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Converging Artificial Intelligence and Quantum Technologies: Accelerated Growth Effects in Technological Evolution

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Abstract: One of the fundamental problems in the field of technological studies is to clarify the drivers and dynamics of technological evolution for sustaining industrial and economic change. This study confronts the problem by analyzing the converging technologies to explain effects on the evolutionary dynamics over time. This paper focuses on technological interaction between artificial intelligence and quantum technologies using a technometric model of technological evolution based on scientific and technological information (publications and patents). Findings show that quantum technology has a growth rate of 1.07, artificial intelligence technology has a rate of growth of 1.37, whereas the technological interaction of converging quantum and artificial intelligence technologies has an accelerated rate of growth of 1.58, higher than trends of these technologies taken individually. These findings suggest that technological interaction is one of the fundamental determinants in the rapid evolution of path-breaking technologies and disruptive innovations. The deductive implications of results about the effects of converging technologies are: (a) accelerated evolutionary growth; (b) a disproportionate (allometric) growth of patents driven by publications supporting a fast technological evolution. Our results support policy and managerial implications for the decision making of policymakers, technology analysts, and R&D managers that can direct R&D investments towards fruitful inter-relationships between radical technologies to foster scientific and technological change with positive societal and economic impcats.

Keywords: quantum technologies; artificial intelligence; technological trajectories; technological interaction; technological evolution; technometrics; technological change; radical technologies; disruptive innovations; converging technologies; R&D management; innovation management

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1. Introduction and Investigation Goal

One of the fundamental problems in science is how a scientific field and related technology evolve and sustain radical scientific and technological change [1–19]. The evolution of new research fields and path-breaking technologies, such as ICTs, nanotechnology, quantum computing, etc., can generate a convergence of fields and technologies that supports disruptive innovations with unparalleled effects in science and society [20–29].

This paper endeavors to analyze the interaction between research fields and path-breaking technologies to assess patterns of growth that clarify the dynamics of technological evolution and sources of scientific and technological change [5,11,30–35]. The development of this study flows from a recognition that research scientists have performed less well in the understanding of how and why certain scientific fields and technologies evolve in the presence of interaction mechanisms [29,36,37]. Kuhn [16] has inspired many theories of scientific development with the notion of paradigm shifts and Lakatos [17] with the management of research programs. Some theories of science development explain the evolution of fields with branching mechanisms, caused by new discoveries [36–40], specialization or merging of different research fields [25,36], or converging disciplines and/or technologies [41]. Other models focus on the synthesis of elements in pre-existing disciplines [42]. Some models point to the self-organizing development of science [43]. Other studies show that the evolution of research fields and technologies is guided by social interactions among scientists within an invisible college [29,44,45] or technological interactions of different systems [32,46–49].

Despite the vast literature, quantitative works on the effects of interaction between emerging research fields and path-breaking technologies are lacking, to date. In particular, how the interaction of research fields can affect patterns of technological growth is a topic hardly known. This paper endeavors to analyze technological interaction and convergence to explain the symbiotic co-evolution of research fields and technologies and consequential scientific, technological, and social change. In particular, this study develops a statistical analysis that focuses on two emerging research fields and technologies given by artificial intelligence technology, in short, AI (the application of computer systems to mimic the problem-solving and decision-making capabilities of the human mind; [50]) and quantum technology, which applies the principles of quantum mechanics—the physics of sub-atomic particles—and has the potential to improve computing and communication technologies with manifold applications [50–56]. The study is based on a large dataset of publications and patents for technometric analyses that show how these research fields and new technologies evolve independently and with interaction processes of convergence [22,57,58]. This study is especially relevant in the presence of innovation-based competition and of processes of 'creative destruction' to clarify sources and dynamics of path-breaking technologies having a high potential of growth to support future industrial and economic change.

2. Theoretical Framework for Scientific Investigation

Artificial intelligence and quantum technologies are new technological systems and a theoretical background on these disruptive technologies can clarify the research context of this study. A destructive technology is a system that generates radical innovations (new products and/or processes), which, with high technical and/or economic performance, destroys the usage value of established techniques previously sold and used in markets, supporting technological, industrial, economic, and social change [59–64]. Adner [65] argues that "disruptive technologies introduce a different performance package from mainstream technologies and are inferior to mainstream technologies along the dimensions of performance that are most important to mainstream customers". Calvano [66] suggests the concept of "destructive creation", in which "a monopolist has the option, at the beginning of each period, to destroy the usage value of all units previously sold and simultaneously introduce a new one". Christensen [67] identifies disruptive technology with specific characteristics: (a) the performance trajectory provided by disruptive technology and (b) the performance trajectory demanded by the mainstream market (cf. also [68]).

Quantum and artificial intelligence technologies are vital disruptive technologies for their radical effects on technological, economic and social systems [25,26,69]. Artificial intelligence (AI) technology is based on complex software and algorithms for devices that foster learning processes from data, information, and experience, adjust and change to new inputs and perform human-like tasks for supporting the effective decision making of people/organizations. Artificial intelligence (AI) is a vast research field and complex technological system that includes different subsets [50]. A main subset in AI is machine learning, which develops algorithms and statistical models that computer systems use to effectively perform a specific task relying on patterns and inference (Figure 1). In machine learning systems, a main subfield is deep learning technology, which develops deep neural networks, recurrent neural networks, and convolutional neural networks for manifold fields, such as computer vision, speech recognition, natural language processing, audio recognition, social network filtering, bioinformatics, medical image analysis, material inspection, etc. [50]. Deep learning and natural language processing in AI technologies can be trained to accomplish specific tasks and problem solving activities by processing large amounts of data and information to recognize patterns and provide appropriate solutions [70].

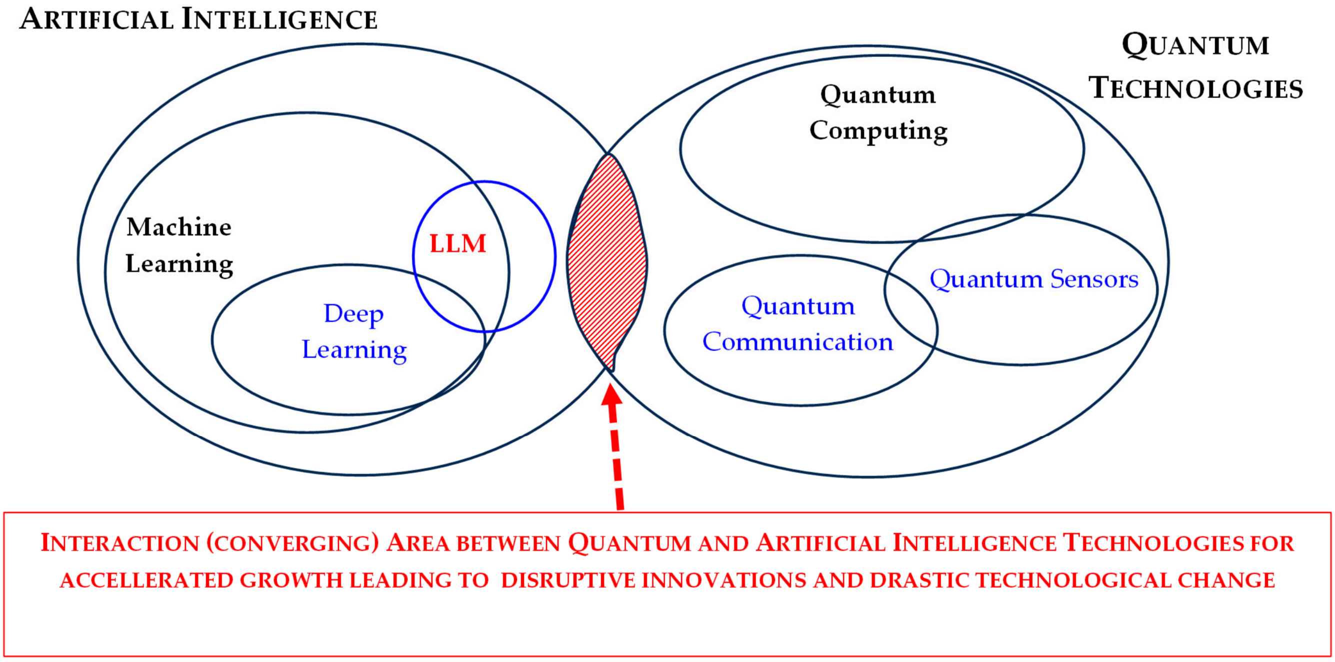

Figure 1. Area of the interaction between artificial intelligence and quantum technologies for promising path-breaking technologies and disruptive innovations. Note: Machine learning methods are a subset of artificial intelligence technology that develops algorithms directed to learn from data and generalize to unseen data, and, thus, performs tasks without explicit instructions. Deep learning techniques are a subset of machine learning methods that involves the use of neural networks to model and solve complex problems. Large language models (LLMs) are deep learning algorithms that can recognize, summarize, translate, predict, and generate content using large datasets. LLMs acquire these abilities by learning statistical relationships from text documents during a computationally intensive self-supervised and semi-supervised training process.

The other disruptive technology under study here is quantum technology. Acín et al. [51] argue that quantum technology includes quantum computation, quantum communication, quantum sensors, and sensing systems [25,26,35,38,39]. Aboy et al. [71] show that patents in quantum technology are largely clustered around six main areas: quantum circuits, quantum dot devices, quantum computing, quantum dot layers, quantum states, and quantum keys. Jiang and Chen [72] present a detailed categorization of quantum technologies, analyzing the patent landscape with a focus on key technological clusters and their rapid evolution. The study by McKinsey [73] shows that the industries with a potential economic impact from quantum computing are mainly the automotive industry, chemical industry, financial services, and life sciences; estimated gain can be about $1.3 trillion in value by 2035.

In this context, the technological interaction of path-breaking AI and quantum technologies can offer mutual and symbiotic advantages for parallel co-evolution having high levels of developments [32,33,46–49]. For instance, the combination of these technologies can be the application of AI methods to create quantum computing and quantum algorithms, as well as using quantum computing can improve many AI applications (Figure 1). Dong and Chen [74] show that the use of AI in association with the Internet of Things can improve the performance of both quantum computing and quantum communication. In addition, quantum computing may also be applied to improve different AI applications. A main instance of fruitful interaction between these radical technologies is higher efficacy and efficiency in criminal justice systems [74]. Zhou et al. [75] argue that the combination of AI and quantum technologies has potential applications in a wide range of fields, such as new AI systems that analyze large healthcare datasets ensuring privacy and security, as well as in quantum optical neural networks; the combination of qubits, optical elements, and conventional neural network layers supports functional AI systems in healthcare analytics and decision-making processes. Liu and Ren [76] maintain that multidisciplinary topics of quantum technologies span various domains, including quantum optics, quantum communication, and quantum cryptography to foster technology in sports based on healthcare artificial intelligence approaches. Overall, then, the interaction between quantum and artificial intelligence technologies can generate main technological shifts that revolutionize a number of industries.

Technology analysis of the interaction of new technologies is fundamental for explaining dynamics of technological evolution for improving technological forecasting that guides R&D investments towards promising innovations having industrial, economic, and social impact [33,48,77–79]. Studies show that the evolution of new technology is affected by many factors, such as the accumulation of knowledge in specific research fields, technological choice of leading firms and nations, application of new materials, social, economic, and political factors, etc. [80–82]. Researchers emphasize that the evolution of technologies is increasingly shaped by dynamic interaction among various technologies, leading to the co-evolution of technological trajectories [32,33,49,83,84]. In a broader perspective, technological evolution is due to scientific advancements, scientific changes, and related technological interactions [29,49]. The exploration of scientific development, which underlies technological change, is typically conducted through the analysis of publications [8,85]. Instead, the analyses of new technologies and path-breaking innovations are done with different approaches, such as Faust [86], who applied patent analysis and new indicators to detect the emergence and development of high-tech products. Jiang and Chen [72] explored the field of quantum technology using patent network analysis and showed the significance of quantum ecosystem, based on interconnected relations between infrastructure, networks of organizations, huma resources, etc. that facilitate the technological interaction and the emergence and development of technological trajectories generating transformative changes in industries and society [69,87]. Coccia [69], using publication and patent data, showed main technological trajectories in quantum computing and their rates of growth, which suggest path-breaking directions in quantum technology, such as quantum optics, quantum information, quantum algorithms, quantum entanglement, quantum communication, and quantum cryptography. Coccia et al. [25] showed that the evolution of quantum computing from 1990 to 2020 has had a considerable average increase of connectivity in the scientific network. This study also suggests that the network of quantum computing has a transition from hardware to software research, which supports accelerated evolution of technological pathways in quantum image processing, quantum machine learning, and quantum sensors.

However, studies of the interaction between quantum and artificial intelligence technologies to show the effects on the dynamics of scientific and technological development are scarce in the literature, also considering that rapid changes in economies continuously affect the dynamics of these radical technologies [23]. This study endeavors to cover this gap and analyzes patenting and publication activity of these drastic technologies and their related interaction to clarify the effects on evolutionary dynamics of scientific and technological development. The next section describes the data and methodology of this study, providing the basis for a technology analysis that extends theoretical and managerial perspectives on the critical drivers of technological evolution of emerging technologies in regimes of rapid changes.

3. Research Methodology

3.1. Sources of Data and Sample

The study uses data from Scopus [87], a multidisciplinary database covering journal articles, conference proceedings, letters, book chapters, and books. The Scopus [87] database also includes patent records from different patent offices worldwide. The window of "Search documents" in the Scopus [87] database online was used to identify scientific documents and patents having in article title, abstract, or keywords including the following terms, from the starting year until July 2023 (when data for this study were downloaded):

- ("quantum technology"), number of publications: 3989; number of patents: 6302, from 1988 to 2022.
- ("artificial intelligence"), number of publications: 463,512; number of patents: 239,210, from 1960 to 2022.
- Combined search: ("quantum" and "artificial intelligence"), number of publications: 60; number of patents: 447, from 2004 to 2022. This combination with the Boolean operator AND represents the interaction and convergence of these two research fields and path-breaking technologies given by quantum and AI technologies. The shorter period is due to the combination of different words in the search tool, which restricts the period, compared to each technology searched individually.

Scientific products and patents represent scientific and technological information and are the basic units of recorded knowledge for scientific and technology analyses, which can clarify the evolution and dynamics of science and technology [72,87–89]. Data did not include the year 2023 because it is ongoing when this research was in progress; this aspect did not affect the analysis of scientific and technological trends under study.

3.2. Measures of Variables

Scientific developments were investigated by considering:

- Number of articles and all scientific products using keywords or a combination of keywords with Boolean operators, as indicated above.

For the technology analysis, this study used patents that indicated inventions and potential innovations [89]:

- Number of patents using keywords or a combination of keywords with Boolean operators, as indicated for the related period.

3.3. Study Design: Technometric Modeling and Data Analysis Procedure for Statistical Experiment

The working hypothesis was that the interaction of scientific fields and related radical technologies increases the co-evolutionary dynamics of growth.

Firstly, trends of research field/technology i over time were analyzed with the following log-linear model:

$$log\ y_{i,t} = a + b{\cdot}t + u_{i,t} \tag{1}$$

where $y_{i,t}$ represents scientific products or patents, a is a constant, b is the coefficient of regression, t is the time in years, considering that data are updated annually in the database, $u_{i,t}$ is the error term, and i depicts technology (*log* has base e = 2.718281).

For a comparative analysis, data are represented over time in figure using a *log* scale on a y-axis.

Secondly, dynamics of research fields and technologies were analyzed with a technometric model in which the number of patents (Y) is a function of the number of scientific production (X) over time. This model measures how the production of publications supports patents' growth and explains the relative rate of combined scientific–technological evolution [82]. The structure of the model is as follows.

Let Y(t) be the advances of technology (e.g., in quantum technology) at the time t (years, considering the database), measured with patents, and X(t) be the scientific production underlying the advances of technology Y. Suppose that both X and Y evolve according to an *S*-shaped pattern that can be represented with a differential equation of logistic function. The logistic model generates a symmetrical *S*-shaped curve with a point of inflection at 0.5 K (the equilibrium level of growth). After some mathematical transformations [82], the differential equation of logistic function is a simple linear relationship (*log*–*log* model):

$$logY = logA + BlogX + \varepsilon \tag{2}$$

where Y represents patents, and the response variable, A is a constant, B is the evolutionary coefficient of growth, X is the scientific production (driver or explanatory variable), and ε the error term (*log* has base $e = 2.718281$).

The coefficient of relative growth B in the model (2) indicates different pathways of technological evolution:

If $B < 1$, it implies that Y (patents) evolves at a lower relative rate of change than X (scientific production); the whole scientific–technological system has a slowing evolution over the course of time. This is referred to as negative allometric growth.

If $B = 1$, then Y and X (patents and publications) have a proportional evolution over time (pathway of proportional growth).

If $B > 1$, then Y evolves at greater relative rate of change than X; the scientific–technological system has an accelerated (disproportionate) evolution of patents Y compared to publications X over the course of time. This is referred to as positive allometric growth.

The models (1) and (2) were estimated using the Ordinary Least Squares (OLSs) method, which determines the unknown parameters in regression models. Statistical analyses were performed with the IBM SPSS Statistics Software®, version 26.

4. Results and Analysis of Findings

Firstly, data were transformed into a logarithmic scale to ensure normality in the distribution of variables for appropriate parametric analyses and robust results.

Table 1 shows that dynamics of quantum technologies, measured with scientific information, have a rate of growth of 0.21 (p-value = 0.001), artificial intelligence technology has also a significantly high growth rate of 0.16. The combination of these two technologies shows the fruitful effects on the evolutionary trend of scientific information in artificial intelligence through the interaction with quantum technologies over time: rate of growth is 0.17 (p-value = 0.001). The F-test of models is highly significant (p-value = 0.001) for each technology, respectively, whereas their interaction is significant, with a p-value = 0.005. The coefficient of determination R^2 shows a high goodness of fit in the range between 61% and 93%.

Table 1. Estimated relationships of scientific publications as a function of time (years).

Dependent Variable: Scientific Products				
	Coefficient b	**Constant a**	**F**	R^2
Quantum technology, Log y pubs	0.206 ***	−410.73 ***	370.47 ***	0.93
Artificial intelligence technology, Log y pubs	0.155 ***	−301.58 ***	720.43 ***	0.92
Artificial intelligence and quantum technology, Log y pubs	0.172 **	−345.00 **	14.89 **	0.61

Note: The explanatory variable is the time in years. b is the coefficient of regression and a is the constant from Equation (1). The interpretation of the estimated coefficient b (from Equation (1)) is that a one-unit increase in X will produce an expected increase in log Y of b units. In terms of Y itself, this means that the expected value of Y is multiplied by e^{b}. *** significant at 1‰; ** 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 (goodness of fit).

Table 2, based on the technological information of patents, shows higher coefficients of regression, which indicate higher rates of growth in technological trajectories: quantum technologies have a rate of growth of 0.22 (p-value = 0.001), artificial intelligence technologies also have a significantly high growth rate of 0.20 (p-value = 0.001). The convergence of these two technologies generates a fruitful technological interaction in the evolutionary trend of patents that has a rate of growth that nearly doubles, achieving almost 0.42 (p-value = 0.05). The F-test of models indicates the ratio of variance explained by the model to unexplained variance, and is significant (p-value = 0.001 and 0.05). Finally, the coefficient of determination R^2 shows a very high goodness of fit (data fits the model) in the range between 72% and 94%, such that the statistical model predicts outcomes very well.

Table 2. Estimated relationships of patents as a function of time (years).

Dependent Variable: Patents				
	Coefficient b′	**Constant a′**	**F**	**R^2**
Quantum technology, Log y Patents $_{i,t}$	0.217 ***	−432.61 ***	516.72 ***	0.94
Artificial intelligence technology, Log y Patents $_{i,t}$	0.199 ***	−391.87 ***	514.97 ***	0.91
Artificial intelligence and quantum technology, Log y Patents $_{i,t}$	0.416 **	−835.95 **	29.60 **	0.72

Note: The explanatory variable is time in years. b′ is the coefficient of regression and a′ is the constant from Equation (1). The interpretation of the estimated coefficient b′ (from Equation (1)) is that a one-unit increase in x will produce an expected increase in log y of b′ units. In terms of y itself, this means that the expected value of y is multiplied by $e^{b'}$. *** significant at 1‰; ** 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 (goodness of fit).

Trends of publications and patents are displayed in Figures 2 and 3. Figure 4, using the coefficients of regression from the estimated relationships of models (1), represented in Tables 1 and 2, reveals that the interaction of quantum and artificial intelligence technology generates a high rate of growth, particularly when technological information based on patents are considered.

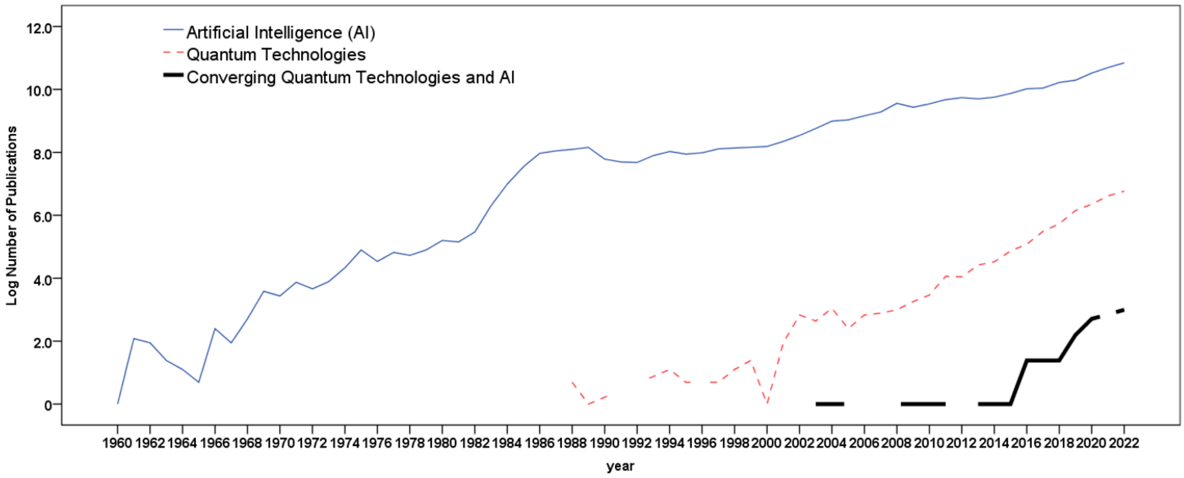

Figure 2. Trends of research fields using data of scientific production (*log* scale on y-axis for comparative analysis). The AI and quantum technologies line has an irregular pathway because of missing values in specific years of the dataset.

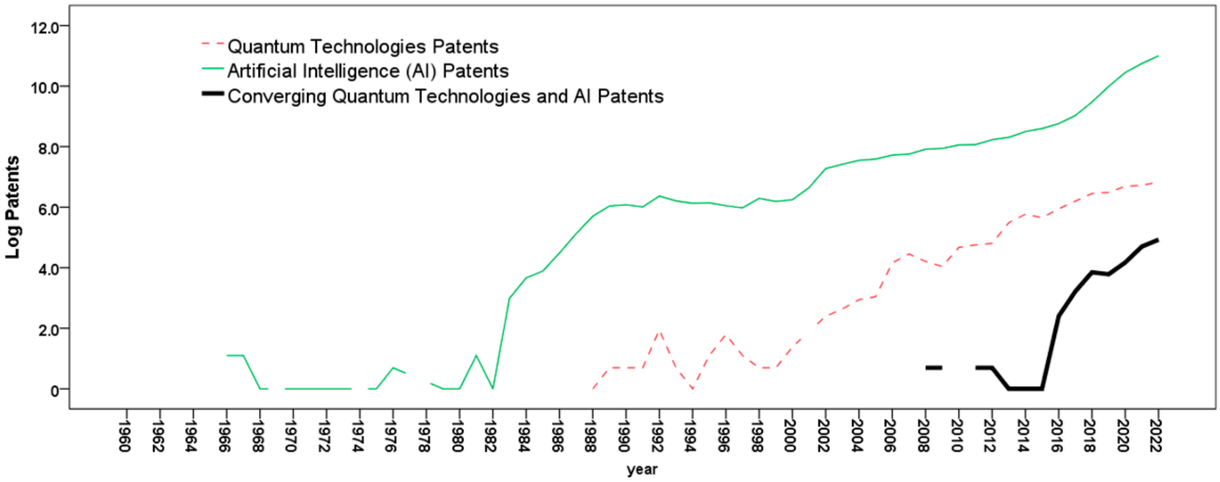

Figure 3. Technological trajectories using data of patents (*log* scale on y-axis for comparative analysis). The AI and quantum technologies line has an irregular pathway because of missing values in specific years of the dataset.

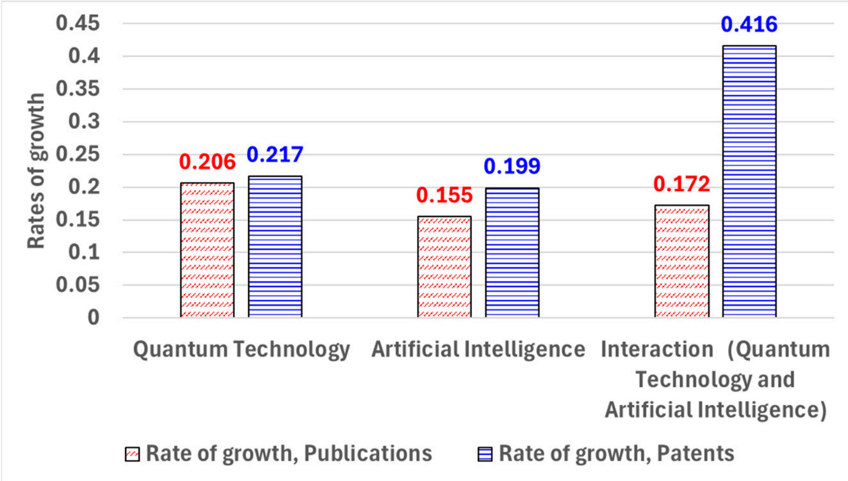

Figure 4. Rates of evolutionary growth of publications and patents in quantum technology, artificial intelligence technology, and their interaction (converging technologies).

Moreover, results, based on Equation (2), show that B > 1 (a disproportionate and accelerated growth of patents compared to publications over time), suggesting that an accumulation of knowledge supports inventions and potential innovations in technologies under study (Table 3). The technometric model of evolution [82], in which patents are driven by publications, shows that the interaction of quantum and artificial intelligence technology has a relative growth of 1.58 (p-value = 0.001), higher than quantum technology at 1.07 and artificial intelligence technology at 1.37, respectively. In particular, the coefficient B of the interaction between AI and quantum technology is 1.58, 15.13% higher than the coefficient of AI technology (given by B = 1.375) and 48.36% higher than the coefficient of quantum technology (i.e., B = 1.067). This result suggests that the interaction of these path-breaking research fields and inter-related technologies is fundamental for accelerating co-evolution, thereby laying the foundations for scientific and technological change based on disruptive innovations under study here. Table 3 also shows that the F-test in models (given by the ratio of variance explained by the model to unexplained variance) is highly significant, with a p-value = 0.001. Finally, the coefficient of determination R^2 shows a very high goodness of fit (data fits the model) greater than 87%, such that the statistical model almost perfectly predicts the outcomes.

Table 3. Parametric estimates of the model of scientific–technological evolution.

		Estimated Relationship	
Model of Equation (2)	*log* Y	*log* A	+B *log* Y
Quantum technology	log Y=	0.257 (0.244) N S	+1.067 log X (0.06) $p < 0.001$
	$R^2 = 0.914$	$S = 0.683$	$F = 288.249$ ***
Artificial intelligence technology	log Y′=	−5.016 (0.477) $p < 0.001$	+1.375 log X′ (0.060) $p < 0.001$
	$R^2 = 0.910$	$S = 1.015$	$F = 529.843$ ***
Quantum technology and artificial intelligence	log Y″=	0.407 (0.412) *N S*	+1.583 log X″ (0.225) $p < 0.001$
	$R^2 = 0.874$	$S = 0.664$	$F = 49.64$ ***

Note: Y = Patents; X = Publications; A=constant; B = coefficient of regression from Equation (2); the interpretation is given as an expected percentage of change in Y when X increases by a one-unit percentage. The standard errors of the regression coefficients are given in parentheses. p is the p-value. R^2 is the coefficient of determination (goodness of fit), and S the standard error of the estimate. F is the ratio of the variance explained by the model to the unexplained variance. N S = not significant; *** significant at 1‰.

5. Discussion

5.1. Details of Proposed Model

The theory underlying the proposed approach is operationalized with a model that is suited to the case of the complementary scientific and technological information given by scientific papers and patents to explain the dynamics of evolutionary process in the convergence of path-breaking technologies [22,82]. The model (2) applied here, drawn from Sahal [82], shows its simplicity because it contains only two parameters. These two parameters of the model (2) reflect the joint influence of scientific and technological information connected with the individual growth of technologies under study. Moreover, the model applied here does not impose theoretical restrictions on the range of data for which the model may be expected to hold. This model (2) is quite robust in the estimated relationships, as indicated by the high R-square (Table 3). A sufficient and not necessary condition for the proposed model to hold is that the individual form of growth in scientific and technological information, as a proxy of technological evolution, can be approximated in terms of some *S*-shaped curves. The coefficient of the independent variable in the model (2) is essentially a measure of the relative growth of patents on the publications. The results in Table 3 indicate that, in three estimated relationships, the relative growth rates are significantly different from unity and greater than 1. Therefore, the evolutionary dynamics of AI and quantum technologies is generally an allometric process of growth, i.e., they have a disproportionate growth of patents in relation to the scientific production. This suggested viewpoint is especially suited for understanding the long-term characteristics of the evolutionary dynamics in converging path-breaking technologies because of its emphasis on the disequilibrium processes of the emerging technological system. Hence, results from the empirical analysis indicate that the proposed model does well in the explanation of interaction of scientific and technological information on these emerging technologies. In a perspective of generalization, an important implication is that the evolutionary dynamics of converging technologies can be unambiguously specified in terms of any *S*-shaped curve [82].

5.2. Explanation of Empirical Results

Using temporal and spatial models of technological evolution (1) and (2), based on data of publications and patents, statistical analyses revealed that the interaction of these path-breaking research fields and technologies (quantum and artificial intelligence technology) has an accelerated rate of growth in patents, reaching 0.42, compared to single technologies individually (artificial intelligence technology with 0.20 and quantum technology with 0.22). Moreover, the model of technological evolution [82], in which patents are driven by publications—Equation (2)—shows that the interaction of quantum and artificial intelligence technology has a relative growth of 1.58, higher than quantum technology with 1.07 and artificial intelligence technology with 1.37, individually. This result suggests that the interaction of path-breaking research fields and radical technologies is a fundamental driving force to accelerate co-evolutionary pathways in innovation ecosystem [87]. Scholars have shown that the interaction among technologies is one of the drivers in technological evolution [32,49], and the result here is consistent with the approach of the multi-modes interaction by Utterback et al. [90], in which symbiotic interaction between technologies enhances the growth rate and consequential co-evolution. The concept of symbiosis, underlying interaction, is closely related to that of mutualism (it is any type of relationships in which each scientific field or technology benefits from the activity of the other; cf., [32]) and commensalism, which refers to any type of relationship between two research fields or technologies where one benefits from the other without affecting it [49]. With respect to the scientific and technological systems of interest here, results suggest a symbiosis that seems to be the more appropriate interaction, supporting the accelerated growth rate of technologies under study. The confluence of these scientific fields and technologies generates a high potential shift for technological and economic change directed towards improving human lives in many ways [53,55]. Hence, a multi-mode framework of technological interaction and convergence can provide a setting within which to better analyze and understand the dynamics of technological change between two or more radical technologies that interact and co-evolve at high pace. The interaction and convergence between scientific fields and technologies create the opportunity for cross-fertilization processes and more strategic opportunities that are not possible with a single technology. In the case under study here, the interaction generates high growth rates and a symbiotic-dependent evolution between research fields and technologies in quantum and artificial intelligence technologies. Revolutionary advances in the interaction between previously separate fields of science and technology are directed to create disruptive innovations, including instruments, analytical methodologies, and radically new systems. Hence, the progress of this fruitful interaction between converging artificial intelligence and quantum technologies can become self-catalyzing and can give the means to deal successfully with challenges in manifold fields and industries, opening completely new scientific and technological opportunities [41,53,54,91,92].

5.3. Deduction from Analysis of Results

Deductive implications of the present study, which create the background for a main generalization about the converging nature of radical technologies for supporting new pathways in technological evolution, are:

(a) The significant differences in the rates of evolution between technologies, and their interaction, which generates synergic effects of accelerated evolutionary growth;
(b) The evolutionary process of converging technologies, which involves a relationship of interaction between the scientific and technological information, generates a process of allometric (disproportionate) growth of patents driven by publications and consequential accelerated co-evolutionary pathways.

6. Conclusions and Prospects

Our results suggest that the current convergence of artificial intelligence and quantum technology is growing at a high pace [26,52,93]. In particular, the findings reveal that the convergence of these research fields and technologies has created a symbiotic interaction with synergic effects on growth rate, leading to a rapid technological development having a high potential impact and pervasive diffusion in industrial and socioeconomic systems. This aspect is important for the emerging quantum technology market size, which, by 2040, should be of about \$105 B with more than 500 start-ups in the innovation ecosystem of quantum technologies and inter-related technologies [69,73,87]. The potential growth is also supported by public investments in this strategic research and technological field by the United States, the European Union, and Canada, which committed an additional \$1.8 billion, \$1.2 billion, and \$0.1 billion, respectively [73].

6.1. Theoretical Implications

Theoretical implications of the interaction of scientific and technological information of drastic technologies under study are:

- a higher growth rate than each domain individually. This process can be due to cross-fertilization effects where each research field and technology enhances the other's growth rate (technological symbiosis by Coccia's theory).
- the learning processes of converging technologies, associated with the interaction processes, are a driving force of a rapid scientific and technological evolution and progress.

6.2. Managerial and Policy Implications

The innovation management implications of results here are that financial resources directed to technological interaction in vital fields of research and technologies can be an accelerator factor for the progress and diffusion of science and technology [94–97]. Policymakers and R&D managers can apply the results of this study for an effective allocation of economic and human resources towards interacting and converging research fields and technologies to foster the development of new knowledge, scientific research, and innovations for a positive impact for industrial, economic, and social change [94,95,97].

6.3. Limitations and Ideas for Future Research

The conclusions of this study are, of course, tentative. The complexity of investigating evolutionary pathways in quantum and artificial intelligence technology is due to different scientific and technological aspects. Although this paper has provided some interesting, albeit, preliminary, results, it has some limitations.

First, natural sciences are well represented in databases, but the literature of technical sciences can be only partly represented in the databases; the research output in engineering and computer sciences, in addition to publications and patents, can also be in the form of software, which is more difficult to detect. In fact, sources under study may only capture certain aspects of the ongoing dynamics of quantum and AI technologies. The databases used in this study are reliable, but their coverage is limited, especially in computer sciences, and they need to enlarge their scope to cover all forms of research outputs in these fields, including software [98].

Second, the search queries generated large datasets, which need, in future research, to be better cleaned and refined to reduce an overlap in data. A complementary approach to refine investigations can be using methods of mapping to analyze the evolution of network structures in quantum and artificial intelligence technologies. For instance, maps of connections between key papers can clarify the pathways of main interactions driving scientific and technological evolution. This mapping can be associated with co-citation analyses, which use multivariate techniques to identify and examine the networks of new scientific domains in innovation ecosystem [99]. Therefore, the analysis of complex fields—e.g., quantum and artificial intelligence technologies—requires a combination of different approaches (e.g., field terminology for appropriate lexical queries, analysis of citation flows, structured interviews with scholars and R&D managers, etc.) to provide comprehensive results.

A third limitations is the presence of inter- or trans-disciplinary research, which plays a vital role in the evolution of quantum and artificial intelligence technologies. To overcome this limit and improve the analysis of technological evolution, future studies should integrate other approaches, such as Leydesdorff and Rafols [100], who have developed citation-based metrics to measure the interdisciplinarity in journals, or the approach by Silva et al. [101].

The fourth limit is due to multiple confounding factors (e.g., R&D investments, collaboration intensity, openness, organization of labs, intellectual property rights, role of institution, etc.) that affect the dynamics of scientific fields and technologies under study and they should be included in future studies to confirm the acceleration dynamics of growth rates in scientific and technological development [102,103].

Despite these limitations, the results presented here illustrate the critical effect of technological interaction and convergence, which generate a higher growth rate, and its potential to lay the foundation for radical scientific and technological change. These results can guide appropriate R&D investments of policymakers and R&D managers to foster higher interaction, which creates the background for discoveries and a variety of innovations, and for increasing beneficial impacts in science, markets, and society [14–107]. The findings of this study can encourage further theoretical exploration in the terra incognita of the interaction in emerging and radical technologies to clarify dynamics and effects on technological evolution. In short, the preliminary results here suggest that there is need for much more detailed research into the investigation of the role of technological interaction and convergence between technologies and research fields to clarify their evolutionary pathways, reduce innovation failure and support implications of technological forecasting and innovation management [9,34,49,108–112].

Overall, then, the results presented here clearly point out the need for more extended scientific and technological analyses in the characteristics of technological convergence and interaction to clarify the drivers and dynamics of the evolution of scientific fields and disruptive technologies and to support appropriate R&D management implications and research policies that accelerate technological and economic change [113,114].

To conclude, if we want the great benefits of quantum and artificial intelligence technology interaction, policymakers and R&D managers should increase investments to foster their convergence and support in functional ecosystem the emergence of radical innovations for technological progress [115]. As a result, the positive impact of guided converging research fields and technologies on current and future human development and quality of life will generate higher benefit in science and society.

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