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PATENT RESEARCH IN LITERATURE. LANDSCAPE AND TRENDS WITH ACADEMIA ON PATENT ANALYSIS

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ABSTRACT

This study uses data to look at patent research,andit uses citation network analysis to group and look at different areas of research. We show that patent research covers many connected topics, including basic patent systems, creating indicators, improving methods, managing intellectual property,and various uses of patents. We highlight key areas like patent strategies,how technology affects things,and studying patent citations. We also point out new areas thatare becoming more important, such as environmental sustainability and corporate innovation. We focus especially on patent analytics,whichare becoming more important for understanding innovation and economic growth. This survey looked athow patents canbe used to measure changes in technology. Atthat time, scholars were interested in using patent citations and considered them"important."

INTRODUCTION

Despite the rapid increase in academic literature exploring patents or leveraging patent documents and data, a current and comprehensive overview that captures the landscape of patent.work on patents and using patent data,there's still no complete and update picture that hows the full picture of patent research. Having sucha broad view is really useful can show where new topics are forming andwhat research is becoming more popular, helping scientists and professionals focus on areas thatare gaining importance. Second, looking at the whole area of patent research can highlight how specialized fields like patent analytics are used andcan do. This helps researchers working on quantitative methods for analyzing patents to concentrate on areas wherethese tools can make the biggest difference. Lastly, understanding the academic landscape can bring together differentbeen working in isolation by showing how patent analytics canbe applied in various ways. To address this gap, our study aims to provide a landscape of patent research within academic literature. By surveying scholarly literature, we uncover major research topics, identify their interrelationships, and track evolving trends over time. We pay particular attention to the distinct and complementary studies of patent analytics, which have grown increasingly important for understanding innovation and economic progress. Specifically, this article addresses the following research questions:

1. How is patent information used in academic research?
2. What are the current trends in patent research?

We explore the relevance of patents and scholarly patent research in general, while covering previous efforts in mapping the field of patent analytics. The methods section details our data extraction and analysis techniques. In the results section, we present our findings on the current landscape of patent research, with a focus on emerging trends and key areas of development. We conclude by discussing future directions for interdisciplinary research and shifts in methodological approaches within the field of patent research and analytics.

PREVIOUS LITERATURE

A landmark contribution came from Trajtenberg (1990), who studied the computed tomography scanner industry. By combining patent data with market information, Trajtenberg demonstrated that while raw patent counts correlated poorly with social value creation, citation-weighted patent counts showed a strong correlation (around 0.75) with total social welfare created. This finding has been corroborated by subsequent studies, such as Harhoff et al. (1999) and Hall et al. (2005), establishing the importance of patent citations as indicators of economic and technological significance.

The analysis of patent citation networks emerged as a distinct field of study in the latter half of the 20th century. Early work by de Solla Price (1965) highlighted the importance of citation analysis in understanding scientific and technological development. The 1980s and 1990s saw the formalization of quantitative approaches, with Narin (1994) introducing various patent metrics for the study of Innovation. The release of the NBER Patent Citations Data File in 1990 provided researchers with a comprehensive dataset, spurring further studies on knowledge spillovers and innovation diffusion (Hall et al., 2001).

More recently, patent analytics has expanded its applications across various domains of technology management and innovation policy. Key areas include competitive intelligence, technology forecasting, R&D planning, merger and acquisition analysis, and policy evaluation. The exponential growth in global patent data, with 2022 alone estimated at 3.46 million patent applications worldwide (WIPO, 2023), has needed the development of more sophisticated and automated methods for analysis. Thus, the field has benefited from the integration of advanced techniques such as text mining, natural language processing, network analysis, and machine learning. This plurality of methodologies and scopes has led to the emergence of various terms describing the field, like patent bibliometrics (Narin, 1994), patinformatics (Trippe, 2003), and technology mining or tech mining (Porter, 2004), each with nuanced scopes and target applications, reflecting its multidisciplinary nature.

The use of patents by academics has been surveyed in the past, with the work of Basberg (1987) being an early example. This survey focused on the use of patents to measure technological change. Scholars at the time were concerned with the use of patent citations, finding “important” patents, and benchmarking innovation across regions. A comprehensive survey by Griliches (1990) reviewed several decades of research on patent statistics as economic indicators. He examined multiple data sources, including patent counts, renewal data, and stock market valuations. His survey synthesized evidence from studies using the U.S. Patent Office data, European patent renewal information, and firm-level R&D expenditure data highlighting critical measurement challenges, including the highly skewed distribution of patent values and variations in patenting propensity across industries and time. Griliches' synthesis helped establish methodological frameworks for evaluating patent quality and understanding the limitations of patent statistics as innovation indicators. More recent efforts have adopted computer-assisted methods to bring a more systematized understanding of the field by using bibliometrics (Mejia et al., 2021). Mikova (2016) analyzed Global TechMining conference proceedings from 2011 to 2015, identifying trends such as the integration of multiple approaches (e.g., bibliometrics, NLP, statistical analysis) and the use of novel data sources (e.g., web data, social media). Aristodemou and Tietze (2018) reviewed 57 articles on applying AI, machine learning, and deep learning to intellectual property data, categorizing them into knowledge management, technology management, economic value, and information extraction/management. The study found a growing interest in intellectual property (IP) analytics but called for more research on use cases and firm-level applications. Karata et al. (2024) analyzed 1,006 papers on “patent analysis,” revealing trough a descriptive approach that “technology” was the most common keyword and that top journals included “Technological Forecasting and Social Change” and “Information Processing & Management.” Hu et al. (2024) explored the foundations and frontiers of technology mining using co-citation analysis, bibliographic coupling, and content analysis of 277 articles. The study identified text analysis, bibliometrics, patent analysis, and strategic technology management as foundational areas, with technology topic analysis, roadmapping, component analysis, opportunity analysis, and management/decision support as frontier clusters.

MATERIALS AND METHODS

To identify relevant articles, a topical search was conducted using the query TS = "patent*", where the asterisk serves as a truncation symbol to accommodate variations of the term (e.g., patents). The search was performed without time constraints, retrieving articles from all available years in the database. Data were retrieved on May 31, 2024, yielding 103,738 articles.

While comprehensive, the query also retrieves articles unrelated to the target topic due to the various meanings of the term "patent". In addition to referring to intellectual property documents, "patent" may be used as an adjective to denote open, unobstructed, or accessible, particularly in biomedical research. For example, there is extensive research on patent ductus arteriosus, a congenital heart defect (Schneider and Moore, 2006). Other deviating meanings include its use as a synonym for obvious, clear, or apparent. From a document retrieval standpoint, it may be tempting to generate a list of banned keywords (e.g., to be used with the NOT operator), but this would result in neglecting patent analytics papers on those alternative meanings [for instance, patent analysis of patent ductus research (Hsieh et al., 2004)]. Therefore, to focus on our target topic, citation networks were employed as both a data-cleaning mechanism and a means to extract thematic clusters.

Academic articles are positioned within a research field by citing previous related research. Articles that do not cite nor are cited by other articles were excluded from the study, as these are the papers that used the keyword "patent" without belonging to the patent research domain. A direct citation network was constructed, establishing linkages between articles when one cites the other (de Solla Price, 1965). Direct citation networks are known to surface research field taxonomies (Klavans and Boyack, 2017) and help identify research fronts (Shibata et al., 2008), making them suitable for long-term bibliometric research. However, this network would also contain papers in other fields of research, such as in biomedicine, that may cover other meanings of patents. To exclude these, thematic clusters were extracted, and after human inspection, unrelated clusters were pruned from the citation network. During this step, the final cleaning was conducted, and unrelated clusters were removed from the study.

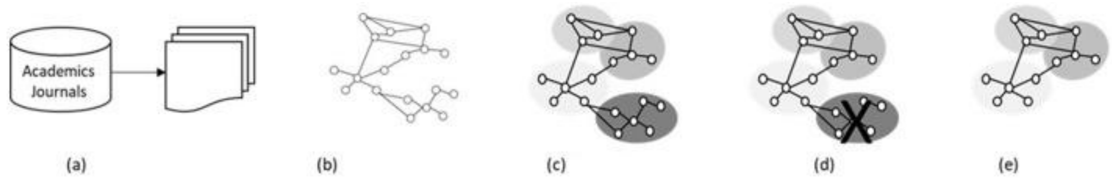

Figure 1 Represents a Summary of the Methodology.

RESULTS

Original dataset, 53,668 articles used alternative meanings of the term “patent” that are not part of the core of patent research. These papers are disconnected from the main corpus of knowledge as they do not cite or receive citations from other patent-related literature. The rest of the articles compose the citation network of patents-related literature, covering 50,070 articles. The US and China have been the largest contributors to patent-related literature, with China consolidating its position as the country with the most publications since 2020. In 2023, more than 35% of publications came from China, while the US followed at 17%. The United Kingdom (UK) has consistently maintained its position as the third-largest contributor. The study of patents spans across various fields, with Economics, Management, and Law being the most prominent.

DISCUSSION

The results show a steady increase in the use of patent documents in academic research. We note that the interest in academia is shared by two distinct but highly integrated groups, one that focuses on management and innovation studies and the other that is more applied to pharma and biomedical research. For instance, clusters such as “Patent Analytics and Innovation Dynamics” and “Advanced Methods in Patent Analytics and Technology Forecasting” dominate the first, while “Patent Systems and Biomedical Innovations” dominates the second. Emerging trends in environmental sustainability and biomedical innovations were identified, as evidenced by the recent and rapidly growing subclusters in these areas. The analysis also revealed the widespread integration of advanced analytical techniques.

CONCLUSION

We identified 93 research streams from academic literature that use the patent document in any form; these topics were evaluated in terms of size, recency, citation impact, and growth, revealing relevant trends. These include an increased focus on AI methods and the application of patent analytics for sustainability and evaluation of corporate performance. We further organized the topics to reach a five-core component framework encompassing fundamentals of patent systems, patents as indicators, methodological developments, IP management practices, and applications. By proposing an integrated framework and identifying key trends and challenges, we contribute to both the theoretical understanding and practical application of patent analytics. Future research should focus on addressing these challenges while continuing to explore novel applications of patent analytics across various domains of science and technology and also in various sectors, such as academia.

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