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Brief Report

Nonlinear regression of AI-related publication growth in PubMed: a biomedical trend relevant to neuroscience

Hana A. Shriner, Jonghoon Kang*

Valdosta State University, Department of Biology, 1500 N Patterson St., Valdosta, Georgia 31698, USA

*Corresponding author: jkang@valdosta.edu

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Abstract

This study quantitatively evaluated the historical development and possible future trajectory of artificial intelligence (AI)-related biomedical research indexed in PubMed. AI-related publications were defined as publications explicitly identifying major AI concepts in their titles or abstracts, encompassing both biomedical applications of AI and studies of AI as a scientific subject. Annual publication output remained low for several decades before increasing sharply, with the most pronounced acceleration occurring in recent years. Two alternative growth descriptions closely represented the observed trend but produced contrasting interpretations of the field's developmental stage. One placed the period of maximum growth near 2025 and projected approximately 184,000 publications in 2035, whereas the other placed maximum growth near 2033 and projected approximately 359,000 publications in 2035. The latter description received greater relative statistical support, although its predicted long-term publication level was associated with substantial uncertainty. These findings demonstrate rapid expansion of AI-related biomedical research and are particularly relevant to neuroscience, where artificial intelligence increasingly intersects with the investigation and computational modeling of learning, perception, reasoning, decision-making, and other neural and cognitive functions. Continued monitoring will determine whether this growth begins to approach saturation or remains accelerated into the next decade.

Keywords: Artificial intelligence; biomedical research; PubMed; bibliometrics; publication trends; nonlinear growth models

1. Introduction

Artificial intelligence (AI) has developed from a specialized area of computer science into a broadly applicable approach for pattern recognition, prediction, classification, and decision-making. In the biomedical sciences, AI-related methods—including machine learning, deep learning, artificial neural networks, and large language models—have been applied to medical imaging, disease diagnosis, drug discovery, genomic analysis, clinical decision support, and the prediction of patient outcomes (Eraslan et al., 2019; Rajpurkar et al., 2022; Thirunavukarasu et al., 2023; Vamathevan et al., 2019; Yu et al., 2018). The expanding range of these applications suggests that AI is becoming an increasingly prominent component of biomedical research.

AI has a particularly close relationship with neuroscience. The neural bases of learning, memory, perception, reasoning, and decision-making are major subjects of neuroscientific investigation, whereas artificial intelligence seeks to reproduce or approximate aspects of these capacities computationally (Hassabis et al., 2017; Kriegeskorte & Douglas, 2018; Richards et al., 2019). Neuroscience examines how such functions emerge from biological systems across cellular, circuit, behavioral, and cognitive levels, while computational models provide a means of linking these levels and testing theories of brain function (Kriegeskorte & Douglas, 2018; Panagiotopoulos & Deriu, 2025; Richards et al., 2019; Tsipourakis et al., 2025). Artificial neural networks were historically inspired by simplified representations of biological neurons and nervous systems (Hassabis et al., 2017; McCulloch & Pitts, 1943; Parida et al., 2024), although contemporary artificial intelligence models do not necessarily reproduce the architecture, learning mechanisms, or operation of biological brains (Hassabis et al., 2017; Zador, 2019). Nevertheless, the continuing interaction between artificial intelligence and neuroscience has generated computational approaches for investigating both biological and artificial intelligence (Hassabis et al., 2017; Kriegeskorte & Douglas, 2018; Loker, 2024; Poznanski et al., 2024; Richards et al., 2019; Saxe et al., 2021).

The influence of AI extends well beyond neuroscience, however. AI methods are now used throughout biomedical science, and PubMed provides an appropriate database for examining this broader development (Kang et al., 2015; Kang & Purnell, 2011). Because PubMed indexes literature across medicine, biology, neuroscience, public health, and related biomedical disciplines, changes in the annual number of AI-related PubMed publications can provide a quantitative representation of the growth of AI research within the biomedical sciences. Publication counts do not directly measure scientific quality, clinical effectiveness, or societal impact, but they provide a reproducible indicator of research activity and the changing attention devoted to a scientific field.

Previous studies have used publication records indexed in PubMed to characterize the historical development of interdisciplinary biological sciences (Kang et al., 2019, 2015; Kang & Purnell, 2011), pollution research (Kang & Kang, 2020), and food science (Kang & Clifton, 2018; Kang et al., 2020). Such analyses demonstrated that annual publication counts can reveal temporal patterns in the emergence, expansion, and maturation of scientific fields. Publication trends can also be examined using nonlinear growth equations, which provide quantitative parameters describing features such as the rate of growth, the timing of maximum growth, and the potential approach toward an asymptotic publication level (Kang et al., 2019, 2015).

Bibliometric studies have documented the rapid expansion of artificial intelligence research in medicine and healthcare, frequently examining publication productivity, citation patterns, geographic and institutional contributions, collaboration networks, and evolving research topics (Guo et al., 2020; Lin et al., 2025). Comparatively less attention has been given to analyzing the long-term annual publication trajectory as a quantitative growth process and determining how the choice of nonlinear model affects its interpretation. This issue is particularly important when different growth models provide similarly strong fits to the observed data but yield substantially different estimates of the inflection point, asymptotic publication output, and future trajectory.

The present study therefore quantitatively analyzed the historical growth of AI-related biomedical research indexed in PubMed from 1963 through 2025. Annual publication counts were fitted using Sigmoid and Gompertz growth models to characterize the temporal pattern of publication growth, compare the performance and parameter estimates of the two models, and project their respective trajectories through 2035. The analysis was intended not to forecast publication numbers with certainty, but to evaluate the developmental pattern of AI-related biomedical research and determine how model selection influences conclusions about its current and potential future growth.

2. Materails and Methods

2.1. PubMed Search

AI-related biomedical publications were identified using PubMed, a database maintained by the National Library of Medicine. The following search query was applied to the Title/Abstract fields: ("artificial intelligence"[Title/Abstract] OR "machine learning"[Title/Abstract] OR "deep learning"[Title/Abstract] OR "neural network"[Title/Abstract] OR "large language model"[Title/Abstract]). In the present study, "AI-related biomedical publications" refers operationally to PubMed-indexed publications containing at least one of these search terms in the title or abstract. This category includes both studies applying artificial intelligence-based methods to biomedical problems and studies examining artificial intelligence or artificial neural systems as scientific subjects. The search was not designed to distinguish between these two categories.

Annual publication counts were obtained using the results-by-year function in PubMed. The analysis included publications indexed from 1963, the first year in which a publication satisfying the search criteria was identified, through 2025, the most recent complete calendar year at the time of analysis. The search was conducted on June 21, 2026. The annual publication counts were transferred to Microsoft Excel for organization and subsequent analysis.

The search was designed to quantify the historical development of research explicitly identifying major AI-related concepts in publication titles or abstracts. No restrictions were imposed regarding publication type, language, organism, country, or specific biomedical discipline. Consequently, the dataset represented AI-related research across the biomedical sciences indexed in PubMed rather than research restricted to neuroscience or a particular clinical field.

2.2. Nonlinear regression analysis

The temporal trend in annual publication counts was analyzed using the three-parameter Sigmoid and three-parameter Gompertz equations, following the nomenclature used in SigmaPlot. The Sigmoid equation was expressed as

$$y = \frac{a}{1 + exp[-(x - x_\circ/b)]} \tag{1}$$

and the Gompertz equation was expressed as

$$y = aexp[-exp[-(x - x_\circ)/b]] \tag{2}$$

In both equations, y represents the annual number of publications, x represents the publication year, a represents the estimated asymptotic maximum number of annual publications, $x_\circ$ represents the year corresponding to the inflection point, and b is a time-scale parameter related to the rate of publication growth. At the inflection point, the predicted publication count is $a/2$ for the Sigmoid equation and a/e for the Gompertz equation. The mathematical meaning of those parameters can be found in our previous paper (Kang et al., 2015).

Nonlinear regression was performed using SigmaPlot, version 15 (Grafiti LLC, Palo Alto, CA, USA). Goodness of fit was evaluated using the coefficient of determination (R2) and the standard error of the estimate. The fitted equations were also used to calculate projected annual publication counts through 2035.

2.3. Calculation of Akaike information criterion

The relative support for the Sigmoid and Gompertz models was evaluated using the Akaike information criterion corrected for small sample size (AICc) (Hurvich & Tsai, 1989; Portet, 2020). Because AICc was not provided directly by SigmaPlot, it was calculated from the residual sum of squares obtained from each nonlinear regression. For least-squares regression, AICc was calculated as

$$AICc = n \ln\left(\frac{RSS}{n}\right) + \frac{2kn}{n-k-1} \tag{3}$$

where n is the number of observations, RSS is the residual sum of squares, and k is the number of parameters used in the AIC calculation. In the present analysis, $n = 62$ and $k = 4$, corresponding to the three fitted parameters (a, b, and $x_\circ$) and one parameter for the error variance. The model with the lower AICc value was considered to have greater relative support among the two candidate models.

3. Results and Discussion

The annual number of publications meeting the operational definition of AI-related research described above exhibited pronounced nonlinear growth over the study period (**Fig. 1**). Publication output remained comparatively low during the earlier decades but increased sharply near the end of the observed period. Both fitted curves closely followed this recent increase and projected continued growth through 2035.

The Sigmoid and Gompertz models both provided excellent fits to the observed data (**Table 1**). The Sigmoid model produced an R2 of 0.994 and a standard error of the estimate of 1,443.7 publications, whereas the Gompertz model produced an R2 of 0.995 and a slightly smaller standard error of 1,364.9 publications. The corresponding AICc values were 907.72 for the Sigmoid model and 900.76 for the Gompertz model, giving a difference of 6.96. Thus, the Gompertz model had greater relative support among the two candidate models. This comparison does not establish that the Gompertz equation represents the uniquely correct growth process; rather, it indicates that it provided the more favorable balance of fit and model complexity within the present analysis.

Although the two equations described the observed data similarly, they produced markedly different parameter estimates and therefore different interpretations of the current developmental stage of AI-related

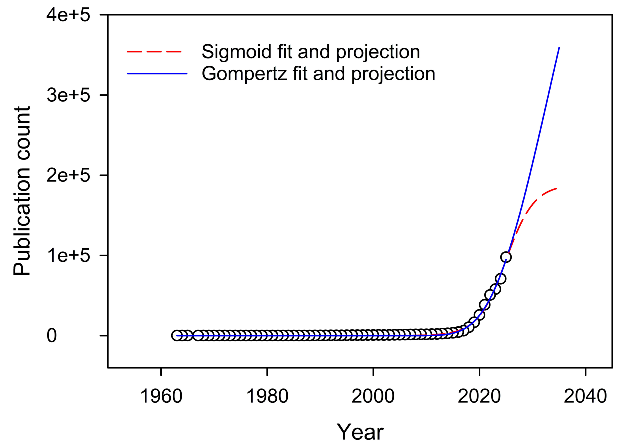

Figure 1 Nonlinear analysis of the annual number of AI-related publications indexed in PubMed. Open circles represent the observed annual publication counts through 2025. The dashed line represents the fit and projection obtained using the three-parameter Sigmoid equation, whereas the solid line represents the fit and projection obtained using the three-parameter Gompertz equation. Both models were extrapolated through 2035. The fitted curves overlap closely over much of the observed period, and the Sigmoid fit is therefore largely obscured by the Gompertz fit in the plot. Nonlinear regression was performed using SigmaPlot, version 15.

biomedical research. The Sigmoid model estimated an asymptotic annual publication count, a, of 188,573 and an inflection year, $x_\circ$, of approximately 2025. At the inflection point of the Sigmoid equation, the predicted annual publication count is $a/2$, corresponding to approximately 94,287 publications. According to this model, the publication trajectory reached its maximum growth rate near the end of the observed period and should subsequently begin to decelerate as it approaches its estimated asymptote (**Fig. 1**).

In contrast, the Gompertz model estimated a substantially larger asymptotic annual publication count of 839,551 and placed the inflection point at approximately 2033. At the Gompertz inflection point, the predicted annual publication count is a/e, corresponding to approximately 308,854 publications. The Gompertz model therefore indicates that the maximum rate of publication growth has not yet been reached and that AI-related biomedical publication activity may continue to accelerate into the early 2030s (**Fig. 1**). Thus, the Sigmoid model describes a field approaching decelerating growth, whereas the Gompertz model describes a field that remains in an accelerating phase.

The contrasting interpretations are also evident in the projections for 2035. The Sigmoid model predicted 184,347 publications in 2035, a value close to its estimated asymptote. The Gompertz model predicted 358,927 publications, nearly twice the Sigmoid prediction and still well below its estimated asymptote. Both models therefore predict continued expansion, but they

Table 1 Parameter estimates and goodness-of-fit statistics for nonlinear models describing the annual number of AI-related publications indexed in PubMed.*

	Sigmoid	Gompertz
a, publications/year	188573 ± 24426	839551 ± 371313
b, years	2.65 ± 0.14	10.6 ± 1.6
$x_\circ$, year	2025 ± 0.6	2033 ± 3.4
R^2	0.994	0.995
SEE	1443.7	1364.9
AICc	907.72	900.76
Predicted count in 2035	184347	358972

*Values of a, b, and x_circ are parameter estimates $\pm$ standard errors. Parameter a represents the asymptotic annual publication count, b is the time-scale parameter, and x_circ is the year of the inflection point. SEE, standard error of the estimate; AICc, Akaike information criterion corrected for small sample size. Lower AICc values indicate greater relative support among the models compared

differ substantially in the expected magnitude and duration of that expansion. This divergence is one of the principal findings of the study because it demonstrates that models with similarly high R^2 values can produce substantially different projections.

The difference between the projections reflects the mathematical structures of the two equations. The Sigmoid curve is symmetric around its inflection point, whereas the Gompertz curve is asymmetric and reaches its inflection point at a smaller fraction of its asymptotic value. Most of the observed increase in AI-related publications occurred near the end of the study period, meaning that the available data primarily characterize the rapidly rising portion of the trajectory rather than its eventual deceleration or plateau. Consequently, both equations can closely describe the observed data while producing substantially different estimates of the asymptote and inflection year.

The uncertainty associated with the fitted parameters further supports cautious interpretation of the projections. The standard error of the Gompertz asymptote was 371,313 publications, compared with 24,426 publications for the Sigmoid asymptote. The future upper limit predicted by the Gompertz model is therefore much less precisely estimated than that predicted by the Sigmoid model. The 2035 values should accordingly be interpreted as model-dependent projections rather than precise forecasts of future publication output.

The regression diagnostics also require consideration. The residuals from both models failed the tests for normality and constant variance. Because the RSS-based AICc calculation assumes independent Gaussian errors with common variance, the AICc comparison was interpreted as an approximate assessment of relative model support (Motulsky & Christopoulos, 2004; Portet, 2020). In addition, several observations near the rapidly increasing end of the publication trajectory exerted substantial influence on the fitted models, as indicated by their large Cook's distances. These diagnostics do not invalidate the observed pattern of rapid growth, but they indicate that the estimated asymptotes, inflection points, and future projections are particularly sensitive to the most recent publication counts.

The present analysis was designed to characterize AI-related research across the biomedical literature indexed in PubMed rather than within neuroscience alone. The results therefore reflect the expanding use and investigation of AI in medicine, biology, public health, neuroscience, and other biomedical disciplines represented in the database. Nevertheless, the findings have particular relevance to neuroscience because intelligence, learning, perception, reasoning, and decision-making are fundamental subjects of neuroscientific investigation (Hassabis et al., 2017; Kriegeskorte & Douglas, 2018; Loker, 2024; Poznanski et al., 2024; Richards et al., 2019; Saxe et al., 2021). Artificial intelligence provides computational approaches for modeling or reproducing aspects of these functions, while neuroscience examines how they emerge from biological systems operating across molecular, cellular, circuit, behavioral, and cognitive scales. The rapid growth of AI-related biomedical publications therefore represents both a broad methodological development in biomedical science and an expanding area of interaction between biological and artificial intelligence.

Several limitations should be recognized. Publication counts measure research activity and the visibility of AI-related terminology, but they do not directly measure scientific quality, clinical effectiveness, technological importance, or societal impact. The results also depend on the selected PubMed query. Publications that used AI methods without mentioning the selected terms in their titles or abstracts would not have been identified, whereas some publications containing these terms may not have used AI as their primary methodology. In addition, terminology has changed over time; expressions such as "deep learning" and "large language model" are relatively recent, while earlier studies may have described related computational approaches using different terms. The historical trajectory therefore reflects both the expansion of AI research and changes in the language used to describe it.

Overall, AI-related biomedical research indexed in PubMed has entered a period of exceptionally rapid publication growth. The Sigmoid and Gompertz models described the observed data with similar accuracy but generated contrasting estimates of the current growth phase and future trajectory. AICc favored the Gompertz model among the two equations examined, suggesting that continued acceleration into the early 2030s is more strongly supported by the present data. However, the uncertainty of its asymptotic parameter, the residual diagnostics, and the strong influence of recent observations require cautious interpretation. Continued analysis of future publication counts will be necessary to determine whether AI-related biomedical research follows the extended growth predicted by the Gompertz model or begins to approach the earlier saturation predicted by the Sigmoid model.

4. Conclusion

The authors thank the AI-related biomedical research indexed in PubMed has undergone rapid nonlinear growth, with the most pronounced increase occurring during the most recent years. Both the three-parameter Sigmoid and Gompertz equations described the observed publication trend well, but the Gompertz model had the lower AICc and therefore greater relative support among the two models examined. Importantly, the models produced different interpretations of the field's developmental stage. The Sigmoid model placed the inflection point near 2025 and predicted an approach toward approximately 188,000 publications per year, whereas the Gompertz model placed the inflection point near 2033 and predicted continued acceleration toward a substantially higher asymptote. Their projected publication counts for 2035 consequently differed by nearly twofold.

These findings demonstrate that AI-related biomedical research is still expanding rapidly, while also showing that long-term projections depend strongly on the selected growth model. Because the Gompertz asymptote was estimated with considerable uncertainty and the regression residuals did not fully satisfy the assumptions of Gaussian least-squares analysis, the projected values should be interpreted as model-dependent scenarios rather than precise forecasts. Continued analysis of future PubMed publication counts will be necessary to determine whether AI research begins to approach the earlier saturation predicted by the Sigmoid model or follows the more prolonged growth predicted by the Gompertz model.Department of Veterinary Medical Science, University of Bologna, for technical support.

Conflict of interest

The authors declare no competing interests.

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