Research on Interdisciplinary Characteristics: A Case Study in the Field of Artificial Intelligence

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Abstract. In order to show the interdisciplinary laws of the subject fields and analyze the interdisciplinary structure of the field and the contents of knowledge research, a clear-structured framework of interdisciplinary feature recognition is constructed. Taking the field of artificial intelligence as an example, this paper analyzes it from the aspects of disciplinary diversity and disciplinary coherence. Disciplinary diversity is characterized by the distribution of disciplines, Shannon entropy and Rao-Stirling index. Disciplinary coherence is based on network analysis, which mainly includes discipline citation network and core, important and marginal discipline-keyword co-occurrence network at a finer granularity level. These two levels more comprehensively show the distribution and flow of discipline knowledge in this field. Through empirical research, it is found that the field of artificial intelligence involves a variety of disciplines, and its interdisciplinary situation evolves over time, forming clusters of disciplines with tight knowledge flow. In addition, the cross-topic domains of disciplinary research are also different. The results show that the framework system has certain reliability and can provide reference for related research.

1. Introduction

In recent years, with the increase of the scale and complexity of the research projects, the research paradigm of a single discipline has been difficult to meet its needs. Interdisciplinary infiltration has become the trend of development in many subject areas, which promotes interdisciplinary research. There is no consensus on the definition of interdisciplinary concept in the academic circle, and scholars define it from different angles. In this study, the cross of disciplines mainly refers to the process of mutual infiltration of different disciplines, and the article mainly focuses on describing interdisciplinary characteristics from multiple dimensions to show disciplinary correlation.

Interdisciplinary research is of great significance, which can help promote the integration of different disciplines, and is conducive to the use of multidisciplinary theoretical methods to solve problems. Moreover, the multi-disciplinary knowledge flow and integration is easy to generate knowledge innovation points, which can contribute new growth power to the depth and breadth development of disciplines [1]. In addition, interdisciplinary research can provide important basis and decision-making reference for the formulation of science and technology management mechanisms and policies, the optimization and integration of education and scientific and technological resources, and the overall layout of national science and technology development [2]. The existing research
methods on interdisciplinary research can be roughly divided into two categories, top-down method and bottom-up method. The top-down method mainly determines the subject categories and corresponding journals based on pre-defined subject categories, and shows the interdisciplinary proportions and associations by analyzing the subject classifications to which the references belong. The bottom-up method mainly carries on the similarity analysis on the basis of clustering or classification of papers, and visualizes the network structure [3]. In addition, scholars also have designed a variety of measurement indicators based on different perspectives and applied them in empirical research. Moreover, multiple information dimensions are often combined in the process of exploration.

Under the influence of artificial intelligence, a new generation of technological innovation and industrial transformation is gradually fermenting. Whether it can seize the opportunities in the field of artificial intelligence has become an important symbol of the competitiveness of countries in the world in the new era. Governments have also given great attention to the field of artificial intelligence. For example, China has successively issued "New Generation Artificial Intelligence Development Plan" and other policy documents. The United States also issued documents such as "Executive Order on Maintaining American Leadership in Artificial Intelligence", and called on various industry departments to increase resources support for the industries in the field of artificial intelligence.

Since the concept of "artificial intelligence" was first proposed in 1956, it has undergone an ups and downs of development. It has entered a period of stable development since the mid-1990s and has been in a booming period since 2011 [4]. Nowadays, under the theme of artificial intelligence, a number of research branches and corresponding application fields have been developed, involving cross-connections among various disciplines. This paper aims to conduct a multi-dimensional analysis of the interdisciplinary characteristics of the field, and makes an empirical analysis based on the literature collection in the field of artificial intelligence for nearly 20 years. This paper mainly analyses the disciplinary attributes of the thesis itself and its citation, and combines keywords to represent the cross-topic characteristics of this field, so as to provide reference for the relevant research of scholars and the scientific decision-making of the national government.

2. Research framework
Research on interdisciplinary measure can be broadly divided into two categories: disciplinary diversity and coherence. The diversity of disciplines reflects the quantitative statistical characteristics of the interdisciplinary areas, and the disciplinary coherence shows the close relationship among the overall network of disciplinary areas and the status differences of various disciplines [5]. The measurement of disciplinary diversity is often based on the existing subject classification system to calculate the corresponding indicators. Poter and Rafols believe that the diversity of interdisciplinary research should be based on the number of disciplines cited (Variety), the balance of citation discipline distribution (Balance), and the similarity between disciplines (Similarity) [6]. The application of these three aspects of index research is more common, such as disciplinary category statistics and specialization index in disciplinary richness [7], Shannon entropy (SE) [8], Gini coefficients (GC) [9] and citations outside category (COC) [10] in disciplinary balance, and Intergration indicators [7] and Rao-Stirling indicators [11] that can measure disciplinary difference.

In this paper, the measurement of disciplinary diversity is mainly reflected by the distribution of disciplinary categories and the widely used Shannon entropy and Rao-Stirling indicators. Among them, the calculation of Shannon entropy [8] is shown in (1), and $p_i$ represents the probability distribution of different disciplines. The Rao-Stirling index proposed by A. Stirling [11] can measure the difference between disciplines by considering the distance between disciplines. The higher the value, the greater the difference and the stronger the intersectionality. The calculation of Rao-Stirling index is shown in (2), $p_i$ and $p_j$ are probability distributions of different disciplines, $d_{ij}$ represents the distance between different disciplines in the disciplinary network, and $\alpha$ and $\beta$ are measurement parameters.
Disciplinary coherence research often uses co-citation analysis, co-word analysis or coupled analysis to form network maps, and then analyzes interdisciplinary structural relationships, including network centrality, network density, network average path length and other contents [5].

This paper measures the disciplinary coherence by the discipline citation network and the discipline-keyword co-occurrence network. The discipline citation network consists of the citation relationship between the disciplines of the target literature and corresponding references, which can reflect the knowledge flow of different disciplines. Based on the discipline citation network, the article uses the centrality and edge weights in the social network analysis method to analyze the clusters formed, which can help to further understand the cross-structure characteristics of the subject areas. The above macroscopic analysis involves disciplinary attributes of target literature and references. The disciplinary attributes of the thesis itself are the direct source for measuring the intersection of disciplines. The knowledge and information input of other fields are characterized by the disciplinary attributes of references, which can better measure the phenomenon of knowledge integration and intersection in the discipline field [12]. The discipline citation network mainly shows the interdisciplinary coherence represented by internal target literature and external reference literature. On the other hand, in order to analyze the more fine-grained interdisciplinary relations, the discipline-keyword co-occurrence network of the target literature is constructed from the perspective of the topics, which can analyze the cross-topic that unites different disciplines. Keywords are an important representation of the topics of the papers, which can simply and directly explain the contents of the paper, and establishing the connections between keywords and disciplines is helpful to make a comparative analysis of the similarities and differences among discipline groups. In order to make the analysis of disciplinary topics more pertinent and hierarchical, the discipline groups are divided into three categories based on degree centrality in the co-occurrence network, including core, important and marginal disciplines. And the three types of networks are interpreted separately.

In general, the analysis framework established on the basis of existing research mainly includes two parts, disciplinary diversity and disciplinary coherence. Disciplinary diversity is measured by the distribution of disciplines, Shannon entropy and Rao-Stirling index. Disciplinary coherence includes two aspects, the discipline citation network and the discipline-keyword co-occurrence network. The overall research framework is shown in Fig. 1. In addition, all network maps in this paper are visually displayed using Gephi software. The software can flexibly set the layout, appearance and size of the node label, and can calculate corresponding statistical indicators, such as network density, various centrality, clustering coefficient, modularity and so on. Appropriate adjustments can be made by using relevant methods to finally present a clear, beautiful and highlighted network map.

\[
H = - \sum_i p_i \log(p_i) \tag{1}
\]

\[
D = \sum_{ij(i\neq j)} (p_i p_j - d_{ij}) \beta \tag{2}
\]
3. Analysis of Interdisciplinary Characteristics in Artificial Intelligence

3.1. Data Sources
The research object of this paper comes from Web of Science Core Collection. The search formula is WC = "Computer Science, Artificial Intelligence", and the year is from 1996 to 2017. A total of 771,375 articles were retrieved. The corresponding WC (Web of Science category), CR (References) and DE (Keywords) field are extracted. The WC fields are processed to obtain the disciplinary distribution of the target literature. For the references, since there is no citation category in the "CR" field, it is necessary to index the disciplinary categories for the journals in the references. The corresponding relationship between journals and disciplines in SCI-Expanded (Science Citation Index Expanded), SSCI (Social Sciences Citation Index) and A&HCI (Arts & Humanities Citation Index) has been selected for disciplinary classification in reference journals. There are some references in the "CR" field, such as some conference papers, which are unable to extract journal information, so the effective data are reduced relative to the total number of references cited. After processing, 278,9561 effective citation journal records were obtained, and the corresponding relationship between journals and disciplines were established.

3.2. Analysis of Disciplinary Diversity in Artificial Intelligence

3.2.1. Disciplinary distribution. Since the number of cited disciplines can visually demonstrate the interdisciplinary richness, the number of disciplinary categories involved are used to measure the richness of cross-disciplines. Fig. 2 shows the evolution of the number of disciplines involved in the target literature and its references between 1996 and 2017. It can be seen that with the passage of time, the number of disciplines involved in the target literature floats at around 50, and the proportion of disciplines involved in the general classification system is about 20%. Especially, it reaches its peak of 71 in 2007, showing the rapid development of artificial intelligence in this period, which may be related to the rise of the deep learning boom in 2006. The number of disciplines involved in the target literature with the number of records greater than or equal to 100 is roughly similar to the trend of the total number of disciplines, and the ratio of the number of disciplines (number of records greater than or equal to 100) to the corresponding total number of disciplines is about 50%, indicating the discipline distribution is relatively balanced. The number of disciplines in references has continued to increase since 1996, and has stabilized since around 2002. The types of disciplines involved account for nearly 96% of the total category system, which basically covers all categories in the system. And the discipline coverage is large. On the whole, the number curve of reference disciplines with the number of records greater than or equal to 100 shows an upward trend, indicating that the discipline distributions of citations gradually shift from relative concentration to relative average. That is to say,
the influence of many disciplines in the field of artificial intelligence is gradually increasing, and the fields of knowledge input are more extensive.

![Figure 2. Evolution of the number of disciplines in the field of artificial intelligence](image)

![Figure 3. Disciplinary distribution of artificial intelligence research (top 20)](image)

The discipline frequencies of target literature and reference literature were counted respectively. Due to the limitation of space, the top 20 disciplines of each side were selected, and 12 disciplines in the list of 20 disciplines of both sides were the same, as shown in Fig. 3 above. In addition to the first Computer Science, Artificial Intelligence, it also includes the five subcategories of Theory & Methods, Information Systems, Interdisciplinary Applications, Software Engineering, Hardware & Architecture in the Computer Science category. Obviously, a series of theories, methodologies and applications in the field of computer science are important sources of knowledge input and fusion in the field of artificial intelligence. The remaining six disciplines are Engineering, Electrical & Electronic, Automation & Control Systems, Robotics, Operations Research & Management Science, Mathematics, Applied and Neurosciences. In addition, the target disciplines include Engineering, Mechanical; Engineering, Manufacturing and other related disciplines of engineering, as well as biomedical science and imaging sciences. In the disciplines of references, it also includes Multidisciplinary Sciences, Management, Psychology, Mathematical & Computational Biology, Medical Imaging, etc., which are also important knowledge input channels in the field of artificial intelligence.
3.2.2. Analysis of Interdisciplinary Evolution. The Shannon entropy and Rao-Stirling indicators are used to represent the balance of the disciplinary distribution and the discrepancies between disciplines. The evolution of the disciplines is shown in Fig. 4. The overall fluctuation of Shannon value with time is not large, indicating that the distributions of interdisciplines are relatively balanced as a whole, and the Rao-Stirling value is also generally rising, indicating the expansion of differences between disciplines.

From 1996 to 1999, both the Shannon value and the Rao-Stirling value showed a rising trend. The increase of the Shannon value indicated that the disciplinary category distribution was more balanced. In particular, the Rao-Stirling value had risen rapidly, indicating that a large number of new disciplines had been poured into the field of artificial intelligence at this stage, and these new research methods and theories were gradually developing. A similar situation occurred between 2000-2002 and 2004-2007. From 1999 to 2000, the value of Rao-Stirling declined rapidly, and the value of Shannon also decreased. It indicated that the research of artificial intelligence was been supported by some specific disciplines, and it was relatively concentrated in the discussion of certain fields or hot issues. A similar situation also occurred in 2002-2004, 2007-2008, 2009-2011. From 2008 to 2009, the value of Shannon continued to increase, while the value of Rao-Stirling continued to decline. It showed that the disciplinary gap was decreasing, there were many similar disciplines in the field, and the discipline development was relatively balanced. The theories, methods and related applications involved in the disciplinary groups had been relatively perfect, and the influence of some marginal research fields or methods had gradually decreased [13]. From 2011 to 2017, the value of Shannon was basically stable. The Rao-Stirling value increased slightly from 2011 to 2012, and then remained stable. It showed that the disciplinary groups cited in the field of artificial intelligence had been relatively fixed, and its development had entered a mature stage.

![Figure 4. Evolution diagram of interdisciplinary indicators in the field of artificial intelligence](image-url)
3.3. Analysis of disciplinary coherence in the field of artificial intelligence

3.3.1. Analysis of discipline citation network

Based on the disciplinary categories of literature and their citations extracted above, the corresponding relationship between the two is established. The relevant cited frequencies are counted to form a matrix and then visualized, as shown in Fig. 5. It shows the flow of disciplinary knowledge in the context of artificial intelligence and the four aspects of discipline self-citation rate, discipline inter-citation rate, network characteristics and discipline clusters are analyzed.

a) Discipline self-citation rate

The self-citation rate of a discipline refers to the ratio of the number of citations when the discipline of the document is consistent with its citation discipline to the total number of citations of the discipline, which reflects the active degree of knowledge flow within the discipline. For example, the total citation number of discipline A is M, and the number of discipline A that refers to discipline A is N. Then the self-citation rate of discipline A is equal to N divided by M. From a holistic perspective, the total self-citation rate of the disciplines involved in the data set is about 12%, of which the disciplines with higher self-citation rate are Neurosciences (34%); Radiology, Nuclear Medicine & Medical Imaging (22%); Chemistry, Analytical (18%); Operations Research & Management Science (17%); Computer Science, Artificial Intelligence (17%); Engineering, Manufacturing (14%); Mathematics, Applied (12%) and so on.

b) Discipline inter-citation rate

Inter-citation of disciplines show the flow of knowledge among different disciplines. By observing Fig. 5, it can be found that the most basic structure is the discipline citation network centered on Computer Science, Artificial Intelligence. The main knowledge inflow disciplines of Computer Science, Artificial Intelligence, in addition to itself, also include Neurosciences; Engineering, Electrical & Electronic; Operations Research & Management Science; Computer Science, Theory & Methods; Computer Science, Information Systems; Computer Science, Software Engineering; Computer Science, Interdisciplinary Applications; Mathematics, Applied; Automation & Control Systems; Computer Science, Hardware & Architecture and other disciplines. At the same time, these disciplines have higher values of degree centrality, closeness centrality and between centrality, which are core nodes in the network graph.

c) Network characteristics
In addition to the disciplines mentioned in b), in terms of closeness centrality, Multidisciplinary Sciences; Radiology, Nuclear Medicine & Medical Imaging; Biochemical Research Methods have higher values, indicating that these disciplines are also relatively central in the network and can reach other nodes faster. In terms of between centrality, the values of Radiology, Nuclear Medicine & Medical Imaging; Psychology, Experimental; Mathematical & Computational Biology are relatively high, indicating that these disciplines have a strong mediating role in the network. In terms of eigenvector centrality, Computer Science, Cybernetics; Imaging Science & Photographic Technology; Telecommunications have higher values. Since the eigenvector centrality is calculated according to the importance of its neighbors, it represents the great potential value of these disciplines to a certain extent.

d) Discipline clusters

Five closely related discipline groups are presented (circled sections in Fig. 5). When the target discipline is neuroscience, its input sources include not only a series of disciplines related to computer science, but also Psychology, Experimental; Mathematical & Computational Biology. The frequencies of interdisciplinary citation among Automation & Control Systems; Chemistry, Analytical; Engineering, Chemical; Biochemical Research Methods; Instruments & Instrumentation; Statistics & Probability and Mathematics, Interdisciplinary Applications are relatively high, resulting in the formation of the dense interdisciplinary citation module. In addition, it has formed a collection of medical disciplines represented by Engineering, Biomedical; Neuroimaging; Imaging science & photographic technology; Medical Informatics. It also forms a set of engineering disciplines represented by Engineering, Electrical & Electronic; Engineering, Manufacturing; Engineering, Industrial and Engineering, Multidisciplinary. However, some disciplines such as Management; Business; Economics; Telecommunications; Information Science & Library Science are at the relative edge of the network diagram.

3.3.2. Analysis of Interdisciplinary Topics. In order to more clearly show the interdisciplinary relationships involved in the field of artificial intelligence, the co-occurrence network of the disciplines is constructed as shown in Fig. 6. The disciplines are divided into three levels according to the distribution proportion of related disciplines mentioned above and the degree centrality in Fig. 6. The disciplines with a value range of more than 100,000 are divided into core disciplines, with a total of 10 disciplines; the disciplines with a range of 10,000 to 100,000 are divided into important disciplines, with a total of 25 disciplines; the disciplines with a value range of 10,000 or less are divided into marginal disciplines, with a total of 35 disciplines. Then, according to the division of core disciplines, important disciplines and marginal disciplines, the corresponding records in the dataset are extracted, and the discipline-keyword co-occurrence networks are established to observe the situation of interdisciplinary topics.
Figure 6. The co-occurrence network of the disciplines in the field of artificial intelligence.

a) Cross-topic network analysis of core disciplines

The core discipline-keyword co-occurrence network is shown in Fig. 7. The topic domain represented by computer vision, feature selection, pattern recognition, image processing, neural network, machine learning, evolutionary algorithms, genetic algorithms, data mining and other keywords is located in the center of the network diagram, which connects with multiple disciplines in the graph. It indicates that this part of the topics are the focus of research in the field of artificial intelligence.

Specifically, the overlapping topics of Computer Science, Information Systems; Computer Science, Theory & Methods; Engineering, Electrical & Electronic also include knowledge domains such as deep learning, natural language processing, information retrieval, expert system, recommendation system, social network and knowledge management. The cross topics of Computer Science, Theory & Methods and Engineering, Electrical & Electronic also involve augmented reality, target tracking, biometric identification technology, and some optimization of dimensionality reduction methods. The common research topics of Engineering, Electrical & Electronic and Imaging Science & Photographic Technology include image registration, image segmentation, video coding. The cross topics of Engineering, Electrical & Electronic and Automation & Control Systems cover fault detection and diagnosis, nonlinear systems, fuzzy systems, system identification and some cybernetic contents such as robust control, optimal control, and sliding mode control. The research focus of Automation & Control Systems and Robotics involve mobile robots, adaptive control, path planning, and position locking. Computer Science, Theory & Methods and Computer Science, Information Systems are connected in subject domains of relational data, knowledge representation, online learning, and performance design. And Computer Science, Theory & Methods; Computer Science, Software Engineering and Computer Science, Interdisciplinary Applications are connected at the topics of ontology, multi-agent systems, classification and clustering, simulation and optimization and so on.

In addition, Computer Science, Theory & Methods also involve swarm intelligence, evolutionary computation, genetic programming, rough sets, local search and so on. Computer Science, Information Systems include knowledge discovery, association rules, information extraction, sentiment analysis, decision support and formulation. Engineering, Electrical & Electronic cover image classification, retrieval, recovery, compression, denoising, enhancement, fusion, reconstruction, coding, edge detection and other image processing contents, some contents of signal processing such as speech recognition and synthesis, computer vision and machine vision contents such as target recognition,
detection, tracking, sparse representation, semi-supervised learning, unsupervised learning, and reinforcement learning and other method contents.

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**Figure 7. Core discipline-keyword co-occurrence network**

b) Cross-topic network analysis of important disciplines

The important discipline-keyword co-occurrence network is shown in Fig. 8. Compared with core disciplines involving major subordinate categories of computer science and engineering, important disciplines include some sub-categories of basic disciplines such as mathematics, chemistry and physics, as well as related subordinate disciplines of applied disciplines such as management and medicine.

The common topic areas of Chemistry, Analytical; Mathematics, Interdisciplinary Applications; Instruments & Instrumentation and Statistics & Probability include stoichiometry, variable selection and corresponding partial least squares, multivariate correction, principal component analysis and other principles and methods. And Instruments & Instrumentation tend to use the above methods and related algorithms such as wavelet transform for image processing, process monitoring, fault diagnosis and optimization. In addition, Neurosciences involve the attention, learning and memory mechanisms of brain cognition such as "reinforcement learning" and "working memory." The common research topics of Optics; Mathematics, Applied; Radiology, Nuclear Medicine & Medical Imaging; Engineering, Biomedical are "image processing", "image segmentation", "image registration" and other related research. The research points of Mathematical & Computational Biology mainly focus on biometric recognition, including face recognition, feature extraction and function selection, as well as some applications of swarm intelligence algorithms in this area, such as ant colony algorithm, particle swarm optimization algorithm and so on. Operations Research & Management Science focus more on the use of data envelopment analysis, case-based reasoning, the analytic hierarchy process and some intelligent algorithms to help complete multi-objective optimization, fault diagnosis and prediction, supply chain scheduling, decision making and other tasks.
Figure 8. Important discipline-keyword co-occurrence network

c) Cross-topic network analysis of marginal disciplines

The marginal discipline-keyword co-occurrence network is shown in Fig. 9. The marginal disciplines mainly involve some disciplines related to the application of artificial intelligence, and in contrast, the research topics of the marginal disciplines are relatively independent. The discipline of the network center is Energy & Fuels, its keywords include power system, power quality, power market, voltage control and other topics related to the power industry, and the application of some methods and technologies of artificial intelligence in the power industry, such as artificial neural networks, genetic algorithms, etc. The related methods can be used for voltage control, transient stability analysis and fault diagnosis, which is beneficial to saving cost, balancing power allocation and optimizing system operation. The three disciplines of Business, Finance; Business and Information Science & Library Science all involve the fields of "knowledge management" and "risk management". In addition, the topics of Business, Finance include project management, supply chain management and corporate governance. Information Science & Library Science mainly cover digital library, ontology, visualization and other related research. The main focus of Education & Educational Research is to use data mining, virtual reality and other technologies to help collaborative learning, hybrid learning and the development of intelligent tutoring systems. Through the topic domain of "learning", this discipline is also linked to Psychology, Experimental, which involves extended intelligence, emotional cognition and reinforcement learning. In addition to the above disciplines, the Fig. 9 also shows the Logic, which includes "fuzzy logic", "modal logic" and "multivalued logic", and the Linguistics, which includes "machine translation", "natural language processing", etc.
4. Conclusion

In the past two decades, research in the field of artificial intelligence involves a variety of disciplines. And the number of disciplines in the target literature is relatively stable, while the number of citation disciplines involved gradually increases and eventually covers all categories of systems, showing the diversity of knowledge needs in the field. From the perspective of Shannon entropy and Rao-Stirling value, the field has experienced the stages of large influx of new disciplines, concentrated development of specific disciplines or hotspots, gradual maturity of relevant theoretical methods and applied fields. Specifically, no matter from the perspective of target literature or reference literature, the theories and methods, information systems, interdisciplinary applications and other disciplines under the category of computer science have a high impact. Secondly, Neurosciences; Engineering, Electrical & Electronic; Operations Research & Management Science; Automation & Control Systems and other disciplines also occupy an important position. Through the analysis of the discipline citation network, it is found that Neurosciences and Radiology, Nuclear Medicine & Medical Imaging have high self-citation rates of disciplines, and some typical discipline clusters such as medicine and engineering have been formed by the citation relationship. In addition, the node indicators of the co-occurrence network are used to stratify the disciplines in order to analyze the intersections and differences of the disciplinary topics pointedly. In general, this paper has described disciplinary quantitative characteristics, structural characteristics and thematic characteristics of artificial intelligence in a multi-dimensional way, which is helpful for relevant scholars to understand the disciplinary information in this field.

In addition, the limitation of this study is that it only counts the distribution of the disciplines in journal records included in the citations. The data obtained are representative to a certain extent, but not extensive. In terms of disciplinary topics, although the hierarchy is considered, the analysis of the topics does not take into account the time dimension and ignores the cross-evolution of disciplinary topics. These issues need to be further explored in the future.

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