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The General Theory of Scientific Variability for Technological Evolution

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Abstract: The proposed general theory of scientific variability for technological evolution explains one of the drivers of technological change for economic progress in human society. Variability is the predisposition of the elements in systems to assume different values over time and space. In biology, the variability is basic to explaining differences and development in organisms. In economics of technical change, the effects of variability within research fields on evolutionary dynamics of related technologies are unknown. In a broad analogy with the principles of biology, suggested theoretical framework here can clarify a basic driver of technological evolution: the variability within research fields can explain the dynamics of scientific development and technological evolution. The study sees whether statistical evidence supports the hypothesis that the rate of growth of scientific and technological fields can be explained by the level of variability within scientific fields. The validation is based on emerging research fields in quantum technologies: quantum imaging, quantum meteorology, quantum sensing, and quantum optics. Statistical evidence seems in general to support the hypothesis stated that the rate of growth can be explained by the level of scientific variability within research fields, measured with the relative entropy (indicating the dispersion of scientific topics in a research field underlying a specific technology). Nonparametric correlation with Spearman's rho shows a positive coefficient of 0.80 between entropy measures and rates of growth between scientific and technological fields. The linear model of the relation between rate of growth and scientific variability reveals a coefficient of regression equal to 1.63 (R^2 = 0.60). The findings here suggest a general law that variability within research fields positively drives scientific development and technological evolution. In particular, a higher variability within research fields can support a high rate of growth in scientific development and technological evolution. The proposed general theory of scientific variability is especially relevant in turbulent environments of technology-based competition to clarify a basic determinant of technological development to design strategies of technological forecasting and management of promising innovations.

Keywords: scientific variability; scientific development; technological evolution; technological change; technological trajectories; entropy; systems development; science and technology; creative destruction; quantum technology; quantum science

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1. Introduction and Observations on Evolution in Science and Technology

Technological evolution and scientific change have a basic role in the economic and social development of human society [1–13]. Fleming and Sorenson [14] maintain that invention is due to a combinatorial process of searching. Arthur [2] states that "technologies somehow must come into being as fresh combinations of what already exists." This combination of different elements is organized into systems to create new products/processes for some human purpose [15,16]. Sahal [17] points out that "evolution. . .pertains to the very structure and function of the object (p. 64). . .involves a process of equilibrium governed by the internal dynamics of the object system (p. 69)".

A main problem in social studies of science and technology is how the dynamics of science,—encompassing a complex system of scientific topics, methods, and research fields,—supports the technological evolution [7,18–21]. This study confronts the problem here by developing a general theory of scientific variability, which endeavors to explain the effects of variability within research fields on the dynamics of the scientific and technological evolution. In biology, the role of variation is well known [22,23], but in the study of scientific development and technological evolution, the effects of variability are unknown, but their examination can clarify the determinants and behaviour of evolutionary dynamics in science and technology. In general, differences of topics within scientific fields create variability that underlies the evolutionary processes of technologies and allows adaptation and evolution in changing environments [24–26]. However, to date, no theoretical framework explains how the variability within research fields affects the dynamics of scientific development and evolution in related technologies [27,28].

In a broader analogy with biology, this study propose a general theory that endeavors to explain how the variability within scientific fields affects technological evolution. The general prediction of the proposed theoretical framework is that the scientific variability of topics within research fields can clarify the dynamics of scientific and technological trajectories to support the best practices of technological forecasting and management for driving promising directions of technical change in socioeconomic systems.

2. Critique of Current Theories in Technological Evolution: Incompleteness of Drivers

In order to position our theory in a manner that displays similarities and differences with existing approaches, a critical review of accepted frameworks in the evolution of science and technology is presented here. Quantitative works on emergence and evolution of disciplines are scarce, and this aspect is in part due to the difficulty in detecting and measuring basic sources of scientific change [7,29–32]. Many theories of scientific development have been inspired by the notion of paradigm shifts associated with anomalies and contradictory results in science [33]. Some studies explain the evolution of fields with processes of branching, caused by new discoveries [12,27] or of specialization and fragmentation [34], such as in nanophysics, molecular biology, astrobiology, etc. [11]. Other studies focus on the synthesis of concepts and methods in preexisting disciplines, such as in bioinformatics, quantum computing, plasma physics, etc. [21,35]. The approaches in these researches point to the self-organizing development of science systems [36,37]. However, how the basic characteristics of scientific development affect technological evolution are hardly known.

Theories of technological evolution have also been criticized in the literature because they neglect many determinants and factors that are strongly related to the evolutionary dynamics [38,39]. New studies suggest that technologies evolve with a relationship of mutualistic symbiosis between inter-related research fields and technologies [40–44]. Utterback et al. [45] maintain that the growth of technologies will often stimulate the growth of inter-related technologies, calling this interaction "symbiotic competition" ([45], p. 1). Pistorius and Utterback ([38], p. 67) argue that approaches based on a multi-mode interaction between technologies provide a much richer and more useful theoretical framework to explain scientific and technological change. These approaches are based on a broad analogy between scientific and technological evolution and biological evolution [2,3,41,42,44,46]. In fact, the similarities between biological and scientific– technological evolution have a considerable literature [41,44,47–49]. In general, scientific and technological evolution, alongside biological evolution, displays radiations, stasis, extinctions, and novelty [50]. Sandén and Hillman ([51], p. 407) suggest six typologies of technological interactions using similarity to the interactions in biological species, i.e., neutralism, commensalism, amensalism, symbiosis, competition, and parasitism. Coccia [41], in a broad analogy with the evolutionary ecology of parasites, explains the parasitic-dependence interaction between technologies and related effects for the evolution of technologies [41,44,52]. Fleming and Sorenson [14] maintain that the precise mechanism through which science accelerates the rate of invention remains an open question. Science progress and invention can be due to a combinatorial search process, in which science advances can alter inventors' search processes by leading to useful combinations, eliminating failing paths of research, and triggering them to continue even in the presence of negative feedback, generating learning processes from invention and innovation failure [53]. These mechanisms seem to be useful when inventors attempt to combine highly coupled components; therefore, the elements of scientific research to invention creation have a systematic variability across different fields and technological applications.

Nevertheless, in these topics of research there is an evident incompleteness because no consistent system of factors is capable of explaining the complex structures and dynamics of science and technology in society. In fact, current theoretical frameworks do not explain how the variability of topics within research fields can drive the dynamics of scientific development and technological change, as well as the diversity in evolutionary pathways of technologies. The idea of the study here is that the variability in scientific fields and related technologies can clarify sources and effects of scientific and technological change. Proposed theory of scientific variability here can allow scientists, technology analysts, R&D managers, and policymakers to make more accurate predictions of technological evolution to improve management of promising technologies and innovations [54–58]. Hence, this study suggests a general theory that analyzes and discusses why studying variability is important for understanding the dynamics of scientific development and technological evolution in order to detail challenges and opportunities in technological forecasting to improve innovation and technology management [54,56].

3. Research Methodology

3.1. Research Philosophy of Proposed General Theory of Scientific Variability

The proposed theory of scientific variability here is developed within a perspective of generalized or universal Darwinism to explain sources of scientific and technological change [27,59–61]. Hodgson ([62], p. 260) maintains that "Darwinism involves a general theory of all open, complex systems". In this context, Hodgson and Knudsen [63] suggest a generalization of the Darwinian concepts of selection, variation, and retention to explain how a complex system evolves over time and space [62–65]. In the economics of technical change and in the fields of the Science of Science [7], the generalization of Darwinian principles ("Generalized Darwinism") can assist in explaining the multidisciplinary nature of scientific and technological development [46,60–66]. In fact, the heuristic principles of "Generalized Darwinism" can explain aspects of scientific and technological change considering analogies between evolution in the biological organisms and similar-looking processes of systems in science and technology [67]. Arthur [2] argues that the Darwinism approach can clarify technology and science progress as it has been performed for the development of the species [48,49]. Kauffman and Macready ([68], p. 26) state that "technological evolution, like biological evolution, can be considered a search across a space of possibilities on complex, multipeaked 'fitness', 'efficiency', or 'cost' landscapes". Schuster ([48], p. 8) shows aspects of similarity between technological and biological evolution, such as the principle of selection that works if there are significant differences between elements in a population, such as in research fields, technologies, etc.; i.e., if there is the necessary variability [69]. Variation, associated with selection, generates evolutionary processes through which (human or technological) species evolve and adapt to environmental changes. However, the role of variation within research fields as determinant for the evolution of science and technology is hardly known, but it can be a basic driver to explaining important sources and effects on scientific and technological change. Hence, the theoretical background of "Generalized Darwinism" [63] can frame a broad analogy between science, technology, and evolutionary ecology that provides a logical structure to analyze and explain how the variability in science drives different evolutionary pathways of research fields and technologies in society [41].

3.2. The Extension of Postulates of the Variability in Science

Variability is the predisposition of the elements in system to assume different values over time and space [70]. In biological systems, the role of variation is well known [71,72], whereas the variation in the study of scientific and technological information is unknown, but its examination can explain sources and effects on scientific development and technological evolution. In a broad analogy with principles of biology, in a theoretical framework of Generalized Darwinism, variability can play a central role to explain evolutionary processes in science and technology for determining general properties to support technological forecasting and innovation management [56].

The proposed theory of scientific variability within research fields endeavors to clarify one of the sources driving technological evolution [13]. In fact, the understanding of the role of variability in science and technology can extend the theories of scientific development and technological evolution with a new conceptual element to improve technological forecasting and support the management of technologies towards promising innovations for a fruitful economic and social impact. This study uses the concept "variability" interchangeably with terms of variation, difference, diversity, and disparity [73].

Extension of the Postulates of Variability in the Science and Technology Domain

(a) Scientific topics in research fields have different variability.
(b) Variability in research fields drives the evolution, variability $\Rightarrow$ evolution.
(c) Variability in research fields is basic for evolution and adaptation to changing environments.

3.3. Proposed Theory of Scientific Variability for Technological Evolution

The assumption is that scientific development and the evolution of technologies can be explained by the variability in related research fields.

Figure 1 shows this logical relation.

$$[Scientific\ and\ technological\ evolution_i \ = \varphi\ (\ variability_i)]$$
$$i = research\ and\ technological\ field$$

Figure 1. Scientific and technological evolution as a function (φ) of the variability in research fields.

Prediction of the Theory of Scientific Variability for Technological Evolution

Variability in research fields drives scientific development and technological evolution.

Figure 2 shows the causal relation of the theoretical prediction that scientific variability can drive scientific and technological evolution.

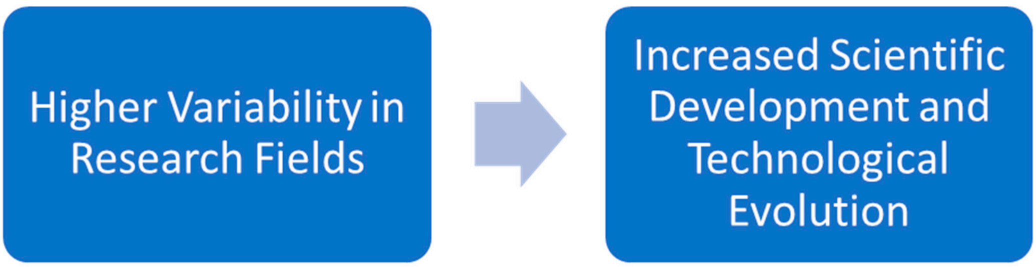

Figure 2. Consequential relation of variability in research fields as driver of scientific and technological change.

The confirmation of prediction, as just mentioned, with empirical evidence can support theoretical, managerial and policy implications to improve technological forecasting and to direct R&D investments towards promising technologies and innovations for science, technology, and socioeconomic progress [74–76].

3.4. Testable Implications of the Prediction of Proposed Theory of Scientific Variability for Technological Evolution

1. Scientific variability changes between research fields of the same discipline.
2. The pace of technological evolution can depend on scientific variability in related research fields.

Research Setting to Test the Predictions: Research Fields in Quantum Technologies

The predictions of the proposed theory of scientific variability for technological evolution will be verified empirically in some main quantum technologies by measuring the variation in scientific and technological information with the entropy index, a measure of changes in a group of individual data points [14]. Quantum science and technology are path-breaking systems having a high potential growth with manifold applications, such as in quantum machine learning [77–79], drug discovery processes [80], cryptographic tasks [81], information processing of big data [29,30,82], etc. [83–86]. Many research fields in quantum technologies are at the initial stage of evolution, but they have different scientific and technological advances that can affect the pathways of scientific development and technological evolution [83,87–89].

The study here focuses on some emerging research fields in quantum science having an independent topic of study, specific methodological approach, and applications [90]. This study analyzes four emerging scientific specialties in quantum science (Quantum Meteorology, Quantum Sensing, Quantum Optics, and Quantum Imaging). The emergence and related evolution of these fields can be due to economic and scientific variables (i.e., competitive position of nations) but also to activities that occur in scientific development given by (*a*) intellectual factors, such as paradigm development, potential discovery, problem success, and puzzle solving and (*b*) social factor, such as communication, co-authorship, colleagueship, and apprenticeship [91]. Wray [92] argues that sociological approaches focus on social and community changes as the source of new specialties, but conceptual changes also play an important role in the creation and evolution of some scientific specialties and related technologies. Conceptual change in research fields can be detected with the variability in topics that clarifies relationships with the evolution of scientific specialization and new technological trajectories.

3.5. Study Design

3.5.1. Sources of Data, Samples, and Measures for the Analysis of Variation in Research Fields

In order to measure the variability within research fields, this study analyzes scientific and technological information given by the number of occurrences concerning research topics in scientific documents (namely 160 keywords, max available number in the database of Scopus, [93]) of four research fields in quantum technologies [94,95]: Quantum Imaging, Quantum Meteorology, Quantum Sensing, and Quantum Optics. Data are from Scopus [93], downloaded on 24 April 2023. In particular, the study considers all available data in:

- Quantum Meteorology: 2028 scientific documents from 1972 to 2023
- Quantum Sensing: 1726 scientific documents from 2000 to 2023
- Quantum Optics: 58,060 scientific documents from 1958 to 2023
- Finally, Quantum Imaging: 753 scientific documents from 1996 to 2023

3.5.2. Sources of Data, Samples, and Measures for Technology Analysis of the Rate of Growth in Research Fields

The analysis of growth rate uses the number of papers in the same four research fields of quantum technologies, i.e., Quantum Imaging, Quantum Meteorology, Quantum Sensing, and Quantum Optics. Data are downloaded on 14 February 2024 from Scopus [96], about one year later the data for variance analysis to logically assess the consequential effect of variability on scientific and technological growth of research fields, as follows:

- Quantum Meteorology: 1851 scientific documents, with 8646 occurrences concerning the first 160 research topics (keywords) having high frequency (all data available from 1972 to 2023).
- Quantum Sensing: 1375 scientific documents, with 6618 occurrences concerning the first 160 research topics having high frequency (data from 2000 to 2023).
- Quantum Optics: 54,332 scientific documents, with 236,887 occurrences concerning the first 160 research topics with high frequency (data from 1958 to 2023).
- Finally, Quantum Imaging: 673 scientific documents, with 3407 occurrences concerning the first 160 research topics having high frequency (data from 1996 to 2023).

3.5.3. Methods for Statistical Analyses of Data

○ Test of the prediction n. 1 stated in Section 3.4 with the analysis of scientific variability based on entropy index

Variation is the quantitative or qualitative difference(s) between two or more entities [70,97]. There is no universal approach to measuring variation across biological as well as technological and other systems. Variation can be classified with numerical or categorical aspects. Numerical variation can be continuous (e.g., differences) or discrete (e.g., number of mutations). Depending on data type and system complexity, different statistical approaches can be applied for quantifying properly variability in systems [98]. The analysis of scientific variability in research topics of four homogeneous groups concerning quantum technologies above can clarify basic effects on scientific development and technological evolution. One of the unifying frameworks to analyze the variability in science is the information theory with entropy index, a measure based on information content [99]. This approach was originally developed to study telecommunications, but it can be also applied in many other fields, such as computer science, biology, statistics, anthropology, economics, etc. [100].

The entropy index is a vital measure of heterogeneity to assess variability within groups [97,101–106]. Given a population (here, scientific information in a specific quantum technology) in which the research topics have a relative frequency Pi, Shannon suggested the degree of indeterminacy in predicting the modality of a unit chosen at random from a population on the basis of the entropy. The entropy index H(X) is a decreasing function of the variability in relative frequencies [101,107–109]. Hence, the entropy H(X) of a single distribution (X) is:

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

where Pi(x) = ni/N, s = distinct modes.

Entropy H(X) has a value of 0 when the whole frequency is concentrated in a single modality. Entropy H(X) gradually increases the values as the heterogeneity of the modalities increases up to the maximum number of (log s) when there are (s) distinct modes all with the same absolute frequency N/s.

The relative entropy index H is:

$$\mathrm{H} = \frac{\mathrm{H(x)}}{\mathrm{logs}} \quad (2)$$

Moreover, the rate of scientific growth in four quantum technologies/research fields under study here is estimated with following linear model of the relationship of the number of publications (P) on time *t*

$$\text{P (publications)}_{i,t} = a + b_{\text{growth}}\,(\text{time})_{i,t} + u_{i,t} \quad (3)$$

P = Publication
a = constant
b_{growth} = coefficient of regression (rate of growth)
u = error term

The estimation of model (3) is performed with the Ordinary Least Squares (OLS) method that determines the unknown parameters in regression models.

○ Test of the prediction n. 2 stated in Section 3.4 that the evolution of technology depends on variability

Correlation analysis. Considering the four research fields under study having scientific and technological information, the association between scientific variability measured with the relative entropy index and the rate of growth measured with the coefficient of regression in the linear model (3) is performed with the Spearman correlation coefficient (Spearman's correlation, for short): a nonparametric measure of the strength and direction of association that exists between two variables. Coefficient is denoted by the Greek letter ρ (rho). The test is used in this case for continuous data that have failed the assumptions necessary for conducting the Pearson's correlation, since only four observations are obtained from four research fields under study.

Finally, previous results of entropy indices and rates of growth are combined to analyze the relation between evolutionary growth and scientific variability in research fields. Model of the rate of growth (b_{growth} = coefficient of regression in Equation (3)) as a linear function of the entropy index h (proxy of variability) in the research fields of quantum technologies is:

$$\mathrm{b}_{\mathrm{growth}\ i,t} = \mathrm{k} + \mathrm{z}\ (\mathrm{h})_{i,t} + \varepsilon_{i,t} \tag{4}$$

b = rate of growth in research fields and related technologies
k = constant
z = coefficient of regression
h = relative entropy index (variability in research fields)
ε = error term

The estimation of model (4) is also with the Ordinary Least Squares (OLS) method, which determines the unknown parameters in regression model.

Statistical analyses are performed with the IBM SPSS Statistics version 26 ®.

4. Empirical Evidence

4.1. Validation of the Prediction That Scientific Variability Changes between different Research Fields in the Same Discipline

Table 1 shows that Quantum Optics has a higher concentration of occurrences in research topics (lower relative entropy = H), whereas Quantum Sensing has higher heterogeneity of these occurrences between manifold research topics (higher relative entropy). This result can be due to the scientific age of Quantum Sensing, which is a shorter period (23 years, in the year 2023) than Quantum Optics, which has an evolutionary period of 65 years (in year 2023). Moreover, higher heterogeneity within a research field suggests that the younger research field has to stabilize the scientific directions and technological trajectories in its evolutionary pattern [110,111].

Table 1. Descriptive statistics and relative entropy in research fields of quantum technologies.

Research Fields	Cases	Arithmetic Mean	Std. Deviation	Relative Entropy H
Quantum Optics	154	1480.48	4235.48	0.827
Quantum Metrology	154	54.04	113.00	0.853
Quantum Imaging	152	21.29	42.10	0.866
Quantum Sensing	153	41.36	46.59	0.925

Table 2 shows that Quantum Sensing has the highest rate of growth 0.27 (p-value = 0.001), Quantum Metrology has also a significant high growth rate of 0.23, followed by Quantum Imaging (0.12) and finally by Quantum Optics (0.08). The F-test of the models is highly significant (p-value = 0.001) and the coefficient of determination shows a high goodness of fit in the range between 66% and 92% in estimated relationships.

Table 2. Results of estimated relationships of scientific production (publications) as a function of time.

Dependent Variable: Scientific Products				
	Coefficient b = Growth Rate	**Constant a**	***F*-Test**	**R^2**
Quantum Imaging, Log y pubs $_{i,t}$	0.121 ***	−240.43 ***	39.89 ***	0.66
Quantum Metrology, Log y pubs $_{i,t}$	0.225 ***	−449.95 ***	247.90 ***	0.92
Quantum Optics, Log y pubs $_{i,t}$	0.079 ***	−151.26 ***	150.47 ***	0.88
Quantum Sensing, Log y pubs $_{i,t}$	0.265 ***	−530.63 ***	238.76 ***	0.92

Note: Explanatory variable is time in years. *** significant at 1‰; F is the ratio of the variance explained by the model to the unexplained variance. R^2 is the coefficient of determination.

Figure 3 synthetizes the relative entropy index and rate of growth in the four research fields of quantum technology under study.

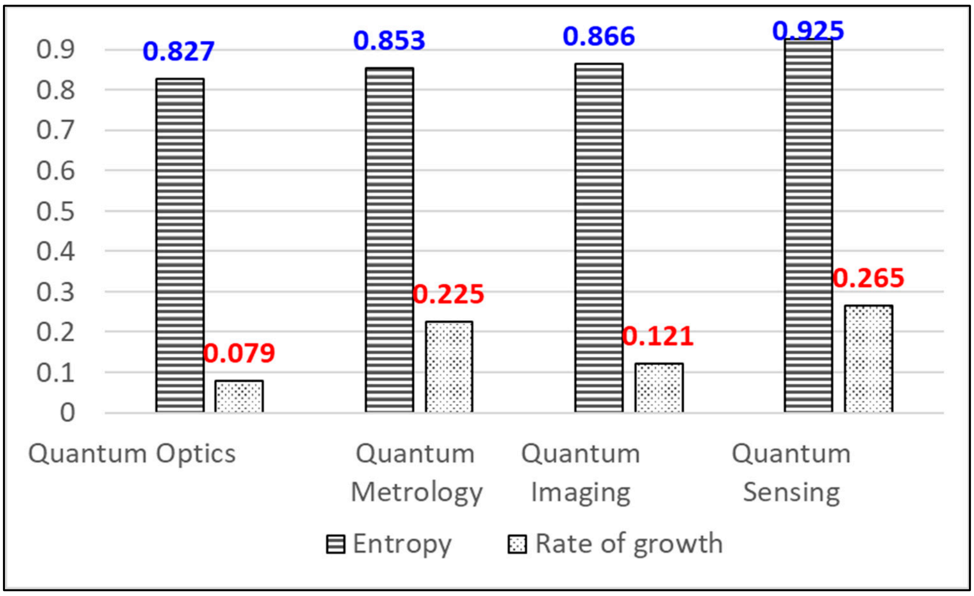

Figure 3. Synthesis of relative entropy index and rate of growth in research fields of quantum technologies using results from Tables 1 and 2.

4.2. Preliminary Validation of the Prediction That Evolution of Scientific and Technological Information = f(Scientific Variability)

Table 3 shows the association between the entropy indices and rates of growth in the four research fields under study with Spearman's correlation (rho): ρ = 0.80 (*p*-value = 0.17), it suggests a positive association between variability (measured with relative entropy) and scientific and technological development (measured with regression coefficient). In short, the results suggest that high variability is associated with higher scientific and technological change during evolutionary patterns of scientific and technological information.

Table 3. Nonparametric correlation between relative entropy index and rate of growth in four research fields of quantum technologies.

		Relative Entropy, H	**Rate of Growth**
Spearman's Correlation, rho	Relative Entropy, H	1	0.800
Sig. (2-tailed)			0.17
N	4		4

Considering the results of the correlation analysis in Table 3, Table 4 shows a preliminary estimated relationship of the rate of growth (b = coefficient of regression as specified in Equation (3)) on the relative entropy index h (proxy of variability) in research fields of quantum technologies: a positive coefficient of regression, z = 1.63, suggests that scientific variability can explain and be a main driver of scientific and technological evolution (R-square of the goodness of fit is about 61%). Figure 3 visualizes the estimated relationship of the rate of growth (b) on the relative entropy index h (proxy of variability) in the research fields of quantum technologies.

Table 4. Results of the estimated relationship of the rate of growth (*b* = coefficient of regression) on relative entropy index *h* (proxy of variability) in research fields of quantum technologies

Dependent Variable: Scientific Products				
Quantum Technologies, i = 1, 2, 3, 4	**Coefficient z**	**Constant k**	***F*-Test**	$\mathbf{R^2}$
b (rate of growth)$_i$	1.63	−1.244	3.07	0.61

Note: Explanatory variable is the relative entropy index h in the quantum research fields. F is the ratio of the variance explained by the model to the unexplained variance. R^2 is the coefficient of determination.

The results suggest that higher variability can support higher rates of growth in the research fields under study. The statistical evidence, described in Table 4 and visualized in Figure 4, seems in general to support the theoretical prediction that the rate of scientific and technological growth can be explained by the level of scientific variability in the research fields (of quantum technology).

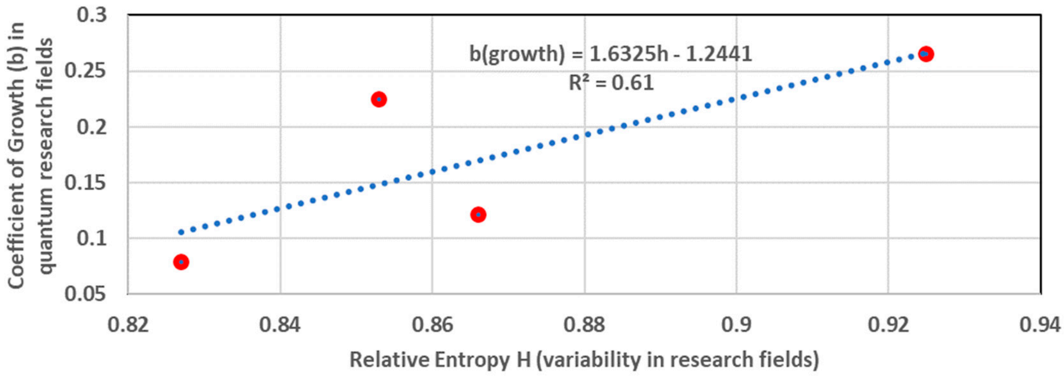

Figure 4. Preliminary estimated relationship of rate of growth on relative entropy index (proxy of variability) in research fields of quantum technologies. Note: Red dots indicate the coordinates of a point given by ordered pair (x,y) where x and y indicate the distance in the direction of a respective axis, i.e., dot = (relative entropy, growth coefficient). Dotted line is the estimated relationship with Ordinary Least Squares (OLS) method of the empirical values. Estimated equation and coefficient of determination (goodness of fit) are above the line.

Although we have only four observations associated with the four research fields under study, the nonparametric correlation coefficient is 0.80. This result is also confirmed, prima facie (accepted as correct until proved otherwise), by the estimated relationship of the linear model with a positive estimated coefficient of regression = 1.63 (Table 4 and Figure 4).

Hence, this empirical evidence can suggest a general law of scientific variability for scientific and technological development given by:

$$\text{Rate of growth} = -1.24 + 1.63\ (\text{Variability}),\ R^2 = 61\%.$$

Overall then, the statistical evidence seems in general to support the theoretical prediction that variability within research fields drives scientific and technological evolution; in particular, a higher variability underlying scientific development can support a high rate of growth in technological evolution.

5. Fundamental Considerations on the General Theory of Scientific Variability for Technological Evolution

5.1. Explanation of Results

Variation is a basic aspect for the process of evolution in biology [72,112]. In analogy with biology, variation can explain characteristics of scientific evolution and may confer adaptation and development of technologies to environmental changes [113]. In particular, in the field of science of the science, the analysis of variability can reveal main properties of the dynamics of scientific development and technological evolution [24–26]. A main prediction of the proposed general theory here, supported by empirical evidence, is that scientific variability seems to explain technological evolution, and a higher level of variability in research fields can increase scientific and technological development. Moreover, higher scientific variability, such as in the field of Quantum Sensing, suggests various underlying causes that affect in different ways the evolutionary patterns:

- The accumulation of scientific knowledge (papers having scientific and technological information) is a factor determining variability. Lower accumulation of scientific products in younger research fields shows a higher variability, associated with a higher technological evolution and uncertainty in technological trajectories, whereas a higher accumulation of scientific outputs in older research fields is associated with a lower variability that guides more stable scientific and technological trajectories.
- The specificity and nature of the research fields and technologies affect the variability and related evolutionary pathways. High variability within the complex system of research fields that are more oriented to support general purpose technologies (diving different technologies), such as Quantum Sensing, seems to induce a high rate of growth in scientific and technological evolution [29,30,83].

Variability in a research field having scientific and technological information may not be independent of the variation in other scientific and technological systems [114]. This mutual influence is a challenge to the study of scientific variability because the determinants of variability in a single research field can have the main consequences for variation and evolution in other scientific disciplines and related technologies [29,30]. Some scholars suggest the concept of "nested ecosystems" [115] that can be also applied per analogy in our context: the changes in a research field and related technology has interdependencies with other research fields and technologies in a larger science and technology ecosystem [116,117]. Thus, variability at one level might influence processes at other levels or in other scientific and technological systems.

The results here also suggest other sources of scientific variation, such as the change in a scientific and technological ecosystem, and related ecotone (transition or tension zone between these domains) in which scientific research and technologies develop [116]. Moreover, endogenous variation in research fields and technologies can be associated with external mechanisms of variability, such as the interaction with different research fields and technologies during evolutionary pathways in turbulent environment [118]. Hence, variability in quantum technologies, driven by the interaction and convergence of different research fields, affects the behavior and evolution of inter-related scientific fields and technologies [44]. This source of variability in research fields can be explained with the theorem of non-independence of any technology by Coccia [43]: the long-term behavior and evolution of any technological innovation is not independent from the behavior and evolution of the other technological innovations.

In general, empirical evidence here shows that variation guides scientific and technological evolution, and it is due to the systematic characteristics of the nature of the scientific fields and related technologies, of the random scientific and technological interaction with other technologies and research fields, and of the changes in surrounding innovation, business and socioeconomic ecosystems and related ecotones (transition zones).

5.2. Deductive Implications of the General Theory of Scientific Variability for Technological Evolution

General changes in the conditions of innovation ecosystems and their interactions in the techno-scientific ecotone (tension zone) trigger scientific and technological variation [24–26,119]. Research fields and technologies exposed to changes in the conditions of ecosystems and related ecotone and to interactions with other research fields have different variability and consequential coevolutionary pathways of growth [24–26,44,120]. Conversely, if it were possible to expose all research fields and technologies over time to absolute uniform environmental conditions, without interactions, there would be no variability [41,86,120,121].

Basic deductions of the proposed theory of scientific variability for technological evolution are:

- Scientific variability in research fields drives technological evolution.
- Variability in research fields and technologies is due to their specific nature, scientific and technological interactions, and changes in the surrounding innovation ecosystem and ecotone (transition zone) that generate turbulence (complexity and uncertainty) and progressive convergence and evolutionary pathways.

6. Conclusions, Limitations and Prospects

The study of scientific variability is basic to explaining the causes underlying scientific and technological evolution of radical and disruptive technologies [13,122–137]. The broad analogy applied here between evolutionary ecology and technological evolution, within a framework of Generalized Darwinism, keeps its validity in explaining how the variability within and between research fields can clarify some aspects of scientific and technological evolution. This study also shows for the first time, to my knowledge, a main prediction of the suggested theory, verified with a preliminary empirical evidence: variability in research fields is a driving force of the scientific development and technological evolution.

6.1. Managerial and Policy Implications

The variability in research fields can guide the decision making of policymakers, technology analysists, and R&D managers: high variability supports a higher rate of scientific and technological evolution associated with a high uncertainty in related trajectories [14]. Efficient decisions of focused R&D investments driven by institutions, considering the role of variability explained here, can support promising scientific and technological trajectories and reduce the risk of innovation failure [53,83,138–140]. Hence, the proposed theory of scientific variability, verified here by a preliminary statistical evidence in quantum technologies, can suggest implications in innovation management based on an ambidexterity strategy [141,142]:

(a) Exploration approaches in research fields and technological pathways to detect promising trajectories, in the presence of high scientific variability, by differentiating R&D investments between different technological and innovation projects present in portfolio of firms and/or nations.
(b) Exploitation strategy, when variability in research fields is low, to direct R&D investments in specific technological and innovation projects having manifold potential applications in different industries and markets.

6.2. Limitations and Future Research

This study provides some interesting but preliminary results in these complex topics concerning the relation between scientific variability and the evolution of emerging scientific fields and technologies [58]. The idea presented in the study here is adequate in some cases but less in others because of the diversity of research fields and technologies, their intrinsic nature and propensity to interact with different complex systems in scientific, business and socioeconomic environments [143]. Current limitations for future challenges to the study of scientific variability for explaining patterns of technological evolution are:

(1) improve the measurement of variability in science and technology domains, considering different scientific and technological information according to the research field under study, such as also software and algorithms in computing sciences; (2) discover manifold socioeconomic, institutional and political drivers of variability within and between research fields; (3) clarify confounding factors (e.g., level of public and private R&D investments, international collaboration, etc.) that affect scientific variability and technological evolution [138,139,144]; (4) enhance data gathering for new technological analyses and apply complementary analysis based on patents for improving theoretical and managerial implications also for more precise technological foresight of promising technologies and innovations [55,145–150].

One of the principal results here is a basic hypothesis of scientific variability, but the study encourages further theoretical exploration in the terra incognita of the variability in scientific fields to clarify sources and effects for scientific and technological evolution.

To conclude, hence, the proposed theoretical framework of variability here based on the analogy of scientific and technological evolution with some evolutionary aspects present in ecology and biology, validated with empirical evidence, suggests to reiterate preliminary results. However, there is need for much more detailed research into the investigation of the role that the variability plays to clarify evolutionary patterns of research fields and technologies in order to support stronger implications for technological forecasting and innovation management having fruitful economic and societal impact in turbulent markets.

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