Dec 11th, 12:00 AM

Models as Social Actors in the Diffusion of AI Innovations: A Multilayer, Heterogeneous, Dynamic Network Perspective

Kaige Gao
Case Western Reserve University, kxg297@case.edu

Youngjin Yoo
Case Western Reserve University, yxy23@case.edu

Aaron Schecter
University of Georgia, aschecter@uga.edu

The Role of Models in the Diffusion of AI Innovations: A Multilayer, Heterogeneous, Dynamic Network Perspective

Short Paper

Kaige Gao
Case Western Reserve University
Cleveland, OH, USA
kxg297@case.edu

Youngjin Yoo
Case Western Reserve University
Cleveland, OH, USA
yxy23@case.edu

Aaron Schecter
University of Georgia
Athens, GA, USA
aschecter@uga.edu

Abstract

Artificial Intelligence (AI) has emerged as a crucial facet of contemporary technological innovation, influencing diverse domains. Consequently, understanding the diffusion and evolution of AI innovations is vital. Scholarly publications have commonly served as proxies for studying these AI innovations. However, previous studies on publication diffusion have largely overlooked the role of models, which is particularly integral for AI innovations as they bridge upstream datasets and downstream applications. Moreover, models form an interdependent network due to their combinational evolution. This paper addresses this gap, examining how the location, movement, and speed of model movement in that model network affect the dissemination of AI research. Using a four-layer network—author collaborations, paper citations, model dependencies, and keyword co-occurrences—we examine 345,383 AI papers from 2000 to 2022. This research aims to contribute to the diffusion of innovation literature and dynamic network analysis, offering several novel insights and advancements.

Keywords: AI Innovations, Heterogeneous Dynamic Network, Diffusion of Innovation, Popularity of papers

Introduction

The rapid advancement of artificial intelligence (AI) has emerged as a pivotal aspect of contemporary technological innovation, exerting influence on diverse domains such as finance, healthcare, transportation, and marketing (Davenport & Ronanki, 2018; Makridakis, 2017). As the role of AI in organizing and promoting innovation continues to expand and evolve at an accelerated pace, it becomes increasingly important to understand the diffusion and evolution of AI technologies, as well as the factors contributing to the popularity of specific AI innovations.

Scholarly publications – both written by academics and practitioners – play a vital role in disseminating AI innovations, serving as one of the most prevalent mechanisms for sharing AI research findings (Frank et al., 2019; Tang et al., 2020). As a result, scholars have used AI-related papers as proxies for studying AI innovation (Tang et al., 2020). We believe that examining the diffusion and popularity of AI publications can help illuminate the broader patterns of AI innovation dissemination.

Previous studies on the citation and diffusion of scholarly publications have typically focused on the effect of authors' social networks and papers' characteristics on the popularity of a paper. For instance, Fleming et al. (2007) demonstrated that researchers who engage in collaborative brokerage in social networks and exhibit generative creativity will have more influential research. Uzzi et al. (2013) highlighted that papers with atypical combinations of existing knowledge would have a higher citation count. We believe the traditional models of scholarly publication citations do not capture the diffusion of AI innovations. In particular, focusing on relationships among authors and topics is likely to leave out a key component in AI innovations models.

Models are particularly critical in the AI field, functioning as essential components that bridge the gap between upstream datasets and downstream applications (Bommasani et al., 2023; LeCun et al., 2015). A prominent example is OpenAI's GPT models, which were trained on an extensive data corpus and utilized in developing interactive applications such as ChatGPT (Brown et al., 2020). Moreover, older models often serve as building blocks for newer ones, resulting in a combinatorial evolution that creates dependency relationships and establishes model-model networks (Arthur, 2009). For example, BERT is originally built on the TensorFlow framework (Devlin et al., 2018), while TensorFlow itself relies on more fundamental packages, including pandas, h5py, and SciPy (Abadi et al., 2016). This dependency network reflects the relationship between models and their popularity, which may, in turn, influence the diffusion of AI papers and innovations. As such, AI papers build on previous models; models build their own sociability and relationality among themselves (Latour, 2007). Therefore, in this study, we emphasize the pivotal roles of models and the relationships among them in influencing the popularity of AI papers based on these models. Although this area holds significant importance, it still needs to be explored.

In addition, most prior research on the popularity of papers has approached the subject from a static network perspective due to limited data availability and computational complexity. As AI innovations and related research exhibit high volatility, examining the popularity of papers from a single time point may not adequately capture the diffusion patterns and dynamic effects of models' relationships on papers' popularity. In particular, we explore the role of changes in the centrality of a model introduced by an AI paper and its changing speed (in a mathematical term, a second derivative of centrality) on the popularity of the AI paper.

To address this gap, this study will investigate the role of models in the popularity of AI research from a dynamic network perspective. We construct a dynamic, multilayer heterogeneous network comprising a model dependency network, a citation network, a coauthor network, and a keyword co-occurrence network, specifically examining how the location, movement, and speed of model movement affect the dissemination of AI research. The empirical context of our study encompasses 345,383 AI papers published between 2000 and 2022. Our research contributes to the diffusion of innovation literature by elucidating the role of models in the popularity of AI research. Furthermore, it also contributes to the dynamic network literature by being the first to explore the momentum of networks.

Literature Review

The Role of Models

Traditionally, models serve as a methodical means of representing nature's realities by capturing relationships between abstract symbols derived from physical objects, extracting theories, and summarizing the rules governing the universe (Simon, 2019). For example, Kepler's laws of planetary motion were developed to describe and understand the rules governing planetary orbits around the sun. Solow's models (Solow I and Solow II) aimed to comprehend economic growth from a macro perspective (Solow, 1956). However, these models typically possess fixed application fields and are based on a limited set of situations and assumptions.

With the advent of the digital age, however, digital technologies have become deeply integrated into our daily lives, profoundly transforming human experiences and the business world (Yoo et al., 2010). This transformation has led to an ontological reversal (Baskerville et al., 2019), wherein digital models precede physical objects and actively shape, create, and influence reality. A notable example is the construction of the Peter B. Lewis Building, in which Gehry first designed 3D models using computers before constructing the building based on the digital model (Boland Jr et al., 2007). This digital transformation and ontological reversal fundamentally alter the role of models in innovation development, making them essential components that both serve and determine innovations. However, contemporary models still exhibit limitations and are often confined to specific application fields.

In the context of artificial intelligence (AI), the role of models becomes various, and models can be seen as significant factors that influence AI innovations. They can function as innovations themselves (Gao et al., 2021), form components of the innovations (Silver et al., 2016), or provide the foundation for the innovation design (Vaswani et al., 2017). More importantly, AI models are characterized by their generality and flexibility, allowing for their application across diverse domains. For instance, GPT-4 can be employed in question-answering, translation, writing, calendar organization, and personal assistance fields (Brown et al., 2020). This flexibility, generativity, and relationality of models propel AI innovation.

While different models may receive varying levels of attention, their associated AI innovations may follow distinct evolutionary paths. ChatGPT, for example, has gained significant popularity due to the flexibility and power of Generative Pre-training Transformer 4 (GPT-4), leading to widespread adoption and the emergence of new research based on this model. In contrast, Bard, a chatbot tool based on the Language Model for Dialogue Applications (LaMDA) model, has not achieved similar success (Ali et al., 2023). Therefore, model characteristics might influence the popularity of AI innovations. Moreover, older models often serve as building blocks for new ones, with previous models being combined and integrated into the structure of new models (Arthur, 2009). The combinatorial evolution of models forms dependency relationships between models, creating a model-model network indicating the evolution patterns and popularity of models. This network may partially reflect researchers' attention and interests, influencing the popularity of papers. Furthermore, these model networks experience high volatility, largely attributed to shifts in models' popularity and their combinational evolution. For example, the BERT model introduced in 2018 starts from an emergent technique to a foundational pillar in AI research. However, by 2022, emergent models such as GPT-3 began to overshadow its preeminence (Zhang & Li, 2021). According to the paperswithcode website, research related to BERT observed a relative decline in comparison to those emphasizing expansive language models. Such volatility not only governs the popularity trajectory of AI models but also considerably impacts the dissemination and reception of scholarly AI articles. Thus, to study the role of models in this process, we should take a dynamic network perspective, considering not only the centrality or location of a model in the network but also the change of the centrality and the changing speed.

Popularity and Diffusion of Papers

Researchers have employed academic publications to examine and track the development pace of artificial intelligence (AI) innovations (Tang et al., 2020). Moreover, most core AI innovations are accompanied by corresponding articles that introduce them to the broader academic community. For example, Thoppilan et al. (2022) published "LaMDA: Language Models for Dialogue Applications" to introduce Google's flagship large language model, capable of providing real-time information sourced from the internet. Similarly, OpenAI introduced their innovation GPT-3 in the paper "Language Models are Few-Shot Learners" (Brown et al., 2020), which serves as the foundation for ChatGPT. These publications offer detailed information about their respective innovations, which are then reviewed, analyzed, and built upon by other developers, academic researchers, and the general public, facilitating the diffusion of innovation (Rogers, 2010). As new innovations are developed and subsequently published, they often build upon the foundations laid by prior ones (Arthur, 2009). Consequently, earlier publications serve as crucial citations for subsequent research. Hence, monitoring the diffusion and shifts in academic AI literature can offer valuable insights into the dissemination and progression of AI innovations. By examining the interrelated nature of these publications, researchers can better understand the ongoing development and evolution of AI technology within the academic community. In this paper, we will use the diffusion of AI publications in the academic field to understand the diffusion of AI innovations.

Researchers have been studying the diffusion and popularity of academic papers for many years, employing various measures to identify the impact and dissemination of scholarly work. These metrics include Mendeley readership (Aduku et al., 2017), the Altmetric score (Sugimoto et al., 2017), PlumX Metrics (Lindsay, 2016), and, most notably, the citation counts (Uzzi et al., 2013; Wang et al., 2013). While Mendeley readership reflects the number of researchers who save a paper to their personal libraries, Altmetric scores and PlumX Metrics capture a paper's broader influence through various channels, such as social media, news outlets, and policy documents; longitudinally tracking these metrics can be challenging due to the dynamic nature of the data sources. Thus, this study uses citation counts to measure a paper's popularity and diffusion.

Previous research has identified various factors that influence the popularity and diffusion of academic papers, which can be broadly categorized as paper-related and author-related. First, studies have shown that the quality of a paper, its previous popularity (Garfield, 2005), the field of study (Hargens, 2000), and certain characteristics such as paper type, length, and the presence of graphs can impact its popularity and future citations (Bornmann & Daniel, 2008). For example, Uzzi et al. (2013) found that papers with moderate novelty and conventionality are more likely to become popular and have a high impact. Second, author-related factors also play a significant role in the diffusion of papers. Factors such as the author's reputation, funding, and social networks have been found to influence the popularity of a paper (Bornmann & Daniel, 2008; Uzzi & Spiro, 2005). For instance, White (2001) found that researchers are more likely to cite works whose authors are within their social networks. However, these studies overlook the role of models in the diffusion process, which is particularly relevant in AI innovation, as models serve as bridges between upstream datasets and downstream applications. We will address this gap in this study.

Moreover, previous research predominantly adopts a static perspective, comparing the popularity of papers at a single time point. This approach may neglect important dynamic factors, such as the speed of diffusion and changes in models' popularity, which could impact the diffusion pattern of AI innovations. Additionally, AI innovation is highly volatile. For example, according to the paperswithcode website, by the end of 2021, 1.17% of papers used BERT, while by the end of 2022, only 0.67% of papers used BERT, and to date, only 0.39% of papers use BERT. To account for these dynamics, this study will use a longitudinal dataset, including AI papers from 2000 to 2020, to investigate how the dynamic effects of models influence the diffusion and popularity of AI innovations.

Theory and Hypotheses Development

Viewing AI innovations from a network perspective, various factors such as authors, keywords, models, and pre-existing papers can be considered as nodes in the network. These nodes interact with each other, forming relationships that influence the development and diffusion of AI innovations. Furthermore, these networks are not static but in continuous construction, maintenance, and modification. This dynamic is driven by a "translation" process in which network nodes negotiate, interpret, and redefine their relationships. To comprehend the influence of these factors on the popularity of AI innovations, we have designed a dynamic, heterogeneous network model. This model is based on longitudinal data, including AI publications from 2000 to 2022. Our proposed network model incorporates four distinct layers: a model-model relationship network, a paper citation network, an author collaboration network, and a keyword co-occurrence network. Since nodes in those four layers are different, it is a heterogeneous network (Chang et al., 2015). The impact of author and paper models has been extensively studied. Therefore, we mainly focus on the model network to explore the role of models in AI innovation popularity.

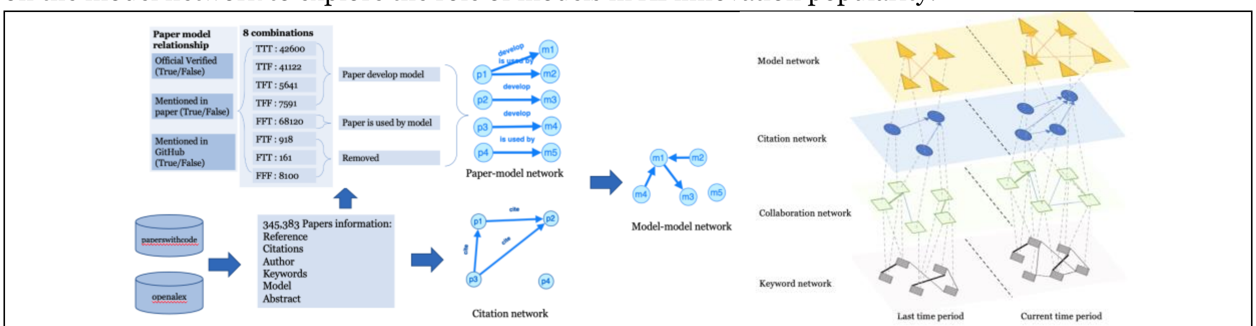

Figure 1: Process of Multilayer Heterogeneous Network Construction

The model-model relational network is a directed network where nodes are models, and edges are the dependency relationships between them. For example, if model 2 is based on model 1, a directed dependency relationship is formed between them. To measure a model's importance, we employ network centrality, a concept that quantifies the relative importance of individual nodes within a network (Freeman, 2002). More specifically, we utilize indegree eigenvector centrality, which considers not only the number of connections but also the importance of nodes connected to a particular node (Bonacich, 1987).

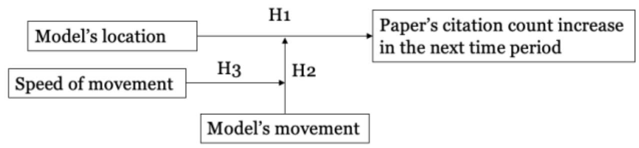

Figure 2: Conceptual Model

In the network, new entities usually tend to connect to well-established entities, thereby reinforcing their prominence (BarabÃ¡si & PÃ3sfai, 2016). Consequently, when a model is in a central network position and possesses high "prestige," new papers are more likely to adopt that model and cite related papers. This phenomenon is also supported by the concept of cumulative advantage and the Matthew effect, whereby early success or recognition generates further recognition, creating a self-reinforcing cycle (Petersen et al., 2011). Based on this theoretical framework, we propose the following hypothesis:

Hypothesis 1: The network centrality of a model in a given time period will positively influence the increase of citation counts of related papers in the next time period.

As a model moves towards a central position in the model-model network, it experiences a concomitant increase in its popularity. This phenomenon is further exacerbated by the contagion effect, wherein developers are more predisposed to imitate their peers and consequently adopt and allocate attention to the model in question (Meade & Islam, 2006). This cyclical interplay between centrality and attention amplifies the model's prominence, thereby ensuring that it continues to attract increasing levels of focus within the community. Within the open-source community, developers' attention is a critical resource (Tuomi, 2002), and models capturing this attention are more likely to evolve and develop further. As these models evolve, they have the potential to inspire the publication of novel research papers and the development of related models, a phenomenon driven by the perception that the model holds significant promise (Crowston et al., 2008). Conversely, a model maintaining the same centrality but moving towards the periphery indicates a decline in related models and research. This shift could signal that the model is becoming outdated, and its popularity and relevance are waning. Recognizing these trends, researchers may adjust their interests accordingly because of the bandwagon effect (Simon, 1954). Therefore, the following hypothesis is proposed:

Hypothesis 2: A model's increase in centrality score in the model-model network will positively moderate the effect of centrality on the change in citation counts of related papers in the next time period.

A fast movement to a central position indicates that the model gains popularity and recognition rapidly within the field (Burt, 2004). Such swift ascension might be attributed to a model's novelty, effectiveness, or ability to address previously unmet needs in the application domain (Crowston et al., 2008). The velocity of a model's movement toward centrality can enhance its visibility and impact on both the academic and practitioner communities. A model that quickly becomes central in a network is more likely to be discussed, utilized, and expanded upon by other researchers, as it garners increased attention and trust within the field (Valente, 1996). Consequently, this heightened visibility might result in a higher rate of citations for the related papers, amplifying the positive moderation effect of the model's centrality movement. Thus, the following hypothesis is proposed:

Hypothesis 3: The speed of a model's increase in centrality score will positively moderate the effect of increasing centrality on the relationship between centrality and change in citation counts of related papers in the next time period.

Data

The dataset utilized in this study was acquired from the reputable PapersWithCode platform (https://paperswithcode.com), which includes 345,383 research papers and 174,253 artificial intelligence (AI) models. However, 74% of papers do not have any associated AI models. As such, this study endeavors to explore the impact of models on paper popularity by conducting two separate investigations. The first analysis uses the complete dataset to assess the impact of the availability of public models on paper popularity. Furthermore, the second analysis focuses exclusively on the subset of papers with related models, which accounts for 88,113 papers, to investigate the specific effects of these models on paper popularity.

To supplement the dataset acquired from PapersWithCode, the OpenAlex website was used to gather citation information for the papers. The final dataset used in this study consists of paper titles, abstracts, keywords, authors, model details, and citations. According to Figure 3, the majority (83%) of AI models are associated with only one paper, while 17,857 models are linked to more than one paper. Further analysis reveals that 10% of models are connected to two papers, while 5900 models are associated with three or more papers.

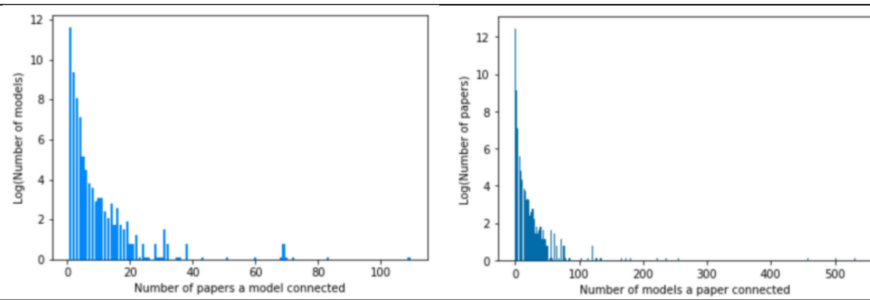

Figure 3: Distribution of Papers and Models

Proposed Methodology and Future Plan

Network Construction

Based on our dataset, the relationship between papers and models is often characterized by a many-to-many correspondence. This relationship can be classified in several ways: official verification, mention in academic papers, or mention in model readme pages. By examining these three types of relationships, we can identify eight distinct connections between papers and models.

When a relationship is officially verified, it is often assumed that the paper's author developed the model, as the verified model is typically created by one of the authors. In cases where the relationship is only mentioned in academic papers, it could indicate a variety of situations, such as using the paper for reference or simply mentioning it in passing. As these relationships are difficult to discern and represent a relatively low proportion (0.6%), they will not be included in our analysis. Conversely, when a relationship is only mentioned in a model's profile, it can be classified as the paper being used by the model, since it suggests that the model has incorporated the paper's ideas and methods for further development and adaptation. Any data without a discernible relationship will also be excluded from consideration. After this filtering process, we are left with a final dataset containing 165,079 paper-model relationships, divided into two categories: "paper develops model" and "paper is used by model." Using this dataset, we constructed a bipartite network called the paper-model network. The process is outlined in Figure 1.

Furthermore, we employed citation relationships to establish a directed paper citation network, wherein nodes represent papers and edges indicate citation connections. Since this network partially mirrors the dependency relationships between papers and their association with models, we can combine the paper-model network with the citation network to generate a directed model-model relationship network. In this network, nodes denote models, and edges symbolize "based on" relationships.

In addition to the aforementioned networks, we also constructed: (1) a weighted author collaboration network, where nodes represent authors and edges indicate the number of collaborations, and (2) a weighted keyword co-occurrence network, with nodes as keywords and edges as the frequency of keyword co-occurrence. By observing annual changes in these four networks, we aim to understand how the dynamic interplay of network structures influences the increase in citations each year.

Location, Movement, and Speed of Movement of Models

We utilize eigenvector centrality to assess the position of a model within a network, as it considers not only the number of connections but also the significance of the connected nodes (Bonacich, 1987). This metric offers valuable insights into the extent to which a model's prominence is influenced by its associations with other influential models. Given that the model-model network is directed, indegree edges represent a based-on relationship. A model with a high outdegree signifies that it is built upon numerous preceding models. Therefore, we utilize only the in-degree eigenvector centrality to evaluate a model's position. For papers associated with multiple models, we consider the official model's location if available. In the absence of an official model, we calculate the average in-degree eigenvector centrality of the connected models and use that as the representative location. To measure the location movement, we subtract the in-degree eigenvector centrality of a model in year t-2 from that in year t-1. For the speed of movement, we compute the ratio of the movement from year t-2 to year t-1 over the movement from year t-3 to year t-2. By examining these metrics, we can better understand the dynamic of model popularity and its influence.

Popularity of Papers

In this study, we use the annual increase in citations as a proxy for measuring the popularity and diffusion of academic papers. Additionally, we control for several potentially confounding variables, including the location of authors, changes in author locations over time, the speed at which a paper receives its first citation, and both the location and changes in the location of keywords. These factors are derived from various networks, such as the author network, keywords network, and citation network.

The analytical model proposed to test our hypotheses is outlined below. For a given paper i at time t, we will examine the relationship between the dependent variable (annual citation increase) and the independent variables (model centrality, location movement, speed of movement, interaction variables, and control variables). This framework will allow us to assess the validity of our hypotheses and gain a deeper understanding of the factors influencing paper popularity and diffusion. Our hypotheses will be evaluated by the sign and significance of coefficients related to models; the remaining terms serve as controls.

$$
\begin{aligned}
&Increase\ of\ citation_{i,t} \\
&\quad = \beta_0 + \beta_1 * Model\ Location_{i,t-1} + \beta_2 * LocationMovement_{i,t-1} + \beta_3 \\
&\quad * MovementSpeed_{i,t-1} + \beta_4 * LocationMovement_{i,t-1} * MovementSpeed_{i,t-1} + \beta_5 \\
&\quad * LocationMovement_{i,t-1} * Model\ Location_{i,t-1} + \beta_6 * MovementSpeed_{i,t-1} \\
&\quad * Model\ Location_{i,t-1} + \beta_7 * MovementSpeed_{i,t-1} * Model\ Location_{i,t-1} \\
&\quad * LocationMovement_{i,t-1} + \beta_8 * Average(Author\ Location)_{i,t-1} + \beta_9 \\
&\quad * Change\ of\ Average(Author\ Location)_{i,t-1} + \beta_{10} * Average(Keyword\ Location)_{i,t-1} \\
&\quad + \beta_{11} * Change\ of\ Average(Keyword\ Location)_{i,t-1} + \beta_{12} * PaperCitation_{i,t-1} + \beta_{13} \\
&\quad * years\ taken\ for\ first\ citation + \sigma_t + \varepsilon_{i,t}
\end{aligned}
$$

Future Plan

In the forthcoming phases of this research, we intend to finalize our data analysis grounded in the extant dataset. Furthermore, we will harness the dataset extracted from OpenAlex, leveraging it to enhance and corroborate the information obtained from paperswithcode. It is imperative to ensure the robustness and integrity of our data sources. We will also explore the potential existence of cross-lagged relationships and investigate alternative measures that could offer additional insights. For instance, incorporating HITS algorithms to identify hubs and authorities of models as a supplementary measure (Kleinberg 1999), and employing nested model analysis to discern the overall impact of models on the distribution of academic papers.

Expected Result and Contribution

This study contributes to extant research mainly in two ways. Firstly, this study extends the discussion on AI innovation diffusion, being the first to analyze the impact of models and provide empirical evidence supporting their importance. Secondly, our research utilizes longitudinal data to track diffusion patterns of papers from a dynamic network perspective, particularly focusing on the momentum of model movements. It may provide some insights for future network analysis. We anticipate that the speed of movement will amplify the positive moderation effect of models moving toward centrality on the relationship between models' location and popularity and dissemination of related papers. By examining the dynamic interplay among models' location, movement, and movement speed, this study aims to deliver a more comprehensive understanding of the factors that drive the popularity and diffusion of AI innovations.

References

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., & Isard, M. (2016). Tensorflow: a system for large-scale machine learning. Osdi,

Aduku, K. J., Thelwall, M., & Kousha, K. (2017). Do Mendeley reader counts reflect the scholarly impact of conference papers? An investigation of computer science and engineering. *Scientometrics*, *112*, 573-581.

Ali, R., Tang, O. Y., Connolly, I. D., Fridley, J. S., Shin, J. H., Zadnik Sullivan, P. L., Cielo, D., Oyelese, A. A., Doberstein, C. E., & Telfeian, A. E. (2023). Performance of ChatGPT, GPT-4, and Google Bard on a Neurosurgery Oral Boards Preparation Question Bank. *medRxiv*, 2023.2004. 2006.23288265.

Arthur, W. B. (2009). *The nature of technology: What it is and how it evolves*. Simon and Schuster.

BarabÃ¡si, A. L. Ã. Ã., & PÃ3sfai, M. Ã. (2016). *Network Science*. Cambridge University Press. https://books.google.com/books?id=iLtGDQAAQBAJ

Baskerville, R. L., Myers, M. D., & Yoo, Y. (2019). Digital first: The ontological reversal and new challenges for IS research.

Boland Jr, R. J., Lyytinen, K., & Yoo, Y. (2007). Wakes of innovation in project networks: The case of digital 3-D representations in architecture, engineering, and construction. *Organization science*, *18*(4), 631-647.

Bommasani, R., Soylu, D., Liao, T. I., Creel, K. A., & Liang, P. (2023). Ecosystem Graphs: The Social Footprint of Foundation Models. *arXiv preprint arXiv:2303.15772*.

Bonacich, P. (1987). Power and centrality: A family of measures. *American journal of sociology*, *92*(5), 1170-1182.

Bornmann, L., & Daniel, H. D. (2008). What do citation counts measure? A review of studies on citing behavior. *Journal of documentation*.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., & Askell, A. (2020). Language models are few-shot learners. *Advances in neural information processing systems*, *33*, 1877-1901.

Burt, R. S. (2004). Structural holes and good ideas. *American journal of sociology*, *110*(2), 349-399.

Chang, S., Han, W., Tang, J., Qi, G.-J., Aggarwal, C. C., & Huang, T. S. (2015). Heterogeneous network embedding via deep architectures. Proceedings of the 21th ACM SIGKDD international conference on knowledge discovery and data mining,

Crowston, K., Wei, K., Howison, J., & Wiggins, A. (2008). Free/Libre open-source software development: What we know and what we do not know. *ACM Computing Surveys (CSUR)*, *44*(2), 1-35.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard business review*, *96*(1), 108-116.

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*.

Fleming, L., Mingo, S., & Chen, D. (2007). Collaborative brokerage, generative creativity, and creative success. *Administrative science quarterly*, *52*(3), 443-475.

Frank, M. R., Wang, D., Cebrian, M., & Rahwan, I. (2019). The evolution of citation graphs in artificial intelligence research. *Nature Machine Intelligence*, *1*(2), 79-85.

Freeman, L. C. (2002). Centrality in social networks: Conceptual clarification. *Social network: critical concepts in sociology. Londres: Routledge*, *1*, 238-263.

Gao, K., Yoo, Y., & Schecter, A. (2021). A Dynamic Analysis of the Complex Interplay Between Internal and External Networks of Open-source Projects on Innovation Behaviors.

Garfield, E. (2005). The agony and the ecstasy—the history and meaning of the journal impact factor. *Journal of Biological Chemistry*, *295*(1), 22.

Hargens, L. L. (2000). Using the literature: Reference networks, reference contexts, and the social structure of scholarship. *American sociological review*, 846-865.

Latour, B. (2007). *Reassembling the social: An introduction to actor-network-theory*. Oup Oxford.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436-444.

Lindsay, J. M. (2016). PlumX from plum analytics: not just altmetrics. *Journal of Electronic Resources in Medical Libraries*, *13*(1), 8-17.

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46-60.

Meade, N., & Islam, T. (2006). Modelling and forecasting the diffusion of innovation–A 25-year review. *International Journal of forecasting*, *22*(3), 519-545.

Petersen, A. M., Jung, W.-S., Yang, J.-S., & Stanley, H. E. (2011). Quantitative and empirical demonstration of the Matthew effect in a study of career longevity. *Proceedings of the National Academy of Sciences*, *108*(1), 18-23.

Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., & Lanctot, M. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, *529*(7587), 484-489.

Simon, H. A. (1954). Bandwagon and underdog effects and the possibility of election predictions. *Public Opinion Quarterly*, *18*(3), 245-253.

Simon, H. A. (2019). *The Sciences of the Artificial, reissue of the third edition with a new introduction by John Laird*. MIT press.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The quarterly journal of economics*, *70*(1), 65-94.

Sugimoto, C. R., Work, S., Larivière, V., & Haustein, S. (2017). Scholarly use of social media and altmetrics: A review of the literature. *Journal of the Association for Information Science and Technology*, *68*(9), 2037-2062.

Tang, X., Li, X., Ding, Y., Song, M., & Bu, Y. (2020). The pace of artificial intelligence innovations: Speed, talent, and trial-and-error. *Journal of Informetrics*, *14*(4), 101094.

Thoppilan, R., De Freitas, D., Hall, J., Shazeer, N., Kulshreshtha, A., Cheng, H.-T., Jin, A., Bos, T., Baker, L., & Du, Y. (2022). Lamda: Language models for dialog applications. *arXiv preprint arXiv:2201.08239*.

Tuomi, I. (2002). *Networks of Innovation: Change and Meaning in the Age of the Internet* (Vol. 249). OUP Oxford.

Uzzi, B., Mukherjee, S., Stringer, M., & Jones, B. (2013). Atypical combinations and scientific impact. *Science*, *342*(6157), 468-472.

Uzzi, B., & Spiro, J. (2005). Collaboration and creativity: The small world problem. *American journal of sociology*, *111*(2), 447-504.

Valente, T. W. (1996). Social network thresholds in the diffusion of innovations. *Social networks*, *18*(1), 69-89.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Advances in neural information processing systems*, *30*.

Wang, D., Song, C., & Barabási, A.-L. (2013). Quantifying long-term scientific impact. *Science*, *342*(6154), 127-132.

White, H. D. (2001). Authors as citers over time. *Journal of the American Society for Information Science and Technology*, *52*(2), 87-108.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). Research commentary—the new organizing logic of digital innovation: an agenda for information systems research. *Information systems research*, *21*(4), 724-735.

Zhang, M., & Li, J. (2021). A commentary of GPT-3 in MIT Technology Review 2021. *Fundamental Research*, *1*(6), 831-833.