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IBID-CCT: A novel model for interdisciplinary breakthrough innovation detection based on the cusp catastrophe theory ☆

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ABSTRACT

Detecting interdisciplinary breakthrough innovations is critical for identifying scientific advances and fostering original innovation. Previous studies primarily focus on single-dimensional publication characteristics, such as reference-based or citation-based metrics, which fail to fully capture the complexity of interdisciplinary breakthrough innovations. This study introduces the **IBID-CCT** model (**i**nterdisciplinary **b**reakthrough **i**nnovation **d**etection based on **c**usp **c**atastrophe **t**heory) to address this gap. We explain the mechanism of interdisciplinary breakthrough innovation and propose metrics based on interdisciplinary knowledge integration, fusion, and diffusion stages, grounded in IBID-CCT. First, we construct an experimental dataset comprising papers from prestigious academic awards, including the Nobel Prize, Wolf Prize, Crafoord Prize, Breakthrough Prize, and Turing Award. Using this dataset, we train machine learning and deep learning models based on IBID-CCT metrics to identify interdisciplinary breakthroughs. The experimental results show that the IBID-CCT model built on LGBM and the one built on BERT achieve the best results with an F1 score of 0.8631 and 0.8604, respectively. To further analyze the impact of each metric in IBID-CCT, SHAP analysis is applied to interpret the LGBM model's results, while word distribution and sentiment analysis are used to interpret the BERT model's outputs. These analyses reveal that interdisciplinary breakthrough innovations typically involve the integration of cutting-edge, diverse knowledge; experience long-term knowledge diffusion; and consistently positively drive multi-field development. Finally, comparative experiments confirm that our IBID-CCT model significantly outperforms existing methods such as the Disruption Index, Reference Interdisciplinarity, and Citation Interdisciplinarity in both breakthrough innovation detection and interdisciplinary breakthrough innovation detection tasks. This research provides a comprehensive framework for understanding the mechanisms of interdisciplinary breakthrough innovations, designing effective models for their detection, and forecasting future trends in innovation. Data and code are available at: https://github.com/wolovecoding/IBID-CCT.

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1. Introduction

The concept of "breakthrough innovation" originates from Schumpeter's "Creative Destruction" theory, which describes breakthrough innovation as transformative progress driven by the adoption of new scientific principles, resulting in products, technologies, or methods that markedly surpass existing ones or offer entirely new capabilities (Azoulay et al., 2010; Burt, 2004; Girotra et al., 2010; Jones, 2009; Kuhn & Hawkins, 1963; Leifer, 2000; Liu et al., 2024; Schumpeter, 2006). Unlike incremental innovation – which instead focuses on refining current products, processes, and structures (Forés & Camisón, 2016) – breakthrough innovation shifts the technological landscape, often triggering scientific revolutions and influencing future technologies through novel trajectories (Kuhn & Hawkins, 1963; McDermott & O'connor, 2002).

Interdisciplinary research, increasingly recognized for its effectiveness in addressing complex societal challenges, fosters scientific growth through the convergence of diverse fields (Thorleuchter & Van den Poel, 2016; Wang, Qiao, et al., 2024; Yang et al., 2025). This integration has become essential for discovery, as notable breakthroughs, including Nobel Prize-winning works, frequently incorporate multidisciplinary insights (Jingjing Ren, 2023; Narin et al., 1997; Schoenmakers & Duysters, 2010; Wei et al., 2023). Consequently, detecting interdisciplinary breakthroughs early and accurately is critical for advancing innovative research and supporting transformative discoveries.

Existing methods for detecting breakthrough innovation generally fall into three categories: (1) assessing the novelty of knowledge combinations through reference records (Shirabe, 2014), (2) analyzing innovation in topics and content through focal papers (Hou et al., 2022; Luo et al., 2022), and (3) evaluating the impact of papers based on a citing paper (Herfeld & Doehne, 2019; Lund et al., 2020). Traditionally, citation counts serve as a measure of impact; however, this metric alone may be insufficient for detecting interdisciplinary breakthrough innovations that often embody unique features (Petersen et al., 2025; Yang et al., 2023), such as disruptiveness, discontinuity, and interdisciplinary knowledge fusion.

Interdisciplinary breakthrough innovations frequently challenge existing theories and combine disparate knowledge areas in unconventional ways, which may delay their recognition and diffusion. This delay introduces bias when using early citation counts for detection, as many groundbreaking contributions are not immediately highly cited (Ponomarev et al., 2014). Detecting interdisciplinary breakthrough innovations, therefore, requires a multidimensional approach that extends beyond simple citation metrics to capture the distinctive, transformative nature of these innovations.

The cusp catastrophe theory (CCT) is a branch of non-dynamic mathematics initially developed to study phase transitions and morphogenesis (Gilmore, 1996). As one of the seven elementary catastrophes, CCT explores the occurrence of sudden state shifts in differential dynamical systems by examining the bifurcation of stable equilibrium states in static systems. The core concept of this theory is to understand system changes and disruptions: in a stable state, a system tends to maintain an ideal equilibrium within a defined range. However, when subjected to external forces, the system initially resists and attempts to return to stability. If the force is sufficiently strong, though, the system undergoes a discontinuous shift to a new equilibrium state (Golubitsky, 1978; Xu et al., 2022). The characteristics of CCT align closely with innovation dynamics, making it a suitable foundation for interdisciplinary breakthrough innovation detection.

This study proposes a novel interdisciplinary breakthrough innovation detection model based on the cusp catastrophe theory, termed IBID-CCT. By focusing on the underexplored perspective of interdisciplinary knowledge flow, this model captures the lifecycle of breakthrough research, from emergence to influence across disciplines. Thus, we establish the following research questions to guide our investigation:

- RQ1: What is the internal generation mechanism of interdisciplinary breakthrough innovation?
- RQ2: What are the essential metrics for identifying interdisciplinary breakthrough innovation?
- RQ3: How to develop an effective machine learning model or deep learning model for the detection of interdisciplinary breakthrough innovations?
- RQ4: How to interpret the outcomes of the machine learning or deep learning models?

For RQ1, we define the internal generative mechanism of interdisciplinary breakthrough innovation as a dynamic process of knowledge integration, fusion, and diffusion across disciplines based on CCT. Initially, knowledge elements from different fields are integrated to form the foundation of innovation. This integration enables the reorganization of heterogeneous knowledge and is, therefore, critical for generating new ideas. In the next phase, these integrated elements undergo fusion, creating new concepts or solutions that transcend traditional disciplinary boundaries. Finally, the fused knowledge diffuses across broader scientific and technological domains, influencing future research and innovation. This process is characterized by its ability to merge previously disconnected areas of knowledge, thereby generating innovations with significant potential for scientific advancement and societal impact.

For RQ2, we propose a set of metrics that measure the processes of interdisciplinary knowledge integration, fusion, and diffusion. These metrics include indicators from bibliometric data (e.g., references, citation counts, author teams, and common measurements such as novelty, disruption, and interdisciplinarity), as well as indicators from scientific and technological domains (e.g., patents and funded projects). Additionally, social media metrics are incorporated to assess the broader societal impact of interdisciplinary breakthrough innovations (Yang et al., 2024). To address the limitations of purely quantitative indicators, we leverage GPT-4o (Achiam et al., 2023) to generate contribution sentences based on paper titles, abstracts, and citation contexts. This content-based approach allows us to identify breakthroughs by analyzing the semantic nuances of scientific contributions (Chen et al., 2022; Pramanick et al., 2024). In summary, these metrics and indicators provide a comprehensive framework for detecting interdisciplinary breakthrough innovation from the perspectives of both bibliometric characteristics and semantic content.

For RQ3, we formulate the detection of interdisciplinary breakthrough innovation as a classification problem, divided into three categories: (1) interdisciplinary breakthrough innovations, (2) breakthrough innovations, and (3) a control group. To develop an effective model, we manually construct a gold standard dataset that comprises papers associated with prestigious academic awards, such as the Nobel Prize, Wolf Prize, Crafoord Prize, Breakthrough Prize, and Turing Award. We conduct classification experiments using machine learning and deep learning techniques on these papers. In the machine learning models, the LGBM model achieves an F1 score of 0.8631 by leveraging bibliometric features. We also fine-tune a BERT-based model within a multimodal framework (Gu & Budhkar, 2021) that integrates textual features (e.g., contribution sentences) with numerical indicators. This model attains an F1 score of 0.8604. The experiments with both the machine learning and deep learning models demonstrate the accuracy and robustness of detecting interdisciplinary breakthrough innovations. Additionally, we conduct comparative experiments to validate the superiority of the LGBM and BERT models in detecting both breakthrough and interdisciplinary breakthrough papers. These models significantly outperform traditional metrics, such as the Disruption Index ($Disruption$), Citation Interdisciplinarity (Cit_D), and Reference Interdisciplinarity (Ref_D). In both tasks, BERT and LGBM achieve much higher performance than other conventional metrics. For identifying breakthrough innovations, LGBM performs best with an F1 score of 0.8889, while BERT excels in detecting interdisciplinary breakthroughs with an F1 score of 0.5811. None of the traditional metrics exceed an F1 score of 0.5.

For RQ4, we apply SHAP (Lundberg, 2017) analysis to assess feature importance and the underlying decision-making process to interpret the results of our machine learning model. SHAP analysis reveals that interdisciplinary breakthrough innovations are typically generated by recombining diverse knowledge from multiple fields and often represent cutting-edge research with significant future impact. For the deep learning model, we examine the relationship between semantic content and interdisciplinary breakthrough innovations through word distribution and sentiment analysis. Using TF-IDF to analyze word distribution, we find that interdisciplinary breakthrough papers tend to integrate knowledge from various disciplines. Additionally, sentiment analysis indicates that these papers often exhibit positive sentiment in their textual expression. This suggests that such papers not only contribute to new research directions but also enhance their visibility in scientific, technological, and societal contexts.

The article is organized as follows: Section 2 reviews the related works. In Section 3, we analyze the mechanism of interdisciplinary breakthrough innovation. Section 4 introduces the methodology, followed by the experiment and discussion of results in Section 5. Section 6 discusses the findings and implications of the paper. Finally, Section 7 concludes with a discussion of limitations and future research directions.

2. Related works

2.1. Characteristics of breakthrough innovation

Breakthrough innovation is defined as "a process of unprecedented improvement based on newly adopted one or several scientific principles to lead the products, technologies and methods in a significant advance better than existing ones, or deliver an entirely new set of performance features" (Azoulay et al., 2010; Burt, 2004; Girotra et al., 2010; Leifer, 2000). Research on the characteristics of breakthrough innovations indicates that these advances often emerge by recombining knowledge from distant or previously unconnected domains (Fleming, 2001; Haas & Ham, 2015; Morgan, 1953; West, 2002). This approach generally starts with incremental steps that gradually transform into entirely new methodologies.

Studies such as Andersen et al. (2006) have shown that breakthrough innovations initially conflict with established cognitive frameworks, which paradoxically enhances their potential to disrupt and transform existing fields. Moreover, there is growing evidence that breakthrough innovations increasingly arise from interdisciplinary collaboration (Bessant et al., 2014; Winnink et al., 2019). While these innovations are both novel and disruptive, they are not created in isolation; rather, they integrate diverse knowledge fields, merging insights from multiple disciplines to achieve significant theoretical or technological advances (Yang et al., 2024).

2.2. Methods for breakthrough innovation detection

Breakthrough innovation detection methods can be grouped into three primary approaches: (1) evaluating the novelty of knowledge combinations from references, (2) assessing topic and content innovation from focal literature, and (3) analyzing influence and innovation through citation analysis.

Measuring the Novelty of Knowledge Combinations from References. Research based on references suggests that breakthrough innovation arises from recombining existing elements (Fleming, 2001) or adapting known elements to new contexts (Hargadon & Sutton, 1997). This approach quantifies the novelty of knowledge combinations using indicators, such as reference discipline, citation frequency, and reference age. For example, Dahlin and Behrens (2005) developed a metric for "radicalness" based on patent citation data, revealing that patents with diverse citation structures signify greater novelty. However, these methods focus solely on the novelty of knowledge combinations without evaluating the impact of breakthroughs on future research.

Measuring Topic and Content Innovation from Focal Literature. This approach assumes that a key discovery initiates a new technological or theoretical path, sparking further innovation (Silverberg, 2002). Text mining methods like keyword extraction and topic modeling identify core concepts and shifts within a field by analyzing changes in keywords or topics across publications (Nichols, 2014; Xu et al., 2016). Although this method provides insights beyond citation counts, its reliance on current terminology can limit its applicability in capturing deep interdisciplinary knowledge connections.

Measuring Influence and Innovation through Citing Literature. Given the broad influence of breakthrough innovations across disciplines, researchers have analyzed citations to gauge their impact. Specific indicators, such as field diffusion breadth (Liu & Rousseau, 2010) and diffusion speed (Yue et al., 2022), help quantify interdisciplinary knowledge spread. Citation frequency is commonly used to approximate impact; for instance, Zang et al. (2014) assessed the influence of patents by measuring post-publication citation counts, while Fontana et al. (2013) observed that impactful scientific breakthroughs typically garner extensive citations due to their disruptive nature. However, citation counts alone may not accurately capture breakthrough innovations. Methods like the Disruption Index (DI) (Wu et al., 2019) considers the citation structure of a work and its references, and attempts to quantify a publication's value. Yet, the DI method may miss interdisciplinarity's role in innovation, as it disregards citation diversity across disciplines and can introduce time-sensitive biases (Leibel & Bornmann, 2024).

While these methods offer valuable perspectives, most focus on unidimensional publication characteristics, either reference-based or citation-based. However, scientific breakthroughs, particularly interdisciplinary ones, manifest in diverse forms by combining heterogeneous knowledge from various fields, altering paradigms, and profoundly influencing subsequent research (Runhui et al., 2025; Wei et al., 2023). Current approaches lack comprehensive metrics to fully capture the essence of innovation, potentially leading to biased evaluations that impair decision-making quality.

2.3. Applications of the cusp catastrophe theory in innovation evaluation

CCT, a branch of bifurcation theory, examines dynamical systems to explain sudden shifts in behavior as systems transition from one stable state to another. Rooted in topological dynamics and the singularity theory, it analyzes discontinuous mutations in response to continuous changes in system parameters. As observed by Prigogine and Lefever (1968), when a nonlinear open system is far from equilibrium, minor parameter changes can trigger abrupt transitions through fluctuations, leading to phase shifts. This makes CCT applicable for identifying and predicting transformative research topics.

Three key studies have applied CCT in innovation evaluation (Perla & Carifio, 2005; Seif, 1979; Xu et al., 2022). Seif (1979) used it to construct a qualitative, macroscopic model for assessing thyrotropic responsiveness, focusing on treatment effects in hyperthyroidism and ecological dynamics. Perla and Carifio (2005) developed a catastrophe model to gauge shifts in knowledge potential by quantifying changes in evolving theories, finding that greater differences between new and established theories heighten breakthrough potential. More recently, Xu et al. (2022) employed the catastrophe theory to forecast transformative research topics. This study used 11 indicators across four dimensions – growth rate, socio-economic impact, network characteristics, and uncertainty – and revealed distinctions between emerging topics within stem cell research and their capacity to drive innovation. Their findings offered valuable insights for research planning, policy-making, and management.

In contrast to prior studies that focus on breakthrough detection within single disciplines or rely on a single metric like citation counts (Huang et al., 2013; Rosenkopf & Nerkar, 2001; Zang et al., 2014), we propose a comprehensive framework, **IBID-CCT**, to detect interdisciplinary breakthrough innovation. By leveraging CCT, our approach emphasizes knowledge exchange across disciplines to identify emerging interdisciplinary innovations with precision.

3. Mechanism of interdisciplinary breakthrough innovation generation

To establish a foundation for this study, we analyze the underlying mechanisms of interdisciplinary breakthrough innovation. Knowledge is dynamic, continuously changing and flowing, and knowledge flow refers to the transfer of knowledge resources between a source and a recipient based on specific needs. Interdisciplinary research fosters a comprehensive understanding of complex problems by nonlinearly integrating knowledge from diverse fields.

The cusp catastrophe theory, a branch of topology rooted in singularity and stability theory, is commonly used to study the characteristics of state shifts within systems as control variables change (Thom, 2018). By examining transitions and patterns among various stable configurations, the catastrophe theory provides insights into abrupt phenomena across mathematics, physics, biology, and social sciences. Unlike traditional linear tools, which often fall short in identifying novel and transformative innovations, the catastrophe theory, as part of nonlinear dynamics, is particularly suited for analyzing state changes driven by both gradual and abrupt shifts. Its core approach involves using mathematical models to abstractly represent system behaviors or states near critical or unstable points (Loren Cobb, 1980).

Due to this nonlinearity, dynamic systems often exhibit divergent behaviors, such as sudden jumps, hysteresis, and bimodality. Similarly, the generation of new knowledge is not strictly linear; it involves both gradual (progressive) and abrupt (mutative) processes, with breakthrough innovation primarily arising from the latter and characterized by sudden, unpredictable shifts. Therefore, we propose a model of interdisciplinary breakthrough innovation generation based on the cusp catastrophe theory. Conceptually, creating new knowledge establishes ordered structures, often through forming novel connections. These connections reduce uncertainty about an object, or "achieve entropy reduction". Consequently, we select the "entropy" of knowledge as the state parameter in our interdisciplinary breakthrough innovation model, whereby greater entropy reduction signifies a higher degree of interdisciplinary breakthrough innovation.

Knowledge mutation occurs only under specific conditions. First, the scientific knowledge system must be open and far from equilibrium to allow the continuous introduction of "negative entropy flow" from external sources. To capture this dynamic, we use "knowledge flow" as a control parameter in generating interdisciplinary breakthrough innovations. Additionally, strong nonlinear interactions are necessary to enable significant fluctuations from cross-disciplinary knowledge exchanges, fostering breakthrough innovation. For this purpose, we use the "coherence effect" as the second control parameter.

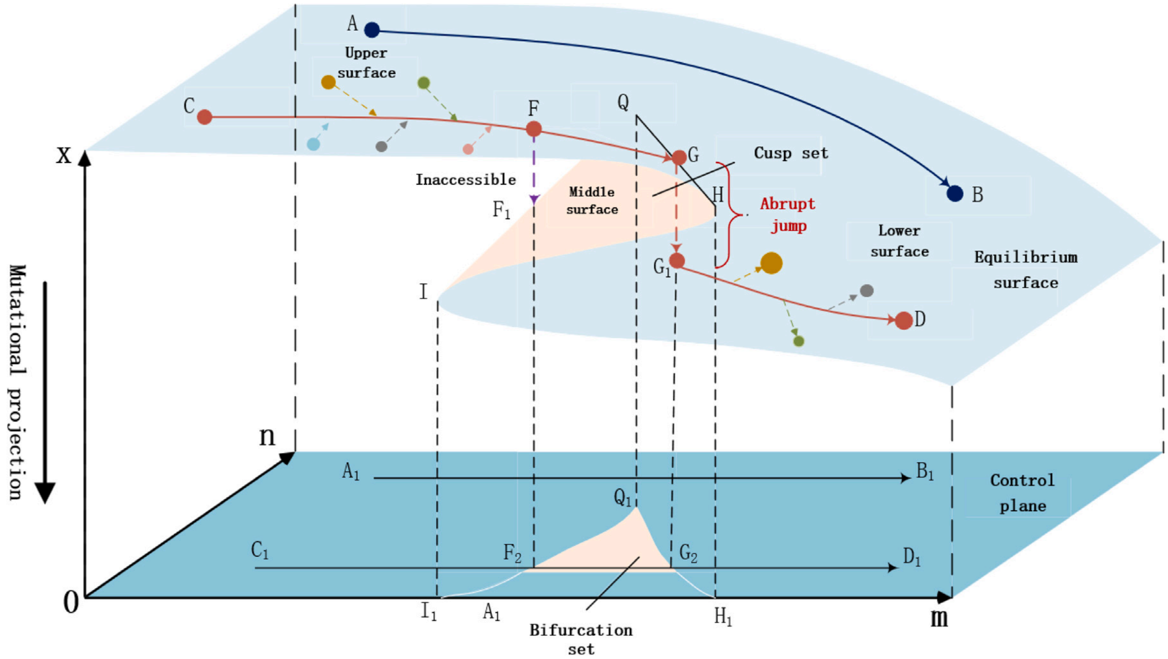


Fig. 1. The interdisciplinary breakthrough innovation generation process model. The x-axis represents the state variable indicating the degree of internal entropy within the knowledge system, while m and n represent the interdisciplinary knowledge flow and the coherence effect among interdisciplinary knowledge elements, respectively. The folded equilibrium surface illustrates both gradual changes and abrupt transitions in the knowledge system, where nodes represent different disciplines and line segments indicate the knowledge distance between disciplines. The system generates interdisciplinary breakthrough innovation through knowledge flow and coherence effects.

Building on this analysis, we develop a model for the generation process of interdisciplinary breakthrough innovation (Tian et al., 2019), as shown in Fig. 1, where variable x represents the state variable, indicating the degree of internal entropy within the knowledge system. The control variables m and n represent the interdisciplinary knowledge flow and the coherence effect among interdisciplinary knowledge elements, respectively. Together, these parameters (x, m, n) form a three-dimensional behavior space that models the process of interdisciplinary breakthrough innovation. Above this behavior space is the equilibrium surface — a folded structure where each point corresponds to a state of knowledge entropy. Nodes on the equilibrium surface represent different disciplines: the node color indicates discipline type, node size denotes influence, horizontal position reflects the time of knowledge introduction, and line segment length represents the knowledge distance between disciplines. The surface's tilt reflects entropy variation across different stages of the interdisciplinary breakthrough process.

The equilibrium surface divides into three regions based on the folding curve, corresponding to different knowledge states: the upper surface represents the stable equilibrium of existing (or "old") knowledge with high entropy, the middle surface is the transitional and unstable state where entropy decreases as old knowledge transforms into new knowledge, and the lower surface represents the stable equilibrium of the newly established knowledge with low entropy. At the base of the behavior space lies the control plane, defined by the control parameters (m, n). The bifurcation set ($Q_1 F_2 G_2$, which is formed by projecting the folded equilibrium surface onto this control plane, serves as the critical area where abrupt shifts in interdisciplinary breakthrough innovation may occur. Here, curve $Q_1 I_1$ represents the initial critical threshold for breakthrough innovation, while $Q_1 H_1$ denotes the termination threshold.

In the model, curve CD and its projection $C_1 D_1$ illustrate the generation of interdisciplinary breakthrough innovation, whereas curve AB and its projection $A_1 B_1$ reflect incremental innovation (not the focus of this paper). The interdisciplinary breakthrough innovation generation process can be further divided into three stages: C→G representing knowledge integration across disciplines; G→G_1 representing interdisciplinary knowledge fusion; and G_1→D signifying interdisciplinary knowledge diffusion.

3.1. Interdisciplinary knowledge integration stage (C→G)

The interdisciplinary knowledge integration stage lays the groundwork for breakthrough innovation, characterized by the continuous accumulation of knowledge within the scientific system. An isolated scientific knowledge system increases internal entropy, leading to chaos and disorder, which is counterproductive for fostering interdisciplinary breakthroughs. Thus, introducing external streams of opposing entropy is essential to maintain the system's potential for innovation.

However, during the C→G stage, due to the large distance between the knowledge of different disciplines, the impact of interdisciplinary knowledge collision on the formation of new knowledge (fluctuation) is weak. Therefore, nonlinear interactions between these diverse knowledge sources remain limited due to insufficient information, meaning the coherence effect stays below the critical threshold, and fluctuations exert minimal impact on the knowledge system. As a result, no state change from old to new knowledge occurs, and the system remains in a stable upper lobe without significant transformation.

This stage highlights the critical role of adequate knowledge flow in generating interdisciplinary breakthrough innovations. Therefore, at this stage, the relevant knowledge of other disciplines should be introduced as much as possible to enrich the material in the process of interdisciplinary breakthrough innovation. Generally, the larger and more heterogeneous the pool of integrated knowledge, the greater the potential for generating innovative ideas, increasing the likelihood for future interdisciplinary breakthrough innovations.

3.2. Interdisciplinary knowledge fusion stage ($G \rightarrow G_1$)

The interdisciplinary knowledge fusion stage is critical for generating breakthrough innovations, as it involves a nonlinear cross-fusion of theories, technologies, methods, and other knowledge elements from multiple disciplines, rather than merely combining them linearly. At this stage, new insights will be put forward, and innovative discoveries will be made. Therefore, interdisciplinary knowledge fusion is often accompanied by the mutation of new knowledge, frequently causing a significant shift in the knowledge state, and creates value-added novelty.

During the $G \rightarrow G_1$ stage, as the amount of information increases, the nonlinear interaction between knowledge elements will be enhanced. When the coherence effect reaches the critical threshold at G, the impact on the knowledge state becomes substantial. Fluctuations are rapidly amplified, affecting the entire knowledge system and prompting a sudden shift to a more ordered state. This transition is characterized by the abrupt breakdown of the stable state of old knowledge; instead of a gradual shift, the knowledge system jumps from G on the upper surface to G_1 on the lower surface, where new knowledge emerges spontaneously in a sudden transformation. This shift from old to new knowledge signifies the formation of interdisciplinary breakthrough innovation, and the scientific knowledge system reaches a new steady state on the lower surface.

On the control plane, this transformative trajectory is projected as G_2. The driving force behind interdisciplinary breakthrough innovations is the substantial fluctuation triggered by the coherence effect among knowledge elements, enabling the system to leap from its current stable state to a higher steady state.

3.3. Interdisciplinary knowledge diffusion stage ($G_1 \rightarrow D$)

Interdisciplinary knowledge diffusion is the stage in which interdisciplinary breakthrough innovations produce practical effects. According to the different effects of interdisciplinary breakthrough innovations on other fields, they can be divided into: upward innovations (advancing effects on other fields) and downward innovations (regressive effects on other fields). Upward interdisciplinary breakthrough innovation is what people need. Analyzing interdisciplinary knowledge diffusion can help identify upward, impactful innovations.

During the interdisciplinary knowledge diffusion stage, this new interdisciplinary breakthrough innovation will spread to other disciplines, initiating another cycle that drives the orderly development of the knowledge system from lower to higher levels, ultimately enabling the spiral evolution of knowledge. Interdisciplinary knowledge diffusion is observed in the transfer and expansion of knowledge across disciplines, often measured by citation patterns in the literature. Here, the influence of key literature on subsequent research is seen through its role in pushing domain knowledge into new areas. This push, or diffusion, is closely tied to the degree of innovation and disruption that the cited literature brings to its domain; focal literature with strong disruptive innovation can significantly enhance interdisciplinary diffusion and accelerate knowledge innovation in subsequent research.

This stage can be effectively measured by examining the breadth, speed, and strength of interdisciplinary knowledge diffusion.

In summary, from a knowledge flow perspective, the formation of interdisciplinary breakthrough innovation is a comprehensive process involving three key stages: interdisciplinary knowledge integration, fusion, and diffusion. Interdisciplinary knowledge integration establishes the foundation, where factors like knowledge age, distance, and influence shape the effectiveness of innovation. The fusion stage drives transformative evolution by nonlinearly combining knowledge from different disciplines, sparking breakthrough innovation. This stage depends not only on team composition but also on assessing impact and potential through metrics, such as disruption and novelty. Finally, interdisciplinary knowledge diffusion spreads and further develops breakthroughs across fields, with citation patterns reflecting its dissemination. The breadth, speed, and intensity of diffusion serve as comprehensive metrics for evaluating the scope of interdisciplinary knowledge spread.

4. Methodology

We develop a detection model for interdisciplinary breakthrough innovation by analyzing the internal mechanisms underlying its generation. Our approach involves three steps, as depicted in Fig. 2. First, we select relevant metrics to identify interdisciplinary breakthrough innovation from the perspectives of knowledge integration, fusion, and diffusion. Second, we develop machine learning and deep learning models to detect these innovations. Third, we evaluate model performance using precision, accuracy, recall, F1 score, and confusion matrices. Additionally, we employ SHapley Additive exPlanations (SHAP) (Lundberg, 2017) to conduct an interpretability analysis of feature importance.

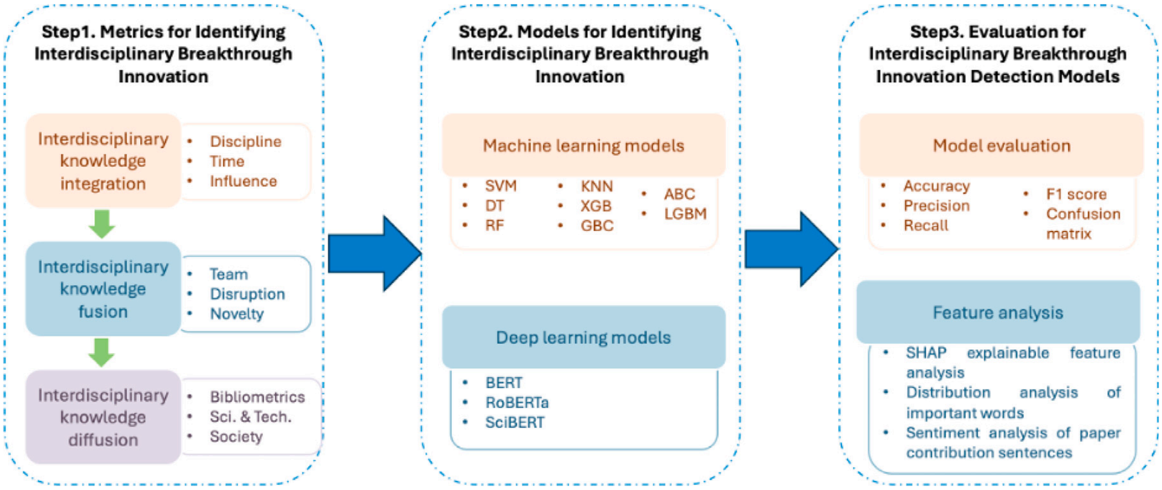


Fig. 2. Workflow of the IBID-CCT model.

4.1. Metrics for identifying interdisciplinary breakthrough innovation

After the analysis of the mechanism of interdisciplinary breakthrough innovation generation, we identify metrics related to interdisciplinary knowledge integration, interdisciplinary knowledge fusion, and interdisciplinary knowledge diffusion, respectively.

4.1.1. Metrics for interdisciplinary knowledge integration

Interdisciplinary knowledge integration involves the continuous accumulation of knowledge across multiple disciplines. By accessing diverse knowledge and resources externally, which cannot be created or provided internally, we can stimulate internal thinking and methodological innovation through varying levels of scientific collaboration, thereby developing new knowledge. To comprehensively measure this interdisciplinary characteristic, we explore suitable metrics from the dimensions of discipline, time, and impact to analyze the features of interdisciplinary knowledge integration.

(1) Discipline dimension

Interdisciplinary knowledge is complex, primarily reflected in the diversity, balance, and disparity among disciplines. Diversity forms the basis of interdisciplinary knowledge, indicating whether the research encompasses a wide range of fields. Balance reflects the evenness of different disciplines in the integration process. Disparity measures the similarity between participating disciplines in knowledge integration; high disparity suggests the integration of heterogeneous knowledge systems, often seen as crucial for innovation. In this study, we quantify the disciplinary characteristics of interdisciplinary knowledge integration using the classic Rao-Stirling Index (Rafols & Meyer, 2010). This index integrates diversity, balance, and disparity into a single measure (Cassi et al., 2017; Yang et al., 2025), with its formula as follows:

$$Ref\_D = \sum_i \sum_j p_i p_j d_{ij} \tag{1}$$

In Eq. (1), $p_i p_j$ denotes the proportion of discipline i and discipline j among all cited disciplines, serving as a measure of disciplinary variety and balance within the distribution; d_{ij} represents the distance between discipline i and j, calculated as $1 - S_{ij}$. Here, S_{ij} represents the similarity between discipline i and j, derived from the citation relationships among papers. The data for the citation matrix is sourced from Wang, Qiao, et al. (2024)'s research.

(2) Time dimension

The time dimension mainly uses the age characteristics of the references to analyze interdisciplinary breakthrough innovation.

Aging: This feature mainly reflects the aging of the knowledge on which the current research depends. A more commonly used measure is the Price Index (Ref_5_Per), calculated as shown in Eq. (2), indicating that the number of references (n_t) published in the past five years accounts for the proportion of all n references. Generally speaking, the larger the Price Index, the faster the aging of the literature.

Age: The ages of references can reflect the tendency of researchers to choose knowledge; i.e., they tend to choose the latest theoretical research or more classical theories for interdisciplinary knowledge integration. These metrics include the median and mean numbers of the reference age.

$$Ref\_5\_Per = \frac{n_{t\leq 5}}{n} \tag{2}$$

The average age of references, denoted as Ref_Avg_Age, can be calculated as:

$$\mathrm{Ref\_Avg\_Age} = \frac{\sum_{i=1}^{n} \mathrm{Age}_i}{n} \tag{3}$$

where Age_i is the age of each reference and n is the total number of references.

The median age of references, denoted as Ref_Median_Age, is given by:

$$\text{Ref\_Median\_Age} = \text{Median}\left(\text{Age}_1, \text{Age}_2, \dots, \text{Age}_n\right) \tag{4}$$

where Age_1, Age_2, …, Age_n are the ages of all of the references.

(3) Influence dimension

The influence dimension evaluates the academic influence of a paper by measuring the papers that cite it, assessing whether the paper significantly contributes to innovation. The primary metrics are the average and median citation counts of the citing papers. The following equations define these metrics:

$$\text{Ref\_Cit\_Mean} = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{5}$$

where C_i is the number of citations for each reference i and n is the total number of references.

$$\text{Ref\_Cit\_Median} = \text{Median}(C_1, C_2, \dots, C_n) \tag{6}$$

where C_1, C_2, …, C_n are the citation counts for all of the references.

$$\text{Reference\_Count} = n \tag{7}$$

where n is the total number of references cited by the paper.

4.1.2. Metrics for interdisciplinary knowledge fusion

Interdisciplinary knowledge fusion involves combining diverse knowledge from various fields to generate new insights. This process enables researchers to develop new understandings and judgments on complex issues, forming new knowledge structures. It relies not only on team composition but also on evaluating impact and innovation potential through metrics like disruption and novelty. These characteristics collectively advance scientific research and innovate knowledge structures.

(1) Team composition dimension

Team composition plays a crucial role in interdisciplinary knowledge fusion. Research indicates that small teams are often associated with disruptive work, while large teams focus on developmental work (Wu et al., 2019). Thus, team size significantly impacts interdisciplinary research and knowledge fusion. In this study, we primarily measure the number of authors ($Team\_Size$) and institutions ($Institution\_Count$) associated with a paper to reflect its team composition.

(2) Disruption dimension

Disruptive innovation can fundamentally alter cognitive structures, described as "interruptions or discontinuities in development". Funk and Owen-Smith (2017) introduced the Disruption Index to measure a paper's disruptiveness. This index is widely used across various disciplines, providing a methodological foundation for significant research (Leibel & Bornmann, 2024; Park et al., 2023; Wu et al., 2019). The DI formula is:

$$D = \frac{n_i - n_j}{n_i + n_j + n_k} \tag{8}$$

where n_i is the number of subsequent works citing only the focal paper, n_j is the number citing both the focal paper and its references, and n_k is the number citing only the focal paper's references.

(3) Novelty dimension

Novelty is another critical feature of interdisciplinary knowledge fusion. Wang, Zhang, Chen, and Chen (2024) defined novelty as a property of knowledge containing "something" new. It stems from creativity, serving as a prerequisite for innovation and disruption, synonymous with originality. The atypical combination theory is widely used to measure scientific output's novelty, viewing a non-traditional recombination of existing knowledge elements as novel. These elements include Refs. (Matsumoto et al., 2021), keywords (Boudreau et al., 2016), terms (Luo et al., 2022), topic (Wang, Zhang, Chen, Feng, & Ding, 2024), etc. Here, we employ Lin et al. (2023)'s novelty metric design by calculating each journal's Z-score for combinations to determine each paper's novelty and conventionality scores.

The Z-score for a given journal pair is computed as follows:

$$Z = \frac{f_{\text{obs}} - \mu_{\text{rand}}}{\sigma_{\text{rand}}} \tag{9}$$

where f_{obs} is the observed frequency of the journal pair in the real citation network, μ_{rand} is the mean frequency of the journal pair across randomized citation networks, and σ_{rand} is the standard deviation of the journal pair frequencies across these randomized networks. This Z-score reflects how much more or less frequently a particular journal pair appears in comparison to random expectations.

For each paper, we use two key metrics based on the distribution of Z-scores across all cited journal pairs. The first is the 10th percentile Z-score (*Atyp_10pct*), which captures the tail novelty:

$$Atyp\_10pct = Z_{\left(\frac{10}{100}\times N\right)} \tag{10}$$

where N is the total number of Z-scores for all journal pairs cited by the paper. The second metric is the median Z-score (*Atyp_Median_Z*), representing the central tendency of conventionality:

$$\text{Atyp\_Median\_Z} = \begin{cases} Z_{\left(\frac{N+1}{2}\right)} & \text{if } N \text{ is odd} \\ \frac{Z_{\left(\frac{N}{2}\right)}+Z_{\left(\frac{N}{2}+1\right)}}{2} & \text{if } N \text{ is even} \end{cases} \tag{11}$$

We also consider the number of journal pairs cited. This is denoted as $Atyp\_Pairs$. The calculation is determined by the total number of unique journal pairs cited by the paper, given as follows:

$$Atyp\_Pairs = |J| \tag{12}$$

where $|J|$ is the set of unique journals cited.

4.1.3. Metrics for interdisciplinary knowledge diffusion

Interdisciplinary knowledge diffusion refers to the process by which scientific achievements spread from one field to another, moving from the laboratory to publications, from science to technology, and then from technology to society (Liu & Rousseau, 2010). This process reflects the inheritance and development of knowledge in the literature, showing the impact of scientific research on other fields and supporting subsequent studies. To describe this diffusion process, we measure its impact across bibliometrics, technology, and society.

(1) Bibliometrics dimension

In the dimension of bibliometrics, the diffusion of scientific papers can be assessed through various concepts, such as breadth, speed, and intensity. Liu and Rousseau (2010) introduced the concept of "breadth of field diffusion", which measures the extent to which a group of articles has been referenced across different academic fields. In our study, we combine interdisciplinary indicators with diffusion breadth using the Rao-Stirling Index to measure the interdisciplinarity of citations (Cit_D). This approach helps reveal the main disciplinary distribution and development trends of interdisciplinary breakthrough innovation.

Knowledge diffusion speed refers to the dynamics of paper citations, such as the time of first citation and citation surge. We use the WSB citation dynamics model developed by Wang et al. (2013), along with the Sleeping Beauty coefficient (Ke et al., 2015), to measure diffusion speed. The Sleeping Beauty coefficient reflects a phenomenon where some papers receive little attention initially but are later "awakened" to become influential. The following equations define these metrics:

The Sleeping Beauty coefficient (SB_B) is defined as:

$$SB\_B = \sum_{t=0}^{t_m} \left(c_t \cdot \left(1 + t_m - t - \frac{c_0}{c_{t_m}} \right) \right) \tag{13}$$

where c_t means citations received by the paper in year t, t_m means year when the paper received its maximum yearly citation c_{t_m}, and c_0 means citations in the year of publication.

The awakening time (SB_T) is defined as:

$$SB\_T = \arg\max_{t \le t_m} d_t \tag{14}$$

where d_t represents the vertical distance from point (t, c_t) to the line connecting points $(0, 0)$ and (t_m, c_{t_m}).

The WSB model captures long-term citation dynamics by combining preferential attachment, aging, and fitness. The cumulative number of citations received by paper i at time t after publication, denoted as c_i^t, is given by:

$$c_i^t = m \left[e^{\lambda_i \Phi\left(\frac{\ln t - \mu_i}{\sigma_i} \right)} - 1 \right] \tag{15}$$

Here, c_i^t represents the cumulative number of citations at time t. $\Phi(x)$ is the standard cumulative normal distribution function. The parameter m denotes the average number of references per paper. The immediacy parameter for paper i is μ_i (WSB_mu), while σ_i (WSB_sigma) represents the longevity parameter for paper i. Finally, λ_i is the fitness parameter for paper i.

The ultimate impact of paper i (WSB_Cinf), denoted as C_i^∞, is given by:

$$C_i^\infty = m \left(e^{\lambda_i} - 1 \right) \tag{16}$$

The intensity of knowledge diffusion reflects the academic impact of scientific papers. The number of citations ($Citation\_Count$) is the most direct indicator of diffusion intensity. Additionally, citation counts over different time windows, such as within five ($C5$) or ten years ($C10$), can reflect a paper's lifecycle. Comparing whether a paper ranks in the top 1% (Hit_1pct), 5% (Hit_5pct), 10% (Hit_10pct), or normalized of citations (C_f) within its field, also measures its impact. On the other hand, citations serve various purposes, such as referencing methods or offering background information, which influences their significance (Ghosal et al., 2021). Analyzing citation intent allows for a more precise evaluation of a paper's impact. We collect the proportion of important citations in each paper, $Important\_Cit\_Per$, representing how many cited papers are significantly influenced by the paper.

Collecting all citation contexts and exploring them semantically offers a more reliable measure of academic impact than purely quantitative metrics (Chen et al., 2022). Given the capabilities of large language models like ChatGPT in text summarization, we plan to use GPT-4o (Achiam et al., 2023) to generate summaries of a paper's contribution based on paper titles, abstracts, and citation contexts. Therefore, we will construct comprehensive metrics to measure knowledge diffusion intensity, including citation counts, five- and ten-year citations, normalized citation numbers, top percentile citations, and influential citation proportions, alongside text-based contributions generated from citation contexts.

(2) Science & Technology dimension

In the Science & Technology dimension, science operates within a vast system that includes papers, patents, clinical trials, and funding projects (Yang et al., 2024). To measure knowledge diffusion, we focus on three specific indicators:

- National funding projects: The number of citations in national funding projects (e.g., National Science Foundation (NSF_Count) and National Institutes of Health (NIH_Count)).
- Patent citations ($Patent\_Count$): The frequency with which scientific papers are cited in patent filings (sourced from USPTO and EPO).
- Clinical trials (NCT_Count): The number of citations in clinical trials, particularly those registered with the National Clinical Trials (NCT) database.

(3) Society dimension

In the society dimension, to measure societal impact, we use diffusion indicators based on social media mentions. These include:

- News mentions ($Newsfeed\_Count$): The number of times a paper is mentioned in news articles (sourced from newsfeeds).
- Tweets ($Tweet\_Count$): The frequency of mentions related to a paper on X (formerly Twitter).

This multidimensional approach helps us understand the complexity of interdisciplinary knowledge diffusion and provides a solid foundation for further research.

4.2. Models for identifying interdisciplinary breakthrough innovation

We apply machine learning and deep learning methods to model the identification of interdisciplinary breakthrough innovations. We use various machine learning models to train numerical features, including Decision Tree (DT), Random Forest (RF), Gradient Boosting Classifier (GBC), AdaBoost Classifier (ABC), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), XGBoost (XGB), and LightGBM (LGBM).

In terms of deep learning, we use the multimodal toolkit (Gu & Budhkar, 2021) framework to concatenate contribution texts generated from citation contexts with numerical features. This multimodal approach enhances the model's ability to understand complex datasets. Based on this, pre-trained language models, such as BERT, RoBERTa, and SciBERT, are fine-tuned to improve the accuracy of text feature extraction. BERT (Kenton & Toutanova, 2019) is well-known for its bidirectional encoder representations. RoBERTa (Liu et al., 2019) further optimizes BERT's performance through larger datasets and longer training times, while SciBERT (Beltagy et al., 2019) focuses on the scientific literature domain.

4.3. Evaluation for interdisciplinary breakthrough innovation detection models

When evaluating interdisciplinary breakthrough innovation detection models, we use several metrics: accuracy, precision, recall, F1 score, and the confusion matrices. These metrics comprehensively reflect the model's performance across various dimensions. Furthermore, considering the imbalance in different categories within the dataset, we apply a weighted average to the results. The specific formulas are as follows:

$$\text{Accuracy} = \frac{TN + TP}{FN + FP + TN + TP} \tag{17}$$

$$\text{Precision} = \frac{TP}{FP + TP} \tag{18}$$

$$\text{Recall} = \frac{TP}{FN + TP} \tag{19}$$

$$F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{20}$$

To further analyze how different metrics affect the machine learning model for interdisciplinary breakthrough innovation identification, we utilize SHAP for feature interpretability analysis. SHAP (Lundberg, 2017), based on Shapley values, assigns a contribution value to each feature to explain model predictions. It calculates a feature's contribution by comparing predictions with and without that feature. This enhances model interpretability and credibility by explaining why certain papers are recognized as breakthroughs. For deep learning models, the input text consists of contribution sentences generated by GPT-4o. We explore factors influencing the identification of interdisciplinary breakthrough innovations at the sentence content level, focusing on the distribution of important words and sentiment analysis.

Furthermore, we conduct comparative experiments to evaluate the effectiveness of our proposed models in detecting interdisciplinary breakthrough innovations by comparing them with three metrics: Disruption Index, Reference Interdisciplinarity (Ref_D), and Citation Interdisciplinarity (Cit_D).

Table 1
Statistics for collected data.

	BP	IBP	CP	Total
Paper Count	414	265	2396	3075
Citation Count	628,541	557,083	154,858	1,340,482
Reference Count	13,224	7851	23,840	44,915

5. Experiment and results

5.1. Data collection

Research on breakthrough innovations is widely recognized by both the scientific community and the public (Jingjing Ren, 2023; Wang, Ma, et al., 2023; Wei et al., 2023). Therefore, we collected significant articles from renowned academic awards. These awards include the Nobel Prize[1] (covering Physics, Chemistry, Physiology or Medicine), the Wolf Prize[2] (covering Agriculture, Architecture, Chemistry, Mathematics, Medicine, Physics), the Crafoord Prize[3] (covering Biosciences, Geosciences, Mathematics and Astronomy, Polyarthritis), the Breakthrough Prize[4] (covering Fundamental Physics, Life Sciences, Mathematics), and the Turing Award[5] in Computer Science.

Initially, we manually retrieved information about awardees from official award websites and Wikipedia. Subsequently, we searched for lists of publications by these awardees using academic databases, such as Google Scholar,[6] Semantic Scholar (Kinney et al., 2023), and AMiner.[7] We then selected each awardee's prize-winning papers from these lists based on the award citations. Since some awardees received multiple awards, we ultimately collected data on 508 awardees and 1,312 breakthrough innovation papers. SciSciNet (Lin et al., 2023) is a large-scale open data lake covering over 134 million scientific publications, while Semantic Scholar is an open data platform containing over 200 million papers. To obtain data on references and citations, we used the SciSciNet dataset and Semantic Scholar database by searching with the DOI of these papers. However, only 679 papers were found in these databases.

After acquiring the breakthrough innovation papers, we needed to identify interdisciplinary breakthrough innovation papers and construct a control group for subsequent experiments. In both the SciSciNet dataset and Semantic Scholar database, each paper can be associated with records from multiple research fields. We considered papers with records in more than two research fields as interdisciplinary breakthrough innovation papers (Wang, Qiao, et al., 2024). For constructing the control group, we selected papers published in the same year as the breakthrough innovation papers, belonging to the same field with a DI difference within 1%, resulting in 31,949 papers. To reduce the disparity in numbers between the control group and breakthrough innovation papers, we added the top five papers with the closest DI difference, ultimately obtaining 2,396 control group papers. We chose to use the DI as a selection criterion because it is a widely recognized indicator for identifying breakthrough research (Leibel & Bornmann, 2024). This ensures that the control group papers possess at least some degree of breakthrough rather than being randomly selected. Consequently, our experimental data comprises 414 breakthrough innovation papers (BP), 265 interdisciplinary breakthrough innovation papers (IBP), and 2,396 control group papers (CP). The count statistics corresponding to these three categories are shown in Table 1.

5.2. Experimental setup

We conducted our experiments on Featurize,[8] an online machine learning platform, using PyTorch v2.2.2 and Python 3.11.8. The experiments were executed on a 16-core AMD EPYC 9354 CPU and an NVIDIA GeForce RTX 4090 GPU.

For machine learning tasks, we utilized grid search to identify the optimal hyperparameters for each classifier. To address class imbalance in the dataset, we applied the SMOTE algorithm for oversampling the training set. We also standardized the features using standard deviation normalization. The dataset was split into training and test sets in an 8:2 ratio. For deep learning tasks, we used pre-trained language models including bert-base-uncased, roberta-base, and scibert_scivocab_uncased. For fine-tuning, we set the batch size to 64, used the Adam optimizer for parameter optimization, and configured the learning rate to 2e-5. The maximum sequence length was set to 512, and a dropout rate of 0.3 was applied to mitigate potential overfitting issues. The data was divided into training, validation, and test sets in an 8:1:1 ratio. We employed five-fold cross-validation to prevent overfitting and used the average result as the final output.

In collecting bibliometric data for calculating metrics, we utilized some indicators from the SciSciNet database and conducted searches through the Semantic Scholar database. To ensure a sufficient citation window, we limited our search to papers published before 2021.

1 https://www.nobelprize.org
2 https://wolffund.org.il/the-wolf-prize/
3 https://www.crafoordprize.se
4 https://breakthroughprize.org
5 https://amturing.acm.org/byyear.cfm
6 https://scholar.google.com
7 https://www.aminer.cn
8 https://featurize.cn/

Table 2
Statistical characteristics of metrics identifying interdisciplinary breakthrough innovations.

Stage	Variable	Correlation	P-value	Count	Max	Min	Mean	Description
Interdisciplinary knowledge integration	Ref_D	0.07	0.000**	2982	0.73	0.00	0.22	Interdisciplinary nature of references
	Ref_5_Per	0.20	0.000**	2982	1.00	0.00	0.85	Proportion of references in the last 5 years
	Ref_Avg_Age	−0.06	0.001*	2982	94.00	0.00	6.75	Average age of references
	Ref_Median_Age	−0.09	0.000**	2982	94.00	0.00	5.65	Median age of references
	Ref_Cit_Mean	0.09	0.000**	2718	89 690.50	1.00	663.42	Average citation count of references
	Ref_Cit_Median	0.04	0.065	2718	89 690.50	1.00	281.57	Median citation count of references
	Reference_Count	0.10	0.000**	3075	4018.00	0.00	18.04	Number of references
Interdisciplinary knowledge fusion	Team_Size	0.05	0.012*	3075	2923.00	1.00	5.25	Number of team members
	Institution_Count	0.04	0.061	1841	777.00	1.00	2.24	Number of institutions
	Atyp_10pct_Z	−0.07	0.001*	1959	4920.83	−65.20	55.65	10th percentile Z-score of the paper
	Atyp_Pairs	0.14	0.000**	1959	5097.00	1.00	63.57	The number of journal pairs cited by the paper
	Atyp_Median_Z	−0.06	0.010*	1959	5253.69	−27.86	148.41	Median Z-score of the paper
	Disruption	−0.01	0.622	3029	1.00	−1.00	0.14	Disruption score of the paper
Interdisciplinary knowledge diffusion	Citation_Count	0.37	0.000**	3075	55 460.00	0.00	738.69	Total citation count of the paper
	C10	0.34	0.000**	3014	15 346.00	0.00	223.28	The number of citations 10 years after publication
	C5	0.35	0.000**	3046	5782.00	0.00	100.67	The number of citations 5 years after publication
	SB_B	0.12	0.000**	2805	3662.77	−10.03	32.63	Beauty coefficient of the paper
	SB_T	0.12	0.000**	2805	107.00	0.00	12.89	Awakening time of the paper
	Patent_Count	0.18	0.000**	3075	10 884.00	0.00	52.61	The number of citations by patents from USPTO and EPO
	Newsfeed_Count	0.23	0.000**	3075	11.00	0.00	0.10	The number of mentions by news from Newsfeed
	Tweet_Count	0.17	0.000**	3075	389.00	0.00	1.79	The number of mentions by tweets from Twitter
	NCT_Count	0.13	0.000**	3075	11.00	0.00	0.04	The number of citations by clinical trials from ClinicalTrials.gov
	NIH_Count	0.03	0.143	3075	8.00	0.00	0.07	The number of supporting grants from NIH
	NSF_Count	0.05	0.004*	3075	3.00	0.00	0.01	The number of supporting grants from NSF
	WSB_mu	−0.11	0.058	294	11.14	5.21	8.15	Immediacy μ of the paper
	WSB_sigma	0.29	0.000**	294	3.33	0.48	1.42	Longevity σ of the paper
	WSB_Cinf	0.35	0.000**	294	125 848	12.00	4771	Ultimate impact of the paper
	Cit_D	0.09	0.000**	2982	0.78	0.00	0.32	Interdisciplinarity of cited references
	Important_Cit_Per	0.06	0.001*	2982	0.67	0.00	0.01	Proportion of significantly influential papers among all cited references
	Hit_1pct	0.73	0.000**	4197	1.00	0.00	0.34	1 if hit paper with top 1% total citations within the same field and year, else 0
	Hit_5pct	0.69	0.000**	4197	1.00	0.00	0.47	1 if hit paper with top 5% total citations within the same field and year, else 0
	Hit_10pct	0.62	0.000**	4197	1.00	0.00	0.55	1 if hit paper with top 10% total citations within the same field and year, else 0
	C_f	0.36	0.000**	4197	1979.71	0.00	31.64	Normalized citation

* Indicates significance at the 5% level.
** Indicates significance at the 1% level.

5.3. Experimental results and analysis

5.3.1. Statistical characteristics of metrics

We conducted a descriptive statistical analysis on the collected metric data. Additionally, we performed Spearman correlation tests for each metric across three categories of papers: IBP, BP, and CP. The results are presented in Table 2.

Through correlation tests, we found that the metrics Ref_Cit_Median, $Institution\_Count$, $Disruption$, NIH_Count, and WSB_mu did not show significant correlations. Therefore, we excluded these metrics in subsequent experiments. The lack of significance for the Disruption metric was due to the control group selected based on this index. On the other hand, we recognized that some metrics might have been affected by the halo effect, where increased attention followed an award. In subsequent experiments, we listed these metrics separately and analyzed the results after removing those affected by the halo effect. These metrics mainly included $Citation\_Count$, SB_B, SB_T, $Patent\_Count$, $Newsfeed\_Count$, $Tweet\_Count$, NCT_Count, NIH_Count, NSF_Count, WSB_mu, WSB_sigma, WSB_Cinf, Cit_D, $Important\_Cit\_Per$, Hit_1pct, Hit_5pct, Hit_10pct, C_f, $Institution\_Count$, Ref_Cit_Median, and Ref_Cit_Mean.

Table 3
Performance metrics for various models.

Model	All metrics				Without Halo effect				Only text			
	Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score	Accuracy	Precision	Recall	F1 Score
DT	0.8280	0.8446	0.8280	0.8353	0.7402	0.7832	0.7402	0.7584	–	–	–	–
RF	0.8576	**0.8647**	0.8576	<u>0.8604</u>	0.8072	0.8199	0.8072	0.8129	–	–	–	–
GBT	0.8563	0.8623	0.8563	0.8590	0.8120	**0.8260**	0.8120	**0.8179**	–	–	–	–
ABC	0.8413	0.8566	0.8413	0.8478	0.7785	0.8031	0.7785	0.7894	–	–	–	–
SVM	0.8140	0.8396	0.8140	0.8247	0.7893	0.7853	0.7893	0.7863	–	–	–	–
KNN	0.7795	0.8239	0.7795	0.7985	0.6696	0.7471	0.6696	0.7014	–	–	–	–
XGB	<u>0.8582</u>	0.8605	<u>0.8582</u>	0.8591	<u>0.8156</u>	<u>0.8213</u>	<u>0.8156</u>	<u>0.8177</u>	–	–	–	–
LGBM	**0.8631**	<u>0.8635</u>	**0.8631**	**0.8631**	**0.8179**	0.8147	**0.8179**	0.8159	–	–	–	–
BERT	**0.8929**	**0.8309**	**0.8929**	**0.8604**	<u>0.8381</u>	**0.8666**	<u>0.8381</u>	<u>0.8491</u>	<u>0.7929</u>	<u>0.8344</u>	<u>0.7929</u>	<u>0.8102</u>
SciBERT	0.7952	0.7620	0.7952	<u>0.7720</u>	**0.8666**	<u>0.8517</u>	**0.8666**	**0.8584**	**0.8666**	**0.8517**	**0.8666**	**0.8584**
RoBERTa	<u>0.8143</u>	<u>0.7644</u>	<u>0.8143</u>	0.7656	0.8047	0.8295	0.8047	0.8122	0.7905	0.6582	0.7905	0.7176

Note: "**Bold**" indicates the best result for each metric, "<u>underlined</u>" indicates the second-best result, and "-" indicates missing data. Due to insufficient text data for some papers, GPT-4o was unable to generate contribution sentences, resulting in different experimental data sizes for the deep learning and machine learning models.

5.3.2. Machine learning model results

(1) Overall model results

The experimental results of the IBID-CCT models built on various machine learning methods for detecting interdisciplinary breakthrough innovations are summarized in Table 3. This table provides a detailed comparison of the models' performance using metrics, such as accuracy, precision, recall, and F1 score. The LGBM model demonstrated the highest performance across most metrics, both with and without considering the halo effect.

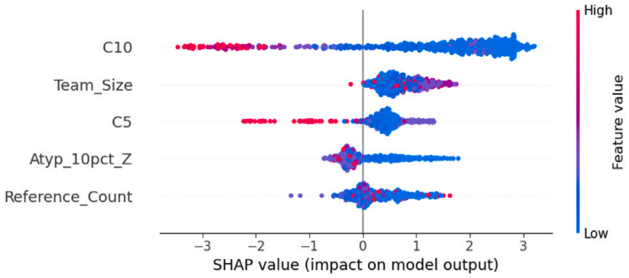
From the results, we make the following observations:

- Model performance comparison: The LGBM model achieved the highest accuracy (0.8631) and recall (0.8631), indicating its superior ability to correctly classify both positive and negative instances compared to other models. RF and GBT also performed well, with RF showing the highest precision (0.8647) among all models. The XGB model closely followed LGBM in terms of accuracy and recall, highlighting its effectiveness as a competitive alternative.
- Halo effect: The halo effect refers to the influence of post-award recognition on various features. These features can potentially skew model performance by inflating perceived innovation impact due to external recognitions rather than intrinsic qualities. When excluding halo effect features, there is a noticeable decline in model performance metrics across all models, indicating the significant impact these features have on model predictions. Despite this decline, LGBM still maintains a leading position, suggesting its robustness and ability to capture underlying patterns beyond those influenced by halo effect features.

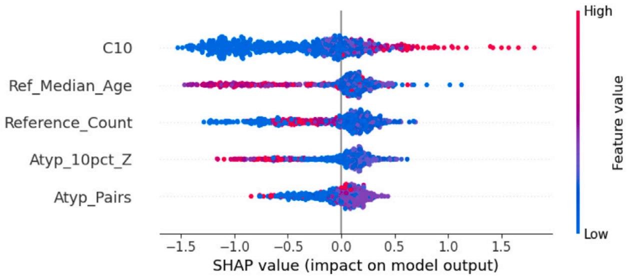
(2) SHAP feature importance analysis

To further analyze the impact of each metric for identification of different categories (IBP, BP, CP) of papers, we employed the SHAP method for interpretability analysis. The distribution of SHAP values for the top five most influential metrics in each paper category is shown in Fig. 3.

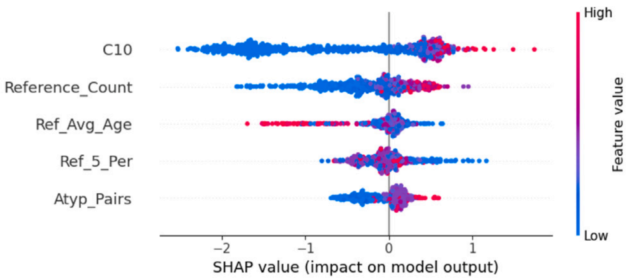
- **Interdisciplinary knowledge integration:** CP maintains moderate reference quantities with stable integration. However, increasing the number of references does not significantly enhance innovation. BP cites fewer references and benefits from appropriately aged sources, though excessively low or high reference quantities may hinder innovation. IBP relies on diverse integration strategies, balancing fewer references, newer sources, and an appropriate proportion of recent literature. Moderate increases in reference quantity and age significantly enhance interdisciplinary innovation. Overall, CP emphasizes stability, BP prioritizes conciseness and age balance, while IBP achieves breakthroughs through the dynamic integration of fewer, newer, and recent references.
- **Interdisciplinary knowledge fusion:** CP exhibits a conservative approach to interdisciplinary knowledge integration, characterized by low atypicality and limited contributions to innovation. It typically relies on small teams to conduct research. BP demonstrates moderate interdisciplinary knowledge integration, incorporating a certain level of heterogeneous knowledge. However, its innovation is sensitive to the atypicality of knowledge combinations, where excessive atypicality may have negative effects. Additionally, BP tends to cite a moderate range of interdisciplinary journal pairs, as balanced knowledge integration enhances its innovative potential. IBP, on the other hand, adopts a more audacious approach, often experimenting with diverse and highly atypical knowledge combinations. By leveraging extensive interdisciplinary integration, it drives frontier innovation and exhibits pronounced interdisciplinary characteristics.
- **Interdisciplinary knowledge diffusion:** CP contributes relatively little to interdisciplinary knowledge diffusion. Its influence tends to remain confined within specific contexts and may even negatively impact knowledge transfer across domains. In contrast, BP shows a growing positive impact on interdisciplinary knowledge diffusion as citation counts increase, highlighting its ability to drive knowledge dissemination more effectively. IBP demonstrates the strongest potential for interdisciplinary diffusion, significantly enhancing knowledge transfer across domains as its citations grow. Overall, these three types of papers



(a) SHAP values distribution for category CP



(b) SHAP values distribution for category BP



(c) SHAP values distribution for category IBP

Fig. 3. Distribution of top five importance metrics SHAP values by paper category (excluding the halo effect). The SHAP value plot shows how different features impact the model's predictions, with blue indicating low feature values and red indicating high feature values. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

differ in the intensity and patterns of their contributions, with BP and IBP playing a more prominent role in fostering knowledge flow, while CP displays relatively limited influence.

In summary, IBP exhibits unique traits distinguishing it from CP and BP. In the integration stage, IBP relies on foundational literature while balancing recent references, emphasizing established knowledge for complex interdisciplinary integration. In the fusion stage, it combines unconventional and conventional knowledge, achieving a balance of novelty and stability. In the diffusion stage, IBP shows gradual yet sustained influence, transitioning from modest impact to long-term breakthroughs across fields. Traditional measures, such as the Disruption Index and novelty measures, capture some aspects of innovation but often fail to fully reflect the complexity of interdisciplinary breakthrough innovations. These methods typically focus on impact or novelty within a single field, overlooking the multi-domain integration and long-term influence required for interdisciplinary breakthrough innovation. Thus, it is crucial to detect IBP through three stages: integration, fusion, and diffusion. This multistage approach offers a clearer framework for identifying IBP and better tools for studying interdisciplinary innovation.

5.3.3. Deep learning model results

(1) Overall model results

We employed a multimodal toolkit (Gu & Budhkar, 2021) to integrate textual and numerical features. This framework begins by fine-tuning a word embedding model, followed by incorporating numerical features within a multilayer perceptron (MLP). The textual data was generated by GPT-4o, which included various inputs, such as paper titles, abstracts, and all citation sentences. The prompt used was: "*As an expert in the academic field with a vast knowledge base, your task is to summarize the groundbreaking*

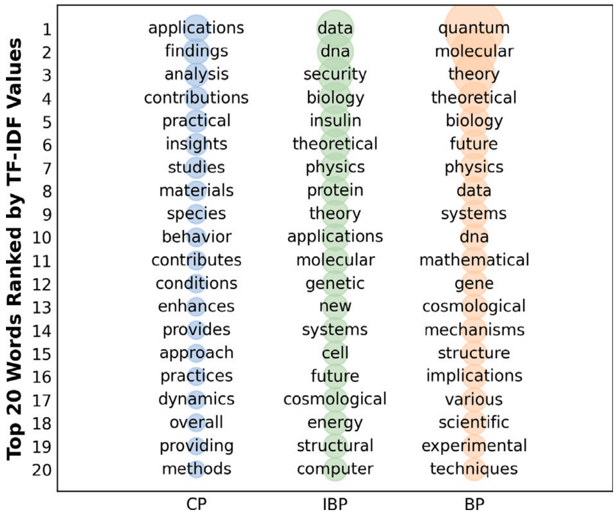


Fig. 4. Distribution of top 20 words by paper category (CP, IBP, BP). Bubble size indicates TF-IDF value. The larger the bubble size, the higher the TF-IDF weight of the word in this category.

contributions of the following paper to knowledge dissemination. If the paper cannot be identified, output 'NOT FOUND'." Due to the lack of textual content in many papers, GPT-4o generated contribution sentences for only 1,398 papers (162 BP, 119 IBP, and 1,117 CP).

The experimental results, as shown in Table 3, indicate significant performance differences among various deep learning models in detecting interdisciplinary breakthrough innovations. The IBID-CCT model built on BERT performed best across all metrics, achieving an accuracy, recall, and F1 score of 0.8929, with a precision of 0.8309. After removing features related to the halo effect, most models showed improved performance. Some features may have influenced the overall judgment of the models by introducing irrelevant or redundant information, thereby reducing their generalizability on new data. When using only textual features, the IBID-CCT model built on SciBERT outperformed other models with an accuracy and recall of 0.8666. The IBID-CCT model built on RoBERTa showed relatively weaker performance across all metrics.

From these results, we make the following observations:

- Advantages of multimodal integration: By combining textual and numerical features, the model's ability to identify interdisciplinary breakthrough innovations is enhanced. This approach improves predictive performance by jointly learning representations from different modalities during training and capturing interactions between data modalities.
- Sensitivity to feature types: Different models exhibit varying sensitivities to feature types. In practical applications, the selection of an appropriate model depends on the task requirements. For instance, SciBERT excels in handling pure textual data due to its pre-training focus on scientific literature, resulting in higher accuracy and recall in this domain. In contrast, BERT has advantages in processing combined features, likely due to its strong semantic understanding capabilities that enable better utilization of multimodal information. Although RoBERTa optimizes BERT's training process, it demands larger datasets to fully leverage its capabilities.

(2) Distribution analysis of important words

Due to the lack of interpretability in deep learning, it is challenging to infer how text influences outcomes solely by comparing model performance metrics. Therefore, we calculated the distribution of the top 20 significant words (with high TF-IDF values) for contribution sentences in each category of papers, as shown in Fig. 4. In analyzing important word distribution, we removed stop words and high-frequency meaningless words like "paper", "work", and "study" from the contribution sentences.

By analyzing Fig. 4, we can draw more detailed and nuanced conclusions:

- BP high-frequency words: Words like "quantum", "molecular", and "theory" have the highest TF-IDF values in BP papers. This indicates a focus on fundamental sciences, particularly quantum physics and molecular science. These words highlight the importance of theoretical research, demonstrating BP papers' contributions to advancing scientific frontiers. Therefore, the degree of innovation in these papers is relatively high.
- IBP high-frequency words: Words like "data", "DNA", and "biology" are prominent in IBP papers, reflecting their interdisciplinary nature in bioinformatics and data science. These keywords illustrate how IBP papers combine methods and techniques from different disciplines to drive new research directions. Therefore, the degree of innovation in these papers is also relatively high.
- CP high-frequency words: Words like "applications", "findings", and "analysis" suggest a focus on applied research and empirical analysis. CP papers typically emphasize the practicality and applicability of research outcomes. Therefore, the degree of innovation in these papers is relatively low.

Table 4
Comparative experimental results.

	Accuracy	Precision	Recall	F1 Score
	Breakthrough Innovation Identification			
BERT	0.8429	**0.8514**	0.8429	0.8463
LGBM	**0.9500**	0.8485	**0.9333**	**0.8889**
Disruption	0.6438	0.1891	0.2349	0.2095
	Interdisciplinary Breakthrough Innovation Identification			
BERT	**0.5862**	**0.5817**	**0.5862**	**0.5811**
LGBM	**0.5862**	0.5385	0.5385	0.5385
Ref_D	0.5089	0.4128	0.3782	0.3947
Cit_D	0.4947	0.3945	0.3613	0.3772

Overall, the keyword distribution in Fig. 4 clearly reveals differences in research focus among the paper categories. BP papers tend to focus on fundamental theory, IBP papers emphasize interdisciplinary integration, while CP papers concentrate on application and empirical work.

(3) Sentiment analysis of paper contribution sentences

We further explored whether the contribution sentences generated by GPT-4o exhibit emotional differentiation. We used a model[9] fine-tuned on a scientific text sentiment classification dataset to classify the sentiment of these sentences as positive, neutral, or negative. The results showed that for BP category papers, 60.5% (98) of the contribution sentences were positive and 39.5% (64) were neutral. For IBP category papers, 64.7% (77) were positive and 35.3% (42) were neutral. For CP category papers, 46.6% (520) were positive and 53.4% (597) were neutral. None of the categories contained negative sentiments. A Spearman correlation test revealed a significant correlation between sentiment categories and paper categories, with a correlation coefficient of 0.123 at a significance level of 1%.

Sentiment analysis highlighted significant differences in emotional expression across different innovation categories. Contribution sentences in the BP category often conveyed higher positive sentiment, possibly reflecting the significant impact and potential value of these innovations. The IBP category had the highest proportion of positive sentiment, which might be linked to interdisciplinary breakthrough innovations involving multi-field collaboration, leading to broader impacts and higher research value. In contrast, the CP category had the lowest proportion of positive sentiment, possibly indicating relatively limited innovation and impact. Therefore, interdisciplinary breakthrough innovations are not only scientifically significant but also have more positive expressions, potentially promoting broader academic communication and attention.

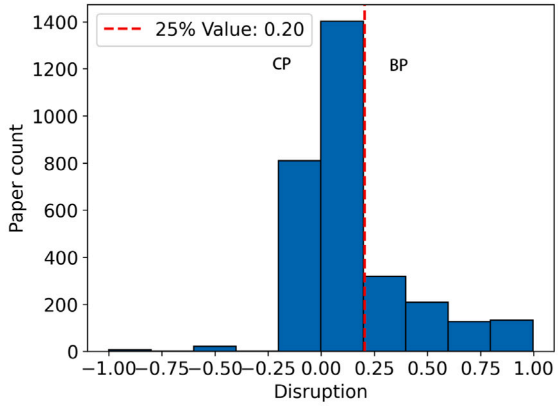
5.3.4. Comparative experiments

To validate the effectiveness of our IBID-CCT model, we compared it with three baselines: the Disruption Index ($Disruption$), the References Interdisciplinarity Index (Ref_D), and the Citations Interdisciplinarity Index (Cit_D). First, we use the papers data in Table 1 as the standard dataset for our comparative experiments. Then, we calculated the $Disruption$, Ref_D, and Cit_D values of papers in this standard dataset, and ranked them from highest to lowest. The distributions of papers based on $Disruption$, Ref_D, and Cit_D metrics are shown in Fig. 5. Taking into account the relative proportions of breakthrough and interdisciplinary breakthrough papers observed in the standard dataset, we set the thresholds so that our classification reflects these empirical ratios. Specifically, papers with a $Disruption$ value larger than 0.20 were classified as BP; papers with a Ref_D value larger than 0.29 were classified as IBP; and papers with a Cit_D value larger than 0.38 were classified as IBP. Finally, to ensure fair comparisons on a unified scale, we excluded papers from the standard dataset that lack textual data which are required by the BERT model. Ultimately, we obtained an experimental dataset of 1,398 papers, specifically including 278 BP, 119 IBP, and 1,001 CP. Finally, based on this dataset, we conducted two comparative experiments: (1) a breakthrough innovation identification experiment, comparing the IBID-CCT models built on BERT and LGBM with $Disruption$, and (2) an interdisciplinary breakthrough innovation identification experiment, comparing the IBID-CCT models built on BERT and LGBM with Ref_D and Cit_D. The experimental results are shown in Table 4.

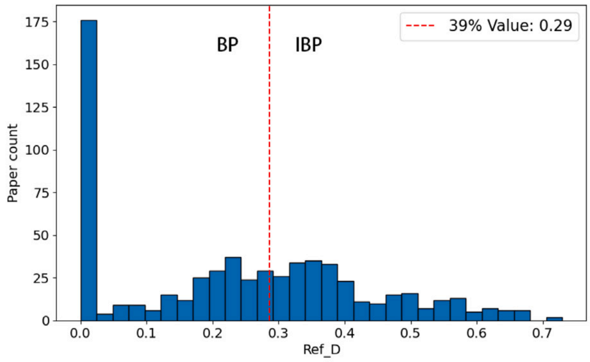
According to the experimental results in Table 4, the IBID-CCT models built on BERT and LGBM significantly outperform other methods in all tasks and metrics. Specifically, in the breakthrough detection task, the IBID-CCT model built on LGBM achieved an F1 score of 0.8889, far exceeding the $Disruption$ score of 0.2095. Although $Disruption$ is a commonly used metric for detecting breakthrough innovations, its effectiveness is highly dependent on the completeness of the bibliometric data. In this experiment, $Disruption$ failed to effectively detect breakthroughs.

In the interdisciplinary breakthrough detection task, we compared the IBID-CCT models built on LGBM and BERT with Ref_D and Cit_D from both the reference and citation perspectives. The results show that neither of these Ref_D and Cit_D metrics achieved an F1 score above 0.5 in the binary classification task, which is significantly lower than the IBID-CCT model built on BERT's score of 0.5811. This indicates that while correlation tests suggest a significant relationship between these metrics and interdisciplinary breakthrough innovation, their predictive power is insufficient when used independently (Petersen et al., 2025; Yang et al., 2023). Therefore, they can serve as input features for the IBID-CCT models built on LGBM or BERT, in combination with other factors, to better predict interdisciplinary breakthrough innovations.

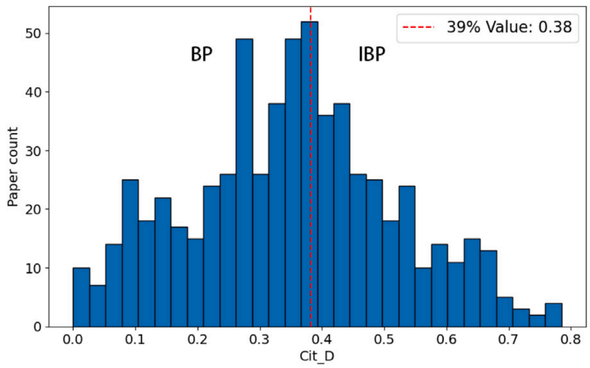
[9] https://huggingface.co/puzzz21/sci-sentiment-classify



(a) Distribution of papers based on the *Disruption* Index



(b) Distribution of papers based on the *Ref_D* metric



(c) Distribution of papers based on the *Cit_D* metric

Fig. 5. Distribution of papers in the comparative experimental dataset. We evaluated papers' breakthrough and interdisciplinary characteristics using distribution histograms of three metrics (*Disruption*, *Ref_D*, and *Cit_D*). These thresholds were determined based on the empirical proportions of BP and IBP in our standard dataset.

6. Discussion

6.1. Effectiveness of different machine learning and deep learning models

In this study, we trained various machine learning and deep learning models to detect interdisciplinary breakthrough innovations, uncovering key differences in their ability to handle structured and unstructured data. Generally, integrating multimodal features, such as numerical data and text, yields a more comprehensive view of the data set. We employed the multimodal toolkit (Gu & Budhkar, 2021) for this purpose, alongside other fusion tools like AutoGluon-Tabular (Erickson et al., 2020) and AutoM3L (Luo et al., 2024). Machine learning models performed well with structured numerical features, while deep learning models achieved good results with unstructured text alone. However, adding numerical features did not consistently improve deep learning performance, likely because the metrics effectively captured interdisciplinary breakthrough characteristics, allowing machine learning models to excel.

The GPT-4o-generated contribution sentences, highlighted through word distribution and sentiment analysis, revealed the distinct visibility of interdisciplinary breakthrough papers, likely enhanced by large language models' familiarity with these works. Here, model interpretability outweighs sheer performance: machine learning models, more interpretable via SHAP (Lundberg, 2017), clearly outline feature importance and combined effects, whereas deep learning models, being less transparent, rely on supplemental analyses like important words and sentiment distributions, although their reasoning on shallow semantic features remains uncertain.

Feature selection is crucial for enhancing model performance and interpreting interdisciplinary breakthroughs. We gathered bibliometric data – such as citation counts, author teams, and innovation metrics – representing knowledge integration, fusion, and diffusion, along with scientific data from fields like grants, patents, clinical trials, and social media. Semantic features derived from GPT-4o contribution sentences provided additional insights by mitigating potential biases in numerical datasets and offering deeper content analysis (Hou et al., 2022; Wang, Ma, et al., 2023; Wang, Zhang, Chen, Feng, & Ding, 2024).

In summary, effective models for identifying interdisciplinary breakthroughs must consider comprehensive feature engineering, blending structured and unstructured data to capture the full lifecycle of innovation. Beyond performance, interpretability is crucial as it facilitates evidence-based decision-making. By harnessing the reasoning capabilities of advanced language models, such as reasoning language models like GPT-o1 (Besta et al., 2025; Wang, Sun, et al., 2023; Wei et al., 2022), the utility of these models can be further enhanced, particularly in identifying interdisciplinary innovations (Lutz Bornmann, 2024).

6.2. Advantages of IBID-CCT over existing methods

Evaluating the innovativeness of scientific papers is inherently complex, requiring a robust framework to establish quantitative metrics, assess their effectiveness in capturing innovation, and determine thresholds to gauge innovation levels. Traditional approaches generally fall into three categories: (1) assessing novelty in knowledge combinations from Refs. (Dahlin & Behrens, 2005), (2) evaluating topic and content innovation in focal literature (Nichols, 2014; Xu et al., 2016), and (3) analyzing influence through citation patterns (Liu & Rousseau, 2010; Yue et al., 2022). While valuable, these methods are often limited by unidimensional metrics, potentially leading to biased evaluations and hindering decision making.

In this study, the proposed IBID-CCT model leverages the cusp catastrophe theory to analyze the internal mechanism of interdisciplinary breakthrough innovation. It conceptualized the lifecycle of interdisciplinary breakthrough innovation as a flow of viewpoints, concepts, and methods across the scientific literature. The process of interdisciplinary breakthrough innovation includes three stages (interdisciplinary knowledge integration, fusion, and diffusion). Key metrics were selected to measure these stages, incorporating bibliometric data (e.g., citation counts, author teams, innovation metrics) and social media data from news articles and tweets. This multidimensional approach quantifies the complexity of knowledge integration, fusion, and diffusion, capturing critical aspects of interdisciplinary breakthrough innovation. Additionally, we integrated textual and numerical features using a multimodal toolkit, with semantic features derived from GPT-generated contribution sentences based on paper titles, abstracts, and citation contexts.

To validate our method, we compared **IBID-CCT** to the **Disruption Index**, **Reference Interdisciplinarity**, and **Citation Interdisciplinarity**. Our model outperformed these metrics across evaluation tasks, demonstrating strong stability and generalization capabilities.

Overall, IBID-CCT provides a comprehensive approach to exploring bibliometric and semantic features of interdisciplinary breakthrough innovation across the interdisciplinary knowledge integration, fusion, and diffusion dimensions. Our findings offer valuable methodologies for advancing innovation evaluation and forecasting future scientific and technological breakthroughs.

6.3. Characteristics of interdisciplinary breakthrough innovation

In this study, we framed the lifecycle of interdisciplinary breakthrough innovation as the dynamic flow of viewpoints, concepts, and methods across disciplines, and proposed the IBID-CCT model based on the cusp catastrophe theory. Our experiments reveal that interdisciplinary breakthrough innovations exhibit the following key characteristics:

- **Integration of Cutting-edge, Diverse Knowledge:** Based on SHAP feature importance analysis, interdisciplinary breakthrough innovations distinguishes itself through its bold strategies of knowledge integration and fusion. The institute emphasizes the incorporation of cutting-edge knowledge and highly heterogeneous combinations across multiple disciplines. Through careful balancing of the quantities of citations and the temporal novelty of references, they show both the depth of academic collaboration and the breadth of interdisciplinary cooperation.
- **Long-term Knowledge Diffusion:** Interdisciplinary breakthrough innovations exhibit the highest potential for long-term interdisciplinary knowledge diffusion. As their citation counts increase, they significantly enhance knowledge transfer across diverse domains, demonstrating a remarkable ability to bridge disciplinary boundaries. They play a critical role in driving and sustaining knowledge dissemination, establishing themselves as central catalysts for fostering intellectual integration and cross-disciplinary innovation over time.

- **Positively drive Multi-field Development:** A key feature of interdisciplinary breakthrough innovation is its broad positive impact and higher research value. Such innovations often arise from multi-field collaboration, creating an “upward” driving effect that advances other fields. They also evoke more positive sentiment in their citations, reflecting their significant influence and potential value, thereby attracting greater attention and promoting knowledge diffusion (Bornmann et al., 2019).

In summary, interdisciplinary breakthrough innovation can be characterized as: boldly integrating cutting-edge knowledge to achieve dynamic flow of viewpoints and methods across disciplines, with long-term knowledge diffusion potential and innovative value in positively driving multi-field development.

6.4. Implications

This paper presents a novel model, IBID-CCT, for detecting interdisciplinary breakthrough innovations based on the cusp catastrophe theory. The implications are as follows:

Theoretical Implications: Our model introduces a new framework for understanding the evolution of scientific paradigms, moving beyond traditional unidimensional metrics (e.g., references or citations). By conceptualizing interdisciplinary breakthrough innovations as a flow of viewpoints, concepts, and methods, IBID-CCT employs “knowledge flow” and the “coherence effect” as control parameters, with internal entropy as the state variable. This three-stage model – comprising integration, fusion, and diffusion – offers a holistic perspective on the role of interdisciplinary breakthrough innovations in technological and societal progress, enriching our understanding of interdisciplinary breakthrough innovation.

Methodological Implications: Our IBID-CCT approach, based on the internal mechanisms of interdisciplinary breakthrough innovations, uses machine learning and deep learning techniques to model interdisciplinary knowledge integration, fusion, and diffusion. By applying SHAP for interpretability in machine learning models and sentiment analysis in deep learning, we uncover how interdisciplinary breakthrough innovations often result from recombining diverse knowledge, leading to significant future impacts. These innovations initially challenge existing paradigms, enhancing their potential to disrupt and shape new research directions. This methodology provides valuable insights for innovation evaluation and forecasting.

Practical Implications: This study provides actionable insights for researchers and policymakers engaged in innovation evaluation and resource management. By elucidating the characteristics and impacts of interdisciplinary breakthrough innovations, our findings support strategic resource allocation for high-impact, high-reward research. Policymakers and funding agencies can leverage these insights to cultivate environments that promote unconventional and transformative ideas, thereby accelerating the advancement of groundbreaking innovations and fostering societal progress.

7. Conclusion

This study introduces the IBID-CCT model to detect interdisciplinary breakthrough innovations. However, certain limitations should be noted. Our experimental dataset was limited, as articles lacking essential data like references and citations were excluded, constraining our analysis of the internal mechanisms of interdisciplinary breakthrough innovations. Additionally, while we used a multimodal toolkit to examine sentence-level factors, the GPT-4o model could not process some papers due to insufficient text data, introducing potential bias.

Our future research will expand the dataset by incorporating multi-source data and employing large language models for model construction and validation (Lutz Bornmann, 2024). Furthermore, to enhance innovation measurement, we plan a fine-grained analysis of citations, examining factors like citation purpose and placement (Runhui et al., 2025). This approach, combined with in-depth text analysis, will allow us to delve into the mechanisms of interdisciplinary breakthrough innovations, providing valuable insights to advance the frontiers of scientific research.

CRediT authorship contribution statement

Zhongyi Wang: Writing – original draft, Software, Methodology, Conceptualization. **Na Wang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Haoxuan Zhang:** Writing – review & editing, Visualization, Validation, Software, Data curation, Conceptualization. **Zeren Wang:** Visualization, Validation, Software, Data curation. **Zhou Wang:** Writing – review & editing, Visualization, Validation, Software, Resources, Formal analysis, Data curation. **Junhua Ding:** Writing – review & editing, Methodology, Conceptualization. **Haihua Chen:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zhongyi Wang reports article publishing charges was provided by National Social Science Foundation of China. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data is publicly available at: https://github.com/wolovecoding/IBID-CCT.

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