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The Evolutionary Characteristics and Interaction of Interdisciplinarity and Scientific Collaboration under the Convergence Paradigm: Analysis in the Field of Materials Genome Engineering

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Abstract: Convergence has been proposed as a revolutionary innovation paradigm that advocates the integration of multidisciplinary knowledge through collaboration to solve complex real-world challenges. From a knowledge perspective, this study examined the evolutionary characteristics and interactions between interdisciplinarity and scientific collaboration in the context of the convergence paradigm using complex networks and bibliometric methods for publications (n = 35,227) in the materials genome engineering (MGE) field in China from 2000 to 2021. The findings are as follows: (1) Under the convergence paradigm, knowledge from five core disciplines forms the skeleton of the multidisciplinary knowledge system in the MGE field. The goal of interdisciplinarity gradually evolves from theoretical exploration to applied research, and the knowledge from various disciplines is increasingly integrated. (2) The development of the scientific collaboration network has gone through three phases: 2000–2009, 2005–2014, and 2015–2021, and its core-periphery structure has been gradually optimized. (3) The evolution of interdisciplinarity is nearly synchronized with the evolution of the scientific collaboration network. (4) The promotion of interdisciplinarity through collaboration is becoming increasingly evident. The proportion of interdisciplinary partnerships increased from 0.66 to 0.87, with the proportion of partnerships involving more than two disciplines increasing from 0.24 to 0.59. (5) Institutions from core and periphery disciplines have diverse partner selection preferences, and disciplinary characteristics related to knowledge similarity and complementarity are important factors influencing scientific collaboration behavior. This study contributes to a more comprehensive understanding of the convergence paradigm and provides insights for better incubating convergence research projects and advancing top-down innovation management in convergence fields.

Keywords: convergence paradigm; co-evolve; interaction; interdisciplinary; materials genome engineering; scientific collaboration

1. Introduction

Climate change, ecological security, food security, resource scarcity, and other issues that endanger humanity’s long-term growth have become increasingly apparent and pressing in recent years. Convergence has been proposed as a new scientific research paradigm in this context, which supports merging theories and methodologies from various fields to find creative answers to difficult problems in order to address the challenges of the complex reality [1,2]. It helps to fully release society’s collective invention potential, support the formation of a new development pattern through innovation, and to contribute to the sustainable development of humankind. Mining the connotation and characteristics of the convergence paradigm can help in providing a reference for convergence science planning and optimization and fundamentally contribute to innovation-driven sustainable development.

In December 2001, the USA originally highlighted the concept of “NBIC converging technologies” in an attempt to promote the full integration of nanotechnology, biotechnol-
ogy, information technology, and cognitive science [3]. Subsequently, in 2004, the High-
Level Expert Group on “Foresight for the New Technological Wave” prepared a report, Converging Technologies—Shaping the Future of European Societies, for the European Commission, dedicated to finding a European pathway for converging technologies [4]. The idea of the convergence paradigm has gradually emerged to guide science and technology development, referred to as the Convergence of Knowledge and Technology for the benefit of Society (CKTS) framework by Roco et al. [5]. The emergence of this idea has affected all aspects from knowledge production to application and is of great significance for countries to strengthen their research and development (R&D) capabilities [6], enhance their competitive advantages and risk response capabilities, and climb to the high end of the global value chain [7].

As an extended form of the interdisciplinary research paradigm, interdisciplinarity and scientific collaboration are two typical features of the convergence paradigm, depicting different, yet closely connected events in the R&D process [8]. Under the convergence paradigm, interdisciplinarity is oriented by engineering applications based on serious human development requirements, with a focus on the inherent integration of science and technology [9], throughout the entire cycle from fundamental research, applied research, and productization, to marketization [10]. This means that multiple disciplines may intersect and integrate more fully at the level of researcher and institution, or even research project and field, and parallel interdisciplinarity and scientific collaboration work together to promote the development of research fields under the convergence paradigm.

Therefore, a crucial scientific question to better understand the convergence paradigm is what are the evolutionary characteristics of interdisciplinarity and scientific collaboration, respectively, and how do they work together to advance the field. In recent years, scholars have studied the convergence paradigm from the perspectives of innovation strategy [11], measurement of convergence [11–13], evolitional features [12–14], influencing factors [15], convergence technology prediction [16,17], technology convergence pattern [7,18], and the impact on innovation [14,19,20]. However, few scholars have included both interdisciplinarity and scientific collaboration in the framework of the convergence paradigm, and many have neglected to distinguish convergent fields from general interdisciplinary fields in their sample selection, resulting in a lack of clarity in the understanding of the convergence paradigm.

It is worth emphasizing that scientific collaboration is regarded as one of the most essential means of integrating disciplines and has garnered considerable scholarly attention. Related research topics include (1) interdisciplinary collaboration barriers [21–23], (2) interdisciplinary collaboration mechanisms [24], (3) sociological factors impacting interdisciplinary collaboration [25], and (4) the evolution of interdisciplinary collaboration. Bellotti et al. [26] examined the relative changes in the number of intra- and interdisciplinary collaborations in Italian academia and compared the patterns of interdisciplinary collaboration in different disciplines. However, the majority of these studies have concentrated on the evolution of the frequency of interdisciplinary collaborations, disciplinary structures, community hierarchies, and so on, with very few studies examining which types of institutions are more likely to form collaborative dyads from a disciplinary perspective, which is important for policymakers. Furthermore, these studies presume that organizations are mono-disciplinary, while research has demonstrated that many organizations are affiliated with several disciplines [27], resulting in bias. Our method makes it possible for research organizations to be linked with multiple disciplines, which makes it more realistic. This is critical for the formulation of policies that encourage convergence science.

This study, which is based on scientific publications in a typical convergence field in China, namely, the field of materials genome engineering (MGE), depicts the evolutionary characteristics and interaction trajectories of scientific collaboration and interdisciplinary intersection under the convergence paradigm. In addition, it attempts to explain the phenomenon from the perspective of knowledge, to lay a foundation for better under-
standing of the convergence paradigm, and provide references for the development of convergence science.

In comparison to previous research, this study makes the following contributions: (1) The majority of studies on the convergence paradigm have investigated the dynamics of disciplinary intersection using two measures: references’ disciplinary categories [28] and discipline co-occurrence [29] in the source journal’s web of science category, ignoring the important influence of scientific collaboration, which has some limitations. This work presents a conceptual framework for the convergence paradigm in which interdisciplinarity and scientific collaboration interact and co-evolve. The findings prove that scientific collaboration fosters interdisciplinarity, and disciplinary knowledge traits influence collaborative behavior. (2) Most previous studies on the relationship between scientific collaboration and interdisciplinarity have focused on the number of interdisciplinary collaborations [25] and the structure of disciplines in scientific collaboration [27]. Our study further divides disciplines into core and peripheral disciplines, and on this basis, depicts the dynamics and pathways of disciplinary intersections in scientific collaboration, enriching the relevant research findings. (3) The MGE field is clearly goal-oriented and vision-driven, intending to accelerate the R&D cycle of materials and lower R&D costs. The aims in the selected sample are thus in line with the convergence paradigm, as described, which allows us to capture interdisciplinary and scientific collaboration more accurately in the context of the convergence paradigm.

This paper is organized as follows: Section 2 sorts out the roles and functions of interdisciplinarity and scientific collaboration in the idea of convergence from a knowledge perspective and presents the research hypothesis. Section 3 discusses sample selection, data collecting, and methodologies. Section 4 illustrates the evolving characteristics of interdisciplinarity and scientific collaboration. Section 5 discusses the interaction between the two and the interpretation of the phenomena from a knowledge standpoint. Section 6 demonstrates the conclusion and discussion.

2. Research Hypotheses

A theoretical explanation of the roles of interdisciplinarity and scientific collaboration under the convergence paradigm in the innovation process is critical to a clear understanding and the execution of convergence-related research.

The innovation process, from a knowledge perspective, is the reorganization of knowledge elements and the emergence of new knowledge element combinations [30,31]. It may also result in the formation of new knowledge elements, even if this is very rare. A knowledge element, in general, is a knowledge unit with complete knowledge expression that can accurately convey the meaning and expansion of knowledge. Therefore, the knowledge elements and structural linkages between them, owned by the innovation subjects, are key resources for developing innovation results [30,32]. Moreover, they form the innovation subjects’ knowledge base (KB) [31]. The characteristics of the knowledge base (for example, knowledge diversity, knowledge distance, knowledge combination opportunities, and so on) are essential factors impacting innovation [32].

Interdisciplinarity and scientific collaboration drive innovation by changing the characteristics of the knowledge base. There are fewer combinatorial links between knowledge elements of distinct disciplines than those of the same discipline, since they operate within separate research paradigms and value systems. Interdisciplinarity, therefore, leads to a greater diversity of the knowledge base and more opportunities for combination [33]. For example, Jung et al. [34] examined the relationship between interdisciplinarity and R&D performance and found that higher interdisciplinarity was significantly associated with greater R&D performance. Simultaneously, scientific collaboration combines both parties’ knowledge bases to conduct research collaboratively, and the disparity between their knowledge bases is an important factor influencing innovation output and impact, which is frequently depicted using knowledge similarity and complementarity [35]. Exces-
sive similarity among collaborating parties might result in a very constrained knowledge search, resulting in knowledge locking [32] and harming innovation output.

A 2014 report by the US National Research Council further argued that the integration of theories and techniques from multiple disciplines and collaboration are aspects that should be emphasized within the convergence paradigm [8]. This is based on the fact that interdisciplinarity and scientific collaboration promote innovation. Furthermore, it has been found that knowledge complementarity is an important basis for the development of partnerships among innovation entities [36], providing a potential pathway for disciplines (collections of knowledge) to impact scientific collaboration. Additionally, although a study in 2004, based on the field of nanotechnology, found no interdisciplinarity [37], some scholars have still discovered a certain amount of interdisciplinary collaboration in fields such as medicine and biology [26]. This leaves the possibility of interaction between scientific collaboration and interdisciplinarity open in the context of the convergence paradigm: scientific collaboration may promote interdisciplinarity, and interdisciplinarity may influence the choice of scientific partners. It is worth noting that interactions between interdisciplinary and scientific collaborations may be a unique feature of the convergence paradigm.

The mindsponge theory proposed by Vong et al. [38,39] has been employed to further explain the possibility of interaction between the two: it is typically used to explain how humans absorb new ideas and incorporate or exclude them from their core cognition. For a researcher, the theories, methods, and tools of his or her own disciplinary body of knowledge constitute the core value system for conducting scientific research. In research collaborations under the convergence paradigm, researchers may frequently be exposed to new knowledge from various disciplines, which initiates a filtering mechanism for the new knowledge. According to Vong et al. [38], when people are exposed to new values, three types of filtering are triggered: determining if a value is meaningful, contributing to the production of particular insights, and enabling new opportunities. The filtering mechanism in the mindsponge theory triggers speculations about the interaction between disciplinary intersections and scientific collaborations; see Figure 1. The box in the figure symbolizes the researcher’s knowledge base, with solid circles representing knowledge elements and their colors distinguishing disciplines. The superimposed circles in the middle of the diagram represent the researcher’s mindsponge, with the red circle illustrating the researcher’s own core body of knowledge and values, the circle outside the red circle within the blue circle representing the comfort zone, and the outer yellow circle indicating the external environment, where the knowledge and values have not yet been assessed. People enable new ideas to converge on a core worldview if new knowledge and beliefs complement current ones. At the moment t₀, disciplinary intersections or scientific collaborations expose the researcher to outside knowledge from other disciplines or potential colleagues. At t₁, this external knowledge to be assessed activates the filtering system of the researcher’s mindsponge, where the researcher scans the new knowledge based on the three criteria of whether it is meaningful, whether it adds insight, and whether it creates new opportunities, and the new knowledge and values may then be accepted and integrated into the comfort zone, or they may be rejected and eliminated. It is vital to highlight that the rigor of the filtering is related to the new knowledge’s proximity to the existing core knowledge. The closer the two are, the more thorough the appraisal procedure. The former usually denotes a successful integration of disparate disciplines or a higher level of confidence amongst potential collaborators, which encourages subsequent creativity, whereas the latter typically indicates the failure of the innovation.

It is worth mentioning that researchers are more likely to perceive the research value of information in their own disciplinary systems than they are to be aware of research concerns in other disciplines. Knowledge from distant disciplines is always more likely to be blocked by the filtering mechanism and lead to the failure of collaboration and innovation. However, knowledge from other disciplines that are somewhat different from the researcher’s core body of knowledge is more likely to increase the researcher’s insights and new opportunities. This may lead to the researcher developing an appraisal
of the importance of potential partners’ disciplinary traits and forming a preference for collaboration based on this judgment. As a result, researchers may choose partners based on expectations of outcomes. This value filtering system exists at both the individual and organizational levels [40].

Based on the above analysis, we formulated the following research hypotheses:

**H1:** The development of the convergence field is driven by both the evolution of interdisciplinarity and scientific collaborations. And there is consistency in the evolutionary stages of the two.

**H2:** There is a two-way influence between interdisciplinary and scientific collaboration in the convergence field. Scientific collaboration promotes interdisciplinarity, and interdisciplinarity is an important factor influencing scientific collaboration behavior.

### 3. Research Design

#### 3.1. Sample Selection and Data Processing

#### 3.1.1. Sample Selection

The field of MGE was chosen in this study for two reasons:

- MGE is a typical convergence field. Firstly, MGE is a disruptive frontier technology in materials science that aims to shorten R&D cycles and reduce R&D costs, thereby accelerating the overall process of materials design for engineering applications [41]. This demonstrates a clear goal-oriented, vision-driven convergence approach. Secondly, MGE deeply integrates the materials-efficient computing, high-throughput experimentation, and big-data technologies that are part of materials science, medicine, and biology, as well as computer science and statistics [41–43]. As a result, the field is distinguished by interdisciplinary integration;

- MGE is crucial for countries to engage in the next industrial and information revolution. It is the key to attaining the commanding heights of advanced materials development, which has been the focus of major countries/regions, such as the United States, the European Union, Japan, Singapore, and China. In June 2011, the US announced the launch of the “Materials Genome Initiative”, which was elevated to a national strategy in 2014. Almost simultaneously, Europe launched the “Accelerated Metallurgy” program. Subsequently, China’s Ministry of Science and Technology also launched a special item plan on MGE in 2015. This study selected the field of MGE as
a sample to inform the development of innovation management policies in the field of MGE.

3.1.2. Data Collection

The scientific literature in the field of MGE in China was searched from the Web of Science (WOS) core collection, with the time window set to 2000–2021. The retrieval was made in January 2022. Since studies in this field are not related to genes in the usual biological sense, it is not possible to accurately search for studies belonging to the field using only the term “genome”. Therefore, this study first searched the relevant review literature in the field of MGE and then attempted to obtain query terms by filtering the keywords of the review the literature’s references. The specific steps for the construction of the WOS query formula and data collection were as follows:

Firstly, we conducted a basic search on the website using “Materials Genome Initiative” as the topic search term, and a total of 7 reviews were obtained. We extracted 704 references from all these reviews and collected and counted the keywords of these references.

Secondly, according to [43,44], the basic technological system of the MGE field covers efficient materials computing, high-throughput experimentation, and big-data technology, including three basic innovation platforms, namely computing, experimentation, and databases. Therefore, we screened the obtained keywords in terms of the six categories of MGE’s basic technology system and basic innovation platform and eliminated irrelevant expressions such as “crystal structure”, “surface”, and “fly”. The final query terms obtained are shown in Table 1.

Table 1. Query formulation of the field of MGE.

<table>
<thead>
<tr>
<th>Keywords</th>
<th>Tags</th>
<th>Booleans</th>
</tr>
</thead>
<tbody>
<tr>
<td>high throughput, high-throughput, machine-learning, machine learning, artificial intelligence, ml, ai, neural network *, big data, text mining, data mining, deep learning, generative model *, supervised learning, support vector, regression, random forest *, regression, clustering, active learning, data augmentation, decision tree, ensemble learning, metric learning, multi-task learning, reinforcement learning, transfer learning, document mining, supervised learning, unsupervised learning, semi-supervised learning, deep data, feature engineering, classification, data repositories, database *, dataset, digital engineering</td>
<td>TS</td>
<td>OR</td>
</tr>
</tbody>
</table>

Thirdly, we set the research area as “Materials Science” to ensure that we could retrieve materials-related results, as the technology associated with MGE is primarily concerned with research in the field of materials science. The literature type was set as “Articles”, the country was set as “PEOPLES R CHINA”, and the search database was set as the “WOS core collection”. We finally obtained a total of 35,227 pieces of literature. The number of publications by year is shown in Figure 2. The rapid rise in the number of annual publications hints at the boom in the field.
3.1.3. Identification of Disciplinary Attributes and Construction of Collaborative Networks

The disciplinary category of an author’s affiliated research institution may, to some extent, reflect the disciplinary orientation of the research he or she conducts [45,46]. Following the method outlined in [46], this study attempted to identify the disciplinary categories of the research institutions in the sample by using discipline-related expressions in the institutions’ names based on two disciplinary classifications: the primary disciplinary classification proposed by the Chinese Ministry of Education and the disciplinary categories of the literature’s source journals provided by the WOS website. As the disciplinary category of corporations and government departments is difficult to define, this study solely used universities and institutes of the Chinese Academy of Sciences as samples. The procedure is described as follows:

1. Entries with discipline-specific attributes were extracted from the complete institutional name in the dataset, such as Mat, Macromol, Polymers, Mol Mat, Composites Special, High Magnet Field, Chem, Biocatalysis, Biochem, Med, Hlth, Radiol, Hosp, Pharmaceut, etc.

2. The term “Web of Science category” provided by WOS characterizes the disciplinary categories of papers’ source publications. In this study, the first-level disciplines list proposed by the Chinese Ministry of Education was matched with the disciplinary classification of all source journals in the MGE field to obtain the final disciplinary catalog list including 25 disciplines.

3. The entries in the institution names obtained in the first step were matched with the corresponding discipline categories obtained in the previous step to generate a matching lexicon of “institutional disciplinary entries—discipline categories” for the MGE field.

4. The disciplinary categories were matched with each research institution.

5. The precision of the matching results was then verified. For a random sample of successful matches, information such as “research directions, names of departments, and research directions of faculty members and specializations studied during the PhD” were manually retrieved from the institution’s official website, and the matching
lexicon was corrected accordingly. If there were cases that could not be matched, the institution’s discipline-specific entries were added to the matching lexicon.

6. Steps 4 and 5 were repeated using the corrected lexicon until it passed the accuracy check.

In addition, a scientific collaboration network (SCN) with institutions as nodes was constructed based on the co-occurrence relationship of authors’ affiliations in the article in order to investigate the evolutionary characteristics of scientific collaboration under the convergence paradigm. When two authors collaborate on a publication, there is a co-occurrence relationship between the institutions to which they belong. Only the first-level institution was selected as a network node.

3.2. Research Methods

3.2.1. Interdisciplinary Measurement

This study examined the evolution of interdisciplinarity in MGE field in terms of three sub-dimensions proposed by Rafols [33]: variety, balance, and disparity, and the true diversity index was calculated, which combines the three sub-dimensions [47]. It can provide an overall measure of interdisciplinarity in MGE.

- **Variety.** Variety is the number of categories to which system elements are assigned, and we characterized variety by the number of disciplinary categories N involved in all research institutions in the MGE field in that year. A higher variety of the field indicates a higher number of disciplines involved.

- **Balance.** Balance characterizes the evenness in the distribution of elements between different categories, and balance, in our study, i.e., the degree of evenness in the counts of institutes in different disciplines, was characterized by the 1-Gini coefficient.

\[
Balance = 1 - \frac{\sum (2i - N - 1)x_i}{(N - 1)\sum x_i}
\]  

(1)

Here, \( i \) is the sequence indicator, \( x_i \) is the number of institutions in the \( i \)-th discipline category, and \( N \) is the number of discipline categories.

- **Disparity.** Disparity is the extent to which elements can be distinguished from each other. The disparity is measured using the average distance between different disciplines, indicating the overall variation in the knowledge body between disciplines within the field. Given the same number of disciplines, the greater the disparity, the lower the degree of knowledge integration across various disciplines.

\[
Disparity = \frac{1}{N(N - 1)}\sum_{i \neq j}(1 - S_{ij})
\]  

(2)

Here, \( S_{ij} \) is the similarity between discipline categories \( i \) and \( j \), characterizing the similarity in the knowledge systems of the two. The more frequently two disciplines co-occur in a journal’s WOS category, the more related the two disciplines are thought to be. The measure was developed by computing the cosine similarity between disciplines using the disciplinary co-occurrence matrix. The acquisition of a final co-occurrence matrix required first creating a co-occurrence matrix for the WOS categories of the current year’s all source journals in the MGE field, which was then aggregated according to the 25 disciplines in this study. Cosine similarity was calculated using Co-Occurrence 12.6 (COOC12.6) [48] software. Unlike the citation matrix between 252 WOS disciplinary classifications over the period 1991–2015 used by Huang et al. [46] to reflect the interactions between disciplines within a scientific field, the disciplinary co-occurrence matrix derived from the MGE field in this study is only a partial indicator. However, it is still useful for sample differentiation in a given research scenario [49] and represents the strength of connections between disciplines.
• True diversity. The true diversity indicator is a three-dimensional measure of the degree of interdisciplinarity that is widely used internationally [47]. It assesses disciplinary diversity on three levels: variety, balance, and disparity; the more diversity, the greater the degree of interdisciplinarity.

\[
TD = \frac{1}{\sum_{i,j=1}^{N} (1 - S_{ij}) p_i p_j}
\]  

(3)

Here, \(p_i\) indicates the number of institutions in discipline category \(i\) as a proportion of the total number of institutions.

3.2.2. Analysis of the Characteristics of Scientific Collaboration

This study described the evolutionary features of SCNs under the convergence paradigm based on a complex network analysis methodology, which can more accurately represent the evolutionary pattern of relationship-related objects.

A reasonable identification of evolutionary stages is important to accurately characterize the evolution of SCNs. Liu et al. [50] argue that the dynamic changes in the number of network nodes may reflect the lifecycle evolution of innovation networks. Following [50], this study used network size (number of nodes, number of edges) as a scale indicator for SCN lifecycle evolution. And a logistic growth model based on network size was used to delineate and identify the SCN lifecycle evolution stages. The specific model form is as follows:

\[
Y_t = A + B \times \exp(-k \times t)
\]  

(4)

where \(Y_t\) is the network size at time \(t\), \(t\) is a time metric, \(A\) is the maximum network size over the entire life cycle, \(B\) is a constant, and \(k\) is the growth rate. The year 2000 was taken as the starting point for the estimation, and the change in the number of nodes and edges from 2000 to 2021 was fitted separately using the observed data.

Changes in network topological characteristics are an outward manifestation of network evolution [50]. The number of edges and nodes in a network measures the size of the network, the network density measures how dense the network is, and the network clustering coefficient characterizes the extent to which structural holes in the network are closed. The degree of correlation of nodes in a network describes the correlation between the node degrees of two connected nodes. If the degrees of two nodes are completely random, the degree correlation is 0 and the network is neutral. If the degree correlation is positive, the node with the higher degree in the network tends to connect to the node with the higher degree, and the network is assortative. If the degree correlation is negative, the higher-degree node in the network tends to connect to the lower-degree node and the network is disassortative. Additionally, the core-periphery theory is often used to analyze the nodal positions in SCN. This study used UCINET software (version = 6.685) to calculate the coreness of nodes, classify nodes accordingly, and examine the changes in node locations in the network.

4. Interdisciplinarity and Scientific Collaboration under the Convergence Paradigm

4.1. Interdisciplinary Dynamics

This study attempted to explore the evolutionary characteristics of interdisciplinarity in the continuing development of the field by analyzing the dynamic process of disciplinary crossover from 2000 to 2021 and to determine the developmental stages of interdisciplinarity through these evolutionary traits.

4.1.1. Disciplinary Intersection with Core Disciplines’ Knowledge as the Backbone

The core disciplines in the convergence field are those whose frequency of occurrence exceeds the average frequency of all disciplines in the year, while the remainder are peripheral disciplines. Figure 3a shows the number of institutions affiliated with various disciplines in the field of MGE. From 2000 to 2004, the core disciplines in this field were
materials science and engineering, physics, chemistry, electronic science, and engineering. Since 2005, medicine has also become a core discipline in the field. The core disciplines remained stable in the field from 2000 to 2021, illustrating knowledge of the core disciplines jointly created the field’s backbone knowledge structure. The number of institutions in each discipline in the MGE field is gradually increasing, with a greater dominance of institutions in the core disciplines.

Figure 3. (a) shows the number of institutions affiliated with various disciplines in the field of MGE. (b) depicts the temporal evolution of the interdisciplinarity of the MGE field. (c) Cumulative histogram of the number of institutions by discipline in MGE. This study divided the period 2000–2021 into three evolutionary stages based on the evolutionary features of disciplinary crossover in the MGE field. (d) gives a schematic representation of the dynamics of the disciplines within the field at each stage.

4.1.2. The Interdisciplinary Structure Evolving from Theoretical Inquiry to Applied Research

Figure 3c shows the proportion of institutions belonging to different disciplines in the MGE field from 2000 to 2021. It can be seen that the proportion of institutions in materials science and engineering was basically stable, and the proportion of institutions in basic disciplines has been decreasing year by year, while the proportion of the applied disciplines’ institutions has been gradually increasing. The proportion of medicine’s institutions increased gradually from 2000 to 2008 and then stabilized. This demonstrates an important convergence feature: in the early stages of the convergence field’s development, science-based institutes primarily participated in research to facilitate the building of a basic theoretical system. After the theoretical foundations were largely developed, research in the field of MGE began to shift toward applied research. Most of the research institutes active in this period were applied research institutes in engineering and medicine.
4.1.3. The Knowledge of Multiple Disciplines Gradually Integrated

The changes in variety, balance, disparity, and true diversity indicators are shown in Figure 3b. All indicators are normalized. The change in variety exhibits that the number of disciplines in MGE fluctuates upwards and tends to stabilize after 2012, indicating that all relevant disciplines have entered the field. With the development of the convergence field, balance generally shows a fluctuating upward trend, and the uniformity of the number of institutions in different disciplines is increasing. The change in disparity indicates a rapid reduction in the degree of variation in the knowledge systems across disciplines and an increasing integration of knowledge. The trend in the true diversity indicator shows a gradual decrease in the disciplinary diversity of the field, which indicates a gradual decrease in interdisciplinarity as the field eventually reaches saturation in variety.

4.2. The Evolution of Scientific Collaboration

4.2.1. Three stages of Evolution

The evolutionary stages of SCN were first identified. To achieve the best fit, and considering that the field is still relatively new and may not have reached maturity (that is, the number of research institutions in the field has not yet reached its maximum), the logistic curve was fitted without a fixed value of A, and the value of k was restricted to [0,1]. The parameters and the goodness of fit were estimated using Origin 2021 software and the result is shown in Figure 4. As can be seen in Figure 4, the evolution of the SCNs in the MGE field can be divided into three stages. The first stage is from 2000 to 2010, when a large number of research institutions entered the SCNs and the growth rate of the number of institutions within the network gradually increased, with almost no growth in the number of edges of the SCN. This indicates that many of the collaborations existed within institutions. The second phase, which lasted from 2010 to 2014, saw an increase in inter-institutional collaborations. The third stage was from 2015 to 2021, when the growth rate of the number of research institutions within the network increased at a high rate, while the number of inter-institutional collaborations began to grow rapidly.

![Figure 4. Identification of SCNs' evolutionary stages in the MGE field. The 95% confidence bands for the fitted curves are given in the figure.](image-url)
The period 2000–2021 was divided into four-time windows to measure the evolutionary characteristics of the SCN. Table 2 shows the topological characteristics of SCN in the MGE field. During the first two stages of evolution, the average degree of the network did not increase significantly, while the average weighted degree increased significantly. This demonstrated that this stage was dominated by the entry of many institutions into the field, with the number of partners per institution remaining broadly stable, but the number of repeat collaborations increasing and the collaboration deepening. Furthermore, when compared to the prior stage, the average degree increased greatly in the third stage, as did the average weighted degree. This suggests that during this phase, research institutions not only acquired new partners but also worked with each partner substantially more frequently, increasing the continuous depth of collaboration. Meanwhile, in terms of network density, the SCN exhibits a distinctly sparse network with a large number of structural holes in the network.

Table 2. Topological characteristics of SCNs.

<table>
<thead>
<tr>
<th>Topological Characteristics</th>
<th>The First Stage</th>
<th>The Second Stage</th>
<th>The Third Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average degree</td>
<td>3.124</td>
<td>4.126</td>
<td>5.531</td>
</tr>
<tr>
<td>Average weighted degree</td>
<td>12.679</td>
<td>48.753</td>
<td>110.293</td>
</tr>
<tr>
<td>Diameter</td>
<td>6</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>Density</td>
<td>0.029</td>
<td>0.019</td>
<td>0.014</td>
</tr>
<tr>
<td>Degree correlation</td>
<td>−0.189</td>
<td>−0.131</td>
<td>−0.104</td>
</tr>
</tbody>
</table>

Note: The average degree is the average of the number of edges connected to each node in the network. The average weighted degree weights the edges in the average degree calculation process, where the weight is the number of times the two institutions have cooperated. Diameter is the maximum value of the distance between any two nodes in the network. Density is the number of edges of the network divided by the number of nodes.

It is also noted that the degree correlation was negative at all evolutionary stages, which indicates that the SCNs are typical disassortative networks. Nodes with high degrees in the network tend to form cooperative relationships with nodes with low degrees, indicating the pattern of collaboration is mainly the “dominant-follow” mode formed by the strong–weak association.

4.2.2. Small-Worldness Analysis of SCNs

Table 3 shows the results of the small-worldness assessment for the SCNs in the MGE field. The results suggest that the observed networks had higher clustering coefficients and approximately the same mean path length compared to the corresponding random network in all four time periods. And the small-world $S^\Delta$ was much greater than 1, indicating that the SCN exhibited significant small-worldness.

Table 3. Results of small-worldness assessment of SCNs in the MGE field.

<table>
<thead>
<tr>
<th>Small-Worldness Assessment</th>
<th>The First Stage</th>
<th>The Second Stage</th>
<th>The Third Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average clustering coefficient</td>
<td>0.489</td>
<td>0.474</td>
<td>0.504</td>
</tr>
<tr>
<td>Average path length</td>
<td>3.146</td>
<td>3.135</td>
<td>3.118</td>
</tr>
<tr>
<td>Equivalent average clustering coefficients</td>
<td>0.028</td>
<td>0.018</td>
<td>0.013</td>
</tr>
<tr>
<td>Equivalent average path length</td>
<td>4.008</td>
<td>3.925</td>
<td>3.697</td>
</tr>
<tr>
<td>$S^\Delta$</td>
<td>21.928</td>
<td>32.322</td>
<td>45.969</td>
</tr>
</tbody>
</table>

Note: The random networks’ statistics in the table for each period are the average of the topological statistics of 1000 random networks with the same number of nodes and edges as the observed SCN. $S^\Delta$ was obtained according to the method proposed by Humphries and Gurney [51]. The clustering coefficients in the table are the transitivity clustering coefficients.
The SCNs’ degree of distribution, demonstrated in Figure 5, follows an exponentially distributed pattern across the phase, showing that the SCNs are single-scale networks. Compared to a scale-free network of the same size, a single-scale network exhibits sparse hub nodes, inefficient knowledge diffusion, and poor overall network learning performance [52].

4.2.2. Small-Worldness Analysis of SCNs

Table 3 shows the results of the small-worldness assessment for the SCNs in the MGE field. The results suggest that the observed networks had higher clustering coefficients and approximately the same mean path length compared to the corresponding random network in all four time periods. And the small-worldness $S_\omega \Delta$ was much greater than 1, indicating that the SCN exhibited significant small-worldness.

Table 3. Results of small-worldness assessment of SCNs in the MGE field.

<table>
<thead>
<tr>
<th>Small-Worldness Assessment</th>
<th>The First Stage</th>
<th>The Second Stage</th>
<th>The Third Stage</th>
<th>The Fourth Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average clustering coefficient</td>
<td>0.489</td>
<td>0.474</td>
<td>0.504</td>
<td>0.501</td>
</tr>
<tr>
<td>Average path length</td>
<td>3.146</td>
<td>3.135</td>
<td>3.118</td>
<td>2.721</td>
</tr>
<tr>
<td>Equivalent average clustering coefficients</td>
<td>0.028</td>
<td>0.018</td>
<td>0.013</td>
<td>0.021</td>
</tr>
<tr>
<td>Equivalent average path length</td>
<td>4.008</td>
<td>3.925</td>
<td>3.697</td>
<td>2.686</td>
</tr>
<tr>
<td>$S_\omega \Delta$</td>
<td>21.928</td>
<td>32.322</td>
<td>45.969</td>
<td>23.550</td>
</tr>
</tbody>
</table>

Note: The random networks’ statistics in the table for each period are the average of the topological statistics of 1000 random networks with the same number of nodes and edges as the observed SCN. $S_\omega \Delta$ was obtained according to the method proposed by Humphries and Gurney [51]. The clustering coefficients in the table are the transitivity clustering coefficients.

Figure 5. Degree of distribution of SCNs.

4.2.3. The Core-Periphery Pattern of SCNs

The core-periphery structure of SCNs can reflect the knowledge-based hierarchical phenomenon of network nodes. Using the CORR algorithm integrated into the UCINET (version = 6.685) to calculate the coreness of nodes in the SCNs and to identify the node positions accordingly, the following four locations can finally be identified. The first is the core level, which is in the vanguard of the field; it engages with the entire network intimately and is the primary source of knowledge overflow. The sub-core level is located on the outskirts of the core level and has built close collaboration relations with core-level nodes. In terms of knowledge stock and cooperation frequency, the sub-core level, which is controlled by the core-level nodes, is inextricably linked to both the core level and the other sub-core level nodes. The semi-perimeter level, which is positioned on the periphery of the sub-core nodes and is largely linked to the core nodes, is the third level. Also, the semi-peripheral level has sparse connections to nodes in the same layer and collaborates more frequently with the outside world. The final level is peripheral, which is on the very perimeter and works primarily with the core nodes, with a low overall collaborative frequency.

The core-periphery structure of the SCNs in the MGE field and its specific evolution are illustrated in Figure 6. The changes from 2000 to 2021 can be summarized by two main features. From the perspective of node status, the Chinese Academy of Sciences (CAS) has been firmly in the lead, holding cutting-edge knowledge in the field and guiding the direction of research development. CAS, Tsinghua University, Peking University, Fudan University, University of Science and Technology of China, Shanghai Jiao Tong University, and Jilin University are at the core level and have close relationships with other
institutions in the network, facilitating the diffusion of frontier knowledge among research institutions and playing the role of “knowledge gatekeeper”. From the perspective of pattern optimization, in the first stage, research institutions at the levels of the periphery and semi-periphery have frequent turnover between levels, and those on the semi-peripheral level become potential boundary crossers. Nodes at the semi-peripheral level with a high frequency of collaboration are likely to enter the sub-core level in the next period, such as Shandong University, Tsinghua University, Peking University, and Nanjing University. In the second and third stages, the semi-peripheral level produces differentiation, with some nodes concentrating upwards to become the new sub-core level and some nodes exiting downwards to the peripheral level. The core-periphery structure of the SCN changed from a four-tier to a three-tier structure in this stage, indicating that research institutions are increasingly focusing on external diversified knowledge acquisition, and the gap between research institutions is gradually narrowing and the core-periphery pattern is optimized.

Figure 6. The “core-periphery” structure of SCNs in the MGE field. Subfigure (a) depicts the “core-periphery” structure of the SCN for the period 2000–2004, (b) for 2005 to 2009, (c) for 2010 to 2014, and (d) for 2015 to 2021.
5. Interaction between Interdisciplinarity and Scientific Collaboration under the Convergence Paradigm

The aforementioned analyses portray the evolutionary characteristics of interdisciplinarity and scientific collaboration under the convergence paradigm. Do multiple disciplines intersect through scientific collaboration? How do disciplines intersect through scientific collaboration? Do interdisciplinarity characteristics influence scientific collaboration? This section investigates these questions in order to examine the interaction between interdisciplinarity and collaboration in the context of the convergence paradigm.

5.1. Multiple Disciplines Converge through Scientific Collaboration

This study counted the percentage of interdisciplinary partnerships from 2000 to 2021 and found that the percentage fluctuated between 40% and 60%. This shows that interdisciplinary scientific collaboration has grown in importance and that many disciplines are cross-fertilized in scientific collaborations.

5.1.1. Interdisciplinarity of Bilateral Scientific Partnerships

Figure 7a depicts a heat map of the number of different disciplines engaging in scientific collaboration from 2000 to 2021. As can be seen in the graph, the percentage of collaborative links that include different disciplinary counts has been increasingly evened out. The majority of scientific collaborations initially only involved one or two disciplines, but as research fields advance, more and more collaborations now involve more than two disciplines. This indicates that the interdisciplinarity of scientific collaborations is becoming more pronounced. Additionally, the number of disciplines that intersect in partnerships is modest. In recent years, the plurality of the number of disciplines involved in scientific collaborations has been two or three, indicating that most scientific collaborations in MGE involve only two or three disciplines.

Figure 7. (a) Heat map of the number of disciplines in a research partnership. (b) Relative magnitude of knowledge similarity and complementarity in three research collaborations based on disciplinary heterogeneity. (c) Evolution of the frequency of the three scientific collaborations based on disciplinary heterogeneity.
5.1.2. Pathways of Interdisciplinary Crossover through Scientific Collaboration

Research institutions were further classified based on whether they are affiliated to a core or peripheral discipline: those affiliated only to core disciplines (A), those affiliated only to peripheral disciplines (B), and those affiliated to both core and peripheral disciplines (C). The examination of the disciplinary combinations formed by research institutions in interdisciplinary scientific collaboration aids in the investigation of the convergence paths of various types of disciplines through scientific collaboration.

Table 4 shows the number and proportion of different disciplinary combinations formed as a result of interdisciplinary partnerships. In the period 2000–2002, the proportion of inter-institutional collaborations involving only core disciplines exceeded 50%. After 2007, the percentage of collaborative ties covering both core and peripheral disciplines increased to approximately 70% of the total links. This demonstrates that the early development of a research field is led by the convergence of various core disciplines to build the fundamental body of knowledge, and that in the middle and later stages, core and peripheral disciplines converge to extend the field’s knowledge outreach and drive the field’s continued development.

Table 4. Disciplinary combinations in interdisciplinary scientific collaborations.

<table>
<thead>
<tr>
<th></th>
<th>A-A</th>
<th>C-C</th>
<th>A-C</th>
<th>C-B</th>
<th>B-B</th>
<th>A-B</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>122</td>
<td>0.71</td>
<td>0</td>
<td>0.00</td>
<td>33</td>
<td>0.19</td>
</tr>
<tr>
<td>2001</td>
<td>147</td>
<td>0.58</td>
<td>12</td>
<td>0.05</td>
<td>70</td>
<td>0.28</td>
</tr>
<tr>
<td>2002</td>
<td>139</td>
<td>0.76</td>
<td>8</td>
<td>0.04</td>
<td>19</td>
<td>0.10</td>
</tr>
<tr>
<td>2003</td>
<td>184</td>
<td>0.57</td>
<td>8</td>
<td>0.02</td>
<td>65</td>
<td>0.20</td>
</tr>
<tr>
<td>2004</td>
<td>131</td>
<td>0.48</td>
<td>15</td>
<td>0.06</td>
<td>66</td>
<td>0.24</td>
</tr>
<tr>
<td>2005</td>
<td>203</td>
<td>0.50</td>
<td>38</td>
<td>0.09</td>
<td>98</td>
<td>0.24</td>
</tr>
<tr>
<td>2006</td>
<td>226</td>
<td>0.46</td>
<td>47</td>
<td>0.10</td>
<td>137</td>
<td>0.28</td>
</tr>
<tr>
<td>2007</td>
<td>240</td>
<td>0.67</td>
<td>36</td>
<td>0.10</td>
<td>14</td>
<td>0.04</td>
</tr>
<tr>
<td>2008</td>
<td>1756</td>
<td>0.42</td>
<td>522</td>
<td>0.12</td>
<td>1244</td>
<td>0.30</td>
</tr>
<tr>
<td>2009</td>
<td>1818</td>
<td>0.42</td>
<td>554</td>
<td>0.13</td>
<td>1536</td>
<td>0.36</td>
</tr>
<tr>
<td>2010</td>
<td>2375</td>
<td>0.41</td>
<td>605</td>
<td>0.11</td>
<td>1871</td>
<td>0.33</td>
</tr>
<tr>
<td>2011</td>
<td>2632</td>
<td>0.41</td>
<td>497</td>
<td>0.08</td>
<td>2123</td>
<td>0.33</td>
</tr>
<tr>
<td>2012</td>
<td>3556</td>
<td>0.40</td>
<td>787</td>
<td>0.09</td>
<td>2866</td>
<td>0.32</td>
</tr>
<tr>
<td>2013</td>
<td>4790</td>
<td>0.41</td>
<td>1188</td>
<td>0.10</td>
<td>3933</td>
<td>0.33</td>
</tr>
<tr>
<td>2014</td>
<td>5123</td>
<td>0.34</td>
<td>1910</td>
<td>0.13</td>
<td>3063</td>
<td>0.33</td>
</tr>
<tr>
<td>2015</td>
<td>1030</td>
<td>0.37</td>
<td>370</td>
<td>0.13</td>
<td>864</td>
<td>0.31</td>
</tr>
<tr>
<td>2016</td>
<td>12,065</td>
<td>0.40</td>
<td>3806</td>
<td>0.13</td>
<td>9135</td>
<td>0.30</td>
</tr>
<tr>
<td>2017</td>
<td>1421</td>
<td>0.30</td>
<td>693</td>
<td>0.15</td>
<td>1602</td>
<td>0.34</td>
</tr>
<tr>
<td>2018</td>
<td>2016</td>
<td>0.32</td>
<td>965</td>
<td>0.15</td>
<td>1949</td>
<td>0.31</td>
</tr>
<tr>
<td>2019</td>
<td>3029</td>
<td>0.30</td>
<td>1677</td>
<td>0.17</td>
<td>2951</td>
<td>0.29</td>
</tr>
<tr>
<td>2020</td>
<td>3448</td>
<td>0.27</td>
<td>2213</td>
<td>0.17</td>
<td>3955</td>
<td>0.31</td>
</tr>
<tr>
<td>2021</td>
<td>3883</td>
<td>0.27</td>
<td>2474</td>
<td>0.17</td>
<td>4406</td>
<td>0.31</td>
</tr>
</tbody>
</table>

Furthermore, as is illustrated in Table 4, institutions in core disciplines primarily collaborate with institutions in composite fields. In all years, the frequency of collaboration between institutions in core and composite disciplines (A-C) was substantially higher than the proportion of inter-institutional collaboration between core and core disciplines (A-A) and core and peripheral disciplines (A-B). Similarly, institutions in peripheral disciplines primarily collaborate with institutions in core disciplines, while institutions in composite disciplines primarily collaborate with institutions in core disciplines. This implies that the process of scientific collaboration follows a convergence rule in which core disciplines connect with peripheral disciplines.

From a knowledge standpoint; this could be due to the fact that research institutions belonging to one or more core disciplines have knowledge that underpins the field’s existence, and therefore they have a strong acumen and competitive advantage in R&D
activities in the convergence field. However, they lack the knowledge to extend the field’s boundary. As a result, institutions in core disciplines are more likely to collaborate with complex research institutions that have some research experience in peripheral disciplines as well as knowledge similarities and complementarities, lowering barriers to cooperation and greatly increasing the possibility of innovation. Institutions in peripheral and composite disciplines may need to seek out coworkers with deep expertise to make up for gaps in their knowledge. In contrast, institutions in core disciplines have a stronger knowledge foundation and a higher desire to broaden their knowledge outreach than institutions in composite disciplines and are thus more likely to cooperate with such potential partners.

5.2. Disciplinary Characteristics as Important Factors Influencing Scientific Collaboration

Most of the collaborators in the sample were research institutes with multiple disciplinary attributes, so this study classified the collaborative relationships into three types based on the disciplinary categories of the collaborators: (1) disciplinary dissimilar collaborations in which the disciplinary categories of the collaborating parties were completely different, (2) disciplinary similar collaborations in which the disciplinary categories of the collaborating parties were partially the same, and (3) disciplinary identical collaborations in which the disciplinary categories of the collaborating parties were completely the same. Figure 7b shows the relative importance of knowledge similarity and complementarity in these three types of collaboration.

Figure 7c depicts the trend in the number of the three types of research partnership from 2000 to 2021. As is shown in the figure, the frequency of the three was basically equal from 2000 to 2010, but since 2011, they have diverged. Although research institutions from completely different disciplines have high knowledge complementarity, which is conducive to high-level innovation, extremely low knowledge similarity makes it more difficult for partners to reach consensus and increases the barriers to cooperation, as well as greatly increasing the chances of failure in knowledge production. Institutes with identical disciplinary categories are not favorable to knowledge development due to the high similarity and minimal complementarity of expertise, resulting in a “knowledge lock.” It is clear that scientific collaboration based on disciplinary complementarity is clearly the main mechanism supporting the production of scientific knowledge, and knowledge-related disciplinary characteristics are the main factors facilitating scientific collaboration during the middle and late stages of the entire convergence field’s growth.

6. Conclusions and Implications

This study explored the evolution and interaction of interdisciplinarity and scientific collaboration in the context of the convergence paradigm using scientific publications in the field of MGE from 2000 to 2021. According to the findings, the evolution and interaction between interdisciplinarity and scientific collaboration under the convergence paradigm jointly contribute to the development of the field. The theoretical roots of the interaction are in the objective evolution of the discipline and knowledge-based partner selection strategies in the innovation process. This study has significance for guiding scientific research efforts under the convergence paradigm, breaking down disciplinary barriers to innovation, and thus realizing a major improvement in productivity and the promotion of sustainable human development.

The main findings are as follows: First, the disciplinary intersection under the convergence paradigm forms the knowledge system of the field, where the knowledge of the core disciplines serves as its backbone. As new knowledge emerges, the field’s evolution has changed from theoretical to applied research, with a gradual increase in the integration of knowledge across disciplines. Second, under the convergence paradigm, SCN exhibits a three-stage evolutionary feature and produces a single-scaled small-world network with a weak information diffusion capability. The third stage is marked by a sharp increase in inter-institutional collaborative links, while the first stage is characterized by an influx of research institutions. During this stage, the distance between research institutions is gradu-
ally closed and the core-periphery pattern of collaboration has been gradually optimized. The consistency of the evolutionary stages of interdisciplinary and scientific collaboration is worth noting.

Additionally, the interaction between interdisciplinary and scientific collaboration is another feature of the convergence paradigm. The convergence paradigm does facilitate disciplinary integration through collaborative partnerships. The core disciplinary institutions converge primarily through research partnerships with complex disciplinary institutions, while peripheral disciplinary institutions enter the research field mainly through research partnerships with core disciplinary institutions. Discipline intersections between core and peripheral disciplines gradually replace disciplinary intersections between core and core disciplines. In the final stages of a study field’s development, disciplinary traits connected to knowledge complementarities and similarities are significant factors influencing scientific collaboration.

The above findings have significant implications for the innovative management of the convergence field: (1) The bottom-up cultivation and management of the convergence field should respect the objective development of interdisciplinarity. Managers should focus on directing the convergence of core and basic disciplines to speed theoretical building and pay attention to the critical role of basic disciplines in the development of the convergence field. To extend engineering application scenarios, attention should be paid to increasing crossover between core and peripheral disciplines, particularly in the middle and late stages of the field’s development. (2) Particular attention needs to be paid to research institutions that combine both core and peripheral disciplines, which are an important vehicle for disciplinary convergence and an engine for the continued development of convergence fields. (3) The emphasis should be on encouraging knowledge diffusion in convergent topics and research collaboration between core and peripheral disciplines, for example, through the organization of academic lectures, academic alliances, and technical training activities in related fields; the improvement of the mechanism for evaluating and rewarding contributions in interdisciplinary research collaboration; and the introduction of supporting scientific and technological management measures to encourage the strong association of research institutions. (4) Our findings can help to improve the innovation efficiency and optimize the innovation environment in the field of materials genome engineering, especially for the development of biomaterials [53–56], functional materials [57], and new energy materials, which are essential for the sustainable development of human beings under the conditions of complex realities.

This study still has some limitations. Due to the complexities of data processing, this study was limited to the field of MGE in China. Other convergence areas, countries, and institutions can be chosen for investigation in future studies to further examine the variations in the evolution of scientific collaboration and disciplinary crossover. To gain more systematic knowledge of the convergence paradigm, the disciplinary and collaborative elements of technological convergence might be investigated from a patent standpoint.

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