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Understanding Global AI Hype Phenomena with Big Data Analytics

Teemu Santonen*

Laurea University of Applied Sciences, Ratatie 22, FIN-01300 Vantaa,
Email: teemu.santonen@laurea.fi

Jari Kaivo-oja

Finland Futures Research Centre, Turku School of Economics, University of Turku, FFRC Unit of Tampere, Åkerlundinkatu 2 A, 4th Floor, 33100 Tampere, Finland, and Kazimieras Simonavičius University (KSU), Dariaus ir Girėno st. 21, Vilnius, LT-02189 Lithuania
Email: jari.kaivo-oja@utu.fi

*** Corresponding author**

Abstract: Artificial Intelligence (AI) encompasses various technologies that mimic human cognitive functions. To comprehend the current state of AI hype and formulate pertinent predictions and scenarios for its future trajectory, we must examine our journey leading up to the present day. AI technologies encompass a wide range of different technologies and applications such as machine learning, natural language processing, and computer vision. A Big Data analysis grounded on Google Trend Index data covering the key AI technology approaches (N=17) was conducted to compare their relative popularity and to reveal the hype curve progresses from the year 2004 to the current day. Key results include AI technologies hype curve visualization, comparison, and classification of upward and downward trend curves. Understanding AI hype as a global phenomenon provides fresh insights into the innovation diffusion process and can help us develop an informed opinion about AI and its social and ethical implications.

Keywords: Artificial intelligence; big data, machine learning, natural language processing, computer vision, deep learning, AI hype phenomena

1. Introduction

Integrating AI and digital technologies into management, decision-making and leadership presents a dynamic landscape with far-reaching implications across various domains of innovation management. This AI hype research and exploration navigate the intricate intersections of technology, ethics, culture, political systems, and society, offering insights into the multifaceted dimensions of AI integration (Buchanan & O'Connell 2006, Berryhill et al. 2019, Corea 2019, Carter 2020, Fosso Wamba et al. 2021). AI has developed strongly since the 2010s. The rise has been made possible by a significant increase in CPU computing power, an increase in the amount of data used to train learning AI, and improved availability of alternative algorithms. Founded as an academic discipline in 1956, AI development has experienced several waves of optimism, disappointments, loss of funding, new approaches, success, and financial recovery. Many different approaches have been tried and rejected in AI research, such as brain simulation, human problem-solving modelling, formal logic, large databases, and mimicking animal behaviour. It can be said that we have applied the "trial and error" method in the development of artificial intelligence. It is also possible that this type of approach will continue to be used in the future. The trial-and-error process refers to the process of verifying that a certain choice is right (or wrong). We simply substitute that special choice into the problem and check. It is always good to remember that some questions can only be solved by the trial-and-error process. For others, we must first decide if there isn't a faster way to arrive at the answer (Starch 1910, Cao 2017, Dick 2019, Batistiˇc et al. 2019, Chui et al. 2020, Broekhuizen et al. 2023, Sanderson 2023).

In this study, we limit our focus on empirical findings of the AI hype phenomenon. A Big Data analysis, based on Google Trend Index data covering 17 key AI technology approaches, was conducted to compare their relative popularity and reveal the progression of the hype curve from 2004 to the current day. At the heart of all AI inquiries lies the critical examination of ethical and moral implications. We can expect that the integration of AI sparks debates around decision-making accountability, transparency, and the moral quandaries inherent in employing AI algorithms to allocate resources and make pivotal choices during R&D developments.

2. Theoretical and operational frameworks

In various technological fields (medicine, gene therapy, engineering, digital technologies, etc.) one can often observe waves of media attention combined with high rising expectations on technological possibilities. We can present various interpretations of the determinants and directions of technical change (see e.g. Dosi 1982, Deuten & Rip 2000, Brown & Michael 2003, Sturken et al. 2004). Both qualitative (narratives) and quantitative variables (numbers) matter when actors shape their expectations. Such psychological and economic expectations play an important role in the emergence of technology by guiding research activities, attracting resources, and creating legitimacy (Guice 1999, Borup et al. 2006). The notion of 'hype' is widely used and represents a tempting way to characterize developments in technological fields and technological waves. The term "hype" appears in business as well as in academic domains. Consultancy firms offer technological hype cycle models to determine the state of development of technological fields to facilitate strategic investment decisions (see e.g. O'Leary 2008).

In Science, Technology, and Innovation (STI) Studies the concept of hype is considered in studies on the dynamics of expectations in innovation processes, which focuses on the performative force of expectations. They share with the marketing literature the conviction that hypes are performative, but have delved more deeply into the complex interactions between 'hype' as a collectively shared rhetoric about emerging technology and the underlying innovative activities. What is still lacking is a theory of hype patterns that can explain the different shapes of hype cycles in different contexts. We expect that S-curves or J-curves can provide an important perspective on what is happening to performance trajectories at average, aggregate levels. In some cases, trends can also be linear. That is why we present some examples of key S-, J- curves and linear trend curves (see e.g. Valente & Rogers 1995, Ayres 1998, Easley & Kleinberg 2010, Blythe & Croft 2012). Today we are facing various challenges to understand artificial intelligence (AI) hype. We expect that AI hype patterns vary a lot and that the interplay of expectations at different levels affects the ability of a field to cope with hype and disappointment. Partly these disappointments can be explained by "try and error" processes.

In this empirical study, our methodological approach is explorative and we aim to describe the hype phenomena of artificial intelligence (AI). The primary objective of exploratory research is to gain insights and gather preliminary information that can help us better define the research problem and develop hypotheses or research questions for further investigation. There are still a need for better theory building and theory testing in the field of hype phenomena and S/J -curve patterns (see Valente & Rogers 1995, Colquitt & Zapata-phelan 2007, Alvesson & Sandberg 2011, Barratt et al. 2011, Easley & Kleinberg 2010). This involves an in-depth analysis of a particular artificial intelligence (AI) study situation to gain insights into the underlying causes, processes, and dynamics of the issue under investigation.

By this approach, we can develop a more comprehensive understanding of a complex AI hype problem, and to identify potential new research questions or hypotheses. The data of this study is based on Google Trends data. This Big Data method involves analysing concepts of artificial intelligence to identify common themes, patterns, and trends. It can be useful in identifying patterns in the data and developing hypotheses or research questions (Carrière-Swallow & Labbé 2011, Fantazzini & Toktamysova 2015, Yakubu & Kwong 2021).

3. Research design

Google Trends analyses the popularity of top search queries in Google Search across various regions and languages. Google Trends can be considered a reliable indicator of general public behaviour since it is a popular search engine with over 90 percent market share. In various domains, scholars have started to recognise the value of Google Trend as a big data source to evaluate market and human interests and behaviour (e.g. Ward and Barker, 2013, Jun et al. 2018, Choi and Varian, 2012, Preis et al. 2013). Google Trends data is anonymized and aggregated, which allows for the evaluation of public interest in a particular topic from around the globe or down to city-level geography. In this study, global-level data from the years 2004-2021 was used. Google Trends analysis normalizes search data, and the resulting numbers are then scaled on a range of 0 to 100 based on a topic's proportion to all searches on all topics included in the search query (Google Support, 2021). The 17 keywords presented in Table 1 were selected to represent different types of artificial intelligence technologies.

Kendall rank correlation coefficients were calculated to detect upward, downward, and horizontal trends since the Google Trend data did not follow a normal distribution. Since monthly time series data are more subject to seasonality, therefore quarterly and annual time series data were also generated based on monthly data. The following criteria were used for interpreting the correlation coefficients: a correlation coefficient of 0.7 or over indicates a high positive correlation, a coefficient of 0.5 or over but less than 0.7 indicates a moderate positive correlation and a coefficient of 0.3 or over indicates weak positive correlation. The same threshold values were used for negative correlations. Trends with a correlation coefficient higher than -0.3 but below 0.3 were considered negligible.

Table 1: Keywords for Google Trend Analysis. Google Trends (2023).

Main Category	*Subcategory*
Artificial Intelligence	
Machine Learning	Supervised Learning
	Unsupervised Learning
	Reinforcement Learning
	Deep Learning
Natural Language Processing	Tokenization
	Entity Recognition
	Sentiment Analysis
	Machine Translation
	Speech Recognition
Computer Vision	Object Detection
	Facial Recognition
	Image Segmentation
	Pose Estimation

4. Results

4.1 Correlation analysis based on the keyword classification schema

Table 1 presents correlation analysis for monthly, quarterly, and yearly data, which indicate the strength of the possible downward or upward trend. The downward trend group consists of Machine Translation, Speech Recognition, Computer vision, and Image Segmentation technologies. Out of these Speech Recognition had the strongest negative correlation in each data set ranging between -0.858**to -0.916**. The second strongest technology was Image Segmentation which correlation remained moderate and ranged between -0.538** to -0.667**. The results for Machine Translation and Computer vision were not as clear. Both had only negligible correlation ranging between -0.188* to -0.226** in monthly and quarterly data. In the case of yearly data analysis correlations did not exist.

Upward trend group technologies were classified into three main groups. The high upward group included Sentiment Analysis, Tokenization, and Deep Learning. For these technologies correlations in all data analysis ranged between 0.763** to 0.945**. The moderate group was composed of Machine learning, Supervised learning, Entity Recognition, Facial Recognition, and Unsupervised Learning. For this group correlations varied between 0.550** to 0.649**. The low upward group consisted of Object Detection, Pose Estimation, Reinforcement Learning, Natural Language Processing and

Artificial intelligence. Artificial intelligence was the only technology that lost its' correlation in the yearly analysis. In all correlations varied between 0.306** to 0.465**.

Only Machine learning technologies resulted in upward trends for all included technologies. In the case of Natural Language Processing three out of five technologies had a negative trend. Finally, one out of four computer vision technologies had a downward trend.

Table 1: Trend analysis based on Kendall rank correlation coefficients for monthly, quarterly and yearly data. Source: Google Trends (2023).

Main category	*Monthly*	*Quarterly*	*Yearly*
Artificial intelligence	.310**	.311**	
Machine learning (ML)	.644**	.637**	.649**
Supervised learning	.610**	.610**	.600**
Unsupervised Learning	.578**	.556**	.550**
Reinforcement Learning	.384**	.371**	.347*
Deep Learning	.768**	.763**	.786**
Natural Language Processing (NLP)	.306**	.335**	.364*
Tokenization	.793**	.831**	.863**
Entity Recognition	.562**	.605**	.600**
Sentiment Analysis	.872**	.907**	.945**
Machine Translation	-.226**	-.217**	
Speech Recognition	-.858**	-.880**	-.916**
Computer vision (CV)	-.203**	-.188*	
Object Detection	.444**	.465**	.438**
Facial Recognition	.553**	.563**	.589**
Image Segmentation	-.538**	-.593**	-.667**
Pose Estimation	.444**	.435**	.347*

Correlation is significant ** at the 0.01 level (2-tailed) and * at the 0.05 level (2-tailed).

4.2 Visual trend analysis

A visual trend analysis was conducted by grouping the technologies based on their yearly correlation analysis results and visually observing the commonalities between the included variables. Technology was excluded from the group if the trend's curve deviated from the other technologies in the group. Figure 1 presents the downward trend of technologies, which at the beginning of the time series had very high values but afterward followed a long downward trend. The included technologies were Natural Language Processing, Machine Translation, Computer Vision, Image Segmentation and Speech Recognition. Compared to other technologies, Natural Language Processing has a shorter downward period and results in a higher upward trend than the others. Interestingly in the year 2021 for each trend, there is a pit, which most likely is associated with the COVID-19 pandemic.

The reverse trends are presented in Figure 2, which at the beginning of the time series had very low values but afterward followed a clear upward trend. The included technologies were Sentiment Analysis, Tokenization, and Deep Learning. A similar pit as in the Figure 1 can detected for Deep Learning and Sentiment Analysis, but not for the Tokinization.

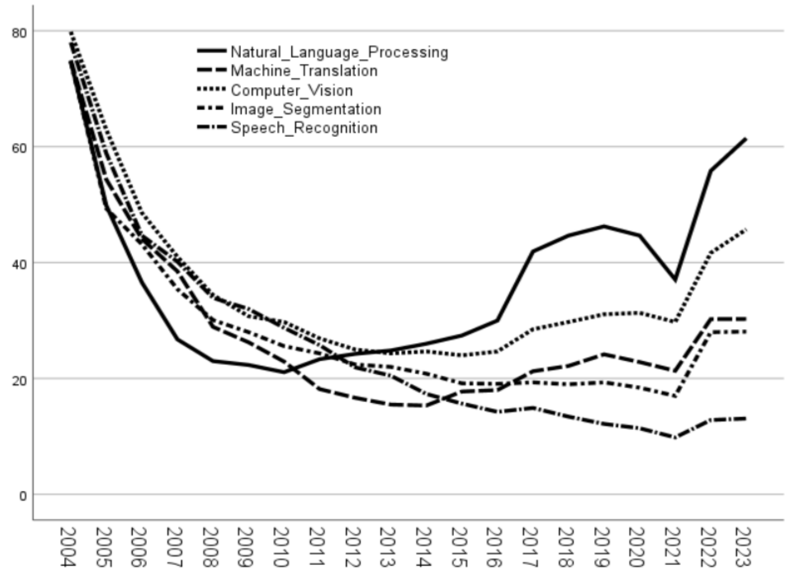

Figure 1: Downward trend technologies visual analysis based on yearly data. Note: These trend curves cannot be used for popularity comparison. Source: Google Trends (2023).

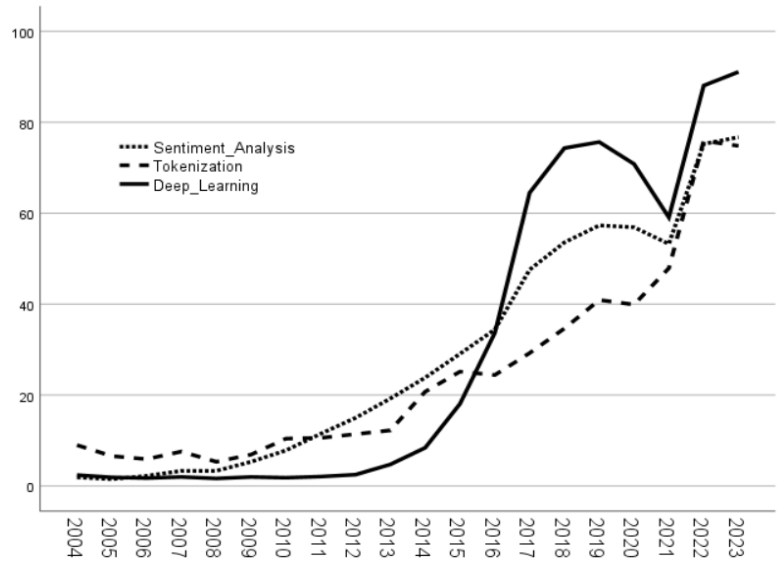

Figure 2: High upward trend technologies visual analysis based on yearly data. These trend curves cannot be used for popularity comparison. Source: Google Trends (2023).

The remaining technologies are visualized in Figures 3 and 4. The main difference between them is the trend's starting values. In Figure 3, starting values in the year 2004 range between 13 to 28, whereas in Figure 4, they vary between 37 to 49. The Figure 3 group includes Machine Learning, Supervised Learning, Unsupervised Learning and Entity Recognition, while Figure 4 is composed of Reinforcement Learning, Artificial Intelligence, Object Detection, Pose Estimation, and Facial Recognition. At the end of the time period, all technologies expect Entity Recognition and Facial Recognition have gained over 80 values. Again, the pit in the year 2021 is evident in the Figures 3 and 4, excluding Supervised Learning. Comparing to other Facial Recognition has deviating profile, since between 2008 to 2016 a bump can be observed, which is unique to this technology.

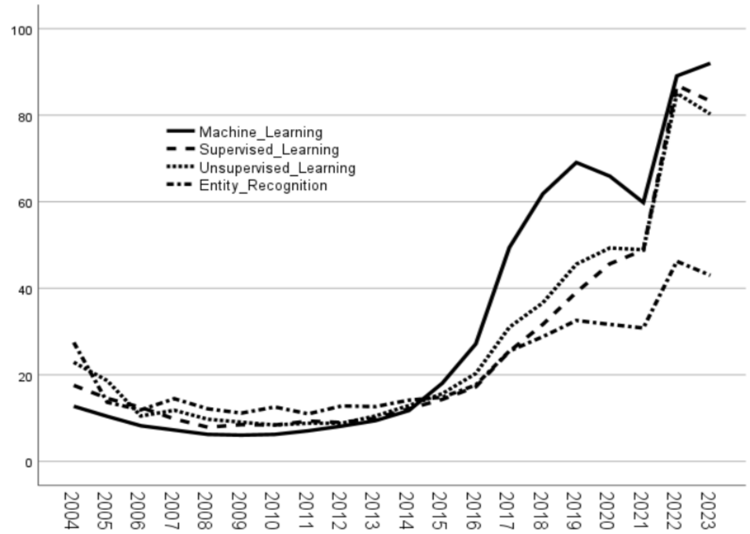

Figure 3: Moderate upward trend technologies visual analysis based on yearly data. These trend curves cannot be used for popularity comparison. Source: Google Trends (2023).

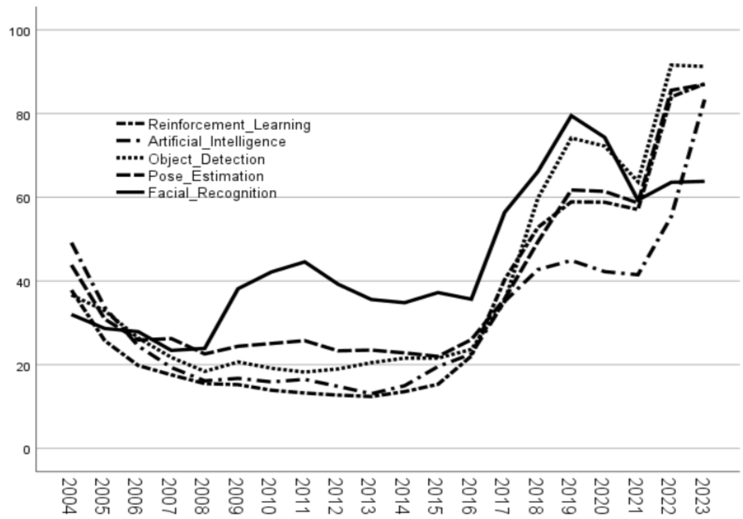

Figure 4: Low upward trend technologies visual analysis based on yearly data. These trend curves cannot be used for popularity comparison. Source: Google Trends (2023).

4.3 Tipping point analysis

In order to identify trend turning points, a tipping point analysis was conducted by splitting each yearly data variable into downward and upward groups based on the lowest data point between years 2004 and 2023. The aim was to identify the highest correlation difference between the downward and upward groups. Table 2 presents tipping point analysis and indicates the year when the change was occurring. Results are listed based on tipping point year starting from the lowest year. Table present also annual average value comparison between years 2004 and 2023 in order identify which of the technologies have increased or decreased their overall popularity.

Table 2: Tipping point analysis based on yearly data**.** Source: Google Trends (2023).

Technology	*Trend before tipping point*	*Tipping point year*	*Trend after tipping point*	*2004 Mean*	*2023 Mean*	*2023 - 2004 change*
Sentiment Analysis		2004	,945**	2	77	75
Tokenization		2004	,863**	9	75	66
Deep Learning		2004	,786**	2	91	89
Facial Recognition	-1,000**	2007	,559**	32	64	32
Natural Language Processing	-1,000**	2010	,884**	75	61	-13
Machine learning	-,878**	2010	,912**	13	92	79
Supervised learning	-,810*	2010	,950**	18	83	66
Unsupervised Learning	-,905**	2010	,950**	23	80	57
Object Detection	-,857**	2011	,812**	37	91	55
Entity Recognition	-0,571*	2011	,872**	28	43	16
Artificial intelligence	-,867**	2013	,818**	49	83	34
Reinforcement Learning	-1,000**	2013	,891**	38	87	49
Machine Translation	-1,000**	2014	,822**	75	30	-45
Pose Estimation	-0,667**	2015	,833**	44	87	43
Computer vision	-,970**	2015	,873**	80	46	-34
Image Segmentation	-,931**	2021	1,000**	75	28	-47
Speech Recognition	-0,987**	2021	1,000**	78	13	-65

Correlation is significant ** at the 0.01 level (2-tailed) and * at the 0.05 level (2-tailed).

The group 1 includes Sentiment Analysis, Tokenization and Deep Learning which have followed clear upward trend since year 2004. Facial Recognition, which had deviating profile forms own group by itself and had its tipping point is 2007. The third group was formed between 2010 and 2011 and includes Machine learning, Supervised learning, Unsupervised Learning, Object Detection and Entity Recognition technologies. Fourth tipping point group occurred between 2013 to 2015 and includes Artificial intelligence, Reinforcement Learning, Machine Translation, Pose Estimation and Computer vision technologies. Final group includes Image Segmentation and Speech Recognition, which tipping point was 2021.

Currently the following technologies are less popular than they were in year 2004 even if at the moment they are in upward trend: Speech Recognition, Image Segmentation, Machine Translation, Computer vision and Natural Language Processing. The remining technologies have been able to increase their popularity. From these Tokenization, Sentiment Analysis and Deep Learning follow linear growth path, whereas the remaining technologies resemble J-shaped relation where the curve initially falls, but then rises to become higher than the starting point.

4.4 Technology Popularity Ranking

Since Google Trends allows only comparing five terms at the same time, a pairwise comparison was conducted to identify relative difference between technology popularity. Table 3 present popularity rankings in January 2004 and November 2023.

Table 3: Technology Popularity Ranking in January 2004 and November 2023. Source: Google Trends (2023).

Technology ranking in 2004	*Ratio**	*Technology ranking in 2023*	*Ratio**
1. Artificial intelligence	207 %	1. Machine learning	129 %
2. Speech Recognition	138 %	2. Artificial intelligence	233 %
3. Computer vision	121 %	3. Deep Learning	294 %
4. Machine learning	175 %	4. Reinforcement Learning	115 %
5. Machine Translation	123 %	5. Computer vision	152 %
6. Image Segmentation	142 %	6. Facial Recognition	104 %
7. Reinforcement Learning	102 %	7. Object Detection	118 %
8. Natural Language Processing	164 %	8. Sentiment Analysis	101 %
9. Facial Recognition	132 %	9. Supervised learning	121 %
10. Object Detection	213 %	10. Unsupervised Learning	108 %
11. Supervised learning	120 %	11. Speech Recognition	100 %
12. Unsupervised Learning	200 %	12. Natural Language Processing	141 %
13. Deep Learning	100 %	13. Tokenization	100 %
14.Pose Estimation	243 %	14. Machine Translation	103 %
15. Entity Recognition**		15. Image Segmentation	250 %
16.Tokenization**		16. Pose Estimation	132 %
17. Sentiment Analysis		17. Entity Recognition	

* Technology and the next in descending order were compared pairwise based on their Google trend value in Jan 2004 and Nov 2024 to illustrate relative difference between the popularity. ** Google trend value in the given time was zero and therefore ratio cannot be calculated

In both cases, the TOP 5 group includes Artificial intelligence, Machine learning, and Computer vision, while the two other technologies are changing. Deep Learning has significantly increased (10) its position from 2004 and climbed from thirteenth to third position. Speech Recognition on the other hand has encountered a substantial position decline (-9) from second to eleventh position. Machine Translation also lost nine positions in 2004 and ended up in the fourteenth position in 2023. The change in the case

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of Reinforcement Learning change (3) has been more modest from seventh to fourth position. Image Segmentation is another big loser since it has lost nine positions and transformed from sixth to fifteenth position, whereas Sentiment Analysis is another technology, which has increased (9) its relative position in the ranking list from the last seventeenth to ninth position. The technologies ranking comparison is visualised in Figure 5. This kind of time-related ranking analysis helps us to assess the stability of AI technology rankings in the long run.

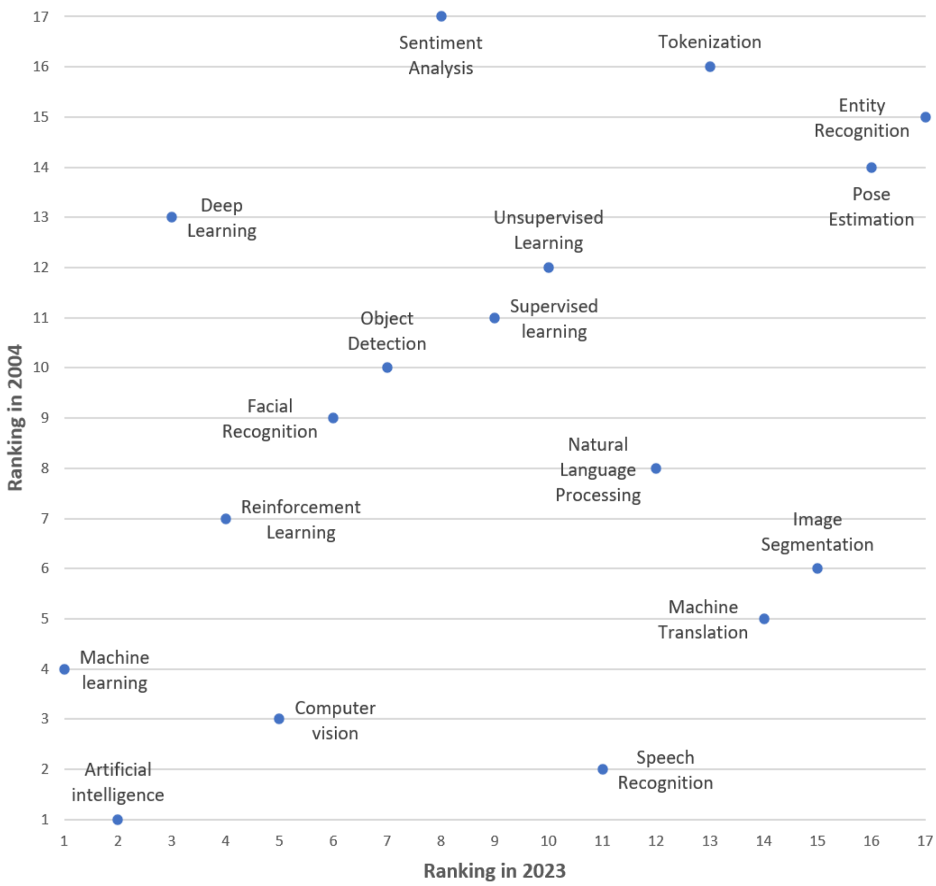

Figure 5: Relative position change comparison from January 2004 to November 2023. Source: Google Trends (2023).

4.5 TOP 5 Popularity Ranking Visualization

A visual trend analysis was conducted among TOP 5 technologies in 2004 (Figure 6) and 2023 (Figure 7). Until June 2014 Artificial Intelligence is the most popular technology. Afterward Machine Learning start leading. In all these two and Deep Learning are clearly more popular than the other technologies.

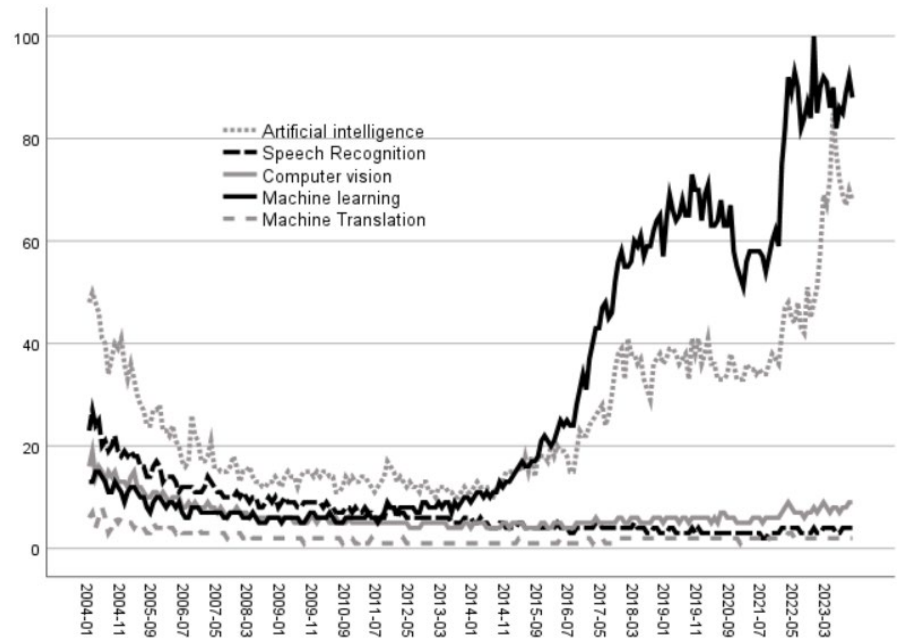

Figure 6: Popularity comparison: Evolution of Top 5 technologies in January 2004. Source: Google Trends (2023).

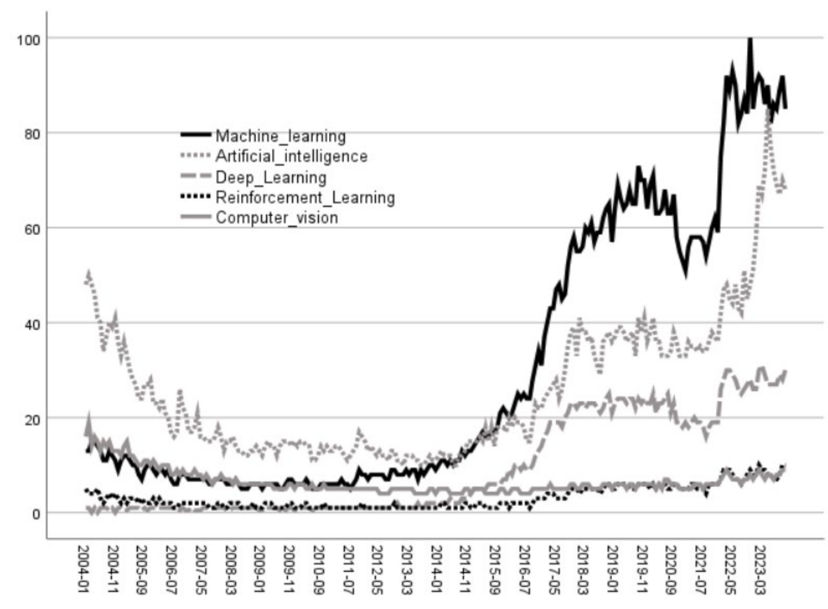

Figure 7: Popularity comparison: Evolution of Top 5 technologies in November 2023. Source: Google Trends (2023).

5. Conclusions

A Big Data analysis grounded on Google Trend Index data covering seventeen key AI technologies was conducted to compare their relative popularity and to reveal the hype curve progressing from year 2004 to the current day. As a result, the following five technologies were following the declining trend and at the moment were less popular than in the year 2004 Speech Recognition, Image Segmentation, Machine Translation, Computer vision, and Natural Language Processing. Tokenization, Sentiment Analysis, and Deep Learning technologies followed a linear growth path. J-shaped trend where the curve initially falls, but then rises to become higher than the starting point was followed by Entity Recognition, Facial Recognition, Artificial intelligence, Pose Estimation, Reinforcement Learning, Object Detection, Unsupervised Learning, and Supervised Learning.

The most popular technologies, which were over the year able to keep their position were Artificial intelligence, Machine learning, and Computer vision. At the moment Deep Learning and Reinforcement Learning are also in the TOP 5 technologies at the moment

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