Financing Futures: How Hype Shapes the Funding and Progression of Quantum Computing and AI

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ABSTRACT
This study examines the influence of media hype on the financing and advancement of artificial intelligence (AI) and quantum computing (QC), with a particular focus on analysing the ways in which various media types — traditional, expert, and new — affect the ability to attract funding both immediately and over time. A regression analysis was used after quantifying hype to assess how it relates to financial investments utilising information from Google Trends, mainstream media, and academic journals. The analysis found that of all three media, expert media consistently demonstrated a significant positive relationship with funding for both technologies. Traditional media on the other hand, impacted only AI funding with a three-year lag, with new media failing to show any significant relationship for either technology. AI, being more mature, demonstrated a stronger relation between media hype and funding compared to QC. The results suggest that the dissemination of knowledge by professional media is essential to the financing of new technology. While the delayed impact of traditional media on AI funding suggests that conventional channels absorb information at a slower rate, the lack of significant correlation for new media implies that public sentiment may have less influence on investment decisions in high-tech fields.

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1.0 INTRODUCTION

In the last two decades, we've seen an explosion of new technologies that have promised to revolutionise the future. With the rate of these developments seemingly hastening, intense competition in both public and private sectors have created a climate of technological saturation. Within such environments, generating sufficient attention and interest for funding and development is paramount. It is within this context that we meet the key technologies, Quantum Computing (QC) and Artificial Intelligence (AI).

Emerging technologies present the opportunity to reimagine future possibilities. However, with the proliferation of these reimagined futures, expectation management becomes crucial. As is often the case, more knowledge about technology leads to its maturity, which in turn reduces public expectations. At the point where knowledge is at its lowest, variation in future projections peaks, potentially causing overinflated expectations with wider impacts and implications than anticipated.

1.1 PROBLEM STATEMENT

Quantum Computing (QC) and Artificial Intelligence (AI) are both rapidly gaining attention and development (Pathak, 2013). As with many novel technologies, an air of hype around the release and mass market push of QC and AI has begun to form. Here, hype, as it pertains to this exploration, refers to the nature of media conversations and the formation of expectations held by the public with regards to a specific topic or technology.

Hype has, in many forms, existed before the advent of the internet, however, since its creation, our expanded means of communication have caused its effect to be amplified (Aral, 2020, as cited in, Ezratty, 2022). Media, defined by mass communication, has evolved greatly overtime post internet. Now, through this, several avenues for information dissemination have made strongholds into the daily lives of many. What was once limited to newspapers, radio and official, centrally organised, widespread announcements has exploded into multiple fields, each with their own standard procedures and generalised uses. Understanding how each of these differing forms of media create and react to factors that drive funding for these technologies is crucial for stakeholders.

To that end, the Gartner Hype Cycle Model (GHC), first published in 1995, was created to measure this media "hype," the trends of interest, and expectations against an emerging technology's life (Gartner, 2021). This model, characterised by peaks of inflated expectations followed by troughs of disillusionment, has been used increasingly to help many interested stakeholders understand the trajectory of emerging technologies (Gartner, n.d.). For this thesis, the GHC model will act as a foundational underpinning tying the ill-defined mechanisms of multi-media 'hype' to concrete and better measured states.

Despite the commercial significance of this model, within the conversation surrounding quantum technologies and outside the confines of strictly peer-reviewed academic literature, public discourse reveals a rather polarised landscape with regards to the viability of the technology (Ezratty, 2022). While less prevalent as a result of the recent explosion of Large Language Models such as ChatGPT, similar conversations surrounding the viability of generalised AI took place in the last decade (Borana, 2016). Looking back to the quantum front, as is often the case, two camps have formed at the extremes, one in favour of the future prospectus of quantum and its full realisation and the other who believe it to be entirely overhyped (Smith III, 2022). Similarly, AI has been both lauded for its potential to solve complex problems and critiqued for its ethical implications and unrealistic expectations set by media and industry hype.

It is at the intersection between these two technologies that knowledge is hardest to come by and potential for the future is highest. The potential held in the promises of quantum technologies and AI has been of great interest for those involved in national security and cryptography (Smith III, 2022). However, there are some that argue more aggressively in opposition to the development of such a future, going as far to state that quantum itself is a "scam created by scientists who found a way to get funding for their research ventures" (Ezratty, 2022, p. 1).

With a high variety of opinion, the views of better-informed industry leaders can significantly impact the flow of funding in and out of industries that are vital for sustained research and development. Thus, the problem statement for this thesis centres on the pivotal role of hype in shaping both the funding and the development of quantum computing and AI.

1.2 Research Question

The research question this thesis will seek to answer is: How do different types of media hype (traditional, expert and new) influence the attraction of funding sources for Quantum Computing and Artificial Intelligence, both in the present and with temporal lags?

Through this question, this thesis attempts to expand on and explore four key objectives: first, an analysis of the relationship between current media hype (traditional, expert, and new) and funding levels for Quantum Computing and Artificial Intelligence; second, the relationship explored by way of temporal lag, assessing the impact of media hype from previous years on current funding levels and vice versa; third, a comparative analysis to compare the influence of media hype on funding between Quantum Computing and Artificial Intelligence; closing with providing recommendations for industry professionals, researchers, and policymakers based on the findings.

1.3 Contributions

With this research, the author seeks to simplify the complicated landscape that is emerging technology and create a capable of turning hype into funding forcasts. Before mass market appeal, many technologies remain within niche circles of dedicated small networks of actors that support innovation based on expectations and visions (Geels, 2019, p. 9). Further, through an exploration of the relationship that funding has with hype, the author seeks to present an academically substantiated view on QC and AI's current trajectory and how the members of niche networks of innovation organise and propel themselves into the future.

With regards to theoretical contributions, the author seeks to integrate hype cycles with funding dynamics and understand development trajectories under the influence of hype. On a practical level, the findings from this study will offer actionable insights for investors, policymakers, and technology managers interested in QC, AI and lay a foundation for approaches to other future emerging technologies.

This research will also contribute to the field of risk management in technology investments. By identifying patterns in how hype influences funding and development directions, investors and companies can better prepare for potential risks associated with the hype cycle's peak and trough phases. Investment in emerging technologies comes with high risk that, if not accompanied with a deep understanding of the landscape, can prove detrimental. Unlike trading on the stock market, much of the deals done between stakeholders within a niche network are completed directly from party to party. This contribution will be particularly crucial in helping avoid the common pitfalls of overinvestment during periods of heightened expectations and underinvestment during periods of disillusionment.

2.0 THEORETICAL FRAMEWORK

To provide the foundation for this thesis' exploration, the theoretical framework herein explores the conceptual and empirical underpinnings of hype cycles as they influence quantum computing, funding sources and innovation paths. This section will present a broad overview on the academic and non-academic literature surrounding QC, AI and hype.

2.1 The Fundamentals

2.1.1 Quantum Computing

Quantum computing is a cutting-edge computational technology that exploits the principles of quantum mechanics to perform operations on data (Vasani et al., 2024; Gyongyos & Imre, 2019). Unlike classical computers that use bits as the smallest unit of data, quantum computers use quantum bits, also known as qubits, which can exist in multiple states simultaneously (known as superposition). On the simplest level, this ability, while difficult to manufacture and maintain, allows quantum computers to process vast amounts of data more efficiently. Quantum computing holds potential for significant advancements in fields such as cryptography, optimisation, and complex system simulations due to these unique properties (Hassija et al., 2020, p. 44).

While there are several benefits to quantum technologies, there remain a significant number of challenges. Chief among these is quantum noise. Simply, quantum noise refers to inescapable undesired interference within quantum systems that lead to significant errors and cause qubits to lose their delicate states of superposition (a process known as decoherance) (Vasani et al., 2024). To counter this, entire fields of study focusing on quantum error correction (QEC) have been formed to improve the potential of quantum computers and systems as a whole.

There is a myriad of academic literature on the applications of quantum computing. The 2024 review "Embracing the quantum frontier: Investigating quantum communication, cryptography, applications and future directions" explores in great detail the current landscape of quantum innovations and presents both technical and theoretical information alongside an assessment of the potential future (Vasani et al., 2024).

2.1.2 Artificial Intelligence (AI)

Artificial Intelligence (AI) has seen an explosion in popularity as a result of one of its commercialised applications, Generative AI (Gartner, 2023). AI as a whole however, is defined as the intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans and other animals (Lakshmi Aishwarya et al., 2022, p. 130). It refers to the capacity of a computer or a robot controlled by a computer to perform tasks that are usually associated with intelligent beings, such as reasoning, learning from past experiences, and problem-solving.

AI aims to replicate human intelligence and is applied in various fields including robotics, machine learning, and natural language processing. In doing so, two primary categorisations of AI exist, strong AI and weak AI. Strong AI is achieved when a computer system is at least as intelligent as a human being without having any external inputs making it "capable of reasoning, perceiving, and making judgments" (Lakshmi Aishwarya et al., 2022, p. 131). With no such system existing, all current AI models are considered weak AI.

As mentioned, much of the popularity that AI startups are receiving are as a result of the explosion of generative AI (GenAI), more specifically, ChatGPT. Since 2022 the hype surrounding GenAI has been climbing with Gartner releasing a figure in 2023 placing it at the peak of its own hype model (Gartner, 2023). There are however many other types of AI that are still being developed beyond the Large Language Models seen here with self-driving cars and robots on the horizon (Lakshmi Aishwarya et al., 2022, p. 130).

2.1.2 Hype

As previously established, hype for this exploration refers to the nature of media conversations and the formation of expectations held by the public with regards to a specific topic or technology. Excluding this definition, hype from a wider perspective is a modern, informal term of hybrid origin partially tracing back to the word hyperbole, referencing exaggerated claims (Ruef & Markard, 2010). As defined by Cambridge Dictionary, hype has three general definitions for British, American, and Business English. Each definition emphasises the creation of excitement and interest, the spread of information via various channels, and the extensive promotion of a subject, product or service. In combining these definitions, then, hype can be defined as the extensive promotion and dissemination of information through various media channels aimed at creating widespread excitement and interest among the public, often to make something appear more important or exciting, particularly in the context of new products or services.

This concept plays a significant role within the field of emerging technologies as a product of its connection to expectations and expectation management. Technological expectations themselves can be defined as "real-time representations of future technological situations and capabilities" and are significantly influenced by hype (Borup et al., 2006, p. 286). These expectations act as the frame upon which legitimacy is built to attract financing; agendas are set to guide innovators, and research directions are set for technical and practical applications (Van Lente et al., 2013).

Through the close connection that these concepts have with one another, a negative connotation forms surrounding hype as it "implies a drop of publicity as well as the possibility of disillusionment or disappointment " (Ruef & Markard, 2010, p. 319).

Amongst analysis and research of hype, a pattern has been observed pertaining to the frequent cycle of hype and disappointment over time. Said pattern is a consequence of the nature of research and is generally logical. To research and develop, funding is required. To secure funding, people need to be excited about the potential output of the research, and to achieve that, narratives are created, and promises are made favourably rather than realistically (Geels & Smit, 2000). In this way, disappointment "seems to be almost built into the way expectations operate in science and technology" (Borup et al., 2006, p. 290). However, while one might assume that these constant cycles embed fatigue into the public, the strong emphasis on unrealized futures and newness often leads to a neglect of the past. This historical amnesia perpetuates the cycle as the past is often rationalised to minimize the threat for the next round of hype (Borup et al., 2006).

In this way, hype builds expectations, which compels innovators to align with prevailing conceptualisations, influencing both strategic decisions and the course of technological development. This process transforms expectations from rhetorical figures into influential forces that shape the evolution of the technological field (Van Lente & Bakker, 2010, as cited in Van Lente et al., 2013).

Amid this climate, sponsors (funding sources), consultants, and professionals alike attempt to navigate new industries, strategically avoiding investments in "overhyped" technologies without ignoring those that are viable if not underdeveloped (Fenn, 2006, as cited in Ruef & Markard, 2010). To assist in this, the Gartner group put forward their Hype Cycle Model that, due to its connections in both professional and academic explorations of hype, will act as the foundational framework for this thesis' analytical exploration.

2.2.3 The Gartner Hype Cycle

The hype cycle is a tool used by consultants to plot the approximate path of an emerging technology across the axis of time and expectations (Steinert & Leifer, 2010). More loosely, the hype cycle acts as an instrument for assessing the trends that follow technology prediction and the science of expectations. This model follows Amara's law stating that "We tend to overestimate the effect of a technology in the short run and underestimate the effect in the long run" (Amara, 2016).

Since its inception, the Gartner Hype Cycle has been used as both a tool and a subject of analysis across multiple academic disciplines. While more prolific in its use in professional contexts, as its popularity increased in academic settings, deeper investigations into its viability and reliability did so in similar fashion. Dedehayir & Steinert's 2016 review of the model revealed inconsistencies between Gartner's hype cycle assessments and actual data which in turn question the reliable applicability of the hype cycle model for analysing and forecasting technological development (Dedehayir & Steinert, 2016). This isn't a new area of exploration for this model, the 2010 conference paper "scrutinising the hype cycle" came to similar conclusions suggesting a need for stronger mathematical foundations for the model.

Despite these flaws, the GHC offers an easily recognisable, simplified guide to established complicated relationships that can act as the springboard for deeper analysis.

At a simple level, the Hype Cycle provides a graphical representation of the maturity, adoption, and social application of specific technologies (Fenn & Raskino, 2008). It plots the expectations or visibility of a technology (y-axis) against time (x-axis), typically over a five to ten-year period. The model blends two distinct curves: the human-centric hype level curve that describes the initial surge of enthusiasm and excitement surrounding a new technology's introduction, and the technology S-curve that illustrates the technology's maturation process based on its technical performance and innovation trajectory (Fenn & Raskino, 2008, as cited in, Dedehayir & Steinert, 2016).

At a glance, Gartner describes technology development in five phases: technology/innovation trigger, peak of inflated expectations, disillusionment, slope of enlightenment, and plateau of productivity (Oja et al., 2020).

The cycle begins with an innovation trigger, typically as a result of a public announcement or demonstration that captures interest and drums up media attention (Fenn & Raskino, 2008, as cited in, Dedehayir & Steinert, 2016). As a result of this sudden buzz, optimism surges as media hype amplifies positive perceptions. This marks the ramp into the peak of inflated expectations. Here, substantial investment initiatives are typically launched without a clear strategic framework. In the coming months and years, the realisation of the overinflated expectations initially placed on the technology begin to take hold and the subsequent disappointment marks the entering of the Trough of Disillusionment phase resulting in disappointment and negative media scrutiny. Finally, as the technology begins to mature, early adopters begin to realise tangible benefits and investment increases (at a rate more reasonable than the initial hype phase). This increased investment and a deeper understanding of the technology drive gradual improvements. Ultimately, the plateau of productivity is attained, marked by a realistic assessment of the technology and widespread adoption following successful demonstrations (Fenn & Raskino, 2008, as cited in, Dedehayir & Steinert, 2016).

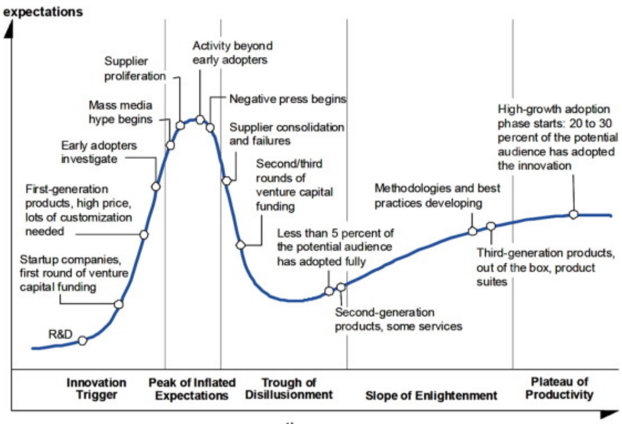

Fig 1: The hype cycle and its stage indicators (Dedehayir & Steinert, 2016).

The period between the peak of inflated expectations and the plateau of productivity was termed the time-to-value gap by Fenn

& Raskino (2008) with the duration varying depending on the specific constraints of a given technology. Gartner themselves have released a more specific assessment of this time-to value gap, categorising technologies as either Fast Track (2-4 year traversal time), Normal (between 5 and 8 years) and long fuse (between 10-15 years) and finally Obsolete (for technologies that never make it to the Plateau) (Fenn & Linden, 2018).

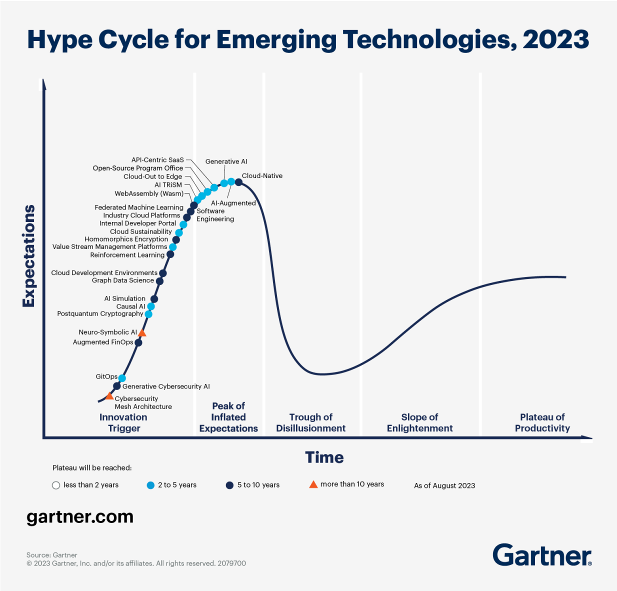

Fig 2. Hype Cycle for Emerging technologies (Gartner, 2023)

With respect to the two focal technologies for this exploration, Fig. 2 presents Gartner's self-published assessment of emerging technologies. While not directly addressing the blanket terms AI or QC, specific applications for both have been plotted. Generative and augmented AI are at the peak of inflated expectations, and Gartner believes their time to value will be 2-5 years. Conversely, AI simulation, Causal AI, Neuro-symbolic AI, and Generative Cybersecurity AI are all placed within the innovation trigger phase with various time-to-values. For Quantum, only one application in Postquantum Cryptography appears within the innovation trigger phase with a time to value between two and five years.

3 METHODOLOGY

3.1 Research Design

The research design for this thesis combines several quantitative methods with the previously explored academic findings to investigate how hype cycles influence the development trajectories and funding for quantum computing and artificial intelligence. This research approach allows for an in-depth exploration of both empirical evidence and expert opinions, providing a comprehensive understanding of the dynamics that are currently at hand. The research will utilise regression analyses to explore both present and temporal influences of media hype on funding allowing for a robust inspection of how various media types of impact funding over time.

3.2 Data collection, processing and analysis

To create a large enough dataset for analysis, several sources were utilized to represent the primary variables in this exploration. These variables were: Traditional Media, Expert Media, and New Media. Each of these variables was first quantified before being normalized and analyzed.

In quantifying the expert media, assessment of academic publication rate across a range of databases was used to approximate research hype. Using the tool Publish or Perish, a number of popular academic literature databases (Google Scholar, Scopus, Crossref, and Open Alex) can be searched, and its results downloaded, finding academic papers (including journals and conference papers) thus allowing further analysis. To quantify the traditional media, the publications of The New York Times, an internationally recognized news outlet, were used as an indicator of media hype. Being a prominent and reputable publication, a look at their publications mentioning QC and AI will provide a measure of what readers are paying attention to. Finally, as a measure of new media, Google Trends, a tool allowing users to analyze search queries, was used to gain an understanding of internet sentiment as a whole.

3.2.1 Data Normalisation

For each of the aforementioned media types, hype scores were normalised to ensure comparability on a scale from 0 to 1 using the equation

$$\frac{x - min(x)}{\max(x) - \min(x)} = \mathrm{Z}$$

Where x is the original datapoint and z is the normalised hype score.

3.2.2 Temporal Analysis

To assess the impact that hype generates on future funding, time lags were applied to each type of medias hype scores.

3.2.3 Quantifying Expert Media Hype

To gather Academic hype, four multidisciplinary databases were searched for mention of “Artificial Intelligence” or “Quantum Computing” within their titles. Due to limitations of database access, a max of 1000 data points were searchable on Open Alex and Crossref with 980 possible on Google Scholar and 200 possible on Scopus. To mitigate the variation this creates, each database was normalised on a scale of 0-1 individually using the above-mentioned normalisation equation before being combined. In said combination, each normalised data set was given an equal weight of 0.25 and added to create an Academic Hype Score for each year from 1995 to 2024.

3.2.2 Quantifying Traditional Media Hype

Using the New York Times API to access all articles posted between now and 1851, two sweeps of the databases were conducted to identify AI and Quantum. First, as a control, a sweep of all articles between 1995 and 2024 was conducted specifically searching for any articles with "Artificial Intelligence" and "Quantum Computing" within their titles. This was done to limit the inclusion of articles outside the scope of AI or QC, isolating only those with relevant headlines. Searching for "Artificial Intelligence" rather than "AI" or its equivalents minimized returns of articles mentioning AIDS or Airbnb, which could skew the data.

The second sweep looked at keywords included in headlines, bylines, or keyword sections of the database. The words selected for the AI search were: 'artificial intelligence', 'machine learning', 'deep learning', 'neural network', and 'Generative A.I.'. For the Quantum Computing search, the chosen keywords were: 'quantum computing', 'quantum computer', 'quantum algorithms', 'quantum supremacy', 'quantum entanglement', 'quantum cryptography', 'quantum mechanics', 'quantum technology', 'quantum bits', and 'qubits'.

These searches, while potentially increasing the number of datapoints outside the desired scope, substantially broadened the returned articles with the selected words aiming to limit errors. After sorting through this data, it was then normalised.

3.2.3 Assessing New Media Hype

To measure public interest via new media, Google Trends was utilised. The data output from Google represents search interest relative to its peak in the given region and time. The search parameters specified for Trends queries prioritised Web searches (as opposed to other google products) as the better fit for this research. The region was set to global, and the time range extended to its maximum, noting that Google's data only extends back to 2004 unlike other sources. Google groups keywords into "Topics," which are groups of terms sharing the same concept across languages and highlighted as research areas. For this study, Topics were used and normalized to produce a Trend score ranging from 0 to 1.

3.2.3 Statistical Software

To conduct the data analysis, the R programming language was used alongside the following packages: dplyr (for data manipulation), stargazer (for generating regression tables), ggplot2 (for visualizations) and readxl (to read excel tables).

3.*4 Justification of Methodological Choices*

This methodology was selected to meet the need for a concrete means to grasp often difficult-to-isolate elements of emerging technologies and their interactions with the public. The quantitative analysis creates a more robust framework for understanding hype cycles and how this is correlated with funding and development trajectories.

4.0 FINDINGS

4.1 Quantifying Hype

The following chapter will highlight the hype scores for each type of media. These hype scores are relative, with a score of 1 indicating the peak of that technology's hype and a score of 0 representing its lowest. While presented overlaid graphically for ease of understanding and with a focus on the media's relationship with funding, the absolute values of these hype scores were omitted due to the significant difference in popularity between AI and QC (AI being far more popular).

4.1.1 Expert Media Hype

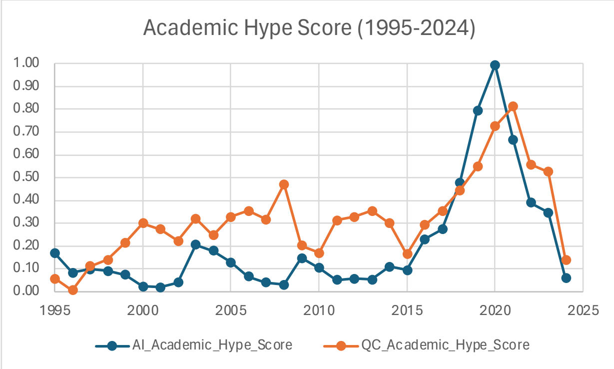

Fig 2: Academic Hype Scores from 1995 to June 2024

Figure 2 illustrates the trends in academic publications mentioning "Artificial Intelligence" (AI) and "Quantum Computing" (QC) from 1995 to 2024. Both technologies follow a remarkably similar path over the years, both peaking at approximately 2020. This rapid rise in expert hype suggest significant academic attention and possibly breakthroughs. However, the subsequent decline may indicate a phase of consolidation or a shift towards more practical applications and challenges rather than theoretical/academic exploration. Worth noting are potential factors influencing the fluctuations seen in the last 5 years that include the date of data collection being June 2024 and the potential influence of the global pandemic COVID-19.

4.1.2 Traditional Media Hype

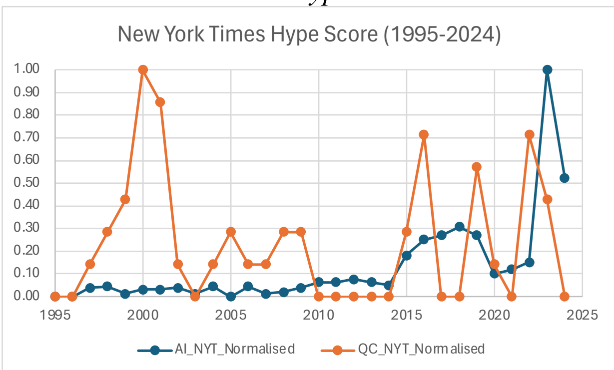

Fig 3: New York Times Hype Scores from 1995 to June 2024

Figure 3 shows the trends in mentions of AI and QC topics within the NYT articles over the period from 1995 to 2024. Unlike with the academic hype scores, Quantum and AI differ vastly over the duration of measurement. The vast fluctuations of Quantum come as a result of the smaller sample size of QC as opposed to AI. While A.I. remained primarily stable until 2015, where in a gradual increase gave way to a sudden spike in 2022, Quantum remained erratic in its performance peaking in 2000 before dropping and fluctuating to this day.

These fluctuations in media hype, particularly the peaks around 2000 and 2020 for QC and AI respectively, point towards periods of intense public and media interest which can drive both public perception and investment.

4.1.3 New Media Hype

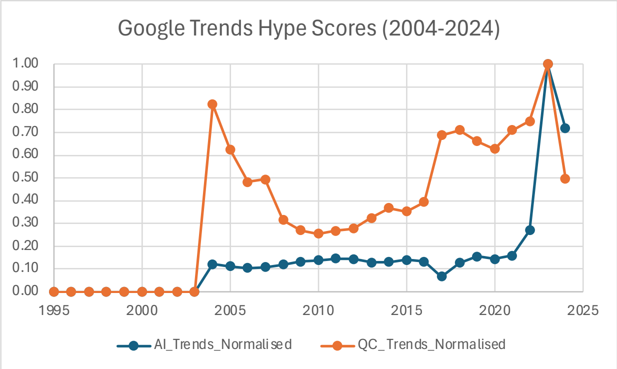

Fig 4: Google Trends Relative Hype Scores from 2004 to June 2024

New Media Hype, as represented through Google Trends, only started in 2004. Again, AI matches well with the professional and academic hype scores tracking relatively stable until 2020 before spiking. Quantum, unlike the other two measures, starts by spiking in 2004 before levelling out and peaking again in 2023 in a similar nature to the academic score. The Google Trends data reflects the level of public awareness and interest in AI and QC with peaks in search activity often coinciding with significant technological advancements, media coverage, or public discourse on these topics.

4.1.4 Comparison of Hype Scores

In looking at all three of these indicators side by side, a pattern emerges between the tendencies of each group, with all three indicators showing alignment in peak periods, particularly around significant technological advancements that have occurred within the last 5 years. Of the three, traditional scores show sharper spikes, highlighting the potentially sensational nature of traditional media coverage. Expert scores show more sustained peaks, indicating deeper engagement, while new media scores reflect transient public interest. However, out of the three, new media scores often lag slightly behind expert and traditional spikes, reflecting the time it takes for public interest to catch up with expert and media topics of discussion.

A 2019 study exploring the relationship between new and old media may explain this observation. The centralised, one-to-many relationship that traditional media has with audiences is characterised as a top-down push relationship, whereas new media (including social media in this context) moves information horizontally, creating a network for information dissemination Further, as a consequence of this more decentralized information network, less emphasis is placed on credibility held by institutions and more on the experience and interest of individuals (Etter et al., 2019). This difference means that information will only reach as far as those who find it interesting, making new media a content-pull relationship and potentially explaining the lag visible between the new and the old.

4.2 Financial Data Analysis

Financial data for emerging industries presents difficulties, as many companies remain private during the early stages of technology development, only occasionally being acquired by larger organisations. To overcome these challenges in collecting first-party data, reports from reputable sources such as McKinsey Consultancy, The Quantum Insider and Statista were utilised to construct a comprehensive understanding of the current state of funding in Quantum Computing (QC) and Artificial Intelligence (AI).

In searching for reliable data, a clear pattern emerged. Likely a product of the different stages of technological development for each technology, information on QC funding on a global level is far more difficult to find and reliably trace. While information on QC can be found, even at the most basic level of a Google search, “Quantum Computing funding” returns About 49,600,000 results, while a search for “AI Funding” returns approximately 1,470,000,000 results. An almost 30 x increase in results.

4.2.1 Presentation of Financial Trends

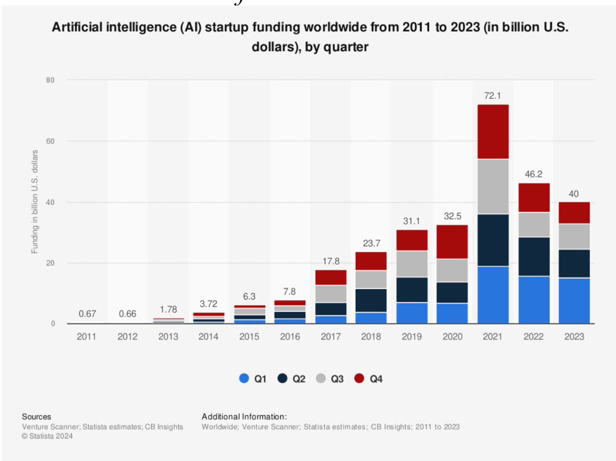

Fig 6: AI Startup funding from 2011 to 2023 (McKinsey & Company, 2023)

Starting with AI, McKinsey’s data reveals a pattern seen within the hype scores. Starting modestly in 2011 and 2012, AI funding begins to pick up more significantly in 2016. Following the sharp jump seen in 2017, a phase of growth began. From a more macro perspective, within the 12 years of this data’s collection, funding grew exponentially from 670 million U.S. dollars in 2011 to 36 billion U.S. dollars in 2020 and ultimately ballooning to 72.1 billion U.S. dollars a year later. While this was corrected in subsequent years, this rapid growth follows approximate estimations in line with hype score growth.

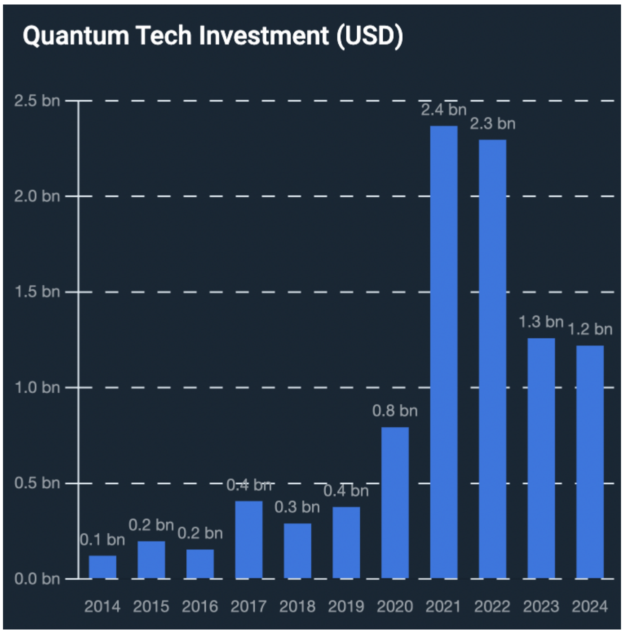

Fig 7: Quantum Technology Global Investment from 2014 to 2024 (USD) (The Quantum Insider, 2024).

Shifting now to Quantum data, Figure 7 shows total funding of quantum technology from 2014 to 2024. Immediately apparent are the significantly smaller numbers with regards to funding in comparison to AI startups. This data's peak of 2.4 billion U.S. dollars, while still significant, would hardly appear on figure 6. Despite this, from this sample, QC funding follows a smaller yet similar upward trajectory. Sources that include datapoints within the pandemic have witnessed a similar explosion witnessed in the field of AI.

4.3 Corelation between Hype and Funding

4.3.1 Comparative analysis

Regression Results without Time Lags

	Dependent variable:	
	Funding	
	AI Funding	Quantum Computing Funding
	(1)	(2)
Traditional Media	-25.845	0.147
	(43.355)	(0.833)
Expert Media	51.058^{***}	1.532
	(15.200)	(1.454)
New Media	51.723	1.194
	(44.782)	(1.609)
Constant	-1.113	-0.576
	(7.855)	(0.823)
Observations	13	11
R^2	0.603	0.383
Adjusted R^2	0.471	0.118
Residual Std. Error	15.905 (df = 9)	0.782 (df = 7)
F Statistic	4.556^{**} (df = 3; 9)	1.448 (df = 3; 7)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 1: Regression analysis results without lags.

In establishing a baseline, two regression models were completed without time lags. In the first model, with AI funding as the dependent variable, neither traditional nor new media produced statistically significant outcomes. However, Expert Media produced a positive and highly significant result, suggesting that an increase in Expert Media hype is associated with a significant increase in AI Funding. The results from this regression indicate that a realitively large 60.3% of the variance in AI Funding is explained by the independent variables in the model with the model itself being statisitcally significant at the 5% level (F Statistic = 4.556**). For Quantums model however, none of the media hype scores show any statistically significant effects nor is the model itself statistically significant. Thus, while Expert Media is a significant predictor of AI funding, no media type significantly impacts Quantum Computing funding, suggesting other factors potentially playing a role.

Regression Results for AI Funding (Lagged)

	Dependent variable:		
		Funding	
	1-Year Lag	2-Year Lag	3-Year Lag
	(1)	(2)	(3)
Traditional Media Lag	-5.920		
	(30.597)		
Expert Media Lag	62.678^{***}		
	(8.958)		
New Media Lag	50.154		
	(61.287)		
Traditional_Media_Lag2		85.842^{**}	
		(30.411)	
Expert_Media_Lag2		47.911^{***}	
		(8.693)	
New_Media_Lag2		72.678	
		(120.463)	
Traditional_Media_Lag3			132.350^{**}
			(43.112)
Expert_Media_Lag3			27.849^{*}
			(12.704)
New_Media_Lag3			24.914
			(172.136)
Constant	-4.632	-14.286	-5.540
	(10.886)	(17.894)	(25.353)
Observations	12	11	10
R^2	0.882	0.906	0.816
Adjusted R^2	0.838	0.866	0.725
Residual Std. Error	8.788 (df = 8)	7.920 (df = 7)	11.121 (df = 6)
F Statistic	19.983^{***} (df = 3; 8)	22.493^{***} (df = 3; 7)	8.890^{**} (df = 3; 6)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: AI regression analysis with 1-, 2- and 3-year lags.

Starting with AI, table 2 presents three models analysing the impact of various types of media, with lags, on AI funding over different time periods (1-year lag, 2-year lag, and 3-year lag). Within the first model (1-year lag), again, only Expert media returns a positive and statistically significant impact on AI funding at a 1% significance level. However, when looking at model fit, results return a statistically significant F Statistic (1% level) and an R-squared of 0.882, signalling that 88.2% of the variance in funding can be the combination of Traditional Expert and New Media hypes, a marked improvement over the baseline established in table 1.

Directing next to the second model (2-year lag), both Traditional and Expert Media indicate a positive and significant relationship at the 5% and 1% levels respectively. With an R-squared of 0.906, indicating that 90.6% of the variance in AI funding is explained by the model and an F Statistic significant at the 1% level indicating the overall model's statistical significance, this model once again improves on the last two models.

Finally, with the last model (3-year lag), both Traditional and Expert Media again return positive and statistically significant impacts (5% and 10% levels respectively). Indicating that 81.6% of the variance in AI funding is explained by the model, the R-squared of 0.816 and F Statistic 5% level, confirm the overall model's statistical significance. While this model presents a slight step down from the significance of the 2-year model, it still highlights the importance of both Traditional and Expert Media over a longer period in influencing AI funding. Media consistently shows a significant positive impact across all models.

In sum, Tables 1 and 2 indicate that traditional and expert medias act as the best indicators for AI funding, performing best with a two year temporal lag.

Regression Results for Quantum Computing Funding (Lagged)

	Dependent variable:		
	Funding		
	1-Year Lag	2-Year Lag	3-Year Lag
	(1)	(2)	(3)
Traditional Media Lag	0.149		
	(0.394)		
Expert Media Lag	4.320^{***}		
	(0.738)		
New Media Lag	-0.760		
	(0.732)		
Traditional_Media_Lag2		0.716	
		(0.723)	
Expert_Media_Lag2		3.116^{*}	
		(1.532)	
New_Media_Lag2		-0.044	
		(1.990)	
Traditional_Media_Lag3			0.779
			(0.932)
Expert_Media_Lag3			-0.344
			(1.592)
New_Media_Lag3			4.773
			(2.304)
Constant	-0.658	-0.588	-1.563
	(0.399)	(0.882)	(1.060)
Observations	10	9	8
R^2	0.882	0.638	0.647
Adjusted R^2	0.823	0.421	0.382
Residual Std. Error	0.351 (df = 6)	0.640 (df = 5)	0.656 (df = 4)
F Statistic	14.974^{***} (df = 3; 6)	2.941 (df = 3; 5)	2.441 (df = 3; 4)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: Quantum regression analysis with 1-, 2- and 3-year lags.

Finally turning to quantum's temporal regression analysis, Table 3 again presents three models analysing the impact of our three types of media, with lags, on Quantum Computing funding over different time periods (1-year lag, 2-year lag, and 3-year lag). As seen in the first model, only Expert media lag presents any statistical significance at the 1% level. Fit-wise, this model improves drastically on the baseline with 88.2% of the variance in Quantum funding being explained by Media Hype and an F-statistic at the 1% level.

Turning now to the second and third models (2-year and 3-year lag), again only Expert media shows a statistically significant relationship, but this time to a lesser degree (10%), and only within the 2-year lag model. Similarly, regarding model fit, neither the 2-year nor 3-year models return statistically significant F-statistics despite similar R-squared values of 0.64 and 0.65 respectively.

In sum, quantum's 1-year lag presents the only statistically significant model by way of F-statistic suggesting that media impacts take form more prominently within a year. On a hype to hype level Expert Media shows a significant positive impact on Quantum Computing funding particularly in the short-term (1-year lag) and to a lesser extent in the 2-year lag with Traditional and New media failing to do so.

5.0 DISCUSSION OF FINDINGS

5.1 Interpretation of results

Throughout this thesis, we aimed to explore how different types of media hype (traditional, expert and new) influence the attraction of funding for Quantum Computing and Artificial Intelligence, both in the present and with temporal lags. To that end, hype scores for each media were created and subsequently tested. Through these tests the following results were drawn.

The Role of Expert Media:

Across both technologies, and both with and without time lags, expert media consistently shows a significant and positive relationship with funding. While the influence on Quantum Funding may be slightly less significant when compared to AI, these findings suggest that expert hype produces an immediate boost in funding, and its effects remain even after two and three years.

The Impact of Traditional Media:

Interestingly, unlike expert media, traditional media (specifically with respect to AI) performs best with a 3-year lag. This delay in impact may be a consequence of the slower dissemination and absorption of information in more conventional channels or the limited capability for influence during the earlier stages of a new technology's development. However, regarding Quantum, traditional media had no statistical influence on funding, both with and without lags. This may be due to the lack of original data points scraped from the NYT database, which itself may be a product of the technologies prematurity.

The Ghost of New Media:

Across all models, both technologies, and all lags, New Media did not show any significant relation to funding, potentially suggesting that for investment-intensive fields like QC and AI, public opinion or sentiment plays an insignificant role. Alturnatively, the audience for New Media may differ from the decision-makers in funding bodies, reducing its immediate impact on funding.

Artificial Intelligence vs. Quantum Computing

As was littered throughout this report, AI as a technology is far more popular and developed than QC with certain applications already playing a significant role in the day to day lives of people. From widespread media attention to niche research communities AI is experiencing something of a boom. In this exploration, significant relationships between the Expert and Traditional media have been highlighted. Both regarding the total research output and the total funding input, Quantum technology remains a long distance from the current Hype and Funding that AI has. The sizable impact of Expert Media and the delayed impact of Traditional Media suggest that AI is a more mature technology with established expert opinions and a broader acceptance in traditional media. As one might imagine, a technology with a stronger footing and better-established backing presents itself far more attractively than the often-unsure climate of emerging technology.

Building on that, the lack of impact as demonstrated within the study suggests that other factors, such as governmental support, strategic investments in cutting-edge technology, and more application-specific breakthroughs, may play a larger role. The distance that many quantum applications, including quantum computers, have from the mass market may be the primary reason why the sector is not yet primarily driven by hype.

In this way, tying the technologies to the GHC, we can conclude that Quantum Technologies remain firmly within the phase of innovation trigger while AI has solidified its position at the peak of inflated expectaions.

5.2 Implications for Stakeholders

This study illustrated that stakeholders, including policy makers and industry experts with an interest in AI, can increase funding through publishing or sponsoring research, joining expert panels, and other means by taking advantage of the intimate relationship that financing has with Expert Media. Long-term tactics intended to increase and sustain visibility in conventional media can be helpful in the context of traditional media. In contrast, given the lack of media hype influence on the quantum front, focus and efforts should be isolated to facts and technological breakthroughs. Further, focusing These findings point to the possibility of a comprehensive predictive model for investment managers.

5.3 Limitations and Future Research Directions

There were a number of constraints, related to the data that could have affected the accuracy of the results, and the ability to thoroughly answer the research question. Firstly, it was difficult to find and verify sources for finantial data, that contained the level of specificity that was needed. In an attempt to avoid this and preserve the integrity of the study, alternate data was used and this impacted the generalizability of the results.

Similary, the small sample size of financial data limited the capabilites the regression models as, what was already a small number of observations, became smaller due to time lags. While gathering enough data for each of the hypes resulted for 29 years worth of entrys (excluding Google Trends as it only began recording after 2004), data for AI and QC funding resulted in 13 and 10 observations respectively. This limitation restricted the capacity to derive longer-term judgments and weakened temporal lag analysis.

The next limitation concerns the study's representation of New Media, which was based on Google Trends data due to the difficulty in accessing social media APIs. Had data from social media APIs (such as Facebook and Twitter) been accessed, new media hype may have been measured with greater precision and depth.

In a similar vein, the New York Times was the only source used in the quantification for Traditional Media Hype. Despite its prominence, incorporating publications from other major newspapers, trade journals, and foreign publications would increase Traditional Media's accuracy in representing the impact of the media on financing decisions.

In order to overcome these constraints, future researchers should make an effort to employ more extensive and authenticated data sources, potentially working with data providers to access paywalled databases. With more concrete data and a potential expansion of variables to include the number of patents filed, research publications, or market size, potential exploration in the direction of creating a forecasting model reliant on hype could become a desirable reality. One that could directly influence investment decisions and expectations.

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