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Mining Collective Intelligence and Predicting Disruptive Paradigm Shifts via Human-Aware AI

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ABSTRACT
Scientific progress hinges on the interplay between collective intelligence and transformative paradigm shifts, yet predicting these revolutionary events remains a persistent challenge. This study introduces a novel human-aware AI framework that integrates the evolution of knowledge structures with the social dynamics of scientific communities to forecast groundbreaking innovations. Leveraging graph convolutional neural networks (GCNNs), we construct a hybrid higher-order network that unifies a domain knowledge graph—derived from millions of scientific publications—with a scientist collaboration-competition space, capturing both cooperative and competitive interactions among researchers. This approach quantifies collective intelligence by generating embeddings that reflect the intricate relationships between knowledge content and human agency. By analyzing thematic knowledge distances and social proximities within this integrated network, we identify pairs of scientific domains poised for disruptive convergence. Dynamic analysis of these embeddings further enables temporally precise predictions of paradigm shifts. Applied to the life sciences, our framework successfully aligns with historical milestones, such as Nobel Prize-winning discoveries, demonstrating its predictive power. This work offers a scalable, interpretable tool for anticipating scientific revolutions, bridging the gap between knowledge evolution and social dynamics, and providing actionable insights for fostering innovation across disciplines.

KEYWORDS
Collective intelligence, paradigm shifts, graph convolutional neural networks (GCNNs), collaboration-competition space, human-aware AI

INTRODUCTION
punctuated by rare, transformative paradigm shifts that redefine our understanding of the natural world (Duan et al., 2025; Fortunato et al., 2018; Hill & Stein, 2025a, 2025b; Krieger et al., 2024; Wang & Barabási, 2021; Yang et al., 2025). Collective intelligence, the enhanced problem-solving capacity emerging from group interactions, underpins the steady growth of knowledge through collaboration, peer review, and resource sharing within scientific communities (Belikov et al., 2022; Evans & Foster, 2011; Kang et al., 2025; Sourati & Evans, 2023). In contrast, paradigm shifts, as conceptualized by Kuhn (Kuhn, 1962; Kuhn, 1977), mark revolutionary discontinuities—moments when anomalies dismantle prevailing frameworks, giving way to radical new perspectives, as exemplified by the Copernican revolution or the advent of quantum mechanics. While the former ensures incremental progress, the latter drives exponential leaps, often with profound societal impact. Yet, despite their significance, predicting these disruptive events remains an elusive goal, hampered by the complexity of integrating the evolution of scientific knowledge with the human dynamics that catalyze innovation.

The advent of artificial intelligence (AI) has transformed the landscape of scientific discovery, enabling the analysis of vast datasets to uncover hidden patterns and accelerate research across domains such as drug discovery, materials science, and climate modeling (Gao & Wang, 2024; Sourati & Evans, 2023; Wang et al., 2023). Recent advances in graph-based AI, particularly graph convolutional neural networks (GCNNs), have proven adept at modeling relational systems inherent in scientific data, such as citation networks and knowledge graphs. Simultaneously, the availability of large-scale bibliographic repositories, like PubMed and OpenAlex, offers unprecedented opportunities to map the knowledge space comprehensively. However, current AI-driven approaches predominantly treat scientific literature as an abstract entity, focusing either on knowledge evolution through bibliometric trends or on collaboration networks in isolation (Franzoni & Stephan, 2023; Ghosal et al., 2022; Hoppe et al., 2023; Kumari et al., 2022). This siloed perspective overlooks a critical reality: scientific breakthroughs emerge not merely from ideas but from the interplay of those ideas with the social fabric of the researchers who develop and debate them.

A growing body of evidence suggests that social proximity among scientists—whether through collaboration or competition—can amplify the potential for disruptive innovation, particularly when bridging distant knowledge domains (Lin et al., 2023; Wu et al., 2019; Xu et al., 2022; Xu et al., 2024; Yang, Ding, et al., 2024; Yang, Xu, et al., 2024; Yang et al., 2022). Yet, few frameworks effectively unify these dimensions into a predictive model capable of anticipating paradigm shifts. Traditional scientometric methods, while adept at tracking emerging trends or mapping collaboration networks, rarely connect these insights to the likelihood of transformative outcomes.

Moreover, the temporal dynamics of knowledge convergence and the role of human agency remain underexplored, leaving a critical gap in our ability to forecast when and where scientific revolutions might occur.

Here, we propose a pioneering human-aware AI framework to address these challenges, integrating a domain knowledge graph with a scientist collaboration-competition space within a hybrid higher-order network. Using GCNNs, we generate embeddings that capture the collective intelligence arising from the interplay between scientific content and researcher interactions. By analyzing knowledge distances and social proximities, we identify thematic pairs with high disruptive potential, while dynamic modeling of these embeddings enables us to predict the timing of paradigm shifts. Applied to the life sciences, our approach not only reveals interdisciplinary connections but also aligns with historical breakthroughs, such as Nobel Prize-winning discoveries, validating its efficacy. This framework advances predictive information science by offering a scalable, interpretable tool to anticipate scientific revolutions, with implications for research strategy, funding allocation, and the acceleration of innovation across disciplines. In doing so, it redefines our understanding of scientific progress as a deeply human endeavor, shaped by both the ideas we pursue and the communities we build.

DOMAIN KNOWLEDGE GRAPH AND COLLABORATION-COMPETITION SPACE CONSTRUCTION

To systematically analyze the evolution of scientific knowledge and the dynamics of researcher interactions, we developed a robust methodology for constructing a comprehensive domain knowledge graph and a nuanced scientist collaboration-competition space. Our approach, illustrated schematically in the first part of Figure 1 (using the life sciences as a representative domain), involves a multi-stage process for knowledge extraction and network construction.

Initially, we curated a large-scale corpus comprising tens of millions of scientific publications, including abstracts and full texts, from prominent databases such as PubMed and OpenAlex. This textual data underwent rigorous preprocessing, encompassing sentence segmentation and tokenization, followed by expert-guided manual annotation to establish a high-quality training set for subsequent automated processes. We then employed Named Entity Recognition (NER) to automatically identify and classify key entities within the preprocessed text of each publication. To enhance the robustness and accuracy of entity recognition, we utilized an ensemble of four fine-tuned pre-trained language models, each trained with diverse hyperparameter configurations. The outputs of these individual NER models were aggregated using a voting mechanism to yield a consensus set of extracted entities.

Following entity extraction, we implemented a comprehensive entity cleaning and normalization procedure. This involved employing the Abbreviation Plus Pseudo-Precision method to resolve abbreviations and integrating data from established resources such as MeSH and PubTator for robust synonym mapping and entity standardization. Subsequently, we performed Relation Extraction (RE) to identify and categorize the semantic relationships between the extracted entities. We developed both single-sentence and multi-sentence RE models, fine-tuning PubMedBERT with multiple hyperparameter settings and combining the results through a voting strategy to maximize the reliability of the extracted relationships. Finally, to enrich the relational structure of our knowledge representation, we integrated entity linkage information from external, curated databases such as Hetionet, thereby constructing a comprehensive domain knowledge graph.

While our primary analysis focuses on the paper level, we acknowledge that future research could fruitfully explore the knowledge entity level to provide even finer-grained insights. Utilizing the constructed domain knowledge graph, we proceeded to build a paper-level network, denoted as $G_K = (V_K, E_K)$, where each paper $v \in V_K$ represents a node. An edge $(u, v) \in E_K$ signifies a connection between two papers, established either through the sharing of one or more identical knowledge entities or through the existence of any relational link between their constituent entities within the domain knowledge graph. Furthermore, to capture the semantic content of each paper, we computed a 300-dimensional word embedding vector for each identified knowledge entity using PubMedBERT. A central embedding vector $\boldsymbol{x}_v$ for each paper v was then derived to represent its overall knowledge content.

In the scientific domain, innovation frequently arises from the convergence of diverse knowledge elements, and the collaborative or competitive interactions among scientists play a crucial role in fostering collective intelligence. To uncover these intricate dynamics, we defined a scientist collaboration-competition space, denoted as $G_S = (S, E_S)$, where S is the set of i$s_i \in S, s_j \in S$ is defined based on two key aspects of their interactions:

Collaboration: If scientists s_i and s_j have co-authored one or more scientific publications, then an edge $(s_i, s_j) \in E_S$ is established. The weight of this edge, $w(s_i, s_j)$, is quantified by the total number of joint publications between s_i and s_j, reflecting the strength of their collaborative relationship.

Competition: In the absence of direct collaboration, we infer potential competition between scientists whose research exhibits significant overlap in terms of knowledge entities. Specifically, if papers authored by s_i (set P_i) and s_j (set P_j) share identical knowledge entities or contain entities that are directly connected within the domain

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knowledge graph, we quantify the intensity of this research overlap, $c(s_i, s_j)$, based on the connection density within G_K:

$$c(s_i, s_j) = \frac{|\{(u,v) \in E_K | u \in P_i, v \in P_j\}|}{|P_i| \cdot |P_j|}.$$

Here, $|\{(u, v) \in E_K \mid u \in P_i, v \in P_j\}|$ represents the total number of edges in the knowledge graph G_K that connect any paper u authored by s_i to any paper v authored by s_j, and $|P_i| \cdot |P_j|$ represents the total number of possible paper pairs between the two scientists. A higher value of $c(s_i, s_j)$ suggests a greater degree of research overlap and, consequently, a higher potential for intellectual competition.

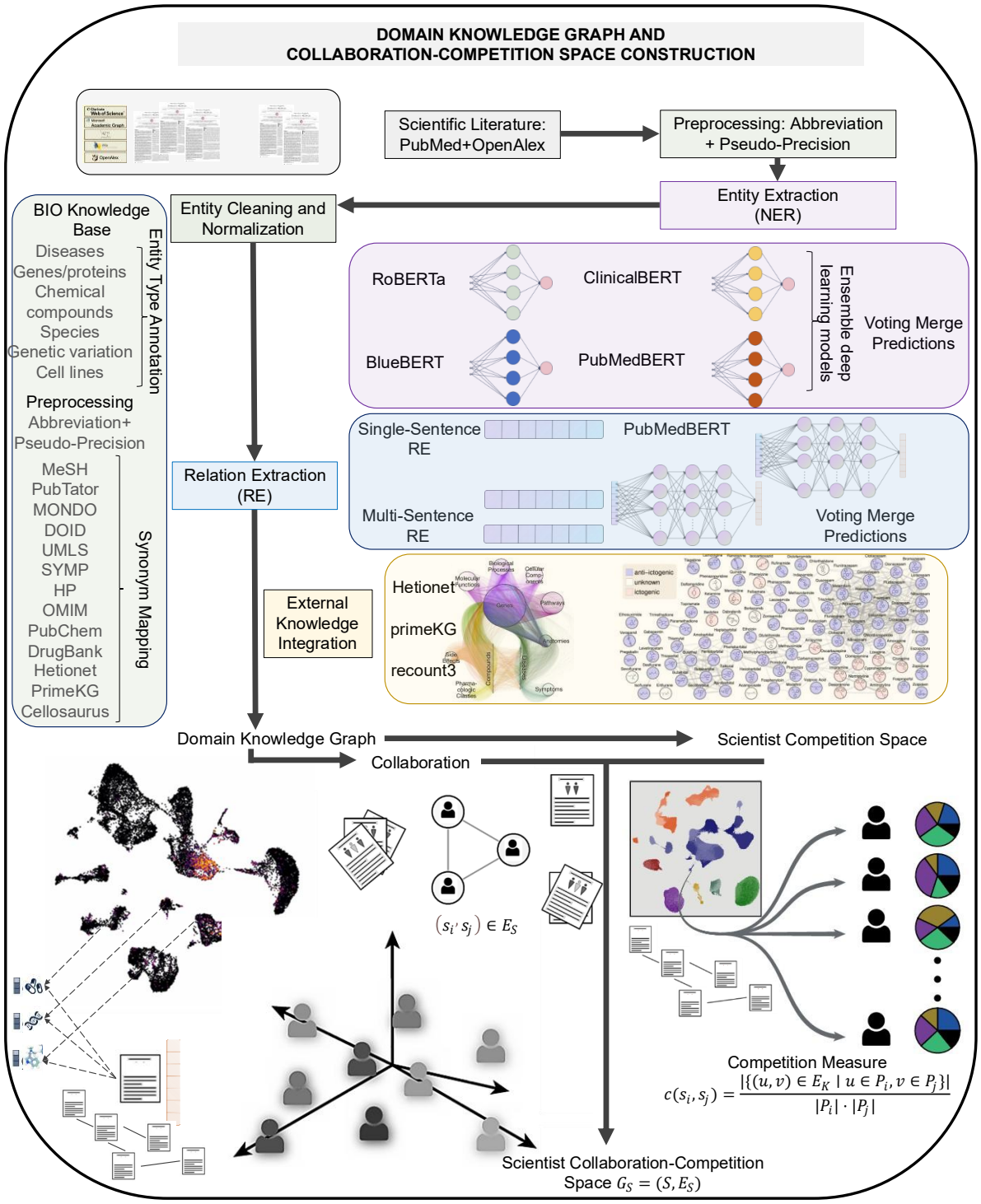


Figure 1. Domain Knowledge Graph and Collaboration-Competition Space Construction

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It is important to note that our representation in G_S does not explicitly delineate between collaboration and competition through distinct edge types. Instead, the network captures a spectrum of interactions, ranging from direct collaboration to indirect competition inferred through shared or related knowledge. Furthermore, our definition of competition extends beyond mere topical similarity to encompass a broader range of interconnected knowledge entities within the domain knowledge graph. Consequently, the constructed scientist collaboration-competition space G_S effectively captures rich interdisciplinary connections among scientists, providing a crucial foundation for mining collective intelligence and ultimately predicting disruptive paradigm shifts in scientific progress.

MINING COLLECTIVE INTELLIGENCE VIA HYBRID HIGHER-ORDER NETWORKS AND GCNN

To effectively mine the collective intelligence embedded within the scientific literature and the interactions of scientists, we developed a novel approach that integrates the paper-paper knowledge network G_K with the scientist collaboration-competition space G_S into a unified hybrid higher-order network, denoted as $H = (V, E)$. This network explicitly models the intricate relationships between scientific knowledge and the human agents who generate and utilize it.

The node set of our hybrid network, $V = V_K \cup S$, comprises two distinct types of nodes: paper nodes V_K, representing individual scientific publications and their associated knowledge entities, and scientist nodes (S), representing the researchers themselves. The connections within this network are captured through hyperedges, where each hyperedge $e \in E$ links a group of related nodes. Specifically, for each paper $v \in V_K$, we define a hyperedge $e_v = A_v \cup \{v\} \cup C_v$. Here, $A_v \subseteq S$ represents the set of authors of paper v, and $C_v \subseteq V_K$ includes other papers that are connected to v through shared or related knowledge entities within the domain knowledge graph G_K. The complete hyperedge set E is then defined as the collection of all such paper-centric hyperedges: $E = \{e_v \mid v \in V_K\}$. This hyperedge formulation allows us to model higher-order relationships, capturing the interplay between a paper, its authors, and the broader knowledge context as defined by its connections to other publications.

To quantify collective intelligence within this hybrid network, we employed a graph convolutional neural network (GCNN) to generate low-dimensional embeddings for each node, preserving both the network's connectivity structure and the inherent features of the nodes. For each paper node $v \in V_K$, the initial feature vector is its 300-dimensional central embedding ($\boldsymbol{x}_v$) derived from PubMedBERT, as described in the previous section. For each scientist node $s \in S$, the initial feature vector $\boldsymbol{x}_s$ is computed as the average of the PubMedBERT embeddings of all papers authored by that scientist:

$$\boldsymbol{x}_s = \frac{1}{|P_s|} \sum_{v \in P_s} \boldsymbol{x}_v,$$

where P_s denotes the set of papers authored by scientist s, and $|P_s|$ is the number of such papers. This aggregation provides an initial representation of a scientist based on the collective knowledge content of their publications.

To model the propagation of information and the influence of connected entities within the hybrid network, we iteratively update the node embeddings using a GCNN architecture. For a paper node $v \in V_K$, the embedding at the $(l+1)th$ layer, $\boldsymbol{h}_v^{(l+1)}$, is computed based on its embedding at the lth layer, $\boldsymbol{h}_v^{(l)}$, and the embeddings of its neighbors within the hyperedges it belongs to (E_v, the set of hyperedges containing v):

$$\boldsymbol{h}_v^{(l+1)} = \sigma\left(\boldsymbol{W}^{(l)} \boldsymbol{h}_v^{(l)} + \sum_{e \in E_v} \frac{1}{|e|} \sum_{u \in e} \boldsymbol{B}^{(l)} \boldsymbol{h}_u^{(l)}\right).$$

Here, $\boldsymbol{W}^{(l)}$ and $\boldsymbol{B}^{(l)}$ are trainable weight matrices at the lth layer, σ represents the ReLU activation function, and $\frac{1}{|e|}$ serves as a normalization factor within each hyperedge, ensuring that the contribution of each neighboring node is appropriately scaled by the size of the hyperedge. This aggregation process allows the embedding of a paper to be influenced not only by its own knowledge content but also by the characteristics of its authors and the knowledge content of related papers. Similarly, the embedding of a scientist node is updated by considering the embeddings of the papers they have authored and the scientists they have collaborated with (through shared hyperedges). After l layers of this GCNN operation, the resulting embedding $\boldsymbol{h}_v$ for each paper node effectively captures both local and global structural information within the hybrid network, reflecting the complex interplay between knowledge content and human interactions.

Following the generation of these integrated embeddings, we define the probability of a paper $v \in V_K$ being accessed or recognized by the broader scientific community, denoted as p_v. This probability is modeled using a softmax function over the learned embeddings:

$$p_v = \frac{\boldsymbol{exp}(\boldsymbol{w}^\top \boldsymbol{h}_v)}{\sum_{\boldsymbol{u} \in \boldsymbol{V}} \boldsymbol{exp}(\boldsymbol{w}^\top \boldsymbol{h}_u)},$$

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where $\boldsymbol{w}^{\top}$ is a learnable weight vector that maps the low-dimensional embeddings to a scalar value representing the tendency of a node to be accessed. The softmax function ensures that the probabilities across all nodes in the hybrid network sum to one ($\sum_{v \in V} p_v = 1$). This probability p_v serves as a proxy for the paper's importance and visibility within the collective cognitive landscape of the scientific community. Furthermore, this measure can be extended to individual knowledge entities by aggregating the access probabilities of the papers in which they appear.

Crucially, because the paper embeddings $\boldsymbol{h}_v$ are derived through the GCNN operating on the hybrid network, the resulting access probability p_v inherently captures higher-order effects, such as the influence of author collaborations, competitive relationships inferred from knowledge overlap, and the interconnectedness of knowledge entities. To optimize the parameters of our GCNN model and the access probability estimation, we employ a cross-entropy loss function:

$$\mathcal{L} = -\sum_{v \in V} y_v \, log \, p_v,$$

where y_v represents the true frequency or a proxy for the real-world access or impact of paper v. By minimizing this loss, we train the model to accurately predict the relative importance and visibility of scientific publications based on the integrated knowledge and social network structures. This learned probability distribution provides a quantitative measure of the collective intelligence surrounding different scientific works and forms a crucial input for our subsequent paradigm shift prediction framework.

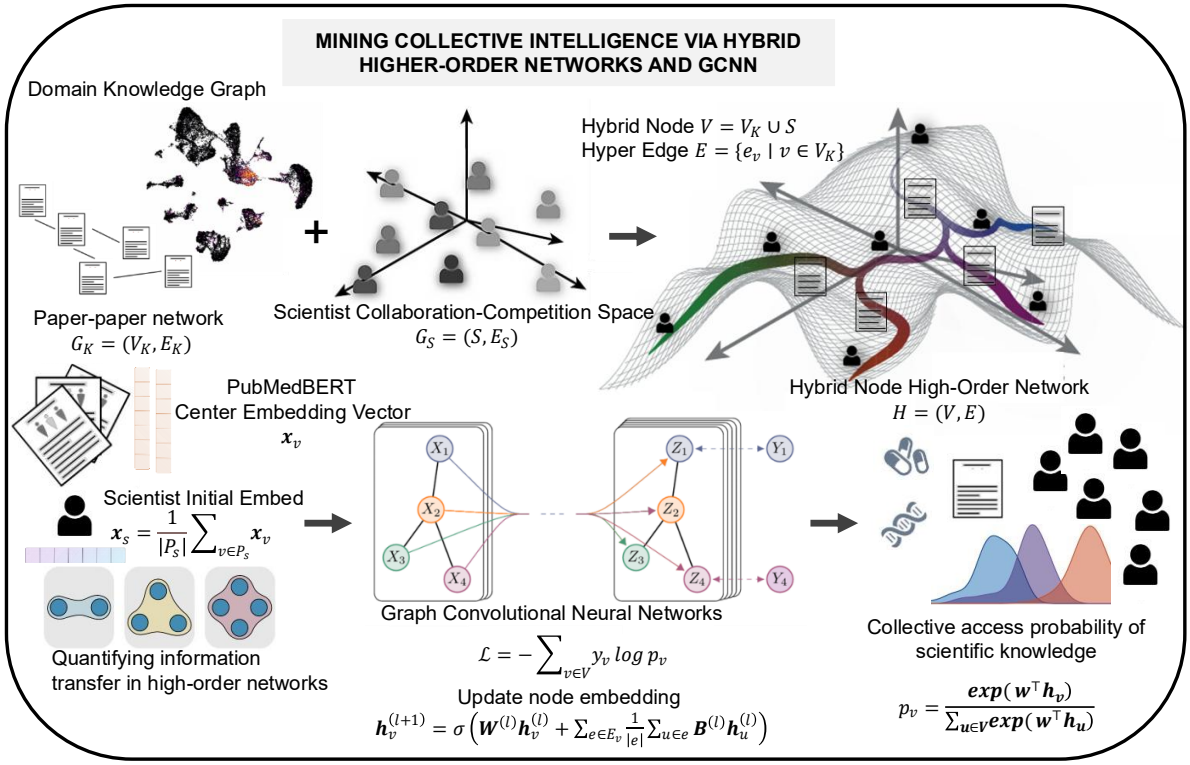


Figure 2. Mining Collective Intelligence Via Hybrid Higher-Order Networks and GCNN

PREDICTING DISRUPTIVE PARADIGM SHIFTS THROUGH DYNAMIC ANALYSIS OF KNOWLEDGE

Disruptive scientific innovations often emerge from the synergistic convergence of previously disparate knowledge domains, areas that may currently be underappreciated but possess the potential for rapid advancement due to the underlying social connectivity of the involved scientists [2, 3]. To identify and predict such transformative shifts, we focused on identifying pairs of scientific themes characterized by significant knowledge dissimilarity, close proximity within the scientist collaboration network, and a high concentration of active researchers. Furthermore, we employed dynamic embeddings and time series modeling to forecast the potential timing of these paradigm shifts.

To identify these themes, we applied the K-means clustering algorithm to the paper embeddings ($\boldsymbol{h}_v$) derived from the GCNN, grouping the set of all papers (V_K) into K distinct scientific themes, denoted as $T_1, T_2, \ldots$. The embedding of each theme, $\overline{\boldsymbol{h}}_T$, was calculated as the centroid of the embeddings of all papers belonging to that theme:

$$\overline{\boldsymbol{h}}_T = \frac{1}{|T|}\sum_{v \in T} \boldsymbol{h}_v.$$

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For each pair of identified themes (T_1, T_2), we quantified the knowledge distance $d_K(T_1, T_2)$ as the Euclidean distance between their respective theme embeddings:

$$d_K(T_1, T_2) = \| \overline{\boldsymbol{h}}_{T_1} - \overline{\boldsymbol{h}}_{T_2} \|_2.$$

A larger knowledge distance between two themes suggests a greater degree of novelty inherent in their potential combination.

To assess the social proximity between themes, we first identified the set of scientists actively contributing to each theme T_i. This scientist set, S_{T_i}, was defined as the union of the author sets (A_v) of all papers v belonging to theme T_i:

$$S_{T_i} = \bigcup_{v \in T_i} A_v.$$

We then calculated the social distance $d_S(T_i, T_j)$ between two themes as the average shortest path length between all pairs of scientists where one scientist belongs to S_{T_i} and the other belongs to S_{T_j} within the scientist collaboration-competition network G_S. A smaller average shortest path indicates a higher degree of social interconnectedness and a greater potential for collaboration and knowledge exchange between the scientists working on these seemingly distant themes.

To account for the level of research activity and potential within each theme, we defined an expert density measure ρ_{T_i}:

$$\rho_{T_i} = \sum_{v \in T_i} |A_v| \cdot p_v.$$

where $|A_v|$ is the number of authors of paper v, and p_v is the collective access probability of paper v as calculated in the previous section. A higher expert density signifies a greater concentration of influential researchers actively publishing within the theme, indicating a stronger potential for future advancements.

We identified candidate disruptive theme pairs T_i, T_j based on the following criteria: a large knowledge distance, a small social distance, and high expert density in both themes, defined by thresholds θ_K, θ_S, and θ_ρ, respectively:

$$d_K(T_i, T_j) > \theta_K \text{ (Novelty)},$$

$$d_S(T_i, T_j) < \theta_S \text{ (Collaboration Potential)},$$

$$\rho_{T_i} > \theta_\rho \; and \; \rho_{T_j} > \theta_\rho \text{ (Knowledge Potential)}.$$

The set of candidate disruptive theme pairs $\mathcal{C}$ was then defined as:

$$\mathcal{C} = \left\{ (T_i, T_j) \mid d_K(T_i, T_j) > \theta_K, d_S(T_i, T_j) < \theta_S, \rho_{T_i} > \theta_\rho, \rho_{T_j} > \theta_\rho \right\}$$

To predict the timing of these potential paradigm shifts, we extended our analysis to incorporate the temporal evolution of the scientific landscape. We constructed a series of time-segmented hybrid networks $\{H_t\}_{t=1}^{T}$, where each H_t represents the network state at a specific time period t. We then updated the node embeddings dynamically using a time-aware GCNN:

$$\boldsymbol{h}_v^{(t,l+1)} = \sigma\left(\boldsymbol{W}^{(l)} \boldsymbol{h}_v^{(t,l)} + \sum_{e \in E_v^{(t)}} \frac{1}{|e|} \sum_{u \in e} \boldsymbol{B}^{(l)} \boldsymbol{h}_u^{(t,l)} e^{-\lambda(t - t_u)} \right).$$

Here, $E_v^{(t)}$ is the set of hyperedges containing node v at time t, and t_u represents the time of publication or activity associated with node u. The exponential decay factor $e^{-\lambda(t-t_u)}$ introduces a temporal weighting, giving more influence to recent neighbors in the embedding aggregation process.

We then tracked the temporal evolution of the knowledge distance between candidate theme pairs:

$$d_K^{(t)}(T_i, T_j) = \| \overline{\boldsymbol{h}}_{T_i}^{(t)} - \overline{\boldsymbol{h}}_{T_j}^{(t)} \|_2.$$

A decreasing trend in $d_K^{(t)}(T_i, T_j)$ over time suggests a growing convergence of the knowledge domains. Simultaneously, we monitored the temporal trends in the collective access probabilities within each theme:

$$p_v^{(t)} = \frac{exp(\boldsymbol{w}^\top \boldsymbol{h}_v^{(t)})}{\sum_{u \in V_t} exp(\boldsymbol{w}^\top \boldsymbol{h}_u^{(t)})},$$

where V_t is the set of nodes in the hybrid network at time t. An increasing trend in these summed probabilities indicates a rising level of attention and interest in the themes from the scientific community.

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To predict the likelihood of a disruptive paradigm shift occurring at a future time point $t + \Delta t$, we trained a Long Short-Term Memory (LSTM) [18] model. The input feature vector $\boldsymbol{x}^{(t)}$ for the LSTM at each time step t consisted of the time-varying knowledge distance, social distance (assumed relatively stable over short timeframes), and expert densities of the candidate theme pair:

$$\boldsymbol{x}^{(t)} = [d_K^{(t)}(T_i, T_j), d_S^{(t)}(T_i, T_j), \rho_{T_i}^{(t)}, \rho_{T_j}^{(t)}].$$

We used historical instances of significant scientific paradigm shifts (e.g., Nobel Prize-winning discoveries that bridged disparate fields) as positive examples to train the LSTM model to predict the probability of a paradigm shift, $p_{\text{change}}^{(t+\Delta t)}$:

$$\boldsymbol{h}^{(t)} = \text{LSTM}(\mathbf{x}^{(t)}, \boldsymbol{h}^{(t-1)}),$$

$$p_{\text{change}}^{(t+\Delta t)} = \sigma(\boldsymbol{w}^{\top}\boldsymbol{h}^{(t)} + b),$$

where $\boldsymbol{h}^{(t)}$ is the hidden state of the LSTM at time t, σ is the sigmoid activation function, $\boldsymbol{w}^{\top}$ is a learned weight vector, and b is a bias term.

Finally, we ranked the candidate disruptive theme pairs based on their predicted probability of a paradigm shift and the estimated time of emergence, allowing us to highlight the most promising areas of scientific inquiry poised for transformative breakthroughs and their anticipated timelines. This approach provides a powerful tool for anticipating future scientific revolutions by integrating the dynamic evolution of both knowledge and social networks.

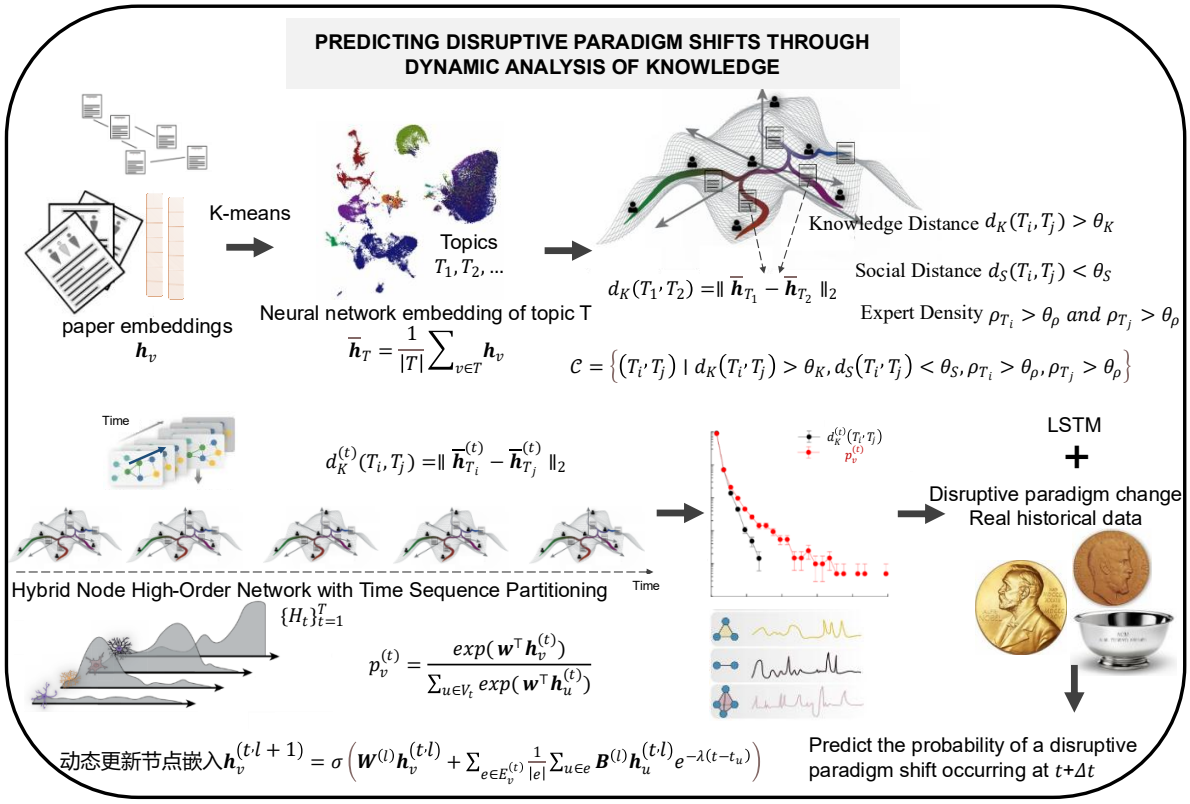


Figure 3. Predicting Disruptive Paradigm Shifts Through Dynamic Analysis of Knowledge

CONCLUSION

In this study, we introduce a human-aware AI framework that redefines the prediction of disruptive paradigm shifts by seamlessly integrating knowledge evolution with the social dynamics of scientific communities. Through the construction of a hybrid higher-order network—unifying a domain knowledge graph and a scientist collaboration-competition space—and the application of GCNNs, we quantify collective intelligence as a product of both intellectual content and human agency. Our methodology identifies thematic pairs with significant disruptive potential, characterized by divergent knowledge domains and tightly knit researcher networks, while dynamic embeddings enable temporally precise forecasts of paradigm shifts. Validated against historical milestones in the life sciences, such as Nobel Prize-winning discoveries, this approach demonstrates robust predictive power and

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generalizability. By offering a scalable and interpretable tool, we not only enhance our understanding of the drivers of scientific revolutions but also provide actionable insights for fostering innovation. This work marks a significant step forward in predictive information science, illuminating the symbiotic relationship between ideas and the communities that shape them, and setting the stage for future explorations across diverse scientific domains.

This study advances the theoretical understanding of scientific progress by bridging two traditionally distinct domains: the evolution of knowledge structures and the social dynamics of scientific communities. By integrating a domain knowledge graph with a scientist collaboration-competition space through a hybrid higher-order network, we provide a novel lens through which to conceptualize collective intelligence as an emergent property of both intellectual content and human interactions. The use of graph convolutional neural networks (GCNNs) to generate embeddings that encapsulate these dual dimensions challenges the conventional view of scientific discovery as a purely epistemic process, emphasizing instead the critical role of social proximity and competition in driving disruptive innovation. Our findings align with and extend Kuhn's [3] paradigm shift theory by offering a quantifiable framework to identify the preconditions—namely, significant knowledge distances coupled with close social connectivity—that precede revolutionary change. Furthermore, this work enriches the literature on collective intelligence [18, 19] by demonstrating how higher-order network structures can capture the interplay between cognitive diversity and social influence, providing a more holistic model of how scientific breakthroughs emerge. This theoretical synthesis opens new avenues for exploring the mechanisms underlying innovation, particularly at the intersection of disparate knowledge domains, and underscores the necessity of human-aware approaches in predictive science.

The human-aware AI framework presented here offers transformative practical applications for stakeholders across the scientific ecosystem. For research institutions and funding agencies, our model provides a scalable tool to identify emerging interdisciplinary fields with high disruptive potential, enabling strategic allocation of resources to catalyze paradigm-shifting discoveries. By pinpointing thematic pairs characterized by large knowledge distances, close social proximity, and high expert density, policymakers can prioritize investments in collaborative initiatives that bridge silos, fostering environments conducive to innovation. Scientists themselves can leverage this framework to explore untapped connections within and beyond their fields, guiding hypothesis generation and collaboration strategies. The temporal predictions generated by our dynamic analysis further enhance decision-making by offering insights into the likely timing of transformative shifts, allowing for proactive planning in research agendas. In educational contexts, this approach can inform curriculum development by highlighting interdisciplinary areas poised for growth, preparing the next generation of researchers for future challenges. Beyond academia, industries reliant on scientific advancements—such as pharmaceuticals or renewable energy—can use these predictions to anticipate breakthroughs, aligning R&D efforts with emerging trends. Ultimately, this framework empowers a proactive rather than reactive approach to scientific progress, amplifying its societal impact.

While our framework represents a significant advancement, several limitations warrant consideration. First, the reliance on publication data from repositories like PubMed and OpenAlex may introduce biases toward well-documented fields, potentially underrepresenting emerging or less formalized areas of inquiry. The focus on co-authorship and inferred competition as proxies for social dynamics overlooks other forms of interaction, such as informal collaborations, mentorships, or conference exchanges, which could further influence innovation. Additionally, the construction of the domain knowledge graph and collaboration-competition space depends on the accuracy of entity recognition and relation extraction, which, despite rigorous preprocessing and ensemble modeling, may still be subject to errors in unstructured text. The generalizability of our findings, while promising, has been primarily validated within the life sciences; its applicability to disciplines with different publication cultures or collaboration norms remains to be fully tested. Finally, the temporal predictions, though aligned with historical breakthroughs, assume a continuity in scientific trends that may be disrupted by exogenous factors—such as technological leaps or global crises—not accounted for in our model. Future iterations could address these constraints by incorporating broader data sources, refining interaction metrics, and extending validation across diverse domains to enhance robustness and scope.

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GENERATIVE AI USE

We confirm that we did not use generative AI tools/services to author this submission.

AUTHOR ATTRIBUTION

A.J.Y.: conceptualization, methodology, data curation, formal analysis, writing – original draft; S.Y.: data curation, formal analysis, visualization, writing – review and editing; Z.S.X.: project administration, funding acquisition,

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supervision, writing – review and editing; Z.Y.: project administration, funding acquisition, supervision, writing – review and editing; D.S.: project administration, funding acquisition, supervision, writing – review and editing.

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