Article

Not peer-reviewed version

Law of Variability in Science Driving Technological Evolution

Mario Coccia *

Posted Date: 5 December 2023

doi: 10.20944/preprints202312.0187.v1

Keywords: Quantum technology; Research fields; Science dynamics; Research topics; Entropy; Variance decomposition; Technological evolution; Variation; Generalized Darwinism; Technological change

 doi:10.20944/preprints202312.0187.v1

Article

Law of Variability in Science Driving Technological Evolution

Mario Coccia

School of Complex Adaptive Systems, CNR -- National Research Council of Italy & Arizona State University, 1031 S. Palm Walk, Tempe, AZ 85281-2701, USA; mario.coccia@cnr.it

Definition: Variability is the predisposition of phenomena to assume different values. Variability is higher when the differences of individual cases from each other are larger or diverge from a specific value, such as arithmetic mean. Characteristics and causes of the variability within and between research topics can explain the evolution of science and technology.

Abstract: A proposed interpretation of the characteristics and causes of the variation in science dynamics for technological evolution is described. The theoretical approach focuses on variability in research topics that guide scientific and technological evolution. Statistical method verifies the proposed approach by applying entropy, measures of dispersion and variance decomposition. The statistical evidence, using data of four main research fields in quantum technologies, suggests the following empirical properties: a) the growth of heterogeneity in research topics is inversely proportional to the age of research fields: recent research fields have a higher variability between topics with uncertainty in evolutionary dynamics, whereas older research fields have a lower variability and more concentration in specific research topics with stable evolution towards clear directions; b) the nature of research fields has a systematic effects in variability guiding the evolution of technologies. The theoretical approach and findings clarify main characteristics and causes of the evolution of science and technologies considering the underlying homogeneity or heterogeneity in research topics, providing main implications to improve the scientific and technological forecasting that may support appropriate R&D investments towards promising research fields and technologies

Keywords: quantum technology; research fields; science dynamics; research topics; entropy; variance decomposition; technological evolution; variation; generalized Darwinism; technological change

---

1. Introduction

Technological evolution has a basic role in scientific, economic and social development of human society (Arthur, 2009; Basalla, 1988; Bryan et al., 2007). The study here endeavors to examine the variability of research topics to explain the causes and different characteristics driving the scientific and technological evolution. Proposed theoretical framework here is developed with an evolutionary perspective of technological change guided by generalized or universal Darwinism (Dawkins, 1983; Nelson, 2006; Levit et al., 2011). Hodgson (2002, p. 260) maintains that: "Darwinism involves a general theory of all open, complex systems". In this context, Hodgson and Knudsen (2006) suggest a generalization of the Darwinian concepts of selection, variation and retention to explain how a complex system evolves (cf., Hodgson, 2002; Stoelhorst, 2008). In the economics of technical change, the generalization of Darwinian principles ("Generalized Darwinism") can assist in explaining the multidisciplinary nature of innovation processes (cf., Hodgson and Knudsen, 2006; Levit et al., 2011; Nelson, 2006; Schubert, 2014; Wagner and Rosen, 2014). In fact, the heuristic principles of "Generalized Darwinism" can explain aspects of technological development considering analogies between evolution in the biological sense and similar-looking processes in the evolution of technology (Farrell, 1993; Oppenheimer, 1955). Arthur (2009) argues that Darwinism can explain

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 December 2023 doi:10.20944/preprints202312.0187.v1

technology development as it has done for the development of species (cf., Schuster, 2016, p. 7). In general, technological evolution, as biological evolution, displays radiations, stasis, extinctions, and novelty (Kauffman and Macready, 1995; Solé et al., 2013). Kauffman and Macready (1995, 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 (2016, p. 8) shows the similarity between technological and biological evolution, for instance technologies have finite lifetimes like biological organisms. In this perspective, the principle of selection can explain the successful in evolution of some technologies (e.g., their survival and diffusion in markets). In particular, the concept of selection works if there are significant differences between the elements making up the population: i.e., it is necessary the variation (Bowler, 2005). Mutatis mutandis for technologies, using the theory of Darwin:

Natural selection is the process through which populations of living organisms adapt and change. Individuals in a population are naturally variable, meaning that they are all different in some ways. This variation means that some individuals have traits better suited to the environment than others. Individuals with adaptive traits—traits that give them some advantage—are more likely to survive and reproduce. ... Over time, these advantageous traits become more common in the population (Natural Geographic, 2023).

In short, variation, associated with selection, generates processes through which (human or technological) species adapt to environments and evolve over time. However, the role of variation in the domain of technologies is hardly known but it can be basic to explain important characteristics and sources of technological evolution. The general theoretical background of "Generalized Darwinism" (Hodgson and Knudsen, 2006), described here, can frame a broad analogy between technologies and evolutionary ecology that provides a logical structure of scientific inquiry to analyze variability in science driving different pathways of technologies and innovations in society (Coccia, 2019). The goal of this study is to clarify the concept of variation within and between technologies to examine the effects in evolutionary pathways. In fact, technology analysis of the variation in technological domains can create the framework within which a synthesis of basic properties on evolutionary pathways could be worked out, extending lines of research of evolutionary economics to clarify the science dynamics and technological evolution. Therefore, as the variation can be considered one of the engines that drives evolution of technologies, it deserves to be investigated because the understanding of the nature of variation in science can extend the theories of technological evolution with a new conceptual element that can explain the emergence, evolution and new directions of technological trajectories in turbulent (complex and uncertain) markets supporting social and economic change. The proposed theory of variability for scientific and technological evolution is verified empirically in main quantum technologies by applying entropy coefficient and other techniques that suggests empirical properties of technological evolution. Findings can support managerial and policy implications to improve technological forecasting and to direct R&D investments towards promising technologies and innovations for science and socioeconomic progress.

2. Data and Methods

2.1. Quantum technologies

This study focuses on vital quantum technologies (quantum computing, quantum communication, quantum optics, etc.) that are basic technological systems having a high potential to improve information processing, communication, etc. (Coccia, 2022; Kozlowski and Wehner, 2019; Scheidsteger et al., 2021; Tolcheev, 2018). Many quantum technologies are at the initial and/or infancy stage of evolution, but they have continuous scientific and technological advances directed to generate promising innovations to solve problems and improve socioeconomic systems (Atik and Jeutner, 2021; Carberry et al., 2021; Gill et al., 2022; Coccia, 2022). In fact, new quantum technologies can support, with powerful algorithms, quantum machine learning (Pande and Mulay, 2020; Rao et

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 December 2023 doi:10.20944/preprints202312.0187.v1

al., 2020), drug discovery process (Batra et al., 2021), cryptographic tasks (Chen et al., 2015), information processing of big data (cf., Latifian, 2022), etc.

2.2. Measures, sample and sources of data

This study uses number of occurrences concerning research topics in scientific documents of main quantum technologies given by: Quantum Imaging, Quantum Meteorology, Quantum Sensing and Quantum Optics. Data are from Scopus (2023), downloaded on 24 April 2023. In particular, the study considers all available data in:

– Quantum Meteorology: 1,851 scientific documents, with 8,646 occurrences concerning the first 160 research topics having the higher frequency (all data available from 1972 to 2023).
– Quantum Sensing: 1,375 scientific documents, with 6,618 occurrences concerning research topics concerning the first 160 research topics having the higher frequency (data from 2000 to 2023).
– Quantum Optics: 54,332 scientific documents, with 236,887 occurrences concerning research topics concerning the first 160 research topics with the higher frequency (data from 1958 to 2023).
– Finally, Quantum Imaging: 673 scientific documents, with 3,407 occurrences concerning research topics with the first 160 research topics having the higher frequency (data from 1996 to 2023).

In particular, the study analyzes the number of occurrences concerning research topics (indicated as number of keywords) in scientific documents of just mentioned quantum technologies over time (Glänzel and Thijs, 2012; Al-Betar et al., 2023; Zhang et al., 2023). Another measure used is the period of time from first available scientific document to 2023 to associate technological analysis to the temporal dimension (*chronos*).

2.3. Methods

The analysis of variation of research topics in four homogeneous groups of quantum technologies above can clarify characteristics and dynamics of the technological evolution over time. The analysis of variation in technologies is based on following measures and statistical techniques.

Variance indicates a measure of dispersion that considers the spread of all data points in a dataset, research topics in this study,

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

$S^2 = Variance$

$x_i = value\ of\ one\ case\ (research\ topics\ in\ a\ year)$

$\bar{x} = average\ value\ of\ all\ cases\ (research\ topics\ of\ all\ years)$

$n = number\ of\ cases\ (years)$

The variance measures the (quadratic) spread around the mean (Girone and Salvemini, 1981).

Entropy is a measure of heterogeneity (Gini, 1912, Nunes et al., 2020, Rényi, 1961; Shannon, 1948, Simpson, 1949; Lin et al., 2021; cf., Takahashi et al., 2023). Given a population (here data on 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 population on the basis of the entropy index. The entropy index is a decreasing function of the variability of the relative frequencies (Grupp, 1990; Jost, 2006, Lin et al., 2021; Zidek and van Eeden, 2003). In brief, H(X) is the entropy of a single distribution (X), given by:

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

where Pi(x) =ni/N

s= distinct modes

H has a value of 0 when the whole frequency is concentrated in a single modality. H gradually increases values as the heterogeneity of the modalities increases up to the maximum of: Max H=log s when there are s distinct modes all with the same absolute frequency N/s. The relative entropy index is:

$$H = \frac{H(x)}{logs} \qquad (3)$$

The correlation coefficient of Pearson between relative indices of entropy in quantum technologies and their scientific age starting from the first scientific document to 2023 (year of the current analysis) suggests the direction of the association. Moreover, simple regression analysis is applied to show a preliminary estimated relationship, using ordinary least squares method, based on inverse model given by:

$$y=\alpha+\beta(1/x) \quad (4)$$

The study also applies the variance decomposition analysis (cf., Gibbons et al., 2014) to analyze the total variance (and therefore the variability) in relation to that of the more homogeneous subgroups (four classes of quantum technologies here). This approach can clarify the search of factors that affect the inequality in statistical units considering the contribution to total deviance (note that deviance is the numerator of variance in eq. 1 above). Finally, in order to verify whether the entity of the deviance between groups is significantly greater than the deviance obtained as a result of the sample fluctuations, it can be compared with the deviance within groups . This statistical analysis is done with the ANOVA ("Analysis Of Variance") F-test.

3. Results

Table 1 shows that quantum optics has a higher concentration of occurrences in research topics (lower relative entropy), whereas Quantum sensing has higher heterogeneity of these occurrences in manifold research topics (higher relative entropy). This result can be due to the scientific age of quantum sensing that is shorter (23 years) than quantum optics that has an evolutionary period of 65 years. Moreover, higher heterogeneity suggests that younger research field has to stabilize the technological trajectories and directions in evolutionary patterns (Dosi, 1988, 1988a).

Table 1. Relative entropy between quantum technologies, and related scientific age

	N	Arithmetic mean	Std. Deviation	Relative H	year of the first scientific product	Scientific age in 2023
Quantum Optics	154	1480.48	4235.48	0.827	1958	65
Quantum Metrology	154	54.04	113.00	0.853	1972	51
Quantum Imaging	152	21.29	42.10	0.866	1996	27
Quantum Sensing	153	41.36	46.59	0.925	2000	23

Table 2 shows r=–0.951 (p-value 0.05): a negative association between relative entropy and scientific age in classes of quantum technologies under study: i.e., younger technologies have a higher entropy index, suggesting a higher heterogeneity of the frequency of occurrences between manifold research topics.

Table 2. Bivariate Correlation between relative entropy and scientific age in quantum technologies

		Relative Entropy, H	Scientific Age of Quantum Technology
Pearson Correlation, r	Relative Entropy, H	1	–0.951*
Sig. (2-tailed)			0.049
N	4		4

* Correlation is significant at the 0.05 level (2-tailed).

Table 3 shows analysis of regression of a preliminary estimated relationship with inverse model concerning entropy on scientific age. Although R^2 is very high, showing a high goodness of fit of the inverse model, coefficient of regression β is not significant because of limited sample. Hence, this analysis provides an approximation of the possible inverse relationship between scientific age of technology and relative entropy that measures indeterminacy and variability of research topics within technologies that are driving evolutionary patterns.

 doi:10.20944/preprints202312.0187.v1

Table 3. Parametric estimates of the relationship with inverse model

Explanatory variable: 1/ scientific age of quantum technology				
Dependent variable	Constant α	Coefficient β	R^2	*F*
Relative Entropy H	78.90***	272.73	.80	7.95

Note: *** p<0.001.

Table 4 shows the deviance decomposition between groups of quantum technologies under study. Results suggest that 91.74% of statistical deviance is within groups, whereas 8.26% is between groups. Although the deviance within groups clearly prevails, the deviance between the groups assumes a non-negligible value. Deviance between groups can be the consequence of the diversity of averages and stand. deviation between the groups of quantum technologies under study, associated with different scientific ages, which lead some technologies to have more occurrences and others (more recently originated fields) to have less ones. Finally, the One-Way ANOVA between groups of quantum technologies shows a high value of F-test that leads to a significance level of 0.001. Therefore, the analysis of the deviance decomposition and ANOVA suggest that the between-group variability is unlikely to be due to circumstances related to the data collection. This result suggests a systematic effect of the nature of specific fields in quantum technology that generates a greater or lesser heterogeneity and diversity of the frequency of occurrences in different research topics during the evolutionary paths of the technologies themselves. *Hence, sources of the variability between research fields can be the specific nature of research fields, their scientific age and magnitude (amount) of scientific production over time.*

Table 4. Deviance decomposition in groups of quantum technologies in percent value and ANOVA

Nature of variability (Deviance)	%	degrees of freedom	F-test	p-value (significance)
BETWEEN GROUPS	8.26	3	18.29	0.001
WITHIN GROUPS	91.74	609		
TOTAL	100	612		

4. Scientific explanation

The study of the variability within scientific and technological pathways can show main characteristics and properties of the dynamics of evolution. Higher variability indicates higher dispersion of values in evolutionary patterns, and in the case of quantum technologies, high variability, measured with relative entropy, reveals that statistical units (occurrences of research topics in scientific documents) of these technologies have a low homogeneity between research topics. This study of the variability is the basis of the scientific investigation of the causes underlying higher or lower dispersion in relation to the nature of the research fields driving technological evolution. The different variability of the observed occurrences in research topics can be used to characterize the specificity of technologies and their evolutionary patterns. Moreover, higher variability, such as in the case of quantum sensing, also indicates a limited possibility of generating reliable technological forecasting, unlike quantum optics that is a more mature research field. In short, results suggest that a high variability in some technologies is a sign of various underlying causes (of random or systematic nature) that affect in different ways the evolutionary patterns. The method of investigation here, based on generalized Darwinism, can suggest basic driving forces of scientific variability driving technologies given by:

- The specificity of the technologies. If the technological nature is more oriented to be a general purpose technology for other inter-related technologies, such as quantum sensing rather than quantum optics, the endogenous variability within the complex system of technology can be higher, suggesting the indeterminacy in evolutionary trajectories and related technological forecasting (Coccia, 2020).

- Scientific age of the scientific production: a shorter age induces a higher variability than technologies having a longer scientific age.
- The accumulation of scientific knowledge (papers) is also a factor determining variability because a lower accumulation of scientific products in younger research fields induces a higher variability and uncertainty in technological trajectories, whereas a higher accumulation of scientific outputs is associated with lower variability in mature (older) technologies.

These results show that the variation can be due to manifold sources. A mechanism determining the variation in just mentioned factors is the change of scientific and technological ecosystem in which scientific research and technologies develop. Moreover, internal mechanisms of variation in technologies can be associated with external mechanisms of variation, such as interaction of different research topics associated with technologies during evolutionary pathways (cf., Ke, 2023). Variability of technologies and in this case of quantum technology has a primary source in the behaviour of technologies that cannot survive and develop as independent systems *per se*, but they can function and evolve in environments in which interact with other inter-related technologies (Coccia and Watts, 2020). Coccia (2018) systematizes this general behaviour of technologies and sources of technological variability with the *theorem of not independence of any technology (Coccia, 2018)*: the long-run behavior and evolution of any technological innovation Ti is not independent from the behavior and evolution of the other technological innovations Tj, $\forall i = 1, \dots, n$ and $j = 1, \dots, m$

Hence, technological interaction in the technological development can be a main source of spatial and temporal variability associated with different relationships between technologies given by (Coccia, 2019): technological parasitism, technological commensalism, technological mutualism and technological symbiosis. In fact, interaction between technologies generates a source of variability leading to coevolution of interrelated technological systems (cf., May, 1981). Hence, some technological variations depend more on the nature of the technology than on the nature of the conditions of ecosystem, but general changes in the conditions of ecosystem trigger scientific and technological variation. This result has a *complementary implication*: if it were possible to expose all technologies over time to absolute uniform environmental conditions, *without* interaction, there would be no variability. Or conversely, if there is variability, technology has to be necessarily exposed to changes in the conditions of ecosystem and interactions between technologies (cf., Coccia and Watts, 2020; Winther, 2000). In addition, changes in the stage of development are necessary conditions to induce variation: in the initial stage of development, variation tends to be high (e.g., in quantum sensing) with manifold potential emerging trajectories; in a stage of advanced development, when technology has a more stable evolutionary structure, variability tends to be lower (e.g., quantum optics). Finally, as mentioned before, with uniform conditions of development and without interactions between technologies, there is no variation and consequential coevolutionary patterns of growth (Coccia, 2019; Tolcheev, 2018; Jang et al., 2022; Winther, 2000).

In general, results here, with the analysis of the variance decomposition, show that variation is due to systematic characteristics of the nature of technology and unsystematic characteristics in innovation ecosystem, such as changes and random technological interaction with other technologies. In brief, the causes of variation in technologies that generate main evolutionary shifts can be: changes in the conditions of ecosystem; the nature of the technology can be more important than the nature of the changed ecosystem in determining the nature of the variation and co-evolution, and finally a larger proportion of variation in technologies is systematic and adaptive in changing socioeconomic systems (Coccia and Watts, 2020).

Principal theoretical implications

These results suggest some properties of variation in science that can contribute to explain the evolution of technologies and support technological forecasting for guiding R&D investments and management of technology for industrial and economic change:

Property 1. the growth of variability in research topics driving the evolution of technologies is inversely proportional to the age of research fields: younger technologies have a higher variability between research topics, whereas older technologies have a lower heterogeneity and more concentration of values in vital research topics suggesting stable evolutionary patterns. The inverse relation can be expressed with the following equation y=α + β (1/x). By using the four technologies under study and empirical value of relative entropy % and scientific age of four research fields in years presented in Table 3, the estimated model is (*law of variability in science guiding technological evolution*):

$$Entropy\ (H\%) = \alpha + \beta\left(\frac{1}{x}\right) \quad = 78.90 + 272.73\left(\frac{1}{age\ of\ scientific\ field}\right)^{.08} \quad R^2 = 0.80$$

Property 2. The nature of research fields has systematic effects in driving technological variability and evolution of technology.

Property 3. Technological life cycles produce similar life cycles unless there are changes in ecosystem leading to technological interaction with other technologies, which generates variability and co-evolutionary patterns.

Property 4. Variation in technologies is due to changes in their related ecosystem, interactions between technologies and transformation of socioeconomic system.

Property 5. The accumulation of scientific knowledge is a factor affecting variability in scientific fields driving technologies: low accumulation of scientific products in emerging technologies induces a higher variability and indeterminate evolutionary pathways of technological trajectories, whereas a higher accumulation of scientific outputs in older research field is associated with a lower variability and more stable evolution of main technological trajectories.

5. Conclusions and Prospects

This study shows for the first time, to my knowledge, an analysis of variation within scientific domains to explain some properties of evolutionary pathways in technologies.. The broad analogy between evolutionary ecology and technological evolution, within a Generalized Darwinism, applied here keeps its validity in explaining the variability within and between research topics to clarify some aspects of technological evolution. However, the idea presented in the study here is adequate in some cases but less in others because of the diversity of technologies, their intrinsic nature and propensity of interaction in different complex systems and socioeconomic environments. These findings here can encourage further theoretical exploration in the terra incognita of the variability in scientific fields to clarify basic properties of technological evolution. The case study of quantum technologies shows different magnitude of variability driven by changes in endogenous dynamics and structure of innovation ecosystem over time (Coccia and Watts, 2020; Sun et al., 2013). Evidence suggests that a lower variability is associated with technologies having a longer scientific age, whereas technologies with a shorter scientific age, they have a higher variability that suggests a not clear direction of technological trajectories. Policymakers and R&D managers can use the findings here for making efficient decisions regarding R&D investments of specific technological trajectories (Coccia, 2022; Roshani et al., 2021; Mosleh et al., 2022).

These conclusions are, of course, tentative. This study provides some interesting but preliminary results in these complex fields of research related to the evolution of emerging technologies. Some limitations are that: 1) scientific outputs and research topics can only detect certain aspects of the ongoing dynamics of quantum research and technology and next study should apply complementary analysis based on patents for improving results and managerial implication also for technological foresight; 2) confounding factors (e.g., level of public and private R&D investments, international collaboration in specific quantum technologies, etc.) affect the evolution of quantum technologies and these aspects have to be considered in future studies to improve data gathering for new technological analyses; 3) An aspect to further investigate is the constraints on variation that technologies have during the adoption; finally, 4) model and estimated relationship between variability and scientific age have to be improved with more data to have robust statistical analyses. In short, there is need for much more detailed research into the investigation of the role of variability to clarify evolutionary patterns of technologies and support implications for innovation management and technological forecasting.

Despite these limitations, the study here clearly illustrates that a different variability can clarify basic characteristics of the technological change. To conclude, the proposed theoretical framework here based on analogy of scientific and technological evolution with some evolutionary aspects present in ecology and biology may lay the foundation for development of more sophisticated concepts and theoretical frameworks in economics of technical change to explain and forecast science dynamics and technological evolution.

Author Contribution: Mario Coccia has developed the conceptualization; methodology; software; validation; formal analysis; investigation.; resources; data curation; writing—original draft preparation.; writing—review and editing; visualization; supervision; project administration.

Funding: "This research received no external funding".

Institutional Review Board Statement: "Not applicable"

Informed Consent Statement: "Not applicable."

Data Availability Statement: Data are available on motivated request.

Acknowledgments: We would like to thank Marco Genovese and all participants to the seminar held at INRiM - National Metrology Institute of Italy (Torino) on 11 May, 2023. All data are available on Scopus (2023). The author declares that he is the sole author of this manuscript, and he has no known competing financial interests or personal relationships that could influence the work reported in this paper. This study has no funders.

Conflicts of Interest: "The author declares no conflict of interest".

References

Acín, A.; Bloch, I.; Buhrman, H.; Calarco, T.; Eichler, C. et al. 2018. The quantum technologies roadmap: A European community view. In: New Journal of Physics 20, Nr. 8, 80201. DOI: https://doi.org/10.1088/1367-2630/aad1ea

Ackoff R. L. 1971. Towards a system of systems concepts. Management Science, 17 (11), pp. 661-671.

Al-Betar, M.A., Abasi, A.K., Al-Naymat, G. et al. 2023. Optimization of scientific publications clustering with ensemble approach for topic extraction. Scientometrics 128, 2819–2877). https://doi.org/10.1007/s11192-023-04674-w

Altuntas S., Aba S. 2022. Technology Forecasting of Unmanned Aerial Vehicle Technologies through Hierarchical S-Curves¸ Defence Science Journal, Vol. 72, No. 1, January 2022, pp. 18-29, DOI : 10.14429/dsj.72.16823

Altuntas, F., Gök, M.Ş. 2021. Analysis of patent documents with utility mining: A case study of wind energy technology. Kybernetes, 50(9), 2548-2582. doi: 10.1108/K-06-2020-0365.

Arthur B. W. 2009. The Nature of Technology. What it is and How it Evolves. Free Press, Simon & Schuster, London.

Atik, J., Jeutner, V. 2021. Quantum computing and computational law. Law, Innovation and Technology, in Press

Barton C. M. 2014. Complexity, Social Complexity, and Modeling. Journal of Archaeological Method and Theory, 21 (2), pp. 306–324, DOI 10.1007/s10816-013-9187-2

Basalla G. 1988. The History of Technology. Cambridge University Press, Cambridge.

Batra, K., Zorn, K.M., Foil, D.H., (...), Lane, T.R., Ekins, S. 2021. Quantum Machine Learning Algorithms for Drug Discovery Applications, Journal of Chemical Information and Modeling, 61(6), pp. 2641-2647

Coccia M., Benati I. 2018. Comparative Evaluation Systems, A. Farazmand (ed.), Global Encyclopedia of Public Administration, Public Policy, and Governance, Springer Nature, https://doi.org/10.1007/978-3-319-31816-5_1210-1

Bowler, P. (2005). Variation from Darwin to the Modern Synthesis. 10.1016/B978-012088777-4/50004-1.

Brandon R. N. 1978. Adaptation and Evolutionary Theory. Stud. Hist. Phil. Sci. 9 (3), pp. 181-206.

Bryan A., Ko J., Hu S. J., Koren Y. 2007. Co-Evolution of Product Families and Assembly Systems, CIRP Annals, vol. 56, n. 1, pp. 41-44, https://doi.org/10.1016/j.cirp.2007.05.012

Carberry D., Nourbakhsh A., Karon, J., (...), Andersson, M.P., Mansouri, S.S.2021. Building Knowledge Capacity for Quantum Computing in Engineering Education, Computer Aided Chemical Engineering 50, pp. 2065-2070

Chen C., G. Zeng, F. Lin, Y. Chou and H. Chaoì 2015. Quantum cryptography and its applications over the internet, IEEE Network, vol. 29, no. 5, pp. 64-69, doi: 10.1109/MNET.2015.7293307.

Coccia M. 2018. General properties of the evolution of research fields: a scientometric study of human microbiome, evolutionary robotics and astrobiology, Scientometrics, vol. 117, n. 2, pp. 1265-1283, https://doi.org/10.1007/s11192-018-2902-8

Coccia M. 2020. The evolution of scientific disciplines in applied sciences: dynamics and empirical properties of experimental physics, Scientometrics, n. 124, pp. 451-487. https://doi.org/10.1007/s11192-020-03464-y

Coccia M. 2022. Probability of discoveries between research fields to explain scientific and technological change. Technology in Society, vol. 68, February, n. 101874, https://doi.org/10.1016/j.techsoc.2022.101874

Coccia M., Watts J. 2020. A theory of the evolution of technology: technological parasitism and the implications for innovation management, Journal of Engineering and Technology Management, vol. 55, n. 101552, https://doi.org/10.1016/j.jengtecman.2019.11.003

Dawkins R. 1983. Universal Darwinism. In: Bendall, D.S. (ed.), Evolution from Molecules to Man. Cambridge University Press, Cambridge, pp. 403 - 425.

Dosi G. 1988a. The Nature of the Innovation Process. In G. Dosi, C. Freeman, R. Nelson, G. Silverberg, & L. Soete (Eds.), Technical Change and Economic Theory (pp. 221-238). London: Pinter.

Dosi, G. 1988. Sources, Procedures, and Microeconomic Effects of Innovation. Journal of Economic Literature, Vol. XXVI (September 1988), pp. 1120-1171

Dowling J. P., Milburn G. J. 2003. Quantum technology: the second quantum revolution. Phil. Trans. R. Soc. A.3611655–1674http://doi.org/10.1098/rsta.2003.1227

Erwin D. H., Krakauer D. C. 2004. Evolution. Insights into innovation. Science, 304 (5674), pp. 1117-9.

Gibbons S., Overman H. G., Pelkonen P. 2014. Area Disparities in Britain: Understanding the Contribution of People vs. Place Through Variance Decompositions. Oxford Bulletin of Economics and Statistics, 2014, vol. 76, issue 5, 745-763

Gill, Sukhpal Singh & Kumar, Adarsh & Singh, Harvinder & Singh, Manmeet & Kaur, Kamalpreet & Usman, Muhammad & Buyya, Rajkumar. (2022). Quantum Computing: A Taxonomy, Systematic Review and Future Directions. Software: Practice and Experience. 52. 10.1002/SPE.3039.

Gini, C. 1912. Variabilità e mutabilità. Contributo allo Studio delle Distribuzioni e delle Relazioni Statistiche (C. Cuppini, Bologna, 1912).

Girone G., Salvemini T. (1981) Lezioni di statistica, vol. I and II, Cacucci Editore, Bari.

Glänzel, W., Thijs, B. Using 'core documents' for detecting and labelling new emerging topics. Scientometrics 91, 399–416 (2012). https://doi.org/10.1007/s11192-011-0591-7

Grupp, H. 1990. The concept of entropy in scientometrics and innovation research. Scientometrics 18, 219–239 (1990). https://doi.org/10.1007/BF02017763

Hodgson G. M. 2002. Darwinism in economics: from analogy to ontology. Journal of Evolutionary Economics, vol. 12, pp. 259–281.

Hodgson G. M., Knudsen T., 2006. Why we need a generalized Darwinism, and why generalized Darwinism is not enough. Journal of Economic Behavior and Organization 61(1), pp. 1-19.

Hodgson G. M., Knudsen T., 2008. In search of general evolutionary principles: Why Darwinism is too important to be left to the biologists. Journal of Bioeconomics, 10(1), pp. 51- 69.

Iacopini I., Milojević S., Latora V. 2018. Network Dynamics of Innovation Processes, Phys. Rev. Lett. Vol. 120, n. 048301, pp. 1-6, https://doi.org/10.1103/PhysRevLett.120.048301

Jang, B., Choung, JY. & Kang, 2022. I. Knowledge production patterns of China and the US: quantum technology. Scientometrics 127, 5691–5719

Jost, L. 2006. Entropy and diversity. Oikos, 113(2), 363–375.

Kauffman S., Macready W. 1995. Technological evolution and adaptive organizations: Ideas from biology may find applications in economics. Complexity, 1(2), pp. 26–43. DOI: 10.1002/cplx.6130010208

Ke, Q. 2023. Interdisciplinary research and technological impact: evidence from biomedicine. Scientometrics 128, 2035–2077. https://doi.org/10.1007/s11192-023-04662-0

Kozlowski, W., & Wehner, S. (2019). Towards large-scale quantum networks. In C. Contag, & T. Melodia (Eds.), Proceedings of the 6th ACM International Conference on Nanoscale Computing and Communication, NANOCOM 2019 [3345497] (Proceedings of the 6th ACM International Conference on Nanoscale Computing and Communication, NANOCOM 2019). Association for Computing Machinery (ACM). https://doi.org/10.1145/3345312.3345497

Latifian, A. 2022. How does cloud computing help businesses to manage big data issues, Kybernetes. Article in Press

Levit G., Hossfeld U., Witt U. 2011. Can Darwinism be "Generalized" and of what use would this be? Journal of Evolutionary Economics, 21(4), pp. 545-562

Lin D., Liu W., Guo Y., Meyer M. 2021. Using technological entropy to identify technology life cycle, Journal of Informetrics, 15(2),101137

Lin, Deming & Liu, Wenbin & Guo, Yinxin & Meyer, Martin, 2021. Using technological entropy to identify technology life cycle. Journal of Informetrics, , vol. 15(2). https://doi.org/10.1016/j.joi.2021.101137

May R. M. 1981. Models for two interacting populations. In May R. M., ed., Theoretical ecology: principles and applications, second edition, Sinauer.

Mazzolini A., Grilli J., De Lazzari E., Osella M., Cosentino Lagomarsino M., Gherardi M. 2018. Zipf and Heaps laws from dependency structures in component systems, Phys. Rev. E 98, 012315 – https://doi.org/10.1103/PhysRevE.98.012315

McNerney J., Farmer J. D., Redner S., Trancik J. E. 2011. Role of design complexity in technology improvement. Proceedings of the National Academy of Sciences, 108 (22), pp. 9008-9013. DOI: 10.1073/pnas.1017298108

Mosleh M., Roshani S., Coccia M. 2022. Scientific laws of research funding to support citations and diffusion of knowledge in life science. Scientometrics. DOI: 10.1007/s11192-022-04300-1

Natural Geographic 2023. Natural selection. https://education.nationalgeographic.org/resource/natural-selection/ (Accessed June 2023)

Nelson R. 2006. Evolutionary social science and universal Darwinism. Journal of Evolutionary Economics, 16 (5), pp. 491-510.

Nunes, A., Trappenberg, T., & Alda, M. (2020). The definition and measurement of heterogeneity. Translational psychiatry, 10(1), 299. https://doi.org/10.1038/s41398-020-00986-0

Oppenheimer R. 1955. Analogy in science. Sixty-Third Annual Meeting of the American Psychological Association, San Francisco, California, September 4.

Pande, M., Mulay, P. 2020. Bibliometric Survey of Quantum Machine Learning. Science and Technology Libraries 39(4), pp. 369-382

Pistorius C.W.I., Utterback J.M., 1997. Multi-mode interaction among technologies. Research Policy, vol. 26, n.1, pp. 67–84.

Rao P., Yu K., Lim H., Jin D., Choi D. 2020. Quantum amplitude estimation algorithms on IBM quantum devices. Proceedings of SPIE - The International Society for Optical Engineering 11507,115070O

Rényi, A. 1961. On measures of information and entropy. Proc. Fourth Berkeley Symp . Math., Stat. Probab. 114, 547–561 (1961)

Roshani S., Bagheri R., Mosleh M., Coccia M. 2021. What is the relationship between research funding and citation-based performance? A comparative analysis between critical research fields. Scientometrics. https://doi.org/10.1007/s11192-021-04077-9

Sahal D. 1981. Patterns of Technological Innovation. Addison-Wesley Publishing Company, Inc., Reading, Massachusetts.

Sandén B. A., Hillman K. M. 2011. A framework for analysis of multi-mode interaction among technologies with examples from the history of alternative transport fuels in Sweden. Research Policy, vol. 40, n.3, pp. 403-414.

Scheidsteger, T., Haunschild, R., Bornmann, L., Ettl, C. 2021. Bibliometric analysis in the field of quantum technology.Quantum Reports, 3(3), pp. 549–575

Schubert C. 2014. "Generalized Darwinism" and the quest for an evolutionary theory of policy-making. Journal of Evolutionary Economics, 24 (3), pp. 479-513.

Schuster P. 2016. Major Transitions in Evolution and in Technology. Complexity, 21(4), pp. 7-13, DOI 10.1002/cplx.21773

Scopus 2023. Start exploring. Documents. https://www.scopus.com/search/form.uri?display=basic#basic (accessed April 2023).

Shannon C.E. (1948). Mathematical Theory of Communication. Bell System Technical Journal. 27 (3): 379–423.

Simon H. A. 1962. The architecture of complexity. Proceeding of the American Philosophical Society, 106(6), pp. 476-482.

Simpson, E. 1949. Measurement of diversity. Nature 163, 688. . https://doi.org/10.1038/163688a0

Smith D. C. 1991. Preface. In Symbiosis as a source of evolutionary innovation, edited by Lynn Margulis and René Fester, The MIT Press, Cambridge (MA).

Solé R. V., Valverde S., Casals M. R., Kauffman S. A., Farmer D., Eldredge N. 2013. The Evolutionary Ecology of Technological Innovations, Complexity, vol. 18, n. 4, pp. 25-27, DOI: 10.1002/cplx.21436

Stoelhorst J.W. 2008. The Explanatory Logic and Ontological Commitments of Generalized Darwinism. Journal of Economic Methodology, 15(4), pp. 343-363.

Coccia M. 2021. Comparative Hypotheses of Scientific Development. J. Econ. Soc. Thoug. vol. 7, n. 3, pp. 153-180

Sun X., Kaur, J., Milojevic' S., Flammini A., Menczer F. 2013. Social Dynamics of Science. Scientific Reports, vol. 3, n. 1069, pp. 1-6, doi:10.1038/srep01069.

Takahashi, R., Kaibe, K., Suzuki, K. et al.2023. New concept of the affinity between research fields using academic journal data in Scopus. Scientometrics 128, 3507–3534. https://doi.org/10.1007/s11192-023-04711-8

Tolcheev, V.O. 2018. Scientometric Analysis of the Current State and Prospects of the Development of Quantum Technologies. Autom. Doc. Math. Linguist. 52, 121–133 (2018). https://doi.org/10.3103/S000510551803007X

Tria F., Loreto V.; Servedio V. D. P., Strogatz S. H. 2014. The dynamics of correlated novelties, Scientific Reports, vol. 4, number: 5890, pp. 1-8, | DOI: 10.1038/srep05890

 doi:10.20944/preprints202312.0187.v1

Utterback J. M., Pistorius C., Yilmaz E. 2019. The Dynamics of Competition and of the Diffusion of Innovations. MIT Sloan School Working Paper 5519-18. Last Revised February 20, 2019

Vespignani A. 2009. Predicting the behavior of techno-social systems. Science, vol. 325, 425–428. DOI: 10.1126/science.1171990

Wagner A., Rosen W. 2014. Spaces of the possible: universal Darwinism and the wall between technological and biological innovation. Journal of the Royal Society Interface, 11, pp.1-11.

Winther, R. G. (2000). Darwin on Variation and Heredity. Journal of the History of Biology, 33(3), 425–455. http://www.jstor.org/stable/4331610

Wright G. 1997. Towards A More Historical Approach to Technological Change, The Economic Journal, vol. 107, September, pp. 1560-1566.

Zhang, T., Lee, B., Zhu, Q. et al. 2023. Document keyword extraction based on semantic hierarchical graph model. Scientometrics 128, 2623–2647. https://doi.org/10.1007/s11192-023-04677-7

Zidek, J. V., & van Eeden, C. 2003. Uncertainty, Entropy, Variance and the Effect of Partial Information. Lecture Notes-Monograph Series, 42, 155–167. http://www.jstor.org/stable/4356236

Ziman J. (ed.) 2000. Technological innovation as an evolutionary process. Cambridge University Press, Cambridge, MA.