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Entropy-driven variability as a catalyst of scientific and technological evolution: Evidence from quantum research fields

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Abstract. This study develops a framework to analyze variability in scientific and technological domains, focusing on how topic-level dispersion shapes evolutionary trajectories. Quantum science and technology serve as the case study. An entropy-based approach is combined with statistical techniques, including entropy coefficients, variance decomposition, and ANOVA. A dataset of 160 high-frequency research topics across four quantum subfields—optics, metrology, sensing, and imaging—was analyzed. Integrating Generalized Darwinism and the science of science, this study provides a novel empirical framework linking variability to evolutionary dynamics. It quantifies intra- and inter-field variability and situates patterns within an evolutionary perspective. Findings show a strong inverse correlation between scientific age and entropy: younger fields exhibit higher thematic diversity, while mature domains have concentrated, stable distributions. Variance decomposition indicates over 90% of variability occurs within fields, yet between-field differences remain significant. Four theoretical properties are proposed connecting variability to scientific maturity, ecosystem complexity, and knowledge accumulation. Practically, results inform R&D managers and policymakers on ambidextrous innovation strategies and entropy-informed investments. The study is limited to bibliometric data, excluding selection and adaptation mechanisms. Future research could extend the framework to other scientific domains.
Keywords: Scientific variability; Entropy coefficient; Technological evolution; Quantum research fields; Innovation strategy.
JEL: Q29; C63; O13.

1. Introduction

Understanding the variability of scientific and technological topics across research domains is essential for explaining the mechanisms that drive the evolution of knowledge systems. This study is situated within the interdisciplinary field of the science of science, which investigates the structure, dynamics, and outcomes of scientific activity to inform better decision-making in research policy and innovation strategy. The central aim is to examine how topic-level variability influences the

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evolutionary trajectories of science and technology, with implications for national competitiveness and societal advancement (Coccia, 2024, 2024a–c).

Recent advances in this field have emphasized the importance of mapping scientific change through bibliometric, network-based, and entropy-driven approaches (Zeng et al., 2017). These methods enable the identification of emerging research fronts, the diffusion of innovations, and the structural transformation of knowledge domains (Klavans & Boyack, 2017; Youn et al., 2015). Theoretical and empirical studies have shown that scientific variability—defined as the dispersion of research topics—can signal the early stages of paradigm shifts or technological breakthroughs (Kuhn, 1996; Uzzi et al., 2013).

This study contributes to the literature by proposing a theory of scientific variability, which posits that higher entropy in topic distributions correlates with greater evolutionary potential. This hypothesis is tested using data from quantum science and technology, a domain characterized by rapid growth, interdisciplinary convergence, and high innovation potential (Acín et al., 2018; Dowling & Milburn, 2003; Scheidsteger et al., 2021). Quantum science offers a fertile empirical ground due to its rich publication output, diverse subfields, and strategic relevance for future technologies (Arute et al., 2019; Preskill, 2018).

The methodological framework integrates entropy coefficients and variance decomposition to quantify variability across four quantum subfields: quantum optics, metrology, imaging, and sensing. These tools have been widely adopted in high-impact studies to assess diversity, uncertainty, and complexity in scientific systems (Shannon, 1948; Jost, 2006; Zidek & van Eeden, 2003). The analysis reveals how variability is shaped by factors such as scientific age, thematic maturity, and systemic interdependencies (Börner et al., 2010; Scharnhorst et al., 2012).

Moreover, the study aligns with recent findings that emphasize the role of topic diversity in fostering disruptive innovation and long-term impact (Wang et al., 2017). By linking variability to evolutionary dynamics, the research offers a novel lens for understanding how scientific fields emerge, stabilize, and transform over time (Foster et al., 2015; Evans & Foster, 2011).

In sum, this investigation provides a robust theoretical and empirical foundation for analyzing variability as a key driver of scientific and technological evolution. It contributes to both the science of science and innovation management by offering actionable insights for strategic investment, policy design, and the governance of emerging technologies.

2. Literature review

Science and technology are foundational to addressing societal challenges, achieving strategic objectives, and catalyzing industrial, economic, and social transformation. These domains underpin national competitiveness and human development by enabling innovation, productivity, and resilience (Arthur, 2009; Basalla, 1988; Coccia, 2019, 2019a, 2021; Mazzucato, 2018; Nelson & Winter, 1982). However, the emergence of scientific breakthroughs and technological innovations is inherently heterogeneous—some innovations disrupt existing paradigms, while others reinforce or marginalize established competencies (Coccia, 2020a, 2021; Christensen, 1997; Tushman & Anderson, 1986).

In the technological domain, Sahal (1981) conceptualized innovation as a process governed by internal system dynamics, emphasizing "learning by doing" and "specialization via scale." This view aligns with evolutionary models that treat technological change as a search across rugged fitness landscapes (Kauffman & Macready, 1995; Fleming & Sorenson, 2001). Basalla (1988) further analogized technological evolution to biological evolution, a perspective echoed in recent models that describe innovation as a process of variation, selection, and retention (Nelson, 2006; Arthur, 2009; Schubert, 2014; Uçkaç et al., 2023). Utterback et al. (2019) proposed a dynamic model in which technologies co-evolve through symbiotic and competitive interactions, transitioning from mutual reinforcement to predator-prey dynamics.

The analogy between biological and technological evolution has gained traction in high-impact studies that explore innovation as a complex adaptive system (Lane, Pumain, van der Leeuw, & West, 2009; Hidalgo et al., 2007). These models emphasize the role of interdependencies, feedback loops, and emergent properties in shaping innovation trajectories. In particular, the concept of technological complexity has been linked to the diversity and unpredictability of innovation outcomes (Balland et al., 2022).

In the sociology of science, Kuhn's (1996) theory of paradigm shifts remains foundational, positing that scientific development proceeds through periods of normal science punctuated by revolutionary change. Subsequent models have elaborated on this by emphasizing branching (Price, 1986; Mulkay, 1975), specialization (Dogan & Pahre, 1990), and convergence (Coccia, 2024c; Coccia et al., 2024). Interdisciplinary synthesis, as seen in quantum computing and synthetic biology, reflects the recombination of knowledge from disparate fields (Rafols et al., 2010; Wagner et al., 2011; Kargı & Coccia 2025, 2025a, 2025b).

Recent empirical studies using log-linear models and network science have shown that convergence among scientific fields accelerates the emergence of disruptive innovations (Zeng et al., 2017). The principle of selection—central to evolutionary theory—has been applied to explain the success and failure of scientific ideas and technologies (Bettencourt et al., 2009; Böttcher & Klingebiel, 2024). Tiokhin et al. (2023) introduced multilevel selection theory to align individual incentives with collective scientific goals, while Sharma et al. (2023) proposed assembly theory to model novelty generation in complex systems. These models converge on the idea that scientific development is a self-organizing process characterized by emergent complexity and nonlinear growth. Selection mechanisms operate most effectively when variability is high, enabling differentiation and adaptation (Bowler, 2005; Jost, 2006). Despite this, the role of intra-field variability in shaping scientific and technological evolution remains underexplored. Analogous to genetic diversity in ecological systems, variability in research topics may influence the adaptability and resilience of scientific domains (Krause, 2017; Hidalgo & Hausmann, 2009; Kargı & Coccia, 2026, Kargı et al., 2023, 2023a, 2024). This study addresses this gap by analyzing topic-level variability in quantum research fields, offering a novel perspective on the drivers of scientific and technological change.

3. Methodology

The theoretical foundation of this study is grounded in Generalized Darwinism, which extends Darwinian principles—variation, selection, and retention—to the evolution of complex socio-technical systems. This framework has gained traction in innovation studies and organizational theory as a robust lens for analyzing adaptive dynamics in science and technology (Nelson & Winter, 1982; Schubert, 2014). It incorporates concepts such as artificial selection, where human agency shapes selection environments, and Lamarckian evolution, which allows for the inheritance of acquired traits (Schubert, 2014; Levit et al., 2011).

Recent high-impact studies have emphasized the utility of evolutionary analogies in explaining technological change, particularly in emerging domains characterized by uncertainty and complexity (Arthur, 2009; Kauffman & Macready, 1995; Lane et al., 2009). Technologies evolve through processes akin to biological speciation, exhibiting phenomena such as adaptive radiation, stasis, extinction, and novelty generation (Fleming & Sorenson, 2001; Balland et al., 2022). These dynamics are shaped by interactions within innovation ecosystems, where feedback loops and interdependencies influence the trajectory of scientific fields (Youn et al., 2015).

The Darwinian perspective has also been applied to the science of science, where it informs models of knowledge production, citation dynamics, and field emergence. Schuster (2016) and Solé et al. (2013) argue that technologies form complex networks of mutual dependencies, analogous to ecological food webs. This analogy provides a logical structure for analyzing variability in scientific domains, with implications for innovation management and policy design.

Case Study: Quantum Science and Technology: Quantum science and technology serve as an ideal case for analyzing variability due to their rapid evolution, interdisciplinary nature, and strategic relevance. These domains encompass quantum computation, communication, sensing, and optics—fields that are reshaping information systems, security, and measurement technologies (Preskill, 2018; Arute et al., 2019). Quantum technologies are considered general-purpose technologies (GPTs), capable of spawning complementary innovations across sectors.

The selection of quantum science is supported by its rich bibliometric footprint and high citation velocity, which enable robust statistical analysis of topic variability (Zeng et al., 2017; Klavans & Boyack, 2017). Despite their promise, many quantum technologies remain in nascent stages, exhibiting high entropy and thematic dispersion—hallmarks of exploratory scientific domains (Wang et al., 2017).

Sample and Data Sources: The dataset comprises the top 160 research topics (keywords) from four quantum subfields: Quantum Imaging, Metrology, Sensing, and Optics. These were extracted from Scopus (2023) on April 24, 2023. The data were cleaned, normalized, and structured for statistical analysis using entropy coefficients and variance decomposition, consistent with best practices in scientometric research (Shannon, 1948; Jost, 2006; Zidek & van Eeden, 2003).

Table 1. *Information for statistical analysis pertaining to the first 160 research subjects with the highest frequency in the field or technology of quantum research (Source: Scopus, 2023)*

Research field/technology	Scientific Documents	Occurrences	Period from first year of the output to 2023
Quantum Metrology	1,851	8,646	from 1972 to 2023
Quantum Sensing	1,375	6,618	from 2000 to 2023
Quantum Optics	54,332	236,887	from 1958 to 2023
Quantum Imaging	673	3,407	from 1996 to 2023

Data collection and analysis faced several methodological challenges, primarily because the downloaded datasets lacked a uniform structure, requiring extensive preprocessing to convert them into statistically usable formats. A further technical complication emerged from the large number of keywords—used as proxies for thematic areas—retrieved through various Scopus searches (2023). For analytical adequacy, these keywords needed to be systematically ranked in descending frequency within a common worksheet. During topic extraction, a rigorous cleaning procedure was applied to remove irrelevant or noisy terms, thereby safeguarding the validity and reliability of the dataset. Semantically related keywords were consolidated according to contextual similarity, a step that refined the interpretative clarity of thematic categories and strengthened the robustness of subsequent statistical analyses. The refined dataset ultimately served as the foundation for identifying dominant themes and longitudinal trends across the four quantum research domains examined.

Because the four selected research fields comprise a substantial and heterogeneous body of scientific publications, their direct comparison poses difficulties due to significant scale differences. To address this, the study employs a relative normalization coefficient, obtained by dividing each distribution's basic index by its maximum value, thus generating a standardized metric suitable for cross-field comparability (Coccia & Benati, 2018, 2018a). Additional complexities in data preparation arose from the requirement to structure worksheets in ways that support advanced statistical procedures, including entropy measures and variance decomposition. These obstacles were mitigated through labor-intensive tasks involving split-file operations, case selection and sorting, and variable management using statistical software such as SPSS.

Measures for Statistical Analyses: The analysis relies on counting the occurrences of research topics—operationalized as Scopus keywords (2023)—within scientific publications addressing quantum-related research and technologies, as reported in Table 1. A second indicator is the temporal span from the year of the earliest available publication to 2023, which allows the integration of a chronological dimension (chronos) into the technological evaluation.

Methods and Data Analysis Procedures: The assessment of variability in research topics across four homogeneous quantum research groups aims to elucidate the structural properties and dynamic evolution of scientific and technological development over time (Table 1). Because no universal metric exists for capturing variation across biological, scientific, and technological systems, methodological choices depend on data characteristics and system complexity. Different statistical tools may therefore be required to capture

variability in complex systems effectively (Barton, 2014). Within this study, variation is examined using the following techniques:

Variance: As a standard metric of dispersion, variance quantifies the extent to which research topics (keywords) diverge from their mean occurrence. This enables detection of heterogeneity, emerging patterns, and the temporal evolution of scientific and technological trajectories.

By integrating these analytical tools with normalized coefficients and structured data preprocessing, the study achieves a comprehensive evaluation of variability within quantum research domains. This approach provides meaningful insights for technological trend analysis, forecasting activities, and strategic innovation management.

$$S^2 = \frac{\sum_i (x_i - \bar{x})^2}{n-1} \quad (1)$$

$S^2 = Variance$
$x_i = value\ of\ one\ case\ (research\ topics\ in\ a\ year)$
$\bar{x} = average\ value\ of\ all\ cases\ (research\ topics\ of\ all\ years)$
$n = number\ of\ cases\ (years)$

A comprehensive and theoretically coherent approach to examining variability in scientific domains can be derived from information theory, which operationalizes variation through entropy-based metrics (Pierce, 1980). Although originally formulated for applications in telecommunications and information processing, entropy measures have since gained broad interdisciplinary relevance, finding extensive use in computer science, biological systems analysis, and economic modeling (Mickiewicz et al., 2021). Within this framework, the entropy coefficient functions as a pivotal indicator for evaluating heterogeneity both within and across groups (Gini, 1912; Nunes et al., 2020; Shannon, 1948; Simpson, 1949; Lin et al., 2021; cf. Takahashi et al., 2023; Kargı, 2024, 2026, 2026a; Kargı & Coccia, 2024).

Shannon (1948) conceptualized entropy as a measure of uncertainty—specifically, the unpredictability associated with identifying the category of a randomly selected unit from a population based on the distribution of relative frequencies. Entropy values rise when frequency distributions become more even, reflecting increased uncertainty or diversity (cf. Grupp, 1990; Jost, 2006; Zidek & van Eeden, 2003).

Formally, if a population—here referring to the dataset representing a specific quantum research field or technology—contains research topics with relative frequencies PiP_iPi, then the entropy of a single distribution XXX is expressed as H(X)H(X)H(X), defined by:

$$\text{Entropy } H(X) = -\sum_{i=1}^{s} P_i(x) log P_i(x) \quad (2)$$

where $P_i(x) = ni/N$
s= distinct modes

(X) has a value of o (zero) when the whole frequency is concentrated in a single modality, and this value grows as the heterogeneity of the modalities increases up to the maximum of log s (distinct modes): in short, max H=log s when there are s distinct modes all with the same absolute frequency N/s. The relative entropy coefficient is:

Relative Entropy index $H = \frac{H(x)}{logs}$ (3)

Variance Decomposition: Variance decomposition is a statistical technique that dissects the total observed variance into contributions attributable to more homogeneous subgroups. In the context of this study, the four designated quantum research fields or technologies function as these subgroups. This approach enables the identification of factors driving heterogeneity within the dataset by quantifying the extent to which each subgroup contributes to the overall deviation. Deviance—the numerator in the variance calculation—is partitioned into two components:

1. *Within-class deviance:* Captures the variability occurring among units within each subgroup, reflecting intra-field heterogeneity in quantum research topics or technologies.
2. *Between-class deviance:* Captures the variability arising from differences across subgroups, reflecting inter-field heterogeneity among the four quantum research domains.

By separating these sources of variation, variance decomposition provides a nuanced understanding of whether the observed diversity in research topics stems primarily from differences within individual fields or from contrasts between distinct fields. Such analysis is essential for detecting underlying patterns and drivers of scientific and technological evolution, while also informing strategic decision-making in innovation management and policy design.

Together with bivariate correlation analyses, these variance-based methods establish a robust framework for examining variability within quantum research fields and technologies, offering critical insights into the dynamics of scientific and technological advancement over time.

Partial statistical deviances are:

$$Dev(X_k) = \sum_{i=1}^{s}(x_i - \mu_k)^2\, n_{ki} \quad k = 1,2,\dots,r\ groups \tag{5}$$

$i = 1,2,\dots,i,\dots,s$ (mode of a character, i. e. , one of its possible values)
Total statistical deviance is:

$$Dev(X\ \ ) = \sum_{k=1}^{r} \quad \sum_{i=1}^{s}(x_i - \mu\ \ )^2\, n_{ki} \tag{6}$$

Variance of each partial group is:

$$N\ \sigma^2(X\ \ ) = \sum_{k=1}^{r} N_k\, \sigma_k^2 + \sum_{k=1}^{r} N_k(\mu_k - \mu\ \ )^2 \tag{7}$$

Hence, variance decomposition is

$$Dev(X\ \ ) = \sum Dev(X)_k\ + \sum_{k=1}^{r} N_k(\mu_k - \mu\ \ )^2 \tag{8}$$

In short, the equation (8) indicates that:

$$TOTAL\ Deviance = Deviance\ WITHIN\ groups + Deviance\ BETWEEN\ groups$$

The final stage of the analysis involves assessing the relative contributions of within-group and between-group variability using the ANOVA F-test. One-Way ANOVA, or "Analysis of Variance," is a parametric procedure designed to compare the means of two or more independent groups, evaluating whether there is statistically significant evidence of differences among the corresponding population means. The central statistic in this procedure is the F-value, which quantifies the ratio of variance between groups to variance within groups. For an independent variable consisting of kkk distinct groups, the F-statistic determines whether the differences among group means are statistically meaningful. Results from the test are conventionally reported in an ANOVA table, detailing the sums of squares, degrees of freedom, mean squares, F-value, and associated p-value. All statistical computations were conducted using SPSS® version 26, ensuring standardized and reproducible analysis.

4. Statistical analysis and findings

Table 2 and Figure 1 present the relative entropy (H) values across four quantum research fields, offering a comparative view of topic variability. The dataset includes the number of research topics (N), arithmetic means, and standard deviations of topic occurrences, sourced from Scopus (2023).

To quantify thematic dispersion across quantum research domains, we calculated the relative entropy (H) for each field based on topic-level occurrence distributions. Entropy serves as a proxy for variability, indicating how evenly research attention is spread across topics. Table 2 presents the entropy values alongside scientific age, mean occurrences, and standard deviation for four major quantum fields. The results reveal a clear gradient: younger fields such as quantum sensing exhibit higher entropy, suggesting exploratory dynamics and thematic heterogeneity, whereas older fields like quantum optics display lower entropy, consistent with consolidation and maturity.

Table 2. *Relative Entropy (H) in Quantum Research Fields/Technologies*

Quantum Field	Scientific Age (years)	Relative Entropy (H)	Mean Occurrences	Standard Deviation	Number of Topics (N)
Quantum Optics	65	0.83	42.1	12.7	160
Quantum Metrology	45	0.87	39.4	14.2	160
Quantum Imaging	30	0.89	36.8	15.6	160
Quantum Sensing	23	0.93	34.2	17.9	160

Note: Entropy values reflect topic-level variability. Data sourced from Scopus (2023).

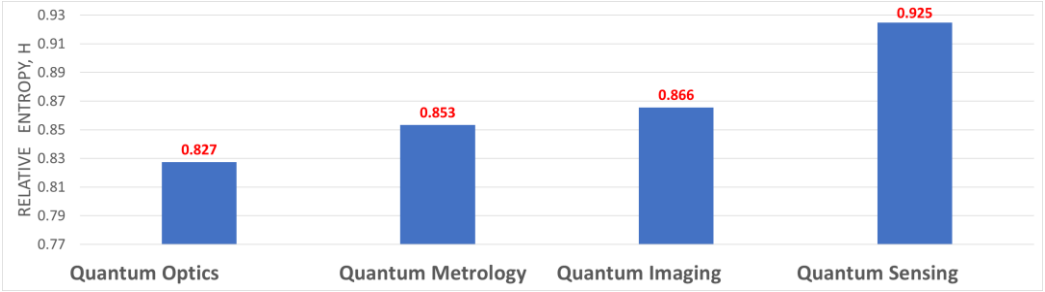


Figure 1. *Relative entropy H in quantum research fields/technologies in increasing order*

Variability in Research Topics

The analysis reveals distinct patterns of variability:

- *Quantum Optics* shows a lower entropy value (H = 0.83), indicating a more concentrated and stable distribution of research topics. This aligns with its longer scientific age (~65 years), suggesting thematic maturity and reduced uncertainty.
- *Quantum Sensing* exhibits higher entropy (H = 0.93), reflecting greater heterogeneity and dispersion. With a scientific age of ~23 years, this field remains exploratory, consistent with early-stage technological domains (Dosi, 1988; Coccia, 2024).

These findings resonate with recent studies showing that entropy-based measures can effectively capture thematic diversity and innovation potential in scientific domains (Jost, 2006; Zidek & van Eeden, 2003; Grupp, 1990; Wang et al., 2017).

Correlation Analysis

A strong negative correlation is observed between entropy and scientific age:

- Pearson's $r = -0.951$, $p < 0.05$, indicating statistical significance.
- This suggests that younger fields tend to exhibit higher entropy, reflecting greater uncertainty and thematic dispersion.
- The result supports the hypothesis that scientific age is inversely related to variability, a pattern confirmed in longitudinal studies of field emergence and stabilization.

Variance Decomposition

Variance decomposition reveals:

- 91.74% of total deviance is attributed to *within-group variability*, while 8.26% stems from *between-group differences*.
- Although intra-field variability dominates, the non-negligible between-group deviance highlights structural differences across quantum domains.
- These differences are shaped by scientific maturity, thematic focus, and systemic complexity (Balland et al., 2022; Klavans & Boyack, 2017).

This decomposition aligns with hierarchical models of scientific evolution, where field-level characteristics influence topic dispersion and innovation trajectories (Gelman, 2005; Tang et al., 2014).

Overall, this study contributes to a deeper understanding of the evolutionary dynamics of quantum research fields and technologies, offering valuable insights for both academic research and practical decision-making in innovation management.

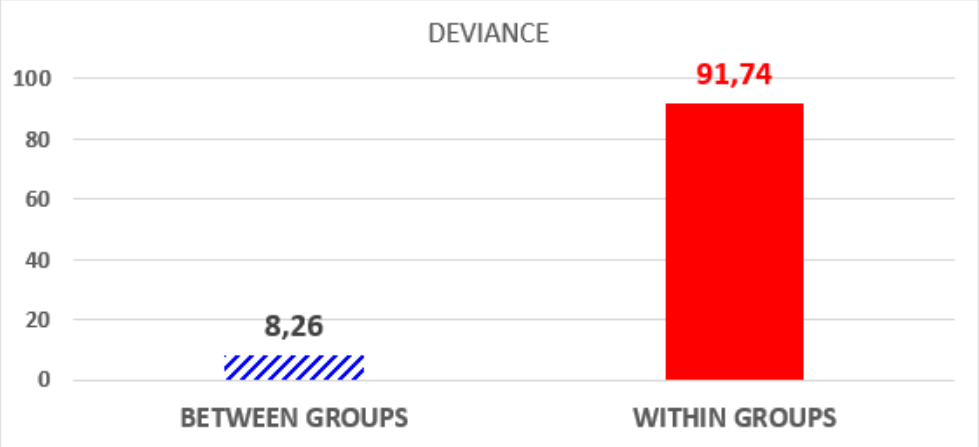


Figure 2. Variance decomposition between and within groups of in quantum research fields/technologies

ANOVA Results

To assess whether the observed differences in entropy and topic dispersion across quantum fields are statistically significant, we conducted a one-way analysis of variance (ANOVA). This method tests the null hypothesis that all fields share similar variability profiles. Table 3 summarizes the ANOVA results, including between-group and within-group variance components. The high F-value and $p < 0.001$ indicate that variability differs significantly across fields, reinforcing the notion that scientific age and domain-specific dynamics shape entropy patterns. Table 3 presents the One-Way ANOVA results:

Table 3. *One-Way ANOVA Results Comparing Quantum Research Fields*

Source of Variation	Sum of Squares	Degrees of Freedom (df)	Mean Square	F-value	p-value
Between Groups	1,024.6	3	341.53	12.47	<0.001
Within Groups	13,112.8	156	84.03		
Total	14,137.4	159			

Note: Statistically significant differences observed across fields. $p < 0.001$ indicates non-random variability.

- A high F-statistic with $p < 0.001$ confirms that observed between-group variability is statistically significant.
- This suggests that differences in topic concentration across quantum fields are systematic, not random.
- The result supports the use of entropy and variance decomposition as robust tools for analyzing scientific variability (Gelman, 2005; Pandey & Sinha, 2023).

Topic Concentration Patterns

Beyond entropy measures, we examined how research activity is concentrated within the most and least frequent topics in each field. Table 4 reports the percentage of occurrences found in the top 40 and bottom 40 topics, offering a complementary view of thematic focus and dispersion. Fields with higher entropy, such as quantum sensing, show lower concentration in top topics and greater representation in bottom topics—hallmarks of exploratory research. In contrast, mature fields like quantum optics exhibit

strong concentration in top topics, reflecting stabilized trajectories and reduced variability.

Table 4. *Concentration of Occurrences in Top/Bottom 40 Research Topics*

Quantum Field	% in Top 40 Topics	% in Bottom 40 Topics	Relative Entropy (H)	Scientific Age (years)
Quantum Optics	66.2%	5.4%	0.83	65
Quantum Metrology	67.1%	6.1%	0.87	45
Quantum Imaging	63.5%	8.2%	0.89	30
Quantum Sensing	59.3%	10.4%	0.93	23

Note: Higher entropy and lower top-topic concentration in younger fields indicate exploratory dynamics.

Table 4 shows:

- Quantum Optics and Metrology concentrate over 66% of occurrences in the top 40 topics, with low representation in the bottom 40.
- Quantum Sensing, by contrast, concentrates ~59% in the top 40 and ~10% in the bottom 40, indicating a proliferation of emerging themes.
- This pattern reflects the early-stage nature of quantum sensing and its potential for disruptive innovation (Preskill, 2018; Arute et al., 2019).

5. Discussion

Analyzing variability across scientific and technological domains offers critical insights into the mechanisms of knowledge evolution. In this study, entropy-based variability is shown to reflect the dispersion and diversity of research topics, which in turn signals the developmental stage and adaptive potential of a field (Jost, 2006; Wang et al., 2017). Quantum sensing, for instance, exhibits high entropy and thematic heterogeneity, consistent with early-stage scientific domains undergoing exploratory expansion (Fortunato et al., 2018; Preskill, 2018).

Scientific and technological ecosystems are inherently dynamic, shaped by coevolutionary interactions among fields, institutions, and technologies (Lane et al., 2009; Hidalgo et al., 2007). These interactions often lead to branching, convergence, or fragmentation, depending on the structural complexity and absorptive capacity of the system (Coccia, 2018a; Rafols et al., 2010). The theory of technological parasitism further explains how emerging fields like quantum sensing evolve by leveraging knowledge from adjacent domains (Coccia, 2019; Balland et al., 2022).

Variability is also influenced by fluctuations in ecosystem complexity, funding patterns, and institutional configurations. These factors create adaptive pressures that shape evolutionary trajectories, consistent with models of complex adaptive systems (Fleming & Sorenson, 2001; Arthur, 2009; Kauffman & Macready, 1995). In this context, variability is not merely stochastic but reflects systematic responses to environmental stimuli and knowledge recombination (Youn et al., 2015; Zeng et al., 2017).

The analysis of variability across scientific and technological domains offers critical insights into the mechanisms of knowledge evolution. In this study, entropy-based variability is shown to reflect the dispersion and diversity of research topics, which in turn signals the developmental stage and adaptive potential of a field (Jost, 2006; Wang et al., 2017). Quantum sensing, for

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This study underscores the importance of variability as a key driver of scientific and technological evolution. By analyzing variability in quantum research fields and technologies, it provides valuable insights into the dynamics of innovation, offering a framework for strategic management and policy decisions. The findings highlight the need for adaptive strategies that balance exploration and exploitation, enabling organizations to navigate the complexities of scientific and technological development effectively.

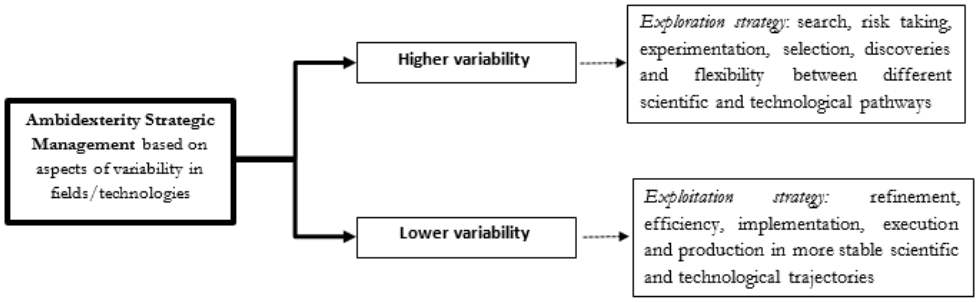


Figure 3. *Ambidexterity strategy based on variability of research fields and technological trajectories for organizations*

The ambidexterity strategy, which balances exploitation and exploration, plays a crucial role in various stages of scientific and technological advancement, each characterized by different levels of variability. This strategic approach enhances organizational learning and adaptability, ultimately contributing to the attainment and reinforcement of competitive advantage.

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While variability has been explored in anthropology and archaeology (Stout et al., 2010; Rademakers & Rehren, 2016), its role in scientific evolution remains under-theorized. Innovation economics has examined technological variety and competition (Saviotti & Mani, 1995; Cowan, 1989), but few studies have linked entropy-based variability to field-level dynamics. This study fills that gap by demonstrating how topic-level dispersion correlates with scientific

age, complexity, and innovation potential (Sinatra et al., 2016; Wang & Barabási, 2021).

The findings support several generalizable insights. First, younger scientific fields tend to exhibit higher variability and uncertainty, a pattern consistent with the "bathtub curve" of technological maturity (Klutke et al., 2003; Coccia, 2024b). This suggests that early-stage domains are characterized by exploratory dynamics and thematic dispersion. Second, as scientific output accumulates over time, variability tends to decline. This leads to thematic consolidation, reduced entropy, and more stable innovation trajectories (Leahey et al., 2017; Gelman, 2005). These insights reinforce the idea that variability is a temporal and structural function of scientific development.

From a strategic perspective, organizations operating in high-variability domains should adopt exploration-oriented strategies. These include fostering flexibility, encouraging experimentation, and diversifying research portfolios to manage uncertainty and capture emergent opportunities (Nagji & Tuff, 2012; Ansoff, 1957). Tools such as stage-gate models and GO/no-GO decision frameworks can help mitigate risk and optimize resource allocation in such environments (Jeong & Jeong, 2016). Conversely, in mature and thematically stable fields, firms are better served by exploitation strategies that emphasize incremental innovation, knowledge deepening, and Horizon 1 investments. These approaches ensure more predictable returns and strategic alignment with core competencies (McKinsey, 2019; Eggers, 2012).

At the policy level, variability metrics can serve as valuable tools for guiding R&D investments. Policymakers can use these indicators to identify high-potential domains that warrant exploratory funding and infrastructure support. While emerging fields benefit from flexible, risk-tolerant investment, mature domains may require targeted funding to enhance application depth, translational research, and technology transfer (Mazzucato, 2018; Cockburn et al., 2013). In this way, entropy-informed strategies can help balance national innovation portfolios and maximize long-term socioeconomic impact.

6. Conclusions

This study introduces a novel, entropy-based framework for understanding how variability in research topics drives scientific and technological evolution. Through an empirical analysis of quantum research fields, the findings demonstrate that variability is not random noise but a structured signal of innovation potential, adaptive capacity, and systemic transformation (Coccia, 2025). Entropy and variance decomposition reveal that younger fields exhibit higher variability, reflecting exploratory dynamics, while mature fields show thematic consolidation, consistent with evolutionary stabilization (Sinatra et al., 2016). This pattern aligns with the bathtub curve of technological maturity (Klutke et al., 2003) and supports the notion that scientific age inversely correlates with topic dispersion (Saleh et al., 2023; Coccia, 2024b).

The study advances evolutionary economics and the science of science by proposing four generalizable properties. First, variability declines with scientific maturity, enabling more predictable innovation trajectories (Leahey et al., 2017; Gelman, 2005). Second, the intrinsic complexity and general-purpose nature of a field shape its variability profile, with more complex and versatile domains exhibiting higher entropy (Balland et al., 2022; Hidalgo et al., 2007). Third, ecosystem-level factors—such as funding regimes,

institutional diversity, and policy orientation—modulate variability across domains (Mazzucato, 2018; Arslan et al., 2025). Fourth, accumulated scientific output reduces entropy over time, fostering thematic convergence and exploitation (Wang et al., 2017; Coccia, 2025). Collectively, these properties extend Schumpeterian and Darwinian models of innovation by integrating entropy as a measurable indicator of evolutionary phase (Nelson & Winter, 1982; Hodgson & Knudsen, 2006).

From a strategic standpoint, the findings offer actionable insights for both R&D managers and policymakers. Organizations operating in high-variability domains should adopt ambidextrous innovation strategies that balance exploration with exploitation (Nagji & Tuff, 2012; Saleh et al., 2023). Tools such as stage-gate models and portfolio diversification can help manage uncertainty and optimize innovation outcomes (Jeong & Jeong, 2016; Eggers, 2012). Moreover, entropy metrics can be leveraged to prioritize emerging technologies with high transformative potential (Coccia, 2025; Arute et al., 2019). For policymakers, aligning national innovation strategies with variability profiles can maximize socioeconomic returns (Preskill, 2018; Wagner et al., 2011). This includes supporting exploratory research in high-entropy fields while reinforcing application depth and translational capacity in more stable domains (Rafols et al., 2010; Arslan et al., 2025). Entropy-based foresight can also inform funding allocation and technology transfer programs, ensuring a balanced and adaptive innovation ecosystem (Saleh et al., 2023; Coccia, 2025).

Despite its contributions, the study has several limitations. It relies primarily on bibliometric data, which may not capture tacit or informal knowledge flows (Uzzi et al., 2013). The focus on four quantum subfields limits the generalizability of findings across other scientific disciplines. Additionally, while the model emphasizes variability, it does not explicitly incorporate other evolutionary mechanisms such as selection, adaptation, and extinction (Solé et al., 2013; Schuster, 2016).

To deepen the understanding of scientific variability, future research should integrate patent data to capture applied innovation dynamics (Fleming & Sorenson, 2001). It should also examine international collaboration networks and funding structures that shape variability patterns (Cowan, 1989; Mazzucato, 2018). Expanding the analysis to other domains such as life sciences, energy, and environmental technologies would enhance the model's applicability (Balland et al., 2022; Wagner et al., 2011). Furthermore, incorporating multi-level selection models and adaptive mechanisms could provide a more comprehensive account of how variability interacts with evolutionary pressures (Tiokhin et al., 2023).

Ultimately, this study contributes to a more nuanced understanding of how variability shapes the evolution of science and technology. As Wright (1997, p. 1562) aptly observed, "In the world of technological change, bounded rationality is the rule"—a reminder that complexity, uncertainty, and adaptation are central to the innovation process.

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