probability distribution [17]. Furthermore, according to [110], the level of uncertainty increases in direct proportion to how evenly execution scenarios are distributed, while complexity is generally associated with the logical gateway elements present in a BPMo. Uncertainty may be deemed as one of the core characteristics of business processes – a part of their foundational nature [76]. Hence, the occurrence of process uncertainty may be embodied by the concept of entropy, and more specifically, by information entropy.

The amalgamation of BPM and information entropy begins with the foundational concept, which will be further explored through real-life applications in *3.4. Epistemological Frontiers of Information Entropy in BPM*, covering both pre- and post-scope periods of this review. To facilitate a smoother transition between BPM and process entropy, it is essential to recognize how process KPIs—typically centered on time, cost, and quality—can be complemented by entropy-based metrics. Empirical evidence suggests that process entropy can gauge similar parameters by addressing variability and uncertainty in execution. For example, [32] links higher entropy in business process models with increased unpredictability in task execution and greater difficulty in scheduling and resource allocation, while lower entropy leads to more efficient planning and reduced delays. Similarly, [33] introduces an entropy-based measure to quantify uncertainty in process models, emphasizing that reducing entropy improves predictability, thus optimizing both cost and time. This complements traditional KPIs, which act as static snapshots of performance rather than dynamic indicators of process variability. Finally, [42] applies entropy in device performance management to enhance short- and long-term performance predictions, which could be extended to BPM for real-time monitoring and optimization. To fully grasp these discussions, a clearer understanding of entropy, particularly information entropy, is crucial.

Information entropy, also known as Shannon[8] entropy, is an essential concept in information theory that measures the level of uncertainty or information contained within a given set of possible outcomes [18], [111]. It is used to describe a discrete random variable that has a set of potential outcomes, each of which is associated with a probability. Shannon entropy is commonly depicted as:

$$\mathrm{H(X)} = \sum_{i=1}^{n} \mathrm{P}(x_i)\mathrm{u}(x_i) = -\mathrm{K}\sum_{i=1}^{n} \mathrm{P}(x_i)\log_2 \mathrm{P}(x_i). \quad (1)$$

$\mathrm{H(X)}$ is the information entropy, where X is a discrete random variable with possible states $x_1, x_2, \dots, x_n$ with corresponding probabilities $\mathrm{P(x)}_1, \mathrm{P(x)}_2, \mathrm{P(x)}_n$, and $i = 1, \dots, n$ is the index of the states. In this equation, entropy represents the expectation of the uncertainty $\mathrm{u}(x_i)$ which is associated with each possible state x_i; uncertainty (or information) for each state is represented by $\mathrm{u}(x_i) = \log_2 \mathrm{P}(x_i)$. Typically, K is set to 1 and can be thus omitted, and $\log_2$ is used to calculate entropy in bits (as Shannon entropy is usually measured in bits when using base-2 logarithms). Information entropy is a fundamental, quantitative metric used to assess the level of uncertainty present within a given dataset. As the distribution of states becomes more uniform, there is a corresponding increase in entropy.

3.2. Physics and Information in Social Sciences

3.2.1. Interdisciplinary Synergies

To synthesize diverse epistemological and methodological frameworks into a cohesive theoretical model, it is essential to map out the intersections and complementarities among different theories. This process involves highlighting how insights from one discipline can fill gaps or offer

8 In 1948, C. Shannon published "A Mathematical Theory of Communication" [67] which revolutionized information theory. Shannon's development of the concept of entropy in information theory led to a dramatic shift in the comprehension and measurement of information and uncertainty.

 doi:10.20944/preprints202501.1628.v1

new perspectives in another, ultimately creating a unified model that integrates these diverse insights [19].

Recent bibliometric research underscores how interdisciplinarity enhances innovation and problem-solving by integrating diverse perspectives and methodologies, specifically, the integration of physics with information or social sciences which leads to a more comprehensive understanding of complex phenomena [112]. This combination allows for the application of quantitative and analytical methods from physics to tackle intricate problems in social sciences, resulting in more effective and innovative solutions.

The potential for interdisciplinary approaches in managerial practices and physics, akin to those in financial economics and social sciences, can be realized by examining four key factors: big data statistics, challenging established norms, academic momentum, and epistemological convergences.

Big Data Statistics

B. B. Mandelbrot's work influenced financial economists like E. F. Fama, who applied contemporary probability theory, specifically the martingale model, to develop the notion of efficient markets [113].

Financial data closely resemble exponential functions and are distinguishable only through extensive empirical evidence, necessitating the use of statistical distributions [114]. Observations akin to this led to the incorporation of contemporary probability theory for financial market assessment, which coincided with a significant breakthrough in the sixties: the creation of comprehensive databases. Advancements in information sciences, big data, and machine learning have enhanced databases, enabling extensive aggregation of historical stock market data. Financial economics now produces large amounts of scientific data, aligning with statistical physics norms, due to market computerization and automation. The availability of big and intraday data has introduced new trend detection techniques, revealing occurrences that were previously undetectable with monthly or daily data [115].

Challenging Norms

From a phenomenological standpoint, stylized facts, persistent macro-regularities unexplained by microeconomic theory, can be understood through the multiple realizability argument, which suggests too many microscopic configurations exist to define individuals precisely [116]. Similar to how different levels of nature can be examined at varying resolutions [117], complex systems can be understood through different scales or layers, each offering unique insights. This multi-scale approach acknowledges that diverse processes and interactions are significant at various levels, enhancing our understanding of natural phenomena. Adaptive decision-making simulations are used to study these stylized facts, providing the micro-foundations of macro-level statistical regularities in economic systems [118]. Based on this observation, it is logical to assume that deep learning algorithms may redefine agent behavior models by refining the characterization of component heterogeneity, improving the accuracy of macro-patterns in statistical models.

Academic Momentum

Econophysics has become a widely researched subject, endorsed by respected academic institutions and physics journals. First used in financial markets and macroeconomics, it now also addresses energy and environmental economics, showing its increasing importance in solving economic problems [47]. The integration of econophysics into curriculums, papers in peer reviewed journals, and academic programs, provided new access points to the field which led to development of further interest in the concept of scientific interdisciplinarity [119].

A recent bibliometric study [48] identified publication patterns in econophysics by examining collaboration networks from 2000 to 2019. Key works include empirical characterization of financial time series, market crash predictions, and network analysis of money markets, world trade, and equities. The study found that self-citations significantly influence overall citations, peaking early and decreasing over time with physics contributing most to the field, followed by economics.

A more recent review has examined how sociophysics and network science might be integrated into academic programs [120]. This study demonstrates how sociophysics is widely acknowledged in academic research and education due to its interdisciplinary approach, which draws on physics, mathematics, economics, and social sciences. However, further advances are required to represent social reality more accurately by linking theoretical models to real-world social complexities.

Epistemological Convergences

Contemporary research showcases this diverse amalgamation of finance and economic systems with statistical physics [121], diverse aspects of social sciences like sociophysics [122] and socioeconomics [123], and network science [124]. Statistical physics' theoretical ability to explain continuous phase transition dynamics and apply renormalization group techniques to stock market scaling was a major milestone in the field's history [125]. Moreover, statistical mechanics effectively explains phenomena where the interaction between microscopic properties and macroscopic behavior is significant [20].

Since the beginning of the twenty-first century, physicists have seen the application of statistical mechanics to the study of social phenomena, including economic systems, as both promising and precarious [126], [127]. Numerous economists have employed statistical mechanics to address various economic challenges. For example, the influence of thermodynamics in shaping neoclassical economics is evident for approximately one hundred fifty years [20]. Specific aspects of social sciences, which have traditionally generated a moderate volume of data, are currently witnessing a significant surge in data [128].

3.2.2. Econophysics

R. N. Mantegna and H. E. Stanley define econophysics as the practice of physicists applying innovative methods from the physical sciences to economic problems to test and analyze them [47].

Econophysics as a science can be traced back to the work of Mandelbrot [49], who combined mathematics and topography to create the field of fractal geometry. His work demonstrated that seemingly irregular and complex forms can exhibit mathematical regularity and self-similarity. Fractals have applications in physics, biology, and finance, dramatically influencing the body of knowledge of natural occurrences and complicated systems [129]. The emergence of econophysics occurred through a cognitive process of analogical reasoning, establishing correlations with widely recognized academic fields.

Essentially, econophysics is a field that investigates economics and finance by employing the principles of statistical and theoretical physics. This cross-disciplinary approach enables the transfer of concepts to produce refined insights across varied fields of study [130]. Over the past twenty years, as scientific collaborations have significantly increased and may be considered essential for high-quality research, econophysics has made substantial advancements, offering new perspectives on financial markets and their dynamics [48].

In this context, it may be inferred that econophysical collaborations imply a tendency among practitioners from diverse fields to seek prospects in financial markets and vice versa. Indeed, such a trend is observable in the employment of physicists in trading or consultancy roles, where they apply their expertise to analyze complex financial systems. [131], [132].

Given the intricate nature of financial markets, it is essential to acknowledge that physics provides a more straightforward approach to navigating these complex systems. Consequently, it is crucial to emphasize the importance and application of econophysics principles and methodologies in complex exchanges. As demonstrated, economists and physicists are increasingly recognizing the effectiveness of econophysics in addressing various economic phenomena. This recognition is driving a natural evolution within the scientific community, namely, incorporating econophysics into diverse and seemingly unrelated fields.

3.2.3. Sociophysics

Mantegna published one of the first econophysics papers, demonstrating the breakdown of the central limit theorem in the stock market [133]. Sociophysics may be viewed as a different manifestation of econophysics and can be understood as the study and prediction of social and behavioral events using mathematical and physical models [120]. It uses statistical physics concepts like phase transitions to examine social systems, focusing on principles such as opinion dynamics, knowledge diffusion, and group decision-making. The field examines social interactions, crowd behavior, and the dissemination of information using empirical data and complex network models [134].

Sociophysics and econophysics differ in that only a holistic approach to economic phenomena, integrating psychology, social psychology, and sociology, can properly describe and understand socio-economic life, including financial markets. Econophysics uses quantitative data to study economic activity, while sociophysics explores a wider array of social phenomena. Despite their distinct boundaries, these fields may support each other. For example, the interaction between econophysics, sociophysics, and the application of leadership could be considered for a more comprehensive analysis in each of these domains as explained in [125].

3.2.4. Network Science

A rather challenging concept in science today is complexity, whether examined from a philosophical, computational, or mathematical perspective [135]. Over the past fifteen years, statistical physics, with robust methodologies for analyzing complexity, has undoubtedly played a vital role in fostering innovations in network research, as is the case, for example, with geometric deep learning and the development of potential applications to quantum networks for communications [136].

Network science has significantly impacted econophysics, leading to novel tools for analyzing complex financial and economic systems. For example, the proximity-based network concept in econophysics studies direct interactions like loans, similarities such as co-ownership, and higher-order relations involving multi-party contracts or multilayer connections [132].

The field now includes a broad range of research, with the study of intra-network interactions being highly significant. According to [137], networks represent both symmetric and asymmetrical links between discrete items in the real world. Common network analysis activities include node categorization, connection prediction, clustering, and visualization, however, as data science and network science advance, network data becomes richer and more diverse.

In quantized information analysis, evidence suggests that network information operators form a proper statistical ensemble, with their superposition creating a density matrix for complex dynamics research [138]. The authors demonstrated that the ensemble's von Neumann entropy can quantify the functional diversity of complex systems, defined by the functional differentiation of higher-order interactions among their components.

Another field of research involves investigating the statistical physics of bionetworks that aggregate or correlate, such as the synchronization of brain activity in socially interacting organisms. Research indicates that these networks demonstrate coalescence phenomena, where smaller units combine to form larger networks [139]. By applying the principle of maximum entropy, these processes can be represented as operations involving density matrices, allowing for the derivation of their entropy additivity and extensivity. This helps differentiate processes that reduce the functional variety of systems.

Association networks are derived by conducting statistical tests to evaluate the impact or interplay among each pair of nodes. They can be obtained through the application of statistical analyses on various combinations of economic actors, especially when regarded macro-economically, including but not limited to Granger causality tests [140].

Due to system interactions and the complexity associated with vast networks, the assessment of pair similarity or pair influence estimation necessitates the inclusion of a statistical examination. To

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obtain these statistical data, it is crucial to perform tests which encompass all conceivable combinations of nodes. This indicates that the management of multiple tests is required for every basic type of network described above. The inherent nature of complex systems necessitates that an adequate number of tests increases exponentially in direct proportion to the number of nodes [141], a phenomenon under study currently in the field of big data.

Contemporary literature offers valuable insights into the implementation of efficient information filtering strategies within networks, such as a widely utilized approach that involves the information filtration process based on the minimum spanning tree [142].

The examination of networks in economics has an extensive history, but only recently has the integration of network science techniques into economic and financial studies gained recognition as a fundamental research component [143]. Certainly, the early empirical investigations into financial systems in terms of networks were undertaken by econophysicists or by interdisciplinary collectives consisting of scholars, including physicists [36].

The interdisciplinarity and inclusion of network concepts and methodologies is indispensable in addressing systemic risk, as evidenced by current research conducted in various disciplines [144].

3.2.5. Infophysics

Informatics integrates information theory, systems engineering, and specialized knowledge applications in various sectors, such as healthcare. For example, [145] demonstrates how medical and biological informatics are significant domains advancing research, particularly as new technologies enhance existing tools and methodologies. A review of advancements in medical imaging informatics [146] focuses on data management and AI-based methods, such as three-dimensional reconstruction, to improve diagnosis, prognosis, and therapy planning. While these advancements have greatly aided in automating the detection of variance in medical practices, less attention has been paid to addressing the root causes of this variation [147].

Informatics has also become increasingly important in other scientific domains, such as bioinformatics, where vast amounts of data are generated through advanced technologies like high-throughput synthesis and sequencing [148]. For instance, bioinformatics research has identified subtle sequence variations in DNA/RNA that conventional methods could not detect, revealing novel relationships between sequences and greatly advancing the field [149].

Moreover, informatics has applications in the social sciences, as demonstrated by shifts in urban informatics [150], where smart urbanism and participatory city-making are driving new paradigms. This shift is motivated by the need for more participatory approaches in urban environments, moving beyond traditional human-computer interaction. Additionally, ethical considerations are paramount as new technologies and AI continue to evolve. There is a growing need for ethical principles and legal frameworks to ensure these innovations benefit society while addressing concerns over privacy, security, and job displacement [151].

In its managerial dimensions, informatics emphasizes continuum thinking to manage the complexity of information governance, especially in the context of big data. With data generation rapidly outpacing governance structures, harmonized governance across interconnected fields is necessary [152]. For example, [46] discusses the integration of ecological science, management, and information and communication technology to handle complex datasets. Similar to other disciplines, ecological data require structured, computer-based management to enhance integration, analysis, and dissemination.

The literature on informatics highlights the creation of widely accepted frameworks, the establishment of specialized platforms for interdisciplinary discourse, and the use of multidisciplinary techniques. This approach is essential for advancing research across diverse fields, combining experimental data with interdisciplinary information science [148]. The need for transdisciplinary and agile thinking is particularly crucial when navigating various levels of granularity, as seen in the application of statistical physics principles from micro to macro systems

[150]. Despite technological advancements, challenges in managing information persist, necessitating innovative approaches for effective information management [152].

To fully leverage the potential synergy between BPM and information entropy and promote interdisciplinarity, a term like infophysics allows for a broader understanding and a unified reference point across fields. Considering this review, infophysics can be defined as an interdisciplinary field that merges information theory and physics to study complex systems. The field integrates concepts from information entropy and data compression [18], [67], [111] with principles from thermodynamics and statistical mechanics to explore the dynamics, efficiency, and effectiveness of information networks. Infophysics aims to leverage physical laws and mathematical models, where applicable, to understand the creation, processing, and dissemination of information across structured systems.

In the context of BPM and entropy, leveraging interdisciplinarity through umbrella terms like infophysics offers the opportunity to create a common framework. This framework, in turn, can serve as a bridge between disciplines, enabling the seamless integration of information theory, physics, and process management. The concept of infophysics, as proposed here, seeks to harness the principles of information entropy alongside those from thermodynamics and statistical mechanics to understand and optimize the dynamics, efficiency, and effectiveness of information-driven processes.

By establishing this conceptual umbrella, infophysics opens pathways for incorporating BPM into its framework. This paves the way for a new sub-field, which would focus on the application of entropy and physical principles to business processes. This sub-field would aim to improve process predictability, optimize resource allocation, and enhance system efficiency by viewing managerial processes through the lens of physical laws and mathematical models. Further discussion on this topic will be the focal point of the *Discussion* section.

3.2.6. Entropy Generalization

Use of the concept of equilibrium may be observed in diverse disciplines via the combination of mathematical formalism with the discipline’s pertinent principles as is evidenced, for example, in the development of the random walk theory [44].

To provide an explanatory framework for empirical results and confidence intervals, a complex open system, near or at equilibrium, should be modeled under specific assumptions; even organizational systems, such as an organization's accounting processes, can be understood thermodynamically as open systems, which may initially seem unconventional [9]. The accuracy of open system modeling is empirically dependent on the model and the assumptions about the stochastic processes defining the system's evolution [20]. Information entropy can be seen as a reliable and versatile approach that offers multifaceted methodological frameworks. For example, by using Kullback-Leibler entropy it is possible to enable signal detection and information filtering in multivariate systems, allowing the extraction of meaningful structures, such as the minimum spanning tree, from correlation matrices of financial asset returns [20].

As mentioned, the model's accuracy depends on assumptions about the stochastic processes characterizing the system's progress toward equilibrium [20]. Examining the statistical interpretation of Granger causality across various domains, such as physical interactions and information exchange [153] or even social systems [154], reveals that the information content of these stochastic processes can be effectively understood through this perspective. The development of nonlinear generalizations of Granger causality in physics, and its equivalence to transfer entropy for Gaussian variables [155], has highlighted the interdisciplinary nature of entropy, bridging physics, statistics, finance, and information theory.

[50] describes how N. Georgescu-Roegen proposed incorporating the concept of energy exchange and its inherent constraints, in accordance with the concept of entropy, to encompass a broader spectrum of resource inputs. This paved the way for the concept to be used in economics, arguing that economic processes are inherently entropic. Emphasis is placed on the idea that energy transformations within economic activities are irreversible, leading to the degradation of useful

 doi:10.20944/preprints202501.1628.v1

energy into less useful forms. This perspective highlights the finite nature of resources and the inevitable increase in disorder, challenging the sustainability of continuous economic growth.

Recent studies have shown an increasing use of entropy in the study of financial market dynamics. Examples of entropy applications in this field include analyzing the dynamics of cryptocurrencies [21], predicting stock market directions [22],[23], examining discrepancies in interlinked financial time series, especially during abnormal market events like the COVID-19 pandemic [156], and developing innovative applications within econophysics related to financial markets [24]. However, some restrictions also persist. For instance, power law distribution of stock market fluctuations extends beyond Lévy processes, showing persistent price variability correlations across time scales. Earlier explanations using stable and exponentially truncated Lévy processes do not fit the empirical evidence well [25]. Nonetheless, a more in-depth analysis would involve examining the phenomenon from a microscopic perspective in conjunction with the emergence of macroscopic properties.

3.3. The Involutional Nexus of Entropy

3.3.1. Entropy's Emergence

The concept of entropy emerged from the understanding of energy in thermodynamics. Initially, energy was introduced to measure interactions in matter and radiation, with its conservation remaining a fundamental law [157]. During the Industrial Revolution, engineers recognized that mechanical work could convert into thermal energy, challenging earlier caloric theories [157]. R. Clausius expanded on this, emphasizing the conversion of heat into work, which led to the formulation of entropy. This shift from caloric to kinetic theory paved the way for modern thermodynamics and statistical mechanics [158].

The drive for industrial efficiency during the First Industrial Revolution [159] spurred the careful study of engine performance, shaping the development of thermodynamics [160]. Engineers like J. Watt and S. Carnot emphasized precise measurement of heat and work, while figures like J. P. Joule and J. R. von Mayer contributed to energy understanding despite facing criticism [161]. This blend of technological advances and evolving philosophical views laid the foundation for modern thermodynamics [162].

3.3.2. Entropy Defined

Entropy is commonly defined as the measure of thermal energy in a system that cannot be effectively utilized, thus limiting process efficiency [26]. The term system pertains to the definition of a thermodynamic system as being classified into three main categories: isolated, closed, and open systems [163]. Defining entropy in nonequilibrium conditions poses challenges [164]. It quantifies uncertainty or disorder, representing possible molecular arrangements and energy distribution [165], [166]. Clausius described entropy as measuring the portion of energy that cannot be converted into work, indicating energy degradation [167]. In chemical thermodynamics, it reflects the dispersion of energy among atoms and molecules during reactions [168]. Academic literature identifies at least three main ways to conceptualize entropy: as a thermodynamic property of physical systems, as a metric for quantifying information generation by ergodic sources, and as a method for statistical inference in multinomial distributions, based on nearly two decades of bibliometric analysis [169].

Clausius was essentially able to provide a comprehensive explanation of why thermal engines perform sub-optimally. He conceptualized entropy as a state function of a system, akin to energy articulating in a precise manner the first and second laws of thermodynamics on the last page of his publication [68] as "*Die Energie der Welt ist constant*" and "*Die Entropie der Welt strebt einem Maximum zu*", which may be translated as "*The energy of the world is constant*" and "*The entropy of the world tends towards a maximum*".

 doi:10.20944/preprints202501.1628.v1

3.3.3. Interdisciplinary Entropy

Clausius recognized entropy as governing transformations [167] within Carnot's reversible cycle, involving isothermal and adiabatic steps where heat and entropy changes occur [170]. Clausius revisited Carnot's work to understand irreversible processes, proposing heat transfer from high to low temperatures, which became the basis of his heat-work theory [37]. Entropy bridges macroscopic and microscopic phenomena, influencing systems in equilibrium or near-equilibrium [43]. Its application spans contemporary physics [171], statistical mechanics [27], cosmology [172], life sciences [173], geosciences [174], social sciences [41], linguistics, economics [20], chemistry [175] and information theory [26]. Especially with regards to information entropy, there is a plethora of interdisciplinary research studying the topic in chemistry [176], geostatistical models [38], finance [23], accounting business processes [9], machine learning [177] and, of course, organizational management [28], [178], [179]. However, its broad usage across these fields has led to differing interpretations and misunderstandings [26] requiring more rigorous analysis.

3.3.4. Foundations and Universality of Entropy

Clausius introduced entropy as a fundamental thermodynamic property indicating energy dissipation, while L. E. Boltzmann and J. W. Gibbs developed mathematical models, contributing key concepts like the Boltzmann constant and distribution [180].

Statistical mechanics problems focus on integrating molecular interactions to analyze overall system averages, like determining temperature from molecular motion in a specific area [181]. In the analysis of entropy, it is imperative to delineate precise variables. In this given context, entropy is denoted by the symbol S, the Boltzmann constant is represented by k_B, and the statistical weight of the macroscopic state of the system is signified by W. These variables are connected via the famous equation:

$$S = k_B \ln W. \tag{2}$$

A key aspect of entropy is that it relies on a foundational set of principles that are universally applicable, independent of specific statistical frameworks or the existence of atoms and molecules. This universality is what allows the concept of entropy to be relevant across various scientific fields as exemplified in [167]. Consequently, any diverse approaches used to measure or compute entropy must yield consistent and epistemologically sound outcomes to maintain their scientific validity [182], [183]. The concept of entropy is independent of any entropic formulation that incorporates probabilities of microstates. Instead, it embodies the inherent probabilistic phenomena observed and measured within the natural world. Entropy is a result of the accumulation of pairs of points in a sequence of events as in an operational process, with each pair preceding the next point in the progression of the unfolding process. The relationship between the process parameters should exhibit logical behavior when considering the configuration and magnitude of variables.

3.3.5. From Thermodynamics to Information

Boltzmann, expanding on J. C. Maxwell's work, contributed to statistical mechanics by modeling gas molecules as point masses, simplifying the study of molecular interactions. In the seminal 1872 publication [69], Boltzmann introduced kinetic gas theory, offering a statistical basis for the second law and showing how probability theory in statistical mechanics helps calculate macroscopic properties like temperature and pressure. Boltzmann's lifetime work has been instrumental in bridging classical and quantum physics, and in shaping key concepts like statistical entropy in thermodynamics [184], [185], paving the way for understanding entropy not only in terms of thermodynamic heat engines but also within broader contexts.

The statistical weight of a macrostate quantifies the possible configurations of an ideal gas's molecules across its microstates [181]. Given N molecules, the total number of microstates can be expressed as [186]:

 doi:10.20944/preprints202501.1628.v1

$$W = N!/\prod N_i!. \tag{3}$$

From (2) and (3), Boltzmann's equation for entropy is derived as:

$$S = k_B \ln\,(N!/\prod N_i!). \tag{4}$$

This principle extends to information theory, where entropy measures uncertainty in the distribution of states. The probability distribution H of states of informational uncertainty is given by Jane's equation [187]:

$$H(p_1 \dots p_n) = -k_B \Sigma p_i \ln p_i. \tag{5}$$

This alternative measure of entropy complements Boltzmann's work, highlighting the probabilistic nature of entropy in both physical and informational contexts. As the number of microstates increases, entropy increases, reflecting greater disorder and uncertainty. The probability of each microstate i is given by:

$$p_i = e^{-\varepsilon_i/(k_B\theta)} / \sum_{j=1}^{N} e^{-\varepsilon_j/(k_B\theta)}. \tag{6}$$

where p_i is the probability of the microstate i, ε_i is the energy of the microstate i, k_B is Boltzmann's constant, and θ represents the temperature.

At this point, it becomes clear how the Gibbs entropy equation enables the calculation of a system's entropy through a probabilistic interpretation of Boltzmann's entropy formula. According to the principle of equal a priori probabilities, every microstate of a given macrostate has an equal probability of occurrence because there are no factors or hidden variables that would assign different probabilities to specific microstates [188], [189], [184]. By denoting Ω as the total number of possible microstates, and since the probabilities of all microstates must sum to 1, the probability of each individual microstate i will be equal to $1/\Omega$. Substituting this into (6), the Boltzmann equation is obtained:

$$S = -k_B \sum_{i=1}^{\Omega} p_i \ln p_i = -k_B \sum_{i=1}^{\Omega} \frac{1}{\Omega} \ln \frac{1}{\Omega} = -k_B \Omega \left(\frac{1}{\Omega} \ln \frac{1}{\Omega}\right) = k_B \ln \Omega, \tag{7}$$

which is widely recognized in the form of (2). The Gibbs entropy equation extends Boltzmann's approach by linking entropy to the probability distribution of microstates, showing that the total entropy depends on the number of possible configurations in a macrostate. Systems naturally favor states of maximum disorder due to the greater number of disordered microstates [190]. Boltzmann and Gibbs demonstrated that in statistical mechanics, macroscopic properties arise from the probabilistic behavior of individual particles, fundamentally connecting thermodynamic and information entropy.

3.3.6. Information and Entropy

Contemporary research highlights the fundamental role of information entropy in various physical, biological, and theoretical contexts. Literature weaves together the role of information entropy across domains, showing its centrality in understanding complex systems, communication, and thermodynamics. In colloidal dispersions, entropy drives the formation of ordered structures, even without direct energetic interactions [191]. Similarly, in biomolecular systems, information entropy manages complexity, especially in non-equilibrium states [29]. Finally, information entropy is crucial for quantifying uncertainty in risk analysis, providing a powerful framework for enhancing risk management strategies across different fields [30]. Collectively, these studies underscore the centrality of information entropy in analyzing and understanding order, complexity, and uncertainty across a wide range of scientific and engineering applications.

Shannon's work in communication theory established a mathematical framework for information transmission, akin to thermodynamic principles, emphasizing the encoding and efficient transmission of data [192]. Shannon identified challenges in communication—capacity limits and noise interference—outlining measurable upper limits for message transmission rates [193]. Using

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Maxwell's demon as a metaphor, Shannon illustrated how information influences system behavior, emphasizing that knowledge and context significantly impact the amount of information required for accurate communication [194]. Despite starting from different disciplines, Shannon and Boltzmann arrived at similar mathematical expressions, underscoring the parallel between statistical mechanics and information theory, where both entropy concepts measure uncertainty and possible system states [31].

Boltzmann's equation (2) for entropy, applies in statistical mechanics and information theory, where entropy measures uncertainty in probability distributions [195]. Statistical entropy measures the number of possible microstates, while information entropy quantifies uncertainty in data transmission. L. Brillouin proposed that information is equivalent to negative entropy, or negentropy, to resolve Maxwell's demon paradox [196]. However, since thermal entropy cannot be negative, and information must remain positive as it is transmitted through physical media; this concept may not be physically valid. This raises questions about Brillouin's assumption and the connection between entropy and information, as equating information to negentropy remains debated [196].

Landauer's principle further connects entropy with information, asserting that irreversible operations, such as data erasure, result in physical irreversibility and heat generation [197], [198], [199]. E.T. Jaynes extended information theory to thermodynamics, proposing that entropy measures missing information about a system's microstates, bridging macroscopic thermodynamic laws and microscopic statistical descriptions [26], [27], [199]. While information entropy and thermodynamic entropy are not equivalent in all contexts, they share conceptual similarities and can be expressed in the same units (bits) [26], [45]. D. Layzer's work proposed that a system's total information includes both known and uncertain information (entropy), reinforcing the conceptual relationship between entropy and information [200]. This view implies that any increase in systemic information (knowledge) corresponds to a decrease in entropy (uncertainty) [201], which resonates with an analogy of reading a manuscript: as understanding increases, the unknown information and entropy decrease.

Landauer's principle states that information loss invariably increases entropy, expressed as:

$$\Delta S_{inf} = \Xi k_B \ln(2), \tag{8}$$

where Ξ represents the number of bits lost [197], [198]. The relationship between entropy production and information modification applies not only within a system but also in the system's external environment. By integrating these concepts, it may be concluded that total entropy and information in the universe remain balanced [202], [203].

3.3.7. Information Entropy

As previously noted, Shannon's seminal work introduced the amount of information and information entropy [67]. If I represents the total amount of information in a message, k is a constant for converting between logarithmic bases or switching units of information, and M denotes the number of possible messages from a finite source, then Shannon's measure of the information that can be successfully transmitted is:

$$I = k\ln(M). \tag{9}$$

For instance, consider an electrical system that can only switch a motor on or off. Such binary systems, exemplified by relay contactors, have two possible states (on/off). For N relay circuits, there are 2^N possible states, transforming the system into a binary representation. The information in such a system is:

$$I = \log_2(2^N) = N. \tag{10}$$

Shannon entropy is typically defined as the average amount of information or uncertainty per symbol in a message, unifying probabilistic entropy formulations [26], [27], [204], [205]. Its

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foundational principles can be understood through Boltzmann's entropy, expressed probabilistically as:

$$S = -K \sum_{i=1}^{n} p_i \ln p_i, \tag{11}$$

where p_i is the probability of successfully transmitting symbol i. The amount of information is the product of bits in a message and the Shannon entropy.

Recently, the concept of Cumulative Residual Entropy (CRE) was introduced as an alternative to Shannon entropy [206]. CRE has been extended to fractional-order scenarios, resulting in a non-linear, positively concave, and non-additive entropy function. It has been shown to effectively calculate the information content of datasets, including those in financial systems with non-parametric data; both CRE and information entropy are effective tools for evaluating data with historical dependencies.

Furthermore, they share a close connection with residual entropy observed in physical systems, such as imperfect crystals near absolute zero [207], [208]. Even in a low-energy state, an imperfect crystal retains some disorder, similar to residual entropy. For example, a string of binary data representing information in this system could be:

$$I_1 = 01101110011101000111001001101111011100000 1111001. \tag{12}$$

At minimal energy, entropy and energy are minimized, and information is maximized. However, with increasing thermal effects, information components may dissipate, shifting the system to a higher-entropy state, such as:

$$I_2 = 011101000111001001101111011100000 1111001. \tag{13}$$

The missing segment from I_1 represents lost information, which dissipates into the environment, increasing the system's entropy. This transformation from an ordered state (low entropy) to a disordered state (high entropy) resembles the transition of an imperfect crystal from solid to gas, where increased molecular motion leads to rising entropy.

Shannon and residual entropy exhibit similarities, both relying on probabilistic principles and statistical frameworks. However, as [70] suggests, entropy has distinct manifestations across different fields, including material sciences (thermal and residual entropy) and information theory (information entropy) [209], [210]. In material sciences, thermal and residual entropy are measured in Joules per Kelvin while information entropy is quantified in bits. Despite their differences, these forms of entropy can be categorized into three primary frameworks:

1. Thermal Entropy:

$$S_{\text{thermal}} = -k_B \sum_{i=1}^{W} p_i \ln p_i = k_B \ln W, \tag{14}$$

where W represents the number of unaligned particles;

2. Residual Entropy:

$$S_{\text{residual}} = -k_B \sum_{i=1}^{W} p_i \ln p_i\,; \tag{15}$$

3. Information Entropy:

$$S_{\text{information}} = -K \sum_{i=1}^{n} p_i \ln p_i. \tag{16}$$

The minus sign in the entropy formula arises because probabilities lead to negative logarithms, since $p_i \in [0,1]$, ensuring entropy remains non-negative. Entropy increases with uncertainty, and since $-x\ln x$ is a concave function as shown in Figure 3, it follows that $S \geq 0$.

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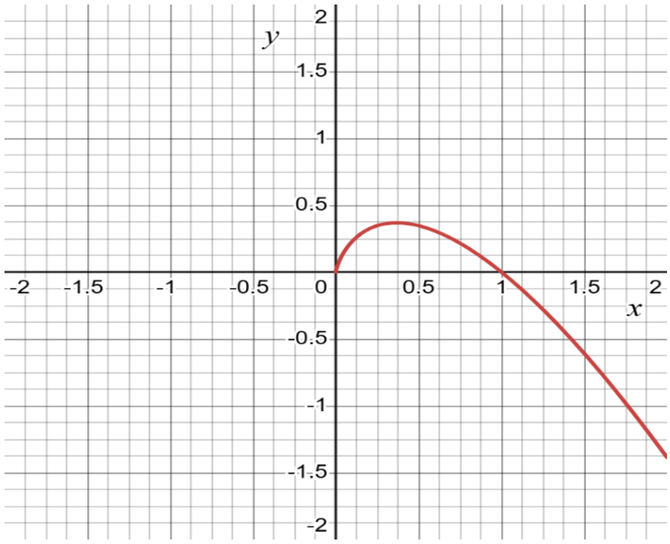

Figure 3. Graphic Representation of $-x\ln x$.

Logarithmic probabilities are practical for computational models in information theory, simplifying large-scale probability operations. For example, the product of two probabilities $p(a)$ and $p(b)$, becomes additive in logarithmic space, simplifying calculations:

$$\log\left(p(a)\,p(b)\right) = \log p(a) + \log p(b). \quad (17)$$

Although Clausius's classical entropy can be negative in some continuous probability distributions, these cases often do not correspond to natural phenomena.

In summary, Shannon and information entropy provide valuable insights into the relationship between disorder, uncertainty, and information. As highlighted in Popovic's review [70] and related literature, the categorization of entropy into thermal, residual, and information entropy remains valid and underscores its wide-ranging applications, from material sciences to information theory. This multifaceted understanding of entropy forms a solid foundation for comprehending both physical systems and information processes, paving the way for its integration into BPM.

3.4. Epistemological Frontiers of Information Entropy in BPM

3.4.1. Foundational Empirical Implementations and Applications

The systematic review, conducted via the PRISMA framework, revealed that the concept of process information entropy was introduced before 2018, with the initial idea presented by J.Y. Jung in 2008 [32]. In this work, entropy was applied to assess uncertainty in BPMOs, particularly in task execution and control flows, highlighting how control flow constructs introduce uncertainty in task execution. This provided a mathematical method to calculate entropy in various process patterns, aiding resource assignment and workflow scheduling. Following this, the idea was further expanded in [33], where the authors proposed a method to quantify uncertainty in BPMOs using an entropy-based measure. Focusing on process variability and uncertainty, this paper captured dynamic process behavior using information entropy, providing explicit forms for various control-flow patterns, and enhancing process design and management.

The next pertinent study [40], focuses on improving resource allocation in BPM by introducing an entropy-based clustering ensemble approach. This method analyzes task preferences and recommends appropriate resources by examining past executions through process mining, identifying key resource characteristics like time, cost, and cooperation to optimize task assignment. The study also addresses dynamic resource allocation, optimizing resource utility and minimizing execution time in concurrent process environments. The approach was evaluated using a real e-healthcare process in a Chinese hospital, showing notable improvements in resource utilization and

 doi:10.20944/preprints202501.1628.v1

workload balancing. Specifically, the entropy-based clustering ensemble method (MCRR) and the Utility-Availability Trade-off Model (UATM), which optimizes resource utility and workload balancing by factoring in task preferences and availability, significantly outperformed existing methods. MCRR achieved high accuracy in predicting task preferences, surpassing k-means, and the Hidden Markov Model (SAHMM), which focuses on proficiency and cooperation. UATM also exceeded strategies like the Reinforcement Learning-based Resource Allocation Model (RLRAM), which optimizes flow time without task preferences, and heuristic methods such as Shortest Queue (SQ) and Shortest Processing Time (SPT), which base allocation on queue length and speed. Unlike these methods, the proposed approach offered a more comprehensive solution by considering multiple factors like task preferences, utility, and workload.

3.4.2. PRISMA-Based Empirical Implementations and Applications

As the pertinent literature fell within the scope of this systematic review, the seminal [9] thoroughly examined how entropy correlated with business information in organizational accounting processes. The study highlighted entropy's impact on non-formal aspects of organizations, such as culture, decision-making, and communication. Using the Scopus database, the researchers analyzed nine hundred eighty articles published between 1974 and 2020. The distribution of articles showed increasing interest in the topic, with sixty-six percent published after two thousand eleven and twelve percent in two thousand twenty alone. The research emphasized that open business organizations, which promoted the flow and exchange of information, were better equipped to handle chaos and uncertainty, thus enhancing adaptability. Five key research lines were identified, including information theory, maximum entropy, decision-making, and business model evaluation systems. The study underscored growing academic interest in the role of entropy in decision-making, resource allocation, and organizational management in an increasingly uncertain business environment.

Another empirical example was presented in [211]. Although the connection to BPM was not explicitly made, the study inferred similar principles by managing the learning process to reduce entropy and enhance resource use. The authors explored how the COVID-19 pandemic influenced the evolution of real-time online courses (RTOCs), showing how social media platforms, initially unsuitable for education, were essential in maintaining learning processes. These platforms facilitated hybrid-learning models combining traditional and online education. A key concept was information entropy, referring to the uncertainty caused by inconsistent content delivery across platforms like Zoom and Moodle. The study highlighted that reducing entropy through better integration significantly improved learning by reducing chaos. The real-life application in hospitality programs across Mainland China, Hong Kong, and Macau demonstrated how managing entropy in education ensured better resource allocation and outcomes, paralleling BPM’s focus on process optimization in times of crisis.

The most recent example up to the finalization of this review can be found in [42]. The authors present a method for evaluating and predicting real-time mobile device performance using Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) combined with the entropy weighting method and time series models. Information entropy is used to measure uncertainty within performance data, assigning greater weight to more variable indicators. This reduces uncertainty, allowing for more accurate real-time performance evaluations and dynamic adjustments to optimize user experience. The use of entropy to streamline device performance management showcases the universality of the significance of reducing variability and improving predictability which are key to optimizing workflows similarly to the principles of BPM and process efficiency.

3.4.3. Analogical Inductions in BPM through Information Entropy

An invaluable insight from the examination of pertinent literature, is that the principle of adiabatic partitioning and recombination stability, which allows a system to be partitioned into components and recombined without altering its fundamental state, could be translated into BPM by

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ensuring that processes can be broken down into smaller, manageable parts like sub-processes or procedures and later reassembled without losing overall efficiency or stability. This approach could help in optimizing workflows, improving flexibility, and maintaining system integrity even when changes or disturbances occur. As is the case, the act of conceptualizing business operations as systems similar to those where information entropy may be measured, reduces uncertainty during the implementation phase, as the model delineates the precise activities and control mechanisms that can be executed. The entropy of BPMOs functions as a measure for quantifying the degree of uncertainty associated with process execution.

By using inductive reasoning and more specifically, analogical induction, when studying the pertinent literature presented in this review, when a methodology A has been successfully implemented in context B, it is worth investigating whether A may also be applicable in context Γ [212], [213]. This statement suggests that similarities between contexts B and Γ make it plausible that A could work in Γ, although this is not guaranteed as this form of reasoning does not offer deductive certainty but instead provides a probabilistic justification for further exploration or investigation.

Building upon the foundational works and empirical implementations discussed in the preceding sections, a clear analogical induction between the use of information entropy in other domains and its application in BPM may be established. The systematic review highlights how information entropy has been employed to manage and optimize processes in diverse fields, from resource allocation in healthcare [40] to real-time performance evaluation in mobile devices [42]. These implementations reveal common principles: reducing uncertainty, optimizing resources, and improving process efficiency, all of which are central to BPM.

For example, the study in [32] laid the groundwork for applying entropy to BPM, using it to measure uncertainty in task execution and control flows, with a focus on process variability. Similarly, the work in [33] quantifies this uncertainty through explicit mathematical measures, capturing the dynamic nature of processes. These approaches align with BPM's need for efficient resource management and workflow optimization, making a strong case for the utility of entropy in process management. [9] thoroughly examined how entropy correlated with business information in organizational accounting processes. Moreover, [40] presents a successful empirical application of entropy-based resource allocation in a real-world BPM scenario, where the method significantly improved resource utilization and reduced execution time. By analyzing task preferences and characteristics like time and cost, this entropy-based method achieved more accurate resource assignment than traditional models, directly supporting BPM's core objectives of efficiency and optimization.

Building on these examples, it becomes clear that analogical induction can be applied effectively in this context. The principles of information entropy, as demonstrated in various domains, provide a theoretical and empirical foundation for enhancing BPM. Entropy allows for the measurement and reduction of uncertainty, which in turn optimizes processes—whether in managing resources, enhancing performance, or streamlining decision-making. This inductive reasoning suggests that the application of entropy-based models in BPM can lead to more efficient, predictable, and adaptable business processes, just as it has improved outcomes in healthcare, mobile performance, and other fields.

So far, this systematic review has established a comprehensive foundation in BPM concepts and methodologies, explored interdisciplinary approaches involving information theory and entropy, and elaborated on the scientific principles of entropy in a way that can be applied to BPM. In the next section, the focus will shift to expanding on the application of entropy within BPM, reflecting on the synergy between the two to manage uncertainty and variability in processes. Additionally, future directions will be discussed, emphasizing how BPM can leverage entropy in areas such as risk assessment, process optimization, and complex systems modeling. While acknowledging the limited empirical evidence in this field, the research will propose suggestions for future studies and potential interdisciplinary advancements. By exploring these theoretical insights, the integration of information entropy into BPM presents an innovative path for advancing research in this emerging area.

4. Discussion

4.1. Interpretation of Findings

4.1.1. Alignment with Previous Studies

The review proposes a framework that integrates process management by merging BPM principles with complex systems analysis, complexity theory, information entropy, and physics. Standardized BPM frameworks improve consistency and efficiency, while recent technologies (e.g., blockchain, AI, big data) expand BPM's relevance to modern business challenges [1], [2], [5], [85], [86], [87].

Entropy, based on Shannon's information theory, serves as a metric for process variability, offering insights beyond standard KPIs [17], [32], [40], [110]. These metrics indicate efficiency and predictability dynamically, with hypothetical applications in fields like healthcare, enhancing resource distribution and workload balance [40]. Popovic's entropy categorization (thermal, residual, information) enriches BPM by capturing different types of process variability [70].

Interdisciplinary approaches from statistical mechanics and econophysics introduce models that optimize BPM for complex economic and social systems [20], [47], [49], [121]. This review suggests managerial infophysics as a framework using entropy to enhance resource allocation and performance, especially in dynamic fields like healthcare, where traditional metrics are insufficient [17], [32], [33], [40].

4.1.2. Evaluation of Working Hypothesis

Hypothesis

The working hypothesis suggests that integrating BPM with information entropy principles could create a cohesive managerial framework, termed managerial infophysics, aimed at enhancing process efficiency through physical principles. This research systematically reviewed literature using the PRISMA framework [51] to validate this integration, revealing a robust theoretical foundation and initial practical applications. Key findings, supported by empirical evidence and theoretical models, confirm the synergy between BPM and entropy, highlighting this framework's potential to optimize business processes, as previously detailed.

Validation and Falsification Criteria

Integrating information entropy into BPM provides a framework to address uncertainties in standardized processes [74], [107]. By quantifying variability, entropy reflects process unpredictability, impacting resource allocation and scheduling [17], [32], [110]. Lower entropy improves efficiency, as shown in BPM models across sectors like mobile performance and healthcare, illustrating entropy's role in real-time optimization [33], [48].

This review validates the hypothesis that BPM, combined with entropy, forms a cohesive framework for managing variability and uncertainty. Interdisciplinary insights from econophysics and statistical mechanics confirm entropy's broad applicability, supporting its theoretical and practical integration in BPM [20], [28], [126], [178]. These findings support managerial infophysics as a unifying framework for efficiency and adaptability across industries.

After establishing the evaluation criteria, a qualitative lemma can be proposed to encapsulate the findings of this systematic review and serve as key support for the hypothesis. The lemma is as follows:

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Lemma 1. *Literary evidence across BPM and information entropy shows a clear converging pattern. When analyzed using inductive reasoning, this pattern supports the unification of these fields under the conceptual metaparadigm of managerial infophysics.*

Lemma 1 synthesizes the inductive insights from the literature, demonstrating that the integration of BPM and information entropy is not only theoretically sound but also observable in practice across the reviewed studies. By defining managerial infophysics as a unified framework, which can be also characterized as a metaparadigm [214], the lemma provides a strong foundation for validating the hypothesis and illustrates how these two disciplines converge under a cohesive conceptual model.

Emergent Research Questions and Expected Outcomes

Automation in BPM could enhance resource allocation and reduce errors, creating a more adaptable system [15]. Integrating econophysics could refine economic theories, offering insights into financial systems and fostering collaboration [35], [47], [52], [118], [125], [215], [216]. In risk management, econophysical models may improve financial resilience, and new statistical methods could deepen understanding of social dynamics, aiding strategic decisions in entropy-based BPM frameworks [35], [36], [47], [125], [132], [144]. As such, the following research questions emerge with their corresponding emergent expected outcomes:

ERQ1: How can comprehensive BPM frameworks tailored to specific industry sectors improve process synchronization and reduce fragmentation within organizations?

EEO1: Enhanced BPM frameworks reduce fragmentation and promote synchronization across industries, boosting operational consistency and efficiency in sector-specific contexts.

ERQ2: In what ways can the integration of automation technologies into BPM reduce manual processes, optimize resource allocation, and enhance process accuracy?

EEO2: Reducing manual processes in BPM, optimizing resource use, and ensuring accurate implementations create a more adaptable, advanced BPM environment with actionable insights for businesses.

ERQ3: How can applying econophysical models in risk management enhance financial resilience and improve risk assessments, and what statistical methods could analyze intraday data effectively to provide insights into social systems and organizational behavior?

EEO3: Applying econophysical models in risk management fosters innovative methods that enhance financial resilience by merging economic and management insights for stronger risk assessments. Advanced statistical methods for intraday data analysis also provide nuanced insights into social systems, benefiting organizational and economic analysis.

4.2. Broader Context and Implications

4.2.1. Advancing BPM through Transdisciplinary Insights and Uncertainty Management

Using the PRISMA framework, this review identifies key BPM publications, outlining a standard BPM life cycle—(re)design, implementation, operation, and control—focused on fostering customer satisfaction and sustainability [3], [5]. Integrated processes are classified by classical pre-operational information and PAIS types: peer-to-peer, person-to-application, and application-to-application [6], [71].

Core BPM principles emphasize Value Creation, Process Optimization, Standardization, and Effective Management, with historical BPM advancements linked to quality control, epistemic management, and IT paradigms [2], [8], [74], [78], [79], [80]. Milestones include post-WWII models like TQM and Six Sigma, which introduced frameworks such as the CMM, while IT advancements through BPR and ERP systems have enhanced productivity [10], [11], [82], [83], [88], [89], [90], [91], [96], [97], [98].

BPM languages, notably BPMN, support decision-making in diverse cases [103], [106]. Probabilistic models employing historical data are able to predict process uncertainty, while complexity metrics and cognitive weights are needed to control structural complexity for emerging synergies like market efficiency and information loss [9], [32], [217], [218], [219].

Transdisciplinary trends merge fields, with entropy now applied to organizational analysis, examining resource and energy relationships [33], [220]. Entropy-based frameworks reveal universal law interconnectedness, with recent research advancing models for energy dissipation in process-oriented entities [215], [221], [222].

4.2.2. Integration Challenges, Limitations and Opportunities

Entropy-Based BPM

[223] highlights a lack of strategic frameworks in applying entropy to business management, despite its fundamental role in addressing organizational unpredictability. Many studies highlight practical obstacles in leveraging entropy, advocating for foundational concepts to assist its integration in organizational management. Creating process-oriented models or paradigms that incorporate physics-based ideas like entropy into operations requires further empirical confirmation.

Managerial infophysics seeks to boost resource flexibility across sectors, moving from theory to practical applications, such as managing entropy in processes. BPM's alignment with entropy principles, via energy exchanges and internal structures, makes it a tool to counter entropy-driven unpredictability impacting operations [33]. Structural entropy, as a topological organizational trait, can lead to inefficiencies, underscoring BPM's role in managing entropy.

Entropy-Driven Management

The connection between process model uncertainty and Shannon's entropy reveals disorder in business systems, where organizational entropy often leads to inefficiencies due to poor structure [33], [224], [225]. Closed systems, prone to inefficiency, contrast with resilient open systems that enhance adaptability through energy exchanges [226], [227], [228]. This entropy-driven, interdisciplinary approach, including econophysics, refines BPM strategies for more adaptive models [229].

Integrating entropy with BPM helps quantify process uncertainty, enabling organizations to better assess performance metrics and inefficiencies. However, challenges in managing diverse activities arise as BPM's component-focused tools can lead to fragmentation [17], [18], [32], [107]. Additionally, consistency and quality are complicated by constructs like the OR-join, which often cause ambiguity and hinder integration [9], [15], [74], [104].

Literature underscores BPM challenges due to outdated methodologies and inconsistent terminology, with terminology variations creating confusion and limiting the efficacy of BPM implementations [5], [6], [230]. Furthermore, insufficient consideration of human interactions within BPM contributes to inefficiencies, ultimately affecting project success [71], [72].

Innovation-Focused BPM

Recent research suggests BPM must become more innovation-driven, moving beyond its traditional focus on operational excellence [216]. BPM prioritizes operational stability, yet balancing standardization with exploration encourages innovation, allowing firms to adopt new technology and business models without sacrificing efficiency [216].

A key challenge is achieving seamless communication between production control systems and PAIS, especially within IIoT environments, where runtime data flow is limited [15]. BPM-IIoT systems currently face scalability and adaptability issues and lack standardized interfaces, highlighting the need for a unified architecture across the BPM lifecycle [15].

Sensor event integration with BPM may enhance control and performance indicators, yet maintaining modeling consistency as new data emerges is complex. Socio-technical barriers also limit data-driven insights, as shown by BPM's limitations during the COVID-19 pandemic [231]. While Digital Process Twins (DPTs) are promising for optimization, balancing predictive accuracy with computational efficiency remains a challenge [231].

Evolving Challenges and Adaptations in BPM

A core BPM challenge is the lack of standardized process descriptions, resulting in inconsistent terminology and detail, particularly in knowledge-intensive areas where granularity is difficult [231]. Additionally, digital transformation disrupts traditional frameworks, as rapid changes create gaps between modeled and actual processes, affecting technology integration [232].

Efficient information processing aligns with business goals by reducing redundancy and enhancing efficiency if structured processing with the right infrastructure improves capabilities through streamlined flow. Sustainable change implementation remains complex, requiring resource allocation to improve KPIs like time, cost, and quality [109].

Applying thermodynamics, particularly entropy, provides a framework to assess BPM system uncertainty, including elements like culture and engagement [9], [33]. However, new modeling languages often lack relevance, becoming outdated by emphasizing context over problem-solving [233]. Real-time data integration remains challenging, as current BPM tools simulate without actionable outcomes, creating inefficiencies [231], [234]. Efforts to measure uncertainty with entropy are complex, as efficiency initiatives can increase complexity and bottlenecks [32], [33], [235], [236].

Interest in expanding econophysics and sociophysics has grown, applying network science to market and social dynamics. Econophysics research covers wealth distribution, market behavior, and risks, while sociophysics improves understanding of hierarchical interactions and social systems through empirical models [47], [237], [238]. Applications to urban segregation and traffic dynamics, for example, indicate potential for predicting complex phenomena, though further refinement is needed for practical use [239], [240].

Empowering process owners is reshaping management, with managers handling resources while leaders advocate client needs to process owners. Unified operations often use shared services or third-party vendors. End-to-end process management enterprises have to involve varied agents to integrate service-oriented architecture with data management. However, structured guidelines are limited, making cross-boundary collaboration essential [232].

Methodological Divergence

As [49] explains, physics and finance economics treat data differently. Physics, with high signal-to-noise ratios and conserved quantities, often requires little statistical validation. In contrast, finance lacks conservation rules and relies on a micro-founded perspective that focuses on agent behavior [241]. Econophysicists, however, assume heterogeneous agent behaviors, where social interactions drive global phenomena. This phenomenological approach uses micro-indeterminism to establish macro-determinism, reducing heterogeneity to collective macro-scale activity [49].

In physical sciences, the coarse-graining technique is well-known and widely applicable [242]; however, it is less prevalent in social sciences, where agents are endowed with intentions. Based on these observations, it can be induced that similar insights can be pursued in related scientific fields, particularly in process management, owing to the apparent connections between intricate financial systems and complex social structures. Following the global financial crisis, research activities increased significantly as traditional economic frameworks were scrutinized for their failure to anticipate such events [243].

Econophysicists have since endeavored to develop innovative frameworks that capture the inherent complexity and nonlinearity of financial systems. Their contributions span diverse fields demonstrating efforts to promote that advancing isolated domains may face challenges without insights from multiple disciplines, highlighting the importance of a multidisciplinary approach [144].

Postulations for Novel BPM Development

Building on a systematic review of relevant literature using the PRISMA framework, this work constructs a robust BPM framework aimed at guiding professionals. This approach enhances innovation, promotes a shared understanding of BPM, and supports effective implementation beyond traditional practices [244]. Thus, a comprehensive framework should adhere to the following postulations for novel BPM methodologies:

1. Tailor to context-specific factors and maintain alignment with organizational culture to ensure continuity and relevance;
2. Identify key competencies and establish governance structures, metrics, and strategies that support effective and measurable outcomes;
3. Involve individuals actively in process design, promoting stakeholder understanding and cognitive clarity to foster adoption;
4. Ensure customization, simplicity, and cost-effective technological compatibility to meet goals and address potential implementation challenges;
5. Provide ongoing feedback on system evolution, driven by dynamic changes to support adaptability and complexity management.

These postulations align BPM with managerial infophysics by emphasizing adaptability, context-awareness, and stakeholder engagement, essential for merging traditional methodologies with complex systems analysis. Integrating information entropy and interdisciplinary insights from physics fosters a dynamic, holistic approach, expanding BPM to meet complex, evolving business needs.

4.3. Future Research Directions

4.3.1. Enhancing BPM Predictive Models Through Entropy and Interdisciplinary Methods

The intersection of BPM and information entropy reveals critical research gaps, especially in developing adaptive predictive models to assess organizational change impacts pre-implementation. These models, enhanced by interdisciplinary approaches such as data analytics, machine learning, and complexity theory, are essential for managing resource, energy, and information exchanges within organizations [245], [246].

Entropy-driven models, proven useful in evaluating organizational performance and growth, underscore the need for sophisticated, adaptable frameworks to handle decision-making uncertainties and support sustainable change [109], [227]. Future research should refine entropy-based models to quantify predictability, manage systemic risks, and enhance BPM's applicability across dynamic environments through advanced tools that promote efficiency and reduce complexity [33], [247], [248].

4.3.2. Evolving BPM for Adaptive Strategy and Innovation Integration

Advancements in BPM are crucial for organizations to navigate instability and adapt to change, with open communication and effective data management enhancing decision-making and adaptability [228]. The evolution of BPM, especially through scientific and technological integration, supports more adaptive strategies to counteract disorder in complex systems.

Explorative BPM introduces an outside-in focus, prioritizing environmental scanning and innovation over traditional internal optimization [216]. This shift encourages the development of frameworks for trend identification and evaluation within BPM practices, aligning with managerial infophysics. Research should further establish tools, evaluation criteria, and methodologies that enhance explorative BPM across different contexts, examining factors such as culture, governance, and leadership essential to support innovation [216].

Maintaining alignment between BPM strategies and changing business environments is a primary challenge, as misalignment can hinder performance. Future studies should investigate methods to keep BPM strategies aligned with evolving objectives and improve adaptability [81].

Additionally, advanced methodologies integrating real-time event data from IIoT with BPM could optimize real-time decision-making, especially through Complex Event Processing (CEP). Enhancing CEP with data analytics and machine learning could improve process execution, insights, and automation potential [15].

4.3.2. Explorative BPM: Innovation and Entropy Modeling

Research on explorative BPM is limited, highlighting the need for practical frameworks to enhance core capabilities and adapt metrics like time, cost, and quality, despite modeling limits [216], [249]. Improved simulation models capturing real-time dynamics and human variability are essential [32]. Organizational entropy, key for BPM efficiency, benefits from Semi-Markov models, while entropy integration supports sustainability, though empirical validation is needed [228], [250], [251], [252], [253]. Interdisciplinary insights, such as from econophysics, help address BPM issues like information loss using tools like Blockchain [254], [255].

Future research should focus on entropy metrics for performance and address BPM tool limitations, ensuring standardized frameworks that incorporate human-system interactions [230]. As literature indicates, innovation-driven BPM promotes adaptability, balancing exploration with efficiency [15], [216] and knowledge-augmented process mining further improves data reliability and reduces redundancy [231].

Digital transformation requires flexible BPM logics, adopting light-touch processes and adaptable infrastructures [232]. Empowering mindful actors boosts responsiveness, with methods like fractal geometry offering insights into complex social systems [256], [257]. Empirical testing is needed for concepts like managerial infophysics, aligning entropy data-driven methods with practice [258]. While entropy-based systems have a solid theoretical foundation, practical applications are limited. Standardized BPM frameworks can reduce fragmentation and improve coordination in smart factory tasks, but enhanced documentation and real-time tools are essential to bridge theory and implementation [84], [96], [231], [233], [259], [260], [261].

4.4. Limitations

4.4.1. Scope, Complexity, and Generalizability Challenges

The integration of entropy into BPM frameworks faces scalability and adaptability challenges due to its theoretical nature, which limits generalizability and necessitates further empirical validation across organizational settings [9], [262]. Existing BPM tools struggle to manage the complexities and unpredictability of modern processes, often constrained by limited handling of variability and real-world inconsistencies, especially in complex industries [17], [32], [33], [74], [107], [110].

Scholars highlight BPM's lack of attention to human elements and strategic alignment, with misalignment between BPM practices and organizational goals impacting effectiveness [71], [72], [81]. Furthermore, the traditional internal focus of BPM limits its adaptability for exploratory innovation, as the lack of structured methodologies restricts BPM's ability to respond to external opportunities and evolving organizational needs [216].

4.4.2. Rigidity, Scalability, and Industry-Specific Adaptations

The rise of PAIS and hyper-automation presents BPM scalability challenges, as manual, design-focused tasks place high cognitive demands [263]. Scaling BPM for both vertical and horizontal automation while preserving structural integrity is essential, yet current architectures often struggle with modern manufacturing complexities and cross-industry applications due to inconsistent terminology and rigid models [231], [259], [264].

Traditional BPM models, designed for stability, struggle to adapt to the real-time demands of digital transformation, limiting flexibility and scalability in rapidly changing environments [232]. While entropy offers valuable insights into process uncertainty, challenges in its integration within

 doi:10.20944/preprints202501.1628.v1

BPM arise from structural and measurement complexities, calling for further refinement to improve its scalability and applicability [33], [206], [265].

The emphasis on isolated components over holistic frameworks in traditional BPM limits its adaptability in managing interconnected, cross-organizational processes. Research should aim to develop more adaptable BPM frameworks that meet the needs of dynamic, evolving industrial contexts.

4.4.3. Data and Methodological Constraints

This study's findings are constrained by data and methodological limitations, particularly in detecting empirical research on quantifying entropy within organizations due to its abstract nature, impacting the robustness of entropy-based models [9]. Future research should focus on advanced modeling and data collection to validate these models. Traditional BPM frameworks often fall short, as static methods overlook the component of uncertainty, highlighting the need for adaptive economic, managerial, and technological integration [266], [267].

BPM also faces socio-technical challenges, particularly in cross-organizational data sharing, where inflexible tools restrict adaptive granularity [231]. Adapting BPM for digital transformation requires evolving infrastructures and real-time responsiveness [232]. Effective entropy integration needs standardized metrics and tools to enhance reliability [255].

Prototype obsolescence highlights the need for robust model guidelines, while hyper-automation introduces additional cognitive risk, suggesting that sustainable and scalable frameworks are essential for BPM's broad industry application [231], [266].

5. Conclusions

Originally, this review aimed to identify literary evidence for merging econophysics and managerial science. However, as the review progressed, it became clear that a more comprehensive framework was needed. The convergence of physics and managerial science, particularly regarding information entropy, also necessitates incorporating informatics—specifically, the intersection of physics and information science. Therefore, after presenting preliminary findings at the 33rd European Conference on Operational Research [268] for feedback, the study's title was revised to better reflect the broad, interdisciplinary scope of these findings in a precise and academically rigorous way.

The findings and trends in this systematic literature review are primarily guided by the PRISMA framework, with select out-of-scope works included for context and historical perspective. Analogous to physics, which often focuses on homogeneous systems in thermal equilibrium yet also values the study of heterogeneous systems near or out of equilibrium exhibiting stationary or quasi-stationary statistical regularities, BPM can similarly examine open, dynamic, and complex systems through the lens of information entropy.

In this review, analogical induction is used as a valid reasoning approach for proposing new interdisciplinary ideas. By identifying parallels between established applications of a concept in one field and suggesting its utility in another, this method supports interdisciplinary innovation, as many breakthroughs arise from transferring concepts across domains. Analogical induction enables reasoned hypothesis formation, allowing plausible suggestions based on success in a different context without claiming certainty. This method is historically grounded, with examples like thermodynamic principles applied to economics or biological models inspiring technology. Recognizing its limitations, this approach proposes ideas that, while plausible, still require empirical validation in the new field.

Analogical induction serves as a valid reasoning tool in this review to propose new interdisciplinary ideas by drawing parallels between concepts across fields [212], [269]. This approach supports interdisciplinary innovation, as transferring established concepts often drives breakthroughs [116], [118]. For instance, thermodynamic principles applied to economics or biological models inspiring technology exemplify how such transfer leads to new insights [125], [157].

Analogical induction enables the formation of reasoned hypotheses based on success in different contexts, suggesting potential applicability without asserting certainty [32], [135]. However, limitations are acknowledged: these interdisciplinary hypotheses still require empirical validation in when novel domains are concerned [226]. This methodological approach, therefore, allows the proposal of plausible connections while maintaining academic rigor and historical precedent.

Applying entropy-based metrics in BPM to measure execution uncertainty represents an innovative use of analogical induction. Entropy, commonly used in fields like thermodynamics, information theory, and economics to quantify uncertainty, could similarly assess variability and unpredictability in business processes [33]. This systematic literature review supports this approach by showing entropy's effectiveness in measuring uncertainty in comparable structured systems, while identifying gaps in BPM research, thus justifying entropy's novel application in this context [6], [9], [18], [20], [32], [33], [111], [176], [270]. Developing a tool for empirically measuring uncertainty with entropy-based metrics would not only test this metaparadigm but also provide a standardized, quantitative approach to enhancing process efficiency. This tool could reveal how execution uncertainty impacts process inefficiency, offering actionable insights for optimization, particularly in dynamic or frequently changing workflows. While analogical induction requires validation due to inherent differences between physical and business systems, this approach's feasibility is strengthened by the adaptable nature of entropy. Implementing and testing such a tool would provide the empirical foundation needed to validate its value and practical relevance in BPM.

Entropy is commonly utilized in several philosophical and scientific domains; however, it is not uncommon to come across misconceptions regarding its application in literature [26], [38], [41], [157], [163], [166], [167], [168], [177]. There are different forms of entropy, including thermodynamic entropy, residual entropy, and information entropy [70]. Information entropy relates to symbol arrangements and structures in communication theory; nonetheless, its overarching nature allows for the utmost diversification in theoretical and applicable frameworks [29], [31], [45], [68], [191], [195], [196], [197], [204], [261].

Entropy serves as a bridge between theoretical understanding and practical application, with potential applications in managerial science, where it supports risk management and informs strategic decisions by assessing resource allocation and variability in systems [9], [167], [169]. In BPM, entropy evaluates characteristics like density, cohesiveness, and complexity, helping identify process uncertainty. Although Shannon entropy and related measures can assess structural complexity via the flow of information, they also have limitations, necessitating ongoing research [29], [32], [204]. Reducing variability and enhancing predictability are essential in business processes, as uncertainty can lead to discrepancies in outcomes [18], [20]. Researchers are now developing models that incorporate cognitive weights and complexity measures, aiming to improve resource allocation and streamline internal processes [6], [270].

Econophysics—a blend of economics and physics—offers insights into financial systems but faces challenges in BPM applications, where practical implementation often lags [9], [125]. Entropy-based metrics, while illuminating uncertainty in business models, reveal areas in need of further exploration [33], [111]. Frameworks that boost process efficacy by optimizing resources and identifying disorder can significantly enhance business operations. Moreover, integrating ideas from econophysics and social sciences offers fresh perspectives for understanding complex social and financial systems [47], [110].

For BPM professionals, contextual frameworks that foster innovation, align with organizational needs, and provide feedback on complexity are essential. Simulation and process mining hold potential for overcoming tool limitations and training gaps, as they clarify relationships between models and event data [269]. Information entropy can thus provide a systematic approach to assessing organizational dynamics, underscoring the importance of transdisciplinary standardization [163].

Entropy is also vital in shaping organizational ethos, decision-making, and teamwork, helping businesses adapt to market demands through resource flexibility [38], [41]. Structured approaches to

 doi:10.20944/preprints202501.1628.v1

quantifying process entropy assist BPM, while Managerial Infophysics suggests a unified framework for measuring disorder and embedding it into business models [132]. To ensure these methods meet industry standards, they require validation against established benchmarks in actual business environments [226].

Managerial infophysics serves as a metaparadigm that views processes as interconnected activities whose outputs define their essential nature. This perspective offers an epistemological basis for BPM, asserting that processes are shaped not only by inherent characteristics but also by the dialectical elements within organizational settings. Managers play a key role in assessing limitations and identifying necessary adjustments. As a philosophical framework, managerial infophysics explores the role of induction in management, emphasizing the mathematical properties of formal and artificial languages, as well as universal qualities of reality, while aiming for formal validity in organizational structures. Its soundness depends on aligning cognitive logic with empirical data, though its speculative nature and lack of empirical study add complexity to its analysis.

Data Availability Statement: The data presented in this study are openly available at: https://www.dropbox.com/scl/fi/66entykq9s1oas6ypsbmb/Prisma-Query-Tables.xlsx?rlkey=3n8e2md3xzf1euf5i3t38esb0&st=d7jbzh1t&dl=0.

Appendix A

Table A1. Thematic Categorization of Identification Terms for PRISMA-Based Research.

Category	Terms
Business and Management Concepts	Business analytics, Actionable guidelines, Adoption of change, Agent-based models (ABM), Automated planning, Balanced Scorecard, BPM (Business Process Management), BPMN (Business Process Modeling Notation), Business excellence models, Business process modeling, Business process performance, Business process re-engineering, Capability maturity model integration, Change adoption, Change agents, Efficient business processes, Future business process management capabilities, Integrating process management, Process-aware information systems, Process models, Quality awards, Quality measurement, Quality requirements, Re-engineering, Reversibility, SIPOC, Systematic literature review, Unified BPM methodologies, Use cases, Value chain processes, Value network.
Corporate Excellence and Strategies	ASQ, Baldrige criteria, Corporate communication, Competitive advantage, Firm performance, Kaplan, Key performance indicators (KPIs), Management, Management theory, Market efficiency, Performance excellence, Porter models, Porter's value chain framework, Quality standards, Scientific management, TQM literature review.
Artificial Intelligence, Machine Learning, and Informatics	Artificial Intelligence (AI), Machine learning (ML), Deep learning, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), Neural networks, Simulation algorithms, Simulation-based estimations.
Informatics and Data	Bioinformatics, Medical informatics, Nursing informatics, Neuroinformatics, Urban informatics, Data analysis, Data science,

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	Data uncertainty, Information systems, Future ERP, Software engineering language selection, Industrial Internet of Things (IIoT).
Entropy, Thermodynamics, and Physics	Aleatoric, Barrow entropy, Basic concepts of classical thermodynamics, Bayesian inference, Boltzmann, Boltzmann entropy, Boltzmann equation, Carnot cycle, Clausius, Diffusion entropy, Disorder, Entanglement entropy, Entropic uncertainty relation, Entropy, Entropy economics, Entropy growth, Entropy maximization, Entropy measures, Entropy research, Equilibrium for a low-density gas, First law of thermodynamics, Finite-time thermodynamic process, Gibbs and Boltzmann entropy, Gibbs free energy, H-theorem, Irreversible entropy production, Landauer's principle, Maximum entropy, Modified cosmology, Renyi entropy, Residual entropy, Second law of thermodynamics, Shannon entropy, Statistical entropy, Statistical mechanics, Thermodynamic entropy, Third law of thermodynamics, Transfer entropy, Von Neumann entropy.
Classical and Modern Physics	A mathematical theory of communication, Alan Turing legacy, Brillouin, Classical mechanics, Claude Shannon, Coalescence processes, Confined quantum systems, Conservation of information, Contributions of Shewhart and Deming, Crystallization, Diffusion rate, Einstein, Heisenberg, Hilbert space, Irreversibility, Ising model, Jaynes, Josiah Willard, Joule, Mayer, Quantum cosmology, Quantum mechanics, Rudolf Clausius, Symmetry, Thomson.
Statistical and Mathematical Modeling	Abductive theory, Algorithmic complexity, Bayesian inference, Complex methods, Complex networks, Complex systems, Complexity economics, Comparative research, Comparative study, Continuous stochastic volatility models, Decision models, Determinism, Dynamic controllability, Dynamical stability, Fat-tailed distributions, Fractional cumulative residual entropy, Geometry, Geostatistical models, Granger causality, Macroscopic behavior, Mathematical modeling, Multivariate probability density, Network analysis, Network structure, Probabilities, Probability, Stochastic processes, Temporal process modeling.
Information Theory and Entropy	Information dynamics, Information entropy system model, Information gain, Information governance, Information theory, Entropy measures, Shannon entropy, Negentropy.
Econophysics and Financial Systems	Economic complexity, Econophysics, Financial economics, Financial inclusion, Financial networks, Financial system networks, Physics of financial networks, Risk, Portfolio allocation.
Decision-Making and Management	Decision models, Decision support systems, DebtRank, Delphi study, MCDM (Multi-Criteria Decision Making), TOPSIS, PDCA.
Technological Innovations	Industry 3.5, 4.0, 5.0, Industrial revolution, Lean Philosophy, Circular value chain, Renewable energy resources, Digital transformation.

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Process and System Improvements	BPMN (Business Process Modeling Notation), Event processing, Process-oriented systems, Re-engineering, iBPM (Intelligent BPM), Integration, Techniques.
Communication Models and Theories	A mathematical theory of communication, Communication, Interactive communication, Message transmission, Corporate communication.
Information and Knowledge	A priori knowledge, Application research, Application scenarios, Bibliometric analysis, Information theory, Information systems, Knowledge-based systems.
Philosophical and Ethical Concepts	Ethical challenges, Ethical concerns, Ethical interventions, Ethics in technology, Philosophical frameworks, Philosophy of economics, Philosophy of physics, Scientific pluralism, Scientific revolution, Scientific method, Scientific transformations.
Historical and Legacy Contributions	Alan Turing legacy, Contributions of Shewhart and Deming, Historical evolution, Historical interpretation, History of management, History of thermodynamics, Michael Porter, Robert Batterman, Rudolf Clausius, Eugene Stanley, Jaynes, Rosario Nunzio Mantegna, Taylorism.
Health Systems and Models	COVID-19 pandemic, Epidemiological models, Healthcare informatics, Biosystems, Biocomplexity.
Miscellaneous Concepts and Theories	Chapman–Jouguet condition, Constantino Tsallis, Field theories, Glasses, Historical overview, Micro-founded approach, Operating organized systems, Social influence dynamics, Sociophysics, Synchronization.

Table A2. Inclusion and Exclusion Criteria Details.

Criteria Details	Auxiliary Information
Missing Keywords	H-Theorem, ASQ, Alan Turing, BPM life cycle, Baldrige, Bibliometric analysis, Biocomplexity, Boltzmann entropy, Coalescence processes, Continuum informatics, DMAIC, Deming, Deming cycle, Deming prize, EFQM, Eco-informatics, Embedding, Empirical study, Enterprise applications, Financial, Financial networks, Granger, Group transfer entropy, Guidelines, ISO, Industrial revolutions, Informatics, Information dynamics, Japan, Juran, M. Porter, Nursing informatics, Ohno, PDCA, Philosophical, Process, Review, Shannon, Shingo, Survey, Systematic literature review, Ten principles of good BPM, Understandable BPMN, Use cases, Automated planning, Business analytics, Dynamic controllability, Modeling.
Appropriate Publication Type	Articles, Articles Compiled into Handbooks or Book Chapters, Entry, Journal Articles, Journals, Research Articles, Review Articles.
Relevant Scope	Applied Software Computing, Artificial Intelligence, Author: Schinckus, Big Data, Business, Chemistry and Earth Sciences, Computer Science, Cosmology, Decision Sciences, Earth Sciences, Econometrics and Finance, Economics, Engineering, History and Philosophical

	Foundations of Physics, Information Technology, Management, Managerial Accounting, Mathematics, Networks, Philosophy, Philosophy of Science, Physics, Physics and Astronomy, Quantitative Finance, Research and Analysis Methods, Software Engineering, Statistical physics and dynamical systems, Statistics, Statistics for Engineering, Thermodynamics

Table A3. Data Extraction and Synthesis Process.

DB	Query No.	ID Terms	Records	Records Removed (Pre-Screening)	Exclusion Criteria (AND)	Inclusion Criteria (AND)	Records Found	Chosen for Screening
Science Direct	1	business analytics, business process performance bper, resource-based view, firm performance	3	2	Record did not include the keywords: business analytics		1	1
Science Direct	2a	industrial internet of things, IoT, integrating process management, system, architecture, event processing, use cases, integration, application scenarios, BPM	20	4		Research Articles	16	1
	2b			15	Record did not include the keywords: use cases		1	
Science Direct	3a	process models, efficient business processes, synchronizations, automated planning, control flow patterns	1.465	935		Computer Science	530	1
	3b			242		Research Articles	288	
	3c			287	Record did not include the keywords: automated planning		1	
Science Direct	4	time aware BPMN, temporal verification, BPMN processes, dynamic controllability, temporal process	70	69		Software Publication	1	1

		modelling, temporal constraints						
Science Direct	5	Porter, circular value chain, value chain processes, Porter's value chain framework, competitive advantage	553	491		Review Articles	62	62
Science Direct	6	project management, enterprise applications	17	8	Record did not include the keywords: enterprise applications		9	9
Science Direct	7	Juran, ASQ	22	20		Review Articles	2	2
Science Direct	8a	bpm definition	5.911	1.658		Research Articles	4.253	168
	8b			3.644		Review Articles	609	
	8c			441		Business, Management and Accounting	168	
Science Direct	9a	PDCA, Deming cycle	192	66	Non-English		126	4
	9b			18		Research Articles	108	
	9c			85		Review Articles	23	
	9d			19	Record did not include the keywords: PDCA, Deming cycle		4	

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Science Direct	10a	SIPOC, DMAIC Methodology	69	8	Non-English		52	3
	10b			4		Research Articles	47	
	10c			0		Review Articles	5	
	10d			54	Record did not include the keywords: DMAIC		3	
Science Direct	11a	quality standards, EFQM, ISO	99	46		Research Articles	53	1
	11b			35		Review Articles	11	
	11c			17	Record did not include the keywords: EFQM, ISO		1	
Science Direct	12a	bpm life cycle approach, process life cycle, design, implementation, integration	719	337		Research Articles	382	2
	12b			246		Review Articles	136	
	12c			134	Record did not include the keywords: bpm life cycle		2	
IEEE Xplore	13a	processing real-time big data stream ,review	963	776		Journals	187	1
	13b			94		Big Data	93	
	13c			92	Record did not include the keywords: review		1	
IEEE Xplore	14	PDCA, Deming cycle	11	9		Journals	2	2
IEEE Xplore	15	peer to peer, person to application, and application to application, process	137	118		Journals	19	19

		aware information systems						
IEEE Xplore	16	capability maturity model integration, systematic literature review	7	6	Record did not include the keywords: systematic literature review		1	1
IEEE Xplore	17	Event-Driven Process Chain, systematic literature review	1	0			1	1
Springer	18	future business process management capabilities, BPM frameworks, traditional information systems, Delphi study	41	31		Research Articles Book Chapters	6 4	10
Springer	19	systematic review, unified, bpm methodologies	17	15		Engineering	2	2
Springer	20a	history of ASQ	528	4	Non-English		524	2
	20b			479		Business, Management	45	
	20c			43	Record did not include the keywords: Juran, ASQ, Deming		2	
Springer	21	Lean Philosophy, Japan, Deming, Shingo, Ohno	18	17	Record did not include the keywords: Japan, Deming, Shingo, Ohno		1	1

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Springer	22	Michael Porter, management theory, porter models, value chain, Japanese	170	167		Review Articles	3	3
Springer	23a 23b 23c	value chain, value network, Systematic literature review, Porter, evolution, intangible assets	80	57 10 12	Record did not cite: M. Porter	Articles Business, Management	23 13 1	1
Springer	24	future ERP, big data, iBPM, process oriented	3	2		Articles	1	1
Springer	25	impact of Alan Turing, formal methods, Andrew Hodges, Alan Turing legacy	3	2	Record did not include the keywords: Alan Turing		1	1
Springer	26a 26b	business process modeling, BPM and software engineering language selection, decision models, decision making, decision support systems, case study research, language selection problem, BPMN, EPC	12	3 4		Articles Computer Science	9 5	5
Cambridge Core	27a 27b	Lean Philosophy, Japan, Deming, Shingo, Ohno	837	744 62		Book Chapters Management	93 31	31
NIH	28	comprehensive, Balanced Scorecard, Kaplan	2	0			2	2
NIH	29	re-engineering, Hammer, Champy, IT	5	3	Medical		2	2
NIH	30	business information-entropy correlation	9	0			9	9
NIH	31	contributions of Shewhart and Deming, TQM literature review	2	0			2	2

NIH	32	Taylor contributions, Taylorism, scientific management, efficiency, history of management	10	0			10	10
MDPI	33a 33b	process scheduling, dynamic controllability	100	4 95	Record did not include the keywords: dynamic cotrollability	Articles	96 1	1
MDPI	34a 34b	business process re-engineering, literature review	4	2 1		Articles IT	2 1	1
Emerald	35a 35b	ten principles of good BPM, vom Brocke	59	1 57	Record did not include the keywords: ten principles of good BPM	Articles	58 1	1
Emerald	36	business excellence models, Baldrige criteria, performance excellence, EFQM, Deming prize, quality awards, comparative study, Europe, Japan, compare, Crosby	3	2	Record did not include the keywords: Baldrige, EFQM, Deming prize, Japan		1	1
Emerald	37	BPMN, communication, cognitive, process modeling, corporate communication, visualization	10	7	Record did not include the keywords: process, modeling		3	3
Science Direct	38a 38b	understandable BPMN, guidelines, Business Process	63	14 40		Research Articles Engineering	49 9	1

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	38c	Modelling Notation 2.0, object management group, BPMN models		8	Record did not include the keywords: understand able BPMN, guidelines		1	
Springer	39a	business process modeling language selection, BPM languages, decision models and multi-criteria decision-making, decision support systems, Software Engineering, BPMN	26	12		Articles	14	5
	39b			6		Computer Science	8	
	39c			3		Software Engineering	5	
Emerald	40	BPM success factors, BPM pitfalls, integrated frameworks, actionable guidelines	4	0				4
Science Direct	41a	KPIs management, KPI taxonomy, key performance indicators management, taxonomy development, qualitative attributes	147	126		Review Articles	21	6
	41b			15		Decision Sciences	6	
MDPI	42	Time-Driven Activity-Based Costing, business process management	2	0				2
Science Direct	43	quality measurement, quality requirements, quality requirements management, quality-related indicators, non-functional requirements, quality indicators metrics, systematic mapping, ARSD	2	1		Research Articles	1	1

MDPI	44	organizational changes, key performance indicators, measures, methods, and techniques	1	0			1
Science Direct	45a 45b	uncertainty quantification, review, ensembles, evidence lower bound, aleatoric, data uncertainty, deep learning, artificial intelligence, applications, Bayesian, research gaps, machine learning	21	15 2	Review Articles Computer Science	6 4	4
MDPI	46	algorithmic complexity, Shannon entropy, decomposition	4	3	Review Articles	1	1
Science Direct	47	Shannon entropy, dynamical stability, diffusion rate, physical instabilities, dynamical indicator, chaos indicators	15	10	Research Articles	5	5
Science Direct	48	econophysics, ising model	1	0	Author: Schinckus	1	1
Springer	49	econophysics, bibliometric analysis, bibliometrics	4	2	Articles	2	2
Science Direct	50a 50b	financial economics, role of econophysics	4	0 1	Author: Schinckus Research Articles	4 3	3
Science Direct	51	stock markets, micro-founded approach, simulation-based estimations, herding behavior, spurious herding, agents-based models	5	2	Research Articles	3	3

Science Direct	52	numerical simulations, coarse-grained bonded particle model, CG-BPM	2	0			2	2
Science Direct	53	macro-theories, micro-theories, macro-level phenomena, Robert Batterman, philosophy of physics for economics	2	1		Research Articles	1	1
arXiv	54	philosophy of physics, indeterminism, determinism, classical physics	7	0			7	7
Emerald	55	ABM, economic complexity, econophysics, perfectly rational ABM	1	0			1	1
JSTOR	56a 56b	interdisciplinary synergies, comparative research, interdisciplinary research	313	131 2	Non-English	Journal Articles	182 180	180
Science Direct	57a 57b	the role of econophysics, financial economics, physics, mutual influence,	23	6 5		Research Articles Economics, Econometrics and Finance	17 12	12
Springer	58	Benoit Mandelbrot, fractal geometry, nature, Physics Wolf Prize, general topology	9	8		Articles	1	1
PLOS ONE	59	interdisciplinarity in physics, PACS	30	15		Research and Analysis Methods	15	15
MDPI	60	comprehensive survey, continuous stochastic volatility models	1	0			1	1

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Science Direct	61	big data, finance, evidence challenges, machine learning, neural network, big data-based evidence, literature review, vector autoregression framework	52	44	Review Articles	8	8
Science Direct	62	Lomax model, Pareto Type-II, arc-sine exponentiation Lomax model	1	0		1	1
MDPI	63	big data, complex phenomena, networks, econophysics	1	0		1	1
Springer	64a 64b	institutionalization, interdisciplinarity, research studies	294	273 11	Philosophy Philosophy of Science	21 10	10
Springer	65	econophysics dynamics, bibliometric analysis, network analysis	10	4	Articles	6	6
arXiv	66	physics of financial networks, complex networks, statistical physics, DebtRank	2	0		2	2
MDPI	67	exponentially decaying coefficients, multivariate HAR model in stock markets	1	0		1	1
Science Direct	68	heterogeneous agent-based two-state sociophysics model, financial markets simulation	8	3	Research Articles	5	5
MDPI	69	systematic review, socio-economic development, financial inclusion,	2	0		2	2

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Science Direct	70	change adoption, change agents, organizational networks, adoption of change, change management scenaria	2	0			2	2
Science Direct	71	econophysics and sociophysics, review, Eugene Stanley, Rosario Nunzio Mantegna	1	0			1	1
MDPI	72	Tsallis entropy, Landau–Ginzburg equation, complex systems	1	0			1	1
MDPI	73	sociophysics, complex networks	3	0			3	3
MDPI	74	entropy economics, econophysics, complexity economics	3	0			3	3
MDPI	75	big data, ethical concerns, social sciences	3	0			3	3
Science Direct	76a	non-Gaussian distributions, financial returns, simulation, fat-tailed distributions, leptokurtic distribution	88	5	Record did not include the keywords: financial	Research Articles	83	8
	76b			54		Mathematics	29	
	76c			21			8	
MDPI	77	depolarization, sociophysics	1	0			1	1
Science Direct	78a	biocomplexity, complexity, complex systems, complexity paradigm, philosophy	7	4		Review Articles	3	1
	78b			2	Record did not include the keywords: biocomplexity		1	
	79a		9	5		Articles	4	1

IOPscience	79b	network entropy, statistical physics, heterogeneity, modularity, network structure, information theory, information dynamics, complexity, quantum networks, machine learning		3	Record did not include the keywords: information dynamics		1	
Nature	80a	physics of financial networks, financial system networks, time-dependent, maximum entropy, statistical mechanics	7	4	Record did not include the keywords: financial networks	Review Articles	3	1
	80b			2			1	
Science Direct	81a	network science, taxonomies, applications, complex systems, network embedding techniques, network evolvement, granularity, heterogeneity, static, dynamic	146	96	Record did not include the keywords: embedding	Review Articles	50	1
	81b			49			1	
Springer	82a	big data, data science, statistics, time series, multivariate data, machine learning, sparse model selection	559	131		Articles	428	4
	82b			424		Artificial Intelligence, Statistics	4	
APS	83a	statistical physics, complex information dynamics, emergent phenomena, information dynamics, von Neumann entropy	136	21		Articles	115	8
	83b			107		Networks	8	
Science Direct	84a	maximum entropy networks, coalescence	22	18		Research Articles	4	1

	84b	processes, complex networks, von Neumann entropy, entropy of network states		3	Record did not include the keywords: coalescence processes		1	
Royal Society Publishing	85	cointegration modelling, Granger causality network modelling, financial equilibrium, financial diffusion paths	1	0			1	1
Science Direct	86a	computational intelligence, time-series studies, financial time series forecasting, RNN based DL models, CNN, LSTM, RNN, deep learning, systematic literature review	159	104		Research Articles	55	3
	86b			34		Computer Science	21	
	86c			18		Applied Software Computing	3	
MDPI	87	multimodal approach, economic growth, multiplex network analysis	1	0			1	1
MDPI	88	macroscopic complexity, microscopic modelling, econophysics	1	0			1	1
arXiv	89a	financial networks, systemic risk, systematic risk, taxonomy, portfolios, correlated portfolios, review, survey	12	0		Quantitative Finance	12	1
	89b			11	Record did not include the keywords: survey		1	
NIH	90	nursing informatics, survey, education, open-ended questionnaires	17	14	Record did not include the keywords: nursing informatics		3	3

IEEE Xplore	91	AI, medical informatics, current challenges, integrative analytics	1	0			1	1
Science Direct	92	informatics literature, MPV studies, medical informatics, review, medical practice variation	20	19		Review Articles	1	1
ACS Publications	93	informatics, chemistry, biology, biomedical sciences, bioinformatics discipline, pharmacoinformatics, neuroinformatics	1	0			1	1
MDPI	94	mathematical modeling, bioinformatics, symmetric distance matrix	1	0			1	1
Emerald	95	urban informatics, citizen-ability	8	6	Record did not include the keywords: informatics		2	2
Science Direct	96a 96b	informatics, ethics, artificial intelligence, super intelligence, ethical challenges, ethical interventions, ethics in technology,	66	55 6		Review Articles Computer Science	11 5	5
Emerald	97	monistic diversity, continuum informatics, informatics, ethics, information governanc	2	1	Record did not include the keywords: continuum informatics		1	1
Emerald	98	eco-informatics, ecological data management	2	1	Record did not include the keywords: eco-informatics		1	1

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MDPI	99	social infuence dynamics, sociophysics models	14	13		Review Articles	1	1
MDPI	100	bibliometric analysis, Granger causality studies	3	2	Record did not include the keywords: bibliometric analysis		1	1
Science Direct	101	P2P lending, profile modelling methods, random walk, financing platforms	7	1		Research Articles	6	6
Science Direct	102	Granger Geweke causality, interpersonal physical interactions, information, information exchange, information flow	1	0			1	1
Annual Reviews	103a	Granger causality, review, mixed-frequency time series, multivariate time series	14	4		Articles	10	1
	103b			9	Record did not include the keywords: Granger		1	
MDPI	104	Reissner–Nordström, entropy, black hole, Roegenian economics	2	0			2	2
Science Direct	105a	Granger-causality tests, group transfer entropy, cryptocurrencies, nonlinear, vector autoregressions	6	1		Research Articles	5	1
	105b			4	Record did not include the keywords: group transfer entropy		1	
Springer	106	financial time series forecasting, Boltzmann entropy, neural networks,	3	2	Record did not include the keywords:		1	1

		regressive models, agent-based model			Boltzmann entropy			
IEEE Xplore	107	effective transfer entropy, machine learning techniques, stock markets	1	0			1	1
Science Direct	108	transfer entropy, option implied volatility, multi variate GARCH forecast, financial assets, portfolio allocation, implied volatility, realized variance,	6	4		Research Articles	2	2
Science Direct	109	transfer entropy, diffusion entropy, normal transfer entropy, nonlinear correlations, short time sequences, stock markets, minimum spanning tree, complex networks	39	36		Research Articles	3	3
IEEE Xplore	110	stock market forecasting, deep learning, systematic review, complex time series	1	0			1	1
MDPI	111	history of thermodynamics, Carnot, Clapeyron, Thomson	1	0			1	1
MDPI	112	Clausius, Second Law of Thermodynamics, equivalence of the transformation of heat to work	1	0			1	1
Science Direct	113a	overview of all industrial revolutions,	50	39		Research Articles	11	1

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	113b	social impacts, historical overview, industry 3.5, 4.0, 5.0, scientific transformations, automation theories		10	Record did not include the keywords: industrial revolutions		1	
IDEAS	114	scientific revolution, industrial revolution, Habbakuk thesis	3	3				3
Springer	115	energy concept, Mayer, Joule, conservation principle, Thomson, Young, Davy	13	10		Articles	3	3
ICI	116	Interdisciplinary ApproachesHistorical InterpretationPhilosophical Frameworks	33	31	Record did not include the keywords: philosophical		2	2
MDPI	117	thermodynamics, information, entropy, Industrial Revolution	2	0			2	2
Springer	118a	first law of thermodynamics, basic concepts of classical thermodynamics, energy transfer quantities, reversibility and irreversibility	45	14		Chapters	31	4
	118b			27		Thermodynamics, Physics, Statistical physics and dynamical systems	4	
MDPI	119	nonequilibrium temperature, irreversibility, Gouy–Stodola theorem	1	0			1	1
SAGE	120	entropy measures, , uncertainty quantification, stochastic processes, review, probabilistic nature, disorder, process, Shannon entropy, Renyi	2	0			2	2

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		entropy, Tsallis entropy,					
Springer	121a	entropy maximization,	21	2	Articles	19	1
	121b	entropy, self-assembly, colloidal systems, colloidal particles, crystals		18	Physics	1	
MDPI	122	entropy universe, information theory	1	0		1	1
MDPI	123	crystallization, entropy, Kauzmann paradox	3	0		3	3
MDPI	124	entropy research, bibliometric	1	0		1	1
MDPI	125	Carnot cycle, reversibility, entropy	1	0		1	1
arXiv	126	Eisenhart lift, field theories	2	0		2	2
arXiv	127	irreversible entropy production, finite-time thermodynamic process	1	0		1	1
MDPI	128	black hole entropy, complex systems	3	0		3	3
MDPI	129	entropy, Constantino Tsallis	17	16	Entry	1	1
arXiv	130	Barrow entropy, modified cosmology	3	0		3	3
MDPI	131	statistical entropy, biosystems, Schrödinger, negentropy	1	0		1	1
MDPI	132	maximum entropy model, geoscience data, information systems	1	0		1	1

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MDPI	133	social entropy, normative networks	1	0		1	1
MDPI	134	partitioning entropy, chemical potentials	1	0		1	1
MDPI	135	information entropy in chemistry	8	7	Review Articles	1	1
Springer	136a	entropy, information, geostatistical models, multivariate probability density, simulation algorithms	53	38	Earth Sciences, Statistics for engineering, physics, computer science, chemistry and earth sciences	15	13
	136b			2	Articles	13	
MDPI	137	forecasting, entropy, machine-learning	2	0		2	2
IEEE Xplore	138	information-based society, information society, sustainable business development	1	0		1	1
IEEE Xplore	139	evaluation method, cost-effectiveness, data, cost management, Entropy Weight Method	1	0		1	1
MDPI	140	hierarchical information entropy, information entropy system model	1	0		1	1
ACS Publications	141	history of thermodynamics, Rudolf Clausius, Josiah Willard	1	0		1	1
Springer	142a	Boltzmann equation, H-Theorem, equilibrium for a low-density gas, entropy	719	306	Chapters	413	1
	142b			185	Physics	228	
	142c			206	History and philosophical foundations of physics	22	

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	142d			21	Record did not include the keywords: H-Theorem		1	
Springer	143a 143b	COVID-19 pandemic, scientific pluralism, epidemiological models	52	43 2		Philosophy of Science Articles	9 7	7
PhilPapers	144	exploratory models, exploratory modeling, science	15	0			15	15
arXiv	145	Gibbs and Boltzmann entropy, classical mechanics, quantum mechanics	1	0			1	1
IOPscience	146	entropy in classical physics, entropy in quantum physics, mathematical definition, historical evolution, Neumann, entanglement entropy, Hilbert space, complexity, Heisenberg, chaotic systems	7	5		Articles	2	2
MDPI	147	statistical mechanics, discrete multicomponent fragmentation	1	0			1	1
IDEAS	148	entropy, generalized maximum entropy	6	0			6	6
MDPI	149	entropy, information, probabilities, Bayesian inference	1	0			1	1
arXiv	150	Bayesian interpretations, quantum mechanics theory	1	0			1	1
arXiv	151	macroscopic behavior, microscopic behavior	2	0			2	2

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Science Direct	152a	Shannon entropy, entropic uncertainty relation, confined systems, information theory, confined quantum systems	70	48		Research Articles	22	19
	152b			3		Physics and Astronomy	19	
Science Direct	153	renewable energy resources, RES, Shannon entropy, MCDM, EDAS	17	16	Record did not include the keywords: Shannon		1	1
NIH	154	Shannon entropy, quantifying uncertainty, quantifying risk	1	0			1	1
Springer	155	IT, Shannon's entropy and information, Claude Shannon, entropy power inequality	28	21		Physics	7	7
Science Direct	156	interactive communication, unknown noise rate, prior knowledge, a priori knowledge, Haeupler	1	0			1	1
MDPI	157	mechanical Maxwell's Demon	2	0			2	2
MDPI	158	Boltzmann, Zipf, Shannon, Jaynes	1	0			1	1
MDPI	159	entropy, Carnot cycle, information theory	1	0			1	1
MDPI	160	Maxwell's demon, information theory, market efficiency, Brillouin	1	0			1	1
MDPI	161	entropy, information, symmetry, Landauer principle	1	0			1	1

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Springer	162	physical foundations, Landauer's principle, loss of information, thermodynamic entropy, transfer of entropy, correlated information	4	0		4	4
Springer	163	entropy, information, probability, statistical mechanics, Landauer-Bennett, Maxwell's demon	25	18	Philosophy	7	7
MDPI	164	conservation of information, entropy, misunderstandings	1	0		1	1
AIP	165	entropy growth, information gain, operating organized systems, negentropy, Boltzmann	1	0		1	1
NIH	166	evolution of biomolecular communication, message transmission, bioinformatic	1	0		1	1
APS	167	boundary conditions, closed cosmologies, Gibbons-Hawking-York, geometry, covariant boundary action, quantum cosmology, information	31	23	Cosmology	8	8
arXiv	168	bouncing cosmology, inhomogeneity problems	1	0		1	1
arXiv	169	similarity theory, Shannon entropy, big data	1	0		1	1
MDPI	170	Boltzmann, Gibbs, Shannon, nonadditive entropies	1	0		1	1

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Science Direct	171	fractional cumulative residual entropy, CRE	21	14		Research Articles	7	7
arXiv	172	residual entropy, glasses, third law	1	0			1	1
Science Direct	173	entropy, perfect crystals, imperfect crystals, enthalpy, third law, Gibbs free energy, Boltzmann equation, thermodynamic, Boltzmann equation, isothermal	29	26		Research Articles	3	3
arXiv	174	thermodynamic criterions, self-assembly processes	1	0			1	1
MDPI	175	information theory, applications, A Mathematical Theory of Communication	3	0			3	3
arXiv	176	application research, TOPSIS, entropy weighting method	1	0			1	1
Science Direct	177a	COVID-19 pandemic, information entropy, Shannon, empirical study, management	161	31		Research Articles	130	2
	177b			128	Record did not include the keywords: empirical study		2	
NIH	178	existing knowledge, inductive reasoning	2	0			2	2
Springer	179	scientific method, abductive theory, complex methods, empirical phenomena, explanatory theories, data analysis, analogical modelling, competing explanations	6	2		Philosophy	4	4

Table A4. Data Extraction and Synthesis Process.

Details	***Auxiliary Information***
Databases and Searches per Database	ACS Publications: 2 times, AIP: 1 time, APS: 2 times, Annual Reviews: 1 time, Cambridge Core: 1 time, Emerald: 8 times, ICI: 1 time, IDEAS: 2 times, IEEE Xplore: 10 times, IOPscience: 2 times, JSTOR: 1 time, MDPI: 47 times, NIH: 9 times, Nature: 1 time, PLOS ONE: 1 time, PhilPapers: 1 time, Royal Society Publishing: 1 time, SAGE: 1 time, Science Direct: 47 times, Springer: 26 times, arXiv: 14 times.
Databases and Records per Database	ACS Publications: 2 records, AIP: 1 record, APS: 167 records, Annual Reviews: 14 records, Cambridge Core: 837 records, Emerald: 89 records, ICI: 33 records, IDEAS: 9 records, IEEE Xplore: 1124 records, IOPscience: 16 records, JSTOR: 313 records, MDPI: 208 records, NIH: 49 records, Nature: 7 records, PLOS ONE: 30 records, PhilPapers: 15 records, Royal Society Publishing: 1 record, SAGE: 2 records, Science Direct: 10405 records, Springer: 2743 records, arXiv: 36 records

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