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Research Article

How Scientific and Technological Interaction Accelerates Co-Evolution of Artificial Intelligence and Quantum Systems

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ABSTRACT

This study investigates the drivers of recent scientific and technological advancements by examining the interaction between quantum and Artificial Intelligence (AI) systems. It analyzes how the scientific and technological coupling of these fields affects the pace of co-evolutionary dynamics. The research employs statistical models of evolutionary growth to analyze publication and patent trends in quantum and AI systems. Comparative growth rates are calculated to analyze synergetic effects between these domains. The results reveal that the coupling between AI and quantum systems exhibits a higher relative growth rate (1.58) compared to each scientific field individually (Quantum: 1.07; AI: 1.37). Statistical evidence indicates that AI, as a general-purpose technology, significantly drives progress in the combined domain. The interaction of these breakthrough fields fosters a mutually reinforcing cycle of scientific and technological advancement, accelerating co-evolutionary pathways. The analysis is based on publication and patent data, which may not fully capture informal knowledge flows or emerging research that has not yet been published. Furthermore, the study focuses on two domains only, limiting generalizability to other scientific and technological interactions. The findings suggest that science policy and R&D strategies should promote cross-domain collaboration and targeted investments directed to interactions in emerging fields. Encouraging integration between AI and quantum systems can amplify both science advances and innovation trajectories. This study provides a novel evidence-based explanation of how interaction-specifically between AI and quantum systems-is a driving force that accelerates scientific and technological evolution. Hence, this study contributes to the theoretical understanding of drivers in scientific and technological change in order to offer new strategies for innovation and science policies.

Keywords: Quantum Science, Artificial Intelligence, Publications, Patent Analytics, Science Dynamics, Scientific Evolution, Interaction, Information Science, Technological Evolution, Scientific Change.

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OBJECTIVES

One of the fundamental problems in science is understanding how research fields and interrelated technologies evolve and sustain scientific and technological change (Arthur, 2009; Coccia, 2018, 2020, 2021; Fortunato *et al.*, 2018; Kuhn, 1962; Lakatos *et al.*, 1980; Price, 1986; Scharnhorst *et al.*, 2012). Emerging scientific pathways and radical technologies-such as genomics, neuroinformatics, cognitive robotics, smart materials and digital twin-often arise from converging research fields and interacting systems (Coccia, 2012, 2022; Dalle Lucca Tosi and dos Reis, 2022; Small and Garfield, 1985; Sun *et al.*, 2013). Classic theories of scientific development, inspired by Kuhn's (1962) paradigm shifts and Lakatos's (1980) research programs, interpret scientific evolution through branching mechanisms generated by discovery-driven growth (Coccia, 2020, 2022; Mulkay, 1975) and by specialization or merging of fields (Coccia, 2018; Coccia *et al.*, 2024). Other studies highlight synthesis processes across preexisting disciplines (Noyons and van Raan, 1998). Overall, science appears as a self-organizing system marked by co-evolution among inter-related fields, often measured through co-citations (van Raan, 1990). The evolution of scientific fields is also shaped by social interactions and invisible colleges (Crane, 1972; Sun *et al.*, 2013; Wagner, 2008; Dalle Lucca Tosi and dos Reis, 2022).

Despite this literature, quantitative analyses of interactions between research fields and technologies remain limited. In particular, how such interactions influence scientific growth is poorly understood, especially in fast-changing scientific and technological regimes (Sun *et al.*, 2013). This study here seeks

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to explain a key driver of the symbiotic co-evolution in science and technology systems. The purpose is to see whether statistical evidence supports the hypothesis that the rate of scientific and technological change can be explained by interactions between fields that generate synergistic and accelerate scientific and technological development. Empirical evidence focuses on two rapidly expanding fields that are crucial for future scientific and socio-economic transformation (Coccia, 2022): artificial intelligence (Coccia, 2020) and quantum systems (Acín *et al*., 2018; Arute *et al*., 2019; Burger *et al*., 2023; Cushing and Osti, 2023; Dhamija and Bag, 2020; Thew *et al*., 2020). Using a large dataset of publications and patents, the study analyzes how these fields evolve independently and in interaction, to clarify their evolutionary and co-evolutionary pathways (Cozzens *et al*., 2010; Scheidsteger *et al*., 2021).

THEORETICAL FRAMEWORK ABOUT THE NATURE OF THE RELATIONSHIP BETWEEN AI AND QUANTUM SYSTEMS

Artificial Intelligence (AI) and quantum systems represent two transformative technological paradigms (Damioli *et al*., 2025; Yigitcanlar *et al*., 2025). A theoretical understanding of these destructive technologies helps contextualize the present study. Artificial Intelligence (AI) is based on software stacks and deep learning architectures-especially transformer-based and other multilayer neural networks-that discover representations from large datasets, generalize beyond training examples, and can be adapted to new contexts through transfer learning, fine-tuning, or prompting. By iteratively optimizing model parameters, these AI systems update their behavior when exposed to new inputs, enabling accurate perception, prediction, language understanding, and decision support in environments that change over time. Consequently, AI can execute tasks once associated with human cognition, such as reliably, consistently recognizing objects, interpreting speech, and generating coherent text (Lippmann, 2023; Schneider *et al*., 2024; Sarker, 2021). The capabilities in AI enhance decision-making processes in dynamic and complex environments, such as medicine, finance and healthcare (Chew and Ngiam, 2025; Coccia, 2020a; Sokol *et al*., 2025; Yüksel *et al*., 2025). quantum technologies encompass quantum computing, communication, and sensing systems. They exploit superposition and entanglement to compute, distribute keys or quantum states securely, and measure time, fields, or gravity with extreme precision, expanding our ability to gather, process, and transmit information beyond classical limits for science, security, and navigation (Acín *et al*., 2018; OECD, 2025). Patent activity in this domain is concentrated in six major areas: quantum circuits, quantum dot devices, quantum computing, quantum dot layers, quantum states, and quantum keys (Aboy *et al*., 2022), with rapidly evolving technological clusters (Jiang and Chen, 2021). According to McKinsey (2023), industries expected to benefit most from quantum computing include automotive, chemicals, financial services, and life sciences, with projected economic value approaching $1.3 trillion by 2035. The relationship between AI and quantum systems increasingly reflects a symbiotic co-evolution (Coccia, 2019, 2024; Coccia and Watts, 2020), with significant implications documented by Zhu and Yu (2023) and Davare (2025). Zhou *et al*. (2024) highlight the transformative potential of integrating quantum and AI technologies across multiple sectors. AI contributes to quantum science by enabling quantum system control (Dong and Chen, 2024), correcting computational errors (Oukaira, 2025), and optimizing experimental parameters for discovering new quantum phenomena (Pan, 2022). Applications span justice systems (Dong and Chen, 2024), autonomous vehicles (Klymenko *et al*., 2025; Heese *et al*., 2025; Sinha *et al*., 2025), and healthcare, where AI-quantum systems process large datasets while ensuring privacy and security (Folajimi, 2025; Non *et al*., 2025). Conversely, quantum technologies advance AI through quantum algorithms-such as the quantum approximate optimization algorithm and quantum support vector machines-that accelerate machine learning (Cuong *et al*., 2025; Oulefki *et al*., 2025). Hybrid quantum neural networks provide exponential speedups for tasks, such as earthquake prediction (Bishschof *et al*., 2025; Dutta *et al*., 2025). High-dimensional Hilbert spaces further enhance complex data processing (Manzoor *et al*., 2025). Emerging quantum machine intelligence synthesizes quantum-enhanced learning with AI-driven hardware optimization (Nguyen and Chen, 2022; Smith and Zhao, 2025). This technological synergy is epitomized by quantum optical neural networks, which now power sophisticated healthcare analytics and strategic organizational modeling (Zhou *et al*., 2024a; Miller, 2026). As AI-designed architectures stabilize quantum states, they enable superior pattern recognition within high-dimensional datasets, effectively bridging the gap between theoretical speedups and industrial utility (Lin and Young, 2024). This interconnected cycle accelerates the co-evolution of both fields, transforming quantum machine intelligence into a cornerstone of modern computational science.

Overall, the interaction between quantum and AI science can generate co-evolutionary pathways and mutual technological advancement (Coccia, 2024), representing a paradigm shift capable of reshaping industries and unlocking unprecedented organizational capabilities.

RESEARCH METHODOLOGY

Measures

Scientific development is examined through the number of articles and scientific products (Coccia, 2018, 2020), while technological evolution is assessed using patents, which indicate inventions and potential innovation pathways (Jaffe and Trajtenberg, 2002). Publications and patents in quantum and AI research fields are identified using keywords and Boolean combinations in Scopus (Massive, multidisciplinary abstract and citation database). Scientific products and patents form the core units of recorded knowledge for analyzing the evolution of science and technology (Glänzel and Thijs, 2012; Jaffe and Trajtenberg, 2002; Jiang and Shin-Liang Chen, 2021). Their relationship reflects the interplay between theoretical progress and practical innovation (Jaffe and Trajtenberg, 2002; Coccia and Roshani, 2024; cf., Figure 1). Publications typically represent early-stage exploration of ideas, theories, and experiments (Coccia, 2018), while patents capture potential applied inventions emerging from foundational research (Jaffe and Trajtenberg, 2002). Firms and research institutions frequently translate published findings into patentable technologies, forming a pipeline from basic research to commercialization, such as in drug discovery (Coccia, 2015). Patents often cite scientific publications to document novelty and non-obviousness (Liu *et al*., 2020), creating networks of intellectual influence that reveal how academia contributes to technological development (Jaffe and Trajtenberg, 2002). Citation networks provide critical structural insights by mapping influential contributors, burgeoning research frontiers, and cross-disciplinary convergences. Contemporary R&D laboratories increasingly leverage these networks-integrated with high-dimensional publication and patent metadata-to systematically detect nascent research trajectories, catalyze design innovations, and forecast technological lifecycles with enhanced predictive accuracy (Coccia, 2015; Gomes *et al*., 2024). Furthermore, the application of graph-based neural networks to these datasets allows for the identification of "hidden" interdisciplinary linkages that traditional metrics often overlook (Chen and Wang, 2025; Hassan and Peters, 2026). For example, a rise in quantum computing publications followed by an increase in patents may indicate a maturing technology approaching commercialization (Hasanovic *et al*., 2022). Joint publication-patent activity also signals collaboration between academia and industry, and with government according to triple helix model (Etzkowitz, 2008), enabling major discoveries and innovations such as in disease research (Unwin *et al*., 2025). Funding agencies and investors assess both scientific and technological outputs to evaluate research impact and expected returns (Adachi *et al*., 2022). Combining publications and patents therefore provides essential information for scientific and technological forecasting: publications measure scientific impact, whereas patents indicate technological advancement (Shen *et al*., 2020).

Data and sources

The study uses data of Scopus (2023), a multidisciplinary database covering journal articles, conference proceedings, letters, book chapters and books. Scopus (2023) database also includes patent records from different patent offices worldwide. The window of "search documents" in the Scopus (2023) database is used to identify scientific documents and patents having in title, abstract or keywords specific queries (Scopus, 2023a). Data under study are from starting year of publication (article or patent) to July 2023 (when data are downloaded). In particular, the search strings, directed to analyze publications and patents of research fields and technologies under study, for a comparative study, are based on a combination of specific keywords and Boolean operators (AND) inserted into the search box of the search engine Scopus (2023) as follows:

("quantum technology").

("artificial intelligence").

combined search: ("quantum" and "artificial intelligence").

Data do not consider 2023 because it is ongoing, when this study was designed, but it does not affect the scientific and technological analysis. Table 1 shows data analyzed.

This methodology relies on specific Boolean queries within the Scopus database to capture the broad evolutionary arcs of AI and Quantum Science. Standardized strings and selection given by "quantum technology" and "artificial intelligence" provide a stable baseline for longitudinal comparison across decades.

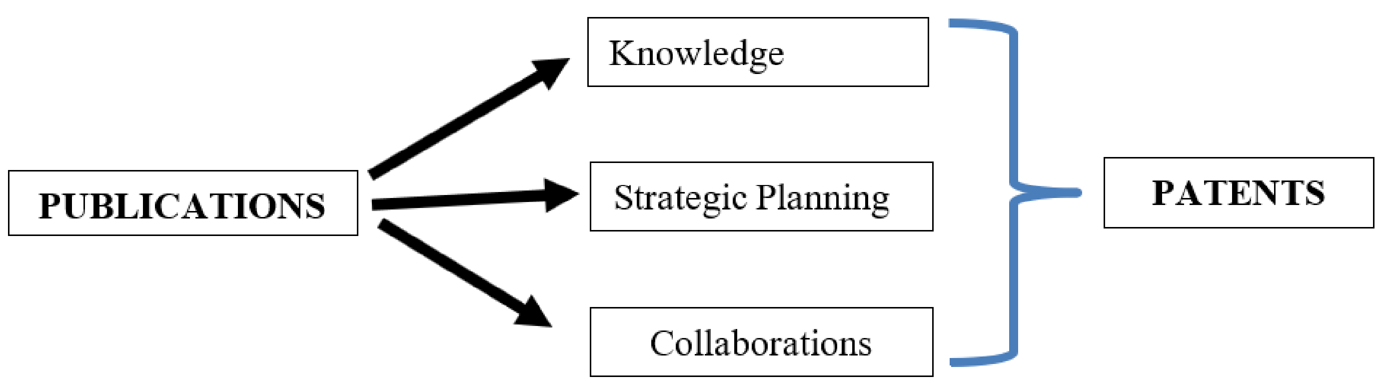

Figure 1: Interplay between Publications and Patents as two primary sources of science and technology advances. Note: Arrows from publications flow into three key areas of interaction, supporting patent and innovative activities: Knowledge Transfer, Strategic Planning, Collaboration.

Table 1: Data of publications and patents in quantum and artificial intelligence systems.

Technological Systems	Number of Publications	Number of Patents	Period, years
Quantum technologies	3,989	63,02	1988-2022
Artificial Intelligence	46,3512	23,9210	1960-2022
Quantum AND Artificial Intelligence	60	447	2004-2022

Note: The combination with Boolean operator "AND" represents the interaction of two research fields and path-breaking technologies given by Quantum and AI systems.

This targeted terminological approach mitigates the "semantic noise" typically generated by peripheral literature, ensuring that identified convergences represent intentional intellectual synergy rather than incidental lexical overlaps (Wang and Lee, 2024). To bolster the robustness of these findings, the analysis explicitly incorporates the systemic temporal lag inherent in the science-to-technology pipeline (Liu *et al*., 2025). While peer-reviewed publications delineate the vanguard of theoretical discovery, patents demarcate the frontier of industrial utility. Consequently, our model accounts for the standard R&D gestation period-the multi-year interval required for a fundamental breakthrough to navigate developmental cycles and legal processing before appearing in patent registries (Park, 2026; Zhao and Schmidt, 2024).

Models and data analysis procedure

The primary objective of this study is to empirically test the overarching hypothesis that the interaction of distinct research fields-specifically Artificial Intelligence (AI) and Quantum Science-generates a synergistic effect for trajectory development. This effect is expected to accelerate the co-evolutionary growth rate of both scientific discovery and technological innovation in these scientific systems beyond what either field achieves independently. To investigate these dynamics, the study employs a multi-stage quantitative approach grounded in the "Science of Science" framework (Fortunato *et al*., 2018), utilizing longitudinal data to map the trajectory of knowledge production and its translation into potential industrial applications (patents).

Data Acquisition and Standardization

The empirical foundation of this research relies on publication and patent data retrieved from the Scopus (2023) database. This database is selected for its comprehensive coverage of peer-reviewed literature, conference proceedings, and global patent records, providing a holistic view of the intellectual landscape. The data includes records from the inception of these fields through 2022. However, for the comparative analysis, the data is standardized to focus on the period from 2000 to 2022. This timeframe is critical as it captures the "take-off" phase of both deep learning in AI and the second quantum revolution (Acín *et al*., 2018). Following the logic by Coccia (2020, 2022a, 2024), scientific publications are treated as proxies for early-stage theoretical exploration, while patents represent the maturation of these ideas into applied, commercializable inventions (Jaffe and Trajtenberg, 2002). By identifying publications and patents through specific keyword queries and Boolean combinations (e.g., "Quantum" AND "Artificial Intelligence"), the study isolates the "convergence zone" where these two systems interact.

Model 1: Analysis of Evolutionary Growth Trends

To establish a baseline for the growth of each field, the study first applies a trend analysis model to measure the velocity of development for research field over time. The growth of scientific products and patents is modeled using an exponential growth function, linearized through a logarithmic transformation:

$$\mathrm{Ln}(y_{i,t}) = a + b\ \mathrm{time} + u_{i,t} \quad [1]$$

In this model:

$y_{i,t}$ represents the volume of scientific products or patents.

t is the chronological time.

a is the constant (intercept).

b is the regression coefficient, indicating the growth rate.

$u_{i,t}$ is the error term.

The coefficient of regression allows for a direct comparison of the "momentum" behind AI and Quantum systems individually versus their combined growth. A higher value of the coefficient based on data associated with combined search of these fields suggests that the interaction is not merely additive but accelerative (Coccia, 2018).

Model 2: The Co-evolutionary Logistic Model by Sahal (1981)

A central component of the methodology is understanding how scientific progress supports technological development. This relationship is often non-linear and follows an S-shaped or logistic pattern (Sahal, 1981). To measure the relative rate of this combined scientific-technological evolution, the study employs a log-log model derived from the differential equation of a logistic function (Sahal, 1981). Let *Y(t)* be the extent of technological advances (measured by patents) and *X(t)* be the underlying scientific production (measured by publications). The relationship is expressed as:

$$\ln(Y) = \ln A + Ev \ln(X) \quad [2]$$

Here, E*v* is the evolutionary coefficient of growth. It serves as the primary metric for assessing the pathway of evolution:

E*v* <1 (Deceleration): Technological growth is slowing relative to scientific production, suggesting a field that is saturating or facing diminishing returns.

Eν =1 (Proportional Growth): Patents and publications evolve at the same rate, indicating a stable, steady-state translation of science into technology.

Eν >1 (Acceleration): Patents are evolving at a greater relative rate than publications. This indicates a highly efficient, synergistic system where theoretical breakthroughs are rapidly and expansively triggering technological inventions.

Moreover, to grasp the intuition behind Sahal's log-log evolutionary coefficient, it is helpful to view it as a measure of "innovation leverage" or elasticity between theory and practice. When we model the relationship as $ln(Y)=lnA + Ev\ ln(X)$, we are essentially asking how much technological "bang" we get for our scientific "buck." If Eν =1, the translation from papers to patents is a steady, proportional march. However, when Eν>1, the AI-quantum system interaction is in an "accelerated" state; every 1% increase in scientific knowledge yields a disproportionately greater increase in technological output. This suggests that the fields are not just growing alongside one another but are becoming exponentially more efficient at turning abstract ideas into protected inventions, much like a maturing engine finding its optimal gear on an S-shaped development curve.

Directional Interaction and Correlation Analysis

To determine the "directionality" of influence-whether AI drives Quantum or vice versa (i.e., A>B or B>A)-the study also performs a robust correlation analysis. By examining the association between Quantum Patents and AI Publications (and vice versa), the research identifies which field acts as the primary catalyst. Factors affecting Quantum Technology (patents) are analyzed in association with:

- Quantum Technology Publications.
- AI Patents.
- AI Publications.
- Combined AI and Quantum Publications.

A higher Pearson correlation coefficient, utilizing a one-tailed test for directional hypotheses, indicates a stronger synergistic effect of one field on the other. This helps clarify if AI is acting as a "General Purpose Technology" (GPT) that provides tools to solve quantum problems, thereby accelerating quantum hardware or software development (Coccia, 2022a). In particular, the selection of one-tailed correlation tests is a deliberate choice rooted in our theoretical framework that science support inventions and innovations, in order to support a positive synergy and mutualistic growth. Because we hypothesize that AI and Quantum systems act as catalysts that specifically drive-rather than hinder-one

Table 2: Estimated relationships of scientific production (publications) as a function of time.

Dependent variable: scientific products concerning scientific fields				
Dependent variable (publications) in technological system	**Coefficient b^1**	**Constant a**	**F**	**R^2**
Quantum Technology, *Log y pubs* $_{i,t}$	0.206***	-410.73***	370.47***	0.93
Artificial Intelligence, *Log y pubs* $_{i,t}$	0.155***	-301.58***	720.43***	0.92
Artificial Intelligence and Quantum Technology, *Log y pubs* $_{i,t}$	0.172**	-345.00**	14.89**	0.61

Note: Model based on equation [1]. Explanatory variable is time in years; *** 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.

Table 3: Estimated relationships of patents as a function of time.

Dependent variable: Patents				
Dependent variable (patents) in technological system	**Coefficient b'^1**	**Constant a'**	**F**	**R^2**
Quantum Technology, Log y Patents $_{i,t}$	0.217***	-432.61***	516.72***	0.94
Artificial Intelligence, 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: Model based on equation [1]. Explanatory variable is time in years; *** 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.

another, a one-tailed test provides a more focused lens to confirm this directional influence. This approach ensures the analysis is strictly testing for the "acceleration" predicted by the Science of Science framework, grounding the math in the reality that these path-breaking fields are collaborative drivers of scientific and technological progress.

Model 3: Comparative Driver Analysis

The model is further extended to analyze the evolution of Quantum Patents as a function of AI scientific production and the combined AI-Quantum output:

Quantum Patents = f(AI Publications, AI Patents, AI and Quantum Science Production)

Conversely, the same logic is applied to AI Patents:

AI Patents = f(Quantum Publications, Quantum Patents, AIand Quantum Science Production)

By applying Ordinary Least Squares (OLS) estimation to these relationships, the study compares the magnitudes of the regression coefficients. A higher coefficient in these cross-domain models suggests a symbiotic co-evolutionary pathway where one field fosters innovation in the other.

Model 4: Multiple Regression and Interaction Isolation

Finally, to isolate the specific effect of convergence from other confounding variables, the study utilizes multiple regression analyses. These models control for the independent growth of each field to see if the *interaction itself* contributes unique value to technological development. The model is:

$$\mathrm{Ln}\,(y) = a + \beta_1 x_1 + \beta_2 x_2 + e \quad [3]$$

Where:

y= Patents in the focal technology (e.g., Quantum system).
x_1= Patents in the secondary technology (e.g., AI systems).
x_2= Scientific interaction (combined publications).
βi= Partial coefficients of regression (i=1,2).

To assess the growth of the interaction itself, the following model is applied:

$$\mathrm{Ln}(f) = a + \beta_1 k_1 + \beta_2 k_2 + e \quad [4]$$

Where f represents the interaction in patent data, while k_1 and k_2 represent the scientific development (publications) in the individual fields. All statistical analyses are performed using IBM SPSS Statistics 29, ensuring a rigorous and standardized computational environment for the OLS estimations.

RESULTS

Figures 2 and 3 show the trends of scientific and technological development of research fields under study. Results clearly displays that the interaction between these research fields has, from 2018, a very high acceleration.

Trends are analyzed with linear regression model having the time as explanatory variable in order to assess the temporal growth rates of the scientific (measured with publications)

Table 4: Evolutionary growth of publications and patents based on coefficients of regression in Tables 1 and 2.

Technological systems	Coefficient of Publications	Coefficient of Patents
Quantum Technology	0.206	0.217
Artificial Intelligence Technologies	0.155	0.199
Quantum and Artificial Intelligence Technologies	0.172	0.416

Table 5: Parametric estimates of the model of scientific-technological evolution based on equation [2].

Techno-scientific systems	Estimated relationship		
Quantum System	log Y=	.257	+1.067logX
		(0.244)	(0.06)
		ns	$p<0.001$
	$R^2=0.914$	S=0.683	F=288.249***
Artificial Intelligence System	log Y’=	-5.016	+1.375logX’
		(0.477)	(0.060)
		$p<0.001$	$p<0.001$
	$R^2=0.910$	S=1.015	F=529.843***
Quantum Technology and Artificial Intelligence Systems	log Y”=	0.407	+1.583logX”
		(0.412)	(0.225)
		ns	$p<0.001$
	$R^2=0.874$	S=0.664	F=49.64***

Note: Y = Patents; X= Publications; The standard errors of the regression coefficients are given in parentheses. *p* is the *p*-value. R^2 is the coefficient of determination, *S* the standard error of the estimate. *F* the ratio of the variance explained by the model to the unexplained variance. *ns*=not significant; *** significant at 1‰.

and technological (measured with patents) development (see, Tables 2 and 3 based on equation [1]). Estimated relationship of scientific development over time in Table 2 shows that coefficient of determination R^2 is high and explains from 61% (Model with interaction of these research fields) to 93% (Model of the time series in quantum technology) of the variance in the data. The *F*-value (the ratio of the variance explained by the model to the unexplained variance) is significant with *p*-value 0.001 per each research fields and with *p*-value 0.01 for their interaction. Table 3 with the estimated relation of technological development (based on patents) shows similar results.

Table 4 summarizes the coefficients of regression in estimated relationships of models [1], represented in Tables 2 and 3, and reveals that the interaction of patents in Quantum and Artificial Intelligence technologies, a main poxy of technological development, generates a rate of growth higher that each individual trend in these technologies (0.41 interaction of AI and quantum systems, *vs.* 0.22 for quantum technology and 0.20 for AI technology).

Model [2] of technological development driven by scientific development is in Table 5. Results show B>1 (a disproportionate and accelerated growth of patents compared to publications over time) that is high with the interaction between quantum and AI technologies (B=1.58) that generates synergetic effects of accelerated development. This finding in Table 5 suggests that scientific advances and knowledge production in converging

Table 6: Correlation one-tailed test for a directional hypothesis from Quantum technologies, Patent (log scale).

Pearson Correlation	Quantum Technologies Patents	Quantum Technologies Pubs	AI Patents	AI Pubs	AI and Quantum Technologies Patents	AI and Quantum Technologies Pubs
Quantum Technologies Patents	1	.956**	.952**	.969**	.809**	.716**
Sig. (1-tailed)		0	0	0	0.001	0.01
N	34	29	34	34	12	10
AI Patents	.952**	.975**	1	.955**	.908**	.936**
Sig. (1-tailed)	0	0		0	0	0
N	34	30	53	53	12	10
AI and Quantum Technologies Patents	.809**	.873**	.908**	.919**	1	.945**
Sig. (1-tailed)	0.001	0	0	0		0
N	12	12	12	12	12	8

** Correlation is significant at the 0.01 level (1-tailed).

Table 7: Estimated relationships *log-log* linear models of simple regression.

Dependent Variable	Explanatory variable	Coeff. b_1	Constant a	Stand. Beta	F	R^2
Quantum Tech Patents	Quantum Tech Pubs	1.07***	0.26	0.96	288.25***	0.91
Quantum Tech Patents	AI Publications	2.31***	-17.45***	0.97	487.60***	0.94
Quantum Tech Patents	Quantum Tech and AI Pubs	0.77*	4.81	0.72	8.39*	0.51
Quantum Tech Patents	AI Patents	1.47***	-7.83***	0.95	322.53***	0.91
Artificial Intell Patents	AI Publications	1.38***	-5.02***	0.96	529.84***	0.91
Artificial Intell Patents	Quantum Tech Pubs	0.71***	5.55***	0.98	531.24***	0.95
Artificial Intell Patents	Quantum Tech and AI Pubs	0.88***	8.06***	0.94	56.76***	0.88
Artificial Intell Patents	Quantum Tech Patents	0.62***	5.54***	0.95	311.53***	0.91
Artificial Intell and Quantum Tech Patents	Quantum Tech and AI Pubs	1.58***	0.41	0.95	49.64***	0.89
Artificial Intell and Quantum Tech Patents	Quantum Tech Pubs	1.50***	-5.52***	0.87	32.07***	0.76
Artificial Intell and Quantum Tech Patents	AI Publications	4.35***	-41.61***	0.92	54.13***	0.84

Note: *** significant at 1‰. ** significant at 1%; ** significant at 5%. *F* is the ratio of the variance explained by the model to the unexplained variance. R^2 is the coefficient of determination.

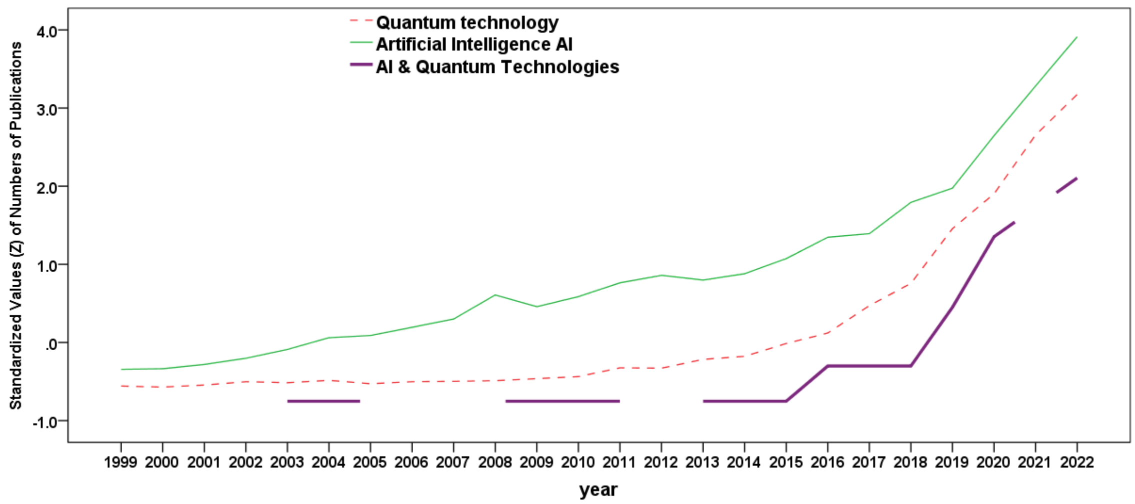

Figure 2: Trends of research fields using data of scientific production (standardized Z for comparative analysis). Note: To show better the trends, the period starts from 2000.

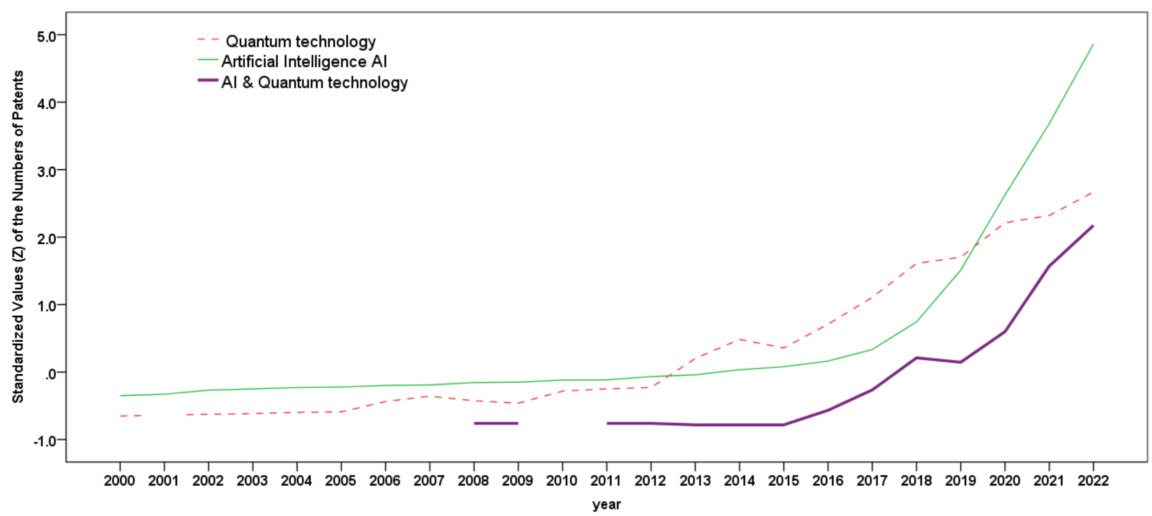

Figure 3: Technological trajectories using data of patents (standardized Z for comparative analysis). Note: To show better the trends, the period starts from 2000.

research fields of quantum and AI systems support a higher accumulation of inventions to support innovations for next industrial and social change.

Tables 6 and 7 evaluate the synergistic relationships and cross-disciplinary influences between quantum and Artificial Intelligence (AI) systems. Specifically, Table 6 presents a one-tailed correlation analysis testing directional hypotheses regarding technological development, proxied by patent activity. The results indicate that quantum patenting is near-perfectly correlated with quantum scientific publications ($r=0.96$, $p<0.01$). Notably, quantum technological growth also demonstrates a robust association with both AI publications and patents ($r>0.95$, $p<0.001$). This interdependence is mirrored in AI patenting trends, where historical quantum scientific and technological outputs serve as significant drivers of progress. A key finding in Table 6 is the interaction between these fields; the technological interaction of quantum and AI (joint patenting) systems shows a stronger correlation with AI scientific development ($r=0.92$, $p<0.01$) than with quantum science ($r=0.87$, $p<0.01$). These high coefficients and significant growth rates suggest a model of mutual reinforcement. Despite observing asynchronous development cycles, the underlying trend remains statistically valid, confirming that theoretical advancements in AI effectively prime the pipeline for subsequent quantum inventions.

To investigate how advancements in one domain catalyze disruptive innovation in the other, we employed a univariate linear regression model (Equation [3]). The findings, estimated via Ordinary Least Squares (OLS) and presented in Table 7, quantify the elasticity of quantum technological growth relative to AI progress. The empirical results reveal a powerful "pull effect" from the AI system:

Scientific Influence: A 1% increase in AI scientific publications corresponds to a 2.31% growth in quantum patent applications.

Technological Influence: A 1% increase in AI patenting activity drives an approximate 1.5% increase in quantum technological development.

The robustness of these models is evidenced by a Coefficient of Determination (R^2) exceeding 0.90, indicating that AI-related variables account for over 90% of the variance in quantum innovation. Furthermore, the F-statistic is highly significant ($p<0.001$), confirming the reliability of AI progress as a predictor for quantum advancement. Theoretically, these findings support the concept of technological convergence, where AI acts as a "meta-discovery" tool or a "method of invention" that reshapes the innovation process itself (Cockburn *et al*., 2018). AI advancements-particularly in machine learning and neural network architectures-provide the computational driver required to simulate complex quantum many-body states and optimize the protocols for quantum error correction (Carleo and Troyer, 2017; Fösel *et al*., 2018). In this symbiotic relationship, AI scientific production serves as the theoretical fuel, offering new algorithmic frameworks that solve long-standing quantum engineering hurdles (Dunjko and Briegel, 2018). As AI matures, it creates a "virtuous cycle": the sophisticated data processing capabilities of AI allow researchers to navigate the high-dimensional design space of quantum hardware more efficiently, effectively lowering the barrier to entry for patentable quantum inventions (Sarma *et al*., 2019). This suggests that quantum progress is not merely an isolated hardware evolution but is deeply contingent upon the software and algorithmic breakthroughs originating in the AI field, functioning as a General Purpose Technology (GPT) that accelerates adjacent domains (Bresnahan and Trajtenberg, 1995).

The most compelling evidence of cross-sectoral influence is found in the drivers of synergistic innovation (joint AI and Quantum patents). The findings in Table 7 suggest that scientific progress in AI acts as the primary engine for this interaction. Specifically, the model reveals a high elasticity of 4.35, indicating that a 1% increase in AI scientific production leads to a 4.35% growth in converged AI-Quantum technological development (beta=4.35, $p<0.001$, $R^2=0.84$). While quantum scientific publications also contribute to these synergistic patents, their impact is notably lower (beta = 1.50, $p<0.001$) compared to the outsized influence of AI science. This disparity suggests that the "virtuous cycle" of quantum-AI integration is predominantly catalyzed by AI-driven methodologies , acting as a GPT. Theoretically, this reinforces the "meta-discovery" hypothesis: AI does not merely complement quantum technology but provides the fundamental algorithmic breakthroughs necessary to unlock new patentable quantum applications. Consequently, the pace of technological convergence in this high-tech frontier is deeply contingent upon the continued maturation of AI research.

To isolate the specific drivers of scientific and technological interaction, we employed multivariate regression analyses to determine the partial coefficients of each explanatory variable while controlling for confounding factors. The results of these estimations (Equation [4]) are detailed in Table 8. The results indicate that quantum patenting is primarily driven by technological spillovers from the AI system. A 1% increase in AI patent production results in a 1.6% growth in quantum patents ($b_1 = 1.60$, $p<0.05$). Interestingly, the interaction between quantum and AI scientific publications does not yield a significant effect in this model, suggesting that at this stage, quantum technological progress relies more on existing AI technical frameworks than on combined basic science. This supports the view, as said before, of AI as a General Purpose Technology (GPT) that provides the necessary infrastructure for adjacent high-tech fields (Bresnahan and Trajtenberg, 1995). Instead, AI patenting displays a more complex dependency. It is influenced by quantum technological progress ($b_1=0.32$, $p<0.05$) and, more significantly, by scientific interaction. A 1% increase in joint quantum-AI scientific publications leads to a 0.65% growth in AI patents ($b_1=0.65$, $p<0.001$). This highlights the high absorptive capacity of the AI field, which effectively translates complex, cross-disciplinary scientific insights into proprietary technological assets (Cohen and Levinthal, 1990).

Table 8: Estimated relationships of *log-log* linear models of multiple regression.

Dependent Variable	Explanatory variable	Coeff. b_1	Stand. Beta	F	R^2
Quantum Tech Patents	Constant	-8.09		10.94**	0.76
	AI Patents	1.60*	1.41		
	Quantum Tech and AI Pubs	-0.65	0.57		
Artificial Intell Patents	Constant	6.55***		53.56***	0.94
	Quantum Tech Patents	0.32*	0.36		
	Quantum Tech and AI Pubs	0.65***	0.68		
Quantum Tech and AI Patents	Constant	-40.79*		24.37***	0.84
	Quantum Tech pubs	0.04	0.02		
	AI Pubs	4.25*	0.90		

Note: *** significant at 1‰. ** significant at 1%; ** significant at 5%. *F* is the ratio of the variance explained by the model to the unexplained variance. R^2 is the coefficient of determination.

The analysis of interacting systems (joint AI-Quantum patents) reveals, as mentioned before, that AI scientific production is the dominant catalyst. A 1% increase in AI scientific publications generates a 4.25% growth in synergistic patents (b_1=4.25, *p*<0.05). Conversely, quantum scientific production alone does not significantly drive these joint inventions. This asymmetry suggests that AI science acts as the "method of invention," providing the algorithmic breakthroughs required to unlock quantum hardware potential (Cockburn *et al*., 2018; Dunjko and Briegel, 2018).

Across all models, the F-statistics are highly significant (*p*<0.01), and the Coefficients of Determination (R^2) explain between 76% and 94% of the variance, confirming the robustness of these predictors.

DISCUSSION AND THEORETICAL PERSPECTIVE

Utilizing temporal and spatial models of technological evolution, this study demonstrates that the synergetic interaction between quantum technology and Artificial Intelligence (AI) acts as a catalyst for accelerated innovation. Empirical analysis reveals that this technological convergence produces a patent growth rate of 0.42, which is significantly higher than the growth rates of AI (0.20) and quantum technology (0.22) when analyzed independently. To further evaluate these trajectories, we applied Sahal's (1981) model of technological evolution, which characterizes patenting activity as a function of scientific publication output. The results yield a relative growth index of 1.58 for the integrated quantum-AI system, substantially exceeding the individual indices of 1.07 for quantum technology and 1.37 for AI. These findings validate the hypothesis that the co-evolutionary dynamics between interacting research fields generate more robust and steeper scientific and technological trajectories than those arising from isolated development. Such cross-pollination effectively lowers the threshold for disruptive innovation, suggesting that the integration of these systems has synergic effects.

Explanation of results

The findings suggest that synergetic interactions among pathbreaking technological systems are fundamental for accelerating coevolutionary pathways and fostering disruptive innovations relevant to scientific, technological, industrial, and societal change. Prior research indicates that interactions among technologies enhance evolutionary potential (Coccia, 2019; Coccia and Watts, 2020; Utterback *et al*., 2019). In this study, synergistic effects are particularly driven by advancements in AI systems: a 1% increase in AI scientific production generates a 4.35% growth in converging quantum-AI patenting. Likewise, the interaction between quantum and AI technologies (Equation [3]) is primarily influenced by scientific advances in AI systems, where a 1% increase in AI publications produces a 4.25% increase in combined technological development. These results highlight a directional asymmetry: AI scientific and technological progress exerts stronger influence on quantum technology than vice versa. This aligns with theoretical expectations of symbiotic technological relationships, where progress in one domain enables accelerated development in another interrelated field (Coccia and Watts, 2020; Utterback *et al*., 2019). The interaction of AI and quantum systems creates scientific crossfertilization and technological opportunities that exceed what either field can achieve alone. Such mutualistic interaction fosters disruptive innovations by enabling each technology to benefit from advancements in the other (Coccia, 2019, 2019a; Coccia and Watts, 2020). This coevolutionary dynamic has substantial implications for industrial productivity and societal advancement. Convergent research fields are known to enhance technological progress and increase human and national productivity (Roco and Bainbridge, 2002). The interaction between AI and quantum systems documented here is progressing rapidly and opening new technological trajectories with the potential to drive major industrial and economic transformations (Burger *et al*., 2023; Dhamija and Bag, 2020). These emerging trajectories lay the foundations for new ecosystems of disruptive innovations, including novel instruments, analytical methods, and systems. Hence, the interaction appears selfcatalyzing, capable of generating compounding benefits across fields, opening new scientific and technological opportunities (Burger *et al*., 2023; Cushing and Osti, 2023; Krinkin *et al*., 2023; Zhao *et al*., 2021).

Critical discussion

The empirical evidence presented in the regression analyses indicates that the interaction of Artificial Intelligence (AI) and Quantum systems is not merely an additive phenomenon but a multiplicative catalyst for radical innovation. The high coefficients of determination, ranging from 0.61 to 0.94, combined with highly significant F-values, underscore a robust structural relationship where time acts as a potent proxy for cumulative learning and strategic resource allocation. A critical examination of growth coefficients reveals a striking disparity: while Quantum and AI maintain steady independent growth rates, their interaction yields a patent growth coefficient of 0.416, which effectively doubles the individual developmental velocity of each field. This surge suggests that the intersectionality of these systems creates a new technological paradigm where the limitations of classical computing are addressed by quantum hardware, while the inherent complexities of quantum systems-such as decoherence and noise-are increasingly managed via AI-driven error correction and heuristic optimization. This dynamic aligns closely with the evolutionary theories of Arthur (2009), who argue that technological change is fundamentally driven by the recombination of existing knowledge bases into novel, higher-order routines. Furthermore, the application of Sahal's (1981) model provides deeper insight into the efficiency of this scientific-technological translation; the evolutionary growth index (Ev) of 1.58 for the interaction signifies an allometric, disproportionate acceleration of patents relative to scientific publications. From a Schumpeterian (1942) perspective, this implies that the quantum-AI nexus has moved beyond latent academic exploration into a new phase of "creative destruction," where theoretical breakthroughs are rapidly codified into intellectual property. This acceleration is particularly sensitive to directional asymmetry, as the data identifies AI as the primary driver of quantum advancements; the finding that a 1% increase in AI scientific production triggers a 4.35% increase in combined patenting underscores the role of AI as a General Purpose Technology (GPT). As defined by Bresnahan and Trajtenberg (1995), a GPT functions as a "method of invention" that provides the analytical scaffolding necessary to unlock the latent potential of other specialized fields. Consequently, the interaction is self-catalyzing: improved AI algorithms facilitate the discovery of new quantum materials, which in turn will eventually provide the computational power to reach a new frontier of AI training efficiency. Critically, this asymmetrical dependence suggests that science policy must move away from siloed funding models toward nexus-based governance. If AI can act as the prime mover for quantum technological maturity, then investments in quantum hardware without concurrent support for AI-mediated quantum control systems may lead to significant bottlenecks (Coccia, 2018a). This supports the necessity of the Multiple Helix model, where institutional collaboration between government, industry, and academia and other subjects must specifically bridge these two domains to sustain co-evolutionary momentum (Etzkowitz, 2008). Theoretical generalizations suggest that this synergy creates a mutualistic dependency where the rate of technological output scales allometrically, necessitating a shift in R&D management toward translation efficiency. By incentivizing interdisciplinary "innovation sandboxes" and implementing adaptive resource allocation based on real-time bibliometric "hot spots," science policy can enable the disruptive innovations required to address the complex industrial and societal challenges of the 21st century.

CONCLUSION AND LIMITATIONS

The results of this study show that Artificial Intelligence (AI) and quantum systems are expanding at an exceptional pace, consistent with evidence from frontier scientific and technological breakthroughs (Arute *et al*., 2019; Coccia *et al*., 2022; Dowling and Milburn, 2003). More importantly, the findings demonstrate that the interaction between these two research fields is generating symbiotic evolutionary dynamics, characterized by synergetic effects that significantly accelerate growth rates in scientific production and technological development. This accelerated coevolution has substantial implications for the emerging quantum technology market, projected to reach $105 billion by 2040, supported by more than 500 startups within a rapidly growing innovation ecosystem (Coccia, 2022a; McKinsey, 2023). Strong public investments further reinforce this development, with the United States, the European Union, and Canada committing an additional $1.8 billion, $1.2 billion, and $0.1 billion, respectively, to quantum research and related technological domains (McKinsey, 2023). A major contribution of this study is the empirical evidence that AI acts as the primary engine driving the interaction between AI and quantum systems. AI possesses the characteristics of a general-purpose technology and invasive technologies capable of enabling advances across multiple sectors (Coccia, 2025). The analysis reveals that a 1% increase in AI scientific output generates a 4.35% rise in joint AI-quantum patenting, while a similar increase in AI research produces a 4.25% increase in synergistic technological development. These findings highlight a directional asymmetry: AI advancements exert a stronger influence on quantum technological progress than the reverse direction, indicating that internal scientific and technological momentum-combined with situational factors-constitutes the core mechanism of convergence in these frontier domains. In particular, while foundational research by scholars such as Coccia (2019) and Utterback *et al*. (2019) established that interactions between technologies generally enhance evolutionary potential, this study represents a significant leap forward by shifting the analytical focus from mere additive observation to multiplicative quantification. It advances the field of scientometrics by demonstrating that the interactions between Artificial Intelligence and Quantum systems creates a self-catalyzing "co-evolutionary loop" where the joint growth rate (0.416) effectively doubles the developmental velocity of the fields in isolation. By uniquely applying Sahal's (1981) model to this specific nexus, the research provides empirical proof of allometric innovation scaling, showing a disproportionate acceleration of technological output (Ev=1.58) relative to scientific input. Furthermore, the study moves beyond the general "mutualistic" claims seen in prior literature by identifying a critical directional asymmetry. While previous theories of symbiotic relationships suggested equal partnership, this data explicitly identifies AI as a General Purpose Technology (GPT), as conceptualized by Bresnahan and Trajtenberg (1995), functioning as the primary "method of invention" that can drive quantum maturation. This specific insight provides evidence needed to dismantle siloed R&D strategies, offering a precise roadmap for policy interventions that target the "connective tissue" of radical innovation rather than the disciplines themselves.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Although the study provides important insights, the conclusions are necessarily tentative due to the complexity of analyzing evolving scientific and technological pathways. First, bibliometric databases are known to represent the natural sciences more comprehensively than technical fields such as engineering and computer science. These domains often generate software and algorithmic outputs that are not systematically captured in traditional publication and patent datasets. Consequently, the present analysis may reflect only part of the dynamic interaction between AI and quantum systems. For future investigations, the expansion of database coverage-especially for software outputs-is essential (Leydesdorff, 2008). Second, the search queries used in this study generate broad datasets that require further refinement. Using standardized strings like "quantum technology" and "artificial intelligence" risks omitting specialized nomenclature or emerging synonyms. Moreover, keyword-based retrieval is inherently limited by semantic drift; as fields mature, their terminology evolves, which can lead to the under-representation of earlier works that used archaic phrasing. Furthermore, reliance on titles and abstracts may miss latent technological developments that do not utilize standardized labels. Future research should also incorporate advanced mapping techniques to visualize and analyze evolving network structures in the quantum and AI systems. Mapping relationships among key papers and patents would clarify core interaction pathways and reveal the underlying mechanisms driving coevolution. Co-citation analysis, using multivariate approaches, can further identify the structural dynamics of emerging scientific fields (Small, 1973; Coccia *et al*., 2024). Third, interdisciplinary and transdisciplinary research plays a fundamental role in the evolution of quantum and AI systems. Methods such as those proposed by Leydesdorff and Rafols (2011) or Silva *et al*. (2013) can be integrated to better quantify interdisciplinarity and understand its impact on technological convergence. Future studies should also control for situational and confounding factors such as R&D investments, collaboration networks, knowledge openness, and intellectual property regimes. These determinants may substantially influence the observed dynamics and should be incorporated to validate the robustness of synergetic growth patterns.

Relevance and Broader Implications

Despite its limitations, this study provides strong evidence that interaction and convergence between pathbreaking scientific fields produce higher growth rates than isolated development. These dynamics illuminate fundamental aspects of contemporary scientific and technological change, increasingly characterized by interaction, merging, and convergence (Fortunato *et al*., 2018). The results underscore the need for policymakers and R&D managers to strategically support research intersections, strengthening areas where synergetic effects are most pronounced. Indeed, fostering interactions between AI and quantum systems may accelerate the emergence of disruptive innovations with wide-ranging benefits for science, industry, and society (Coccia, 2022a). Strategic R&D investment in these converging domains can amplify scientific impact, generate new technological trajectories, and support economic development through innovation (Coccia and Roshani, 2024; Coccia, 2022a, 2024; Mosleh *et al*., 2022; Roshani *et al*., 2021).

Concluding

If society aims to fully realize the transformative potential of AI and quantum technologies, policymakers and R&D leaders must invest in their interaction and convergence, enabling symbiotic evolution and synergetic effects (Coccia and Wang, 2016). Such coordinated investment strategies will be vital to shaping the future of science, technology, and socioeconomic development.

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ABBREVIATIONS

AI: Artificial Intelligence; **R&D:** Research and Development; **OECD:** Organisation for Economic Co-operation and Development; **OLS:** Ordinary Least Squares; **SPSS:** Statistical Package for the Social Sciences; **GPT:** General Purpose Technology; **EV (Ev):** Evolutionary Coefficient of Growth; **Ln:** Natural Logarithm; **AND (Boolean):** Logical Operator for Combined Search; **R^2:** Coefficient of Determination; **F-value:** Ratio of Explained to Unexplained Variance; **p-value:** Probability Value (Statistical Significance); **ns:** Not Significant.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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