Early Identification of Breakthrough Innovation and Weak Signal Analysis: A Review (Postprint)

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Abstract

[目的/意义] Through comparative analysis of different breakthrough innovation identification methods, this study summarizes the existing problems in current approaches and introduces weak signals into breakthrough innovation identification research, focusing on various weak signals in the early stages of breakthrough innovation, particularly weak association relationship analysis, to achieve early prediction.

[方法/过程] First, by investigating existing identification methods, the main problems are extracted and the necessity of studying weak signals is articulated. Then, from different disciplinary perspectives, the connotation and representation forms of weak signals are introduced, their characteristics are summarized, and several identification methods for weak signals are reviewed. Finally, the connotation and application of weak relationship analysis are introduced, proposing that leveraging multi-relationship fusion algorithm models can achieve effective integration of various weak relationships to obtain more explicit information.

[结果/结论] In breakthrough innovation identification research, the most attention is paid to strong relationship data such as citation relationships among publications and semantic relationships between keywords, while weak relationships contain more diversified information. Strengthening weak relationship analysis can enable early prediction of breakthrough innovation research. Future research should seek effective methods for capturing weak associations, focus on the dynamic evolution patterns of topics, such as using high-order network models to analyze effective weak signals, and improve the accuracy of early identification of breakthrough innovation.

Full Text

Abstract

[**Purpose/Significance**] This paper summarizes the disadvantages of various breakthrough innovation identification methods through comparative analysis, introduces weak signals into breakthrough innovation research identification, and focuses on various weak signals in the early stages of breakthrough innovation—particularly weak relationship analysis—to achieve early prediction. [**Method/Process**] First, by investigating existing identification methods, this study extracts current main problems and points out the necessity of weak signal research. Next, it introduces the connotation and representation forms of weak signals from different disciplinary perspectives, summarizes their characteristics, and reviews several identification methods. Finally, it introduces the connotation and application of weak relationship analysis, proposing that a multi-relationship fusion algorithm model can achieve effective integration of multiple weak relationships to obtain clearer information. [**Result/Conclusion**] In breakthrough innovation identification research, most attention has been paid to strong relationship data such as citation relationships between documents and semantic relationships between keywords. However, weak relationships contain more diversified information. Strengthening weak relationship analysis can enable early prediction of breakthrough innovation research. Future research needs to seek effective methods for capturing weak associations, focus on the dynamic evolution patterns of topics, and improve the accuracy of early breakthrough innovation identification—for example, by using high-order network models to analyze effective weak signals.

Keywords: breakthrough innovation; early identification; weak signal; weak relationship; relationship fusion

Introduction

The world today is witnessing the gestation of the sixth scientific and technological revolution, with major breakthroughs continuously emerging in the science and technology system that are profoundly changing the economic landscape of society. Compared with incremental research, breakthrough innovation represents a higher degree of innovation and indicates the most forward-looking development direction in the process of scientific and technological innovation. How to identify and predict major discoveries with breakthrough innovation potential from emerging topics is crucial for policy formulation and corporate strategic layout. However, many scientific breakthroughs and creative discoveries have high uncertainty and ambiguity in their early stages of development, increasing the difficulty of detecting early signs. Therefore, how to pay attention to early signs at the beginning of research projects and predict their future transformative potential is an urgent and challenging problem in science policy and research evaluation.

Although various methods for identifying breakthrough research exist, most identification results already appear during the rapid development or maturity period of research fields, rather than enabling early identification, resulting in insufficient forward-looking prediction. Currently, qualitative methods dominated by expert judgment remain important means for detecting future scientific and technological development trends. However, with the explosion of interdisciplinary integration and data, expert wisdom alone cannot quickly and accurately achieve optimal effectiveness. Quantitative methods commonly used to detect breakthrough innovation, such as citation network analysis, topic mutation detection, Sleeping Beauty literature analysis, and technology evolution methods, mostly focus on "strong signals" like high citations and strong co-occurrence, without deeply utilizing "weak signals" that are helpful for early identification. Weak signals herald future changes, and their specific manifestations are often phenomena, events, opportunities, or threats. Analyzing weak signals can help us understand and control the future development of things earlier.

Given this, this study follows the laws of scientific development, considers the uncertainties in the process of scientific development, reviews weak signal analysis methods, and explores their application in breakthrough innovation identification. This paper first introduces relevant concepts of breakthrough innovation, summarizes its nonlinear and uncertain characteristics, then reviews existing identification methods for breakthrough research and their problems. On this basis, it introduces weak signals, explains their concepts, characteristics, and identification methods, and elaborates on the feasibility of using weak signals for early identification of breakthrough innovation. Finally, it proposes directions for future research on early identification of breakthrough innovation.

2 Research Status

2.1 Connotation of Breakthrough Innovation

2.1.1 Definition of Breakthrough Innovation Breakthrough innovation originated from Schumpeter' s "creative destruction" [1]. After G. Dosi and R. R. Nelson published "Technological Paradigms and Technological Trajectories," which unified breakthrough technological innovation and incremental technological innovation within one theoretical framework, research on breakthrough innovation began [2]. Researchers have different understandings and cognitions of breakthrough innovation. Our investigation reveals that most research focuses on two main aspects: technological improvement, product performance enhancement, and market value; and breakthrough discoveries in scientific research and new theoretical foundations of knowledge. As shown in Table 1 , representative studies include various definitions emphasizing non-continuous, revolutionary innovation with new scientific knowledge and resources that eliminates existing technologies and products.

2.1.2 Characteristics of Breakthrough Innovation The characteristics of breakthrough innovation are complex, and no consistent and comprehensive interpretation has been formed in the academic community. This paper focuses on analyzing researchers' descriptions of breakthrough innovation characteristics in basic scientific research, as summarized in Table 2 : novelty/future-orientation, nonlinearity/discontinuity, and uncertainty. Breakthrough research is usually based on new scientific principles or technical means, leading future scientific and technological development. Scientific development is nonlinear, and breakthrough innovation research may cause discontinuous fault phenomena. Each breakthrough has accidental factors, and breakthrough innovation development contains strong uncertainty, making prediction difficult.

2.1.3 Classification and Predictability of Breakthrough Innovation Breakthrough innovations vary in their opportunities and magnitude of change, appearing in multiple forms that present different challenges for identification and prediction. Currently, there is no unified classification standard. D. E. Koshland reviewed the history of scientific development and divided breakthrough innovation into three types, forming the influential "Cha-Cha-Cha" theory [23], as shown in Table 3 : Charge type (explaining common phenomena), Challenge type (explaining anomalous phenomena), and Chance type (accidental discoveries). Most breakthrough innovations that promote scientific progress are not accidental but require researchers to think about various facts and problems, connecting independent and seemingly unrelated information.

A breakthrough innovation is often considered "discontinuous" in the existing scientific system. However, if we "zoom in" on the specific content at the breakpoint, breakthrough innovation is actually related to previous research. Its generation and development process is "continuous," which is the premise for predictability. As shown in Figure 1 [Figure 1: see original paper], which illustrates the scientific development process in a Cartesian coordinate system, breakthrough innovations (A, B, C) represent "leaps" within four stages of incremental innovation (I, II, III, IV). When magnified, the generation and development of breakthrough innovation are traceable and predictable.

2.2 Breakthrough Innovation Identification Methods

Breakthrough innovation has few early signals and is difficult to identify because it often conflicts with existing scientific theories and exceeds people' s cognition and technical levels, leading to resistance from the scientific community [24]. Researchers have explored identification methods, with expert judgment-based qualitative analysis remaining important. However, in the era of interdisciplinary integration, relying solely on experts may not yield the most accurate results. Data processing, analysis tools, and algorithms have become effective auxiliary means.

Different identification methods have specific applicability, advantages, and disadvantages, as shown in Table 4 : - **Expert judgment**: Uses expert wisdom but is subjective and inefficient in interdisciplinary contexts - **Citation network analysis**: Uses citation relationships but has lag time - **Topic mutation monitoring**: Focuses on keyword changes but ignores semantic associations - **Sleeping Beauty literature analysis**: Explores delayed recognition but covers only a small portion - **Technology evolution perspective**: Identifies track transitions but lacks universal metrics - **Machine learning algorithms**: Handles large complex data but requires expertise and experimentation

2.3 Main Problems with Existing Identification Methods

2.3.1 Focus on Hotspot Monitoring Rather Than Early Identification Current research fails to effectively capture "early signals" of breakthrough innovation topics, causing identification lag. Most methods detect hotspot themes during rapid development or maturity periods rather than early stages. The earlier the stage, the less information available and the greater the difficulty. Knowledge novelty is hard to quantify, and early signals carry uncertainty about future impact.

2.3.2 Insufficient Mining and Analysis of Weak Relationships Existing methods mostly target "strong signals" like highly cited documents. In topic clustering, co-word analysis often uses high-frequency words, while low-frequency word clusters cannot be reflected. Breakthrough innovations often exist as weak associations (weak relationships) between topics in their infancy. These weak relationships represent different data objects from high-frequency words and strong relationships, possibly reflecting true nature. However, due to technical limitations and cognitive levels, weak associations only serve as simple auxiliary monitoring means without being fully mined.

2.3.3 Lack of Universal Evolutionary Patterns for Breakthrough Innovation Topics Identifying breakthrough innovation requires understanding knowledge states before and after its emergence and having a holistic understanding of knowledge diffusion. Topic evolution patterns can reveal generation, development, evolution, and decline processes, enabling trend inference. Although researchers have introduced time series and deep semantic associations, results remain limited due to scientific uncertainty and difficulty in designing quantitative measurement methods that accurately show evolution patterns.

3 Weak Signals and Their Identification and Application

3.1 Concepts of Weak Signals

The term "signal" first appeared in electronic communications and military fields, generally including optical, acoustic, and electrical signals—physical quantities or pulses that carry information [48]. Early signals often carry effective information about future development but are weak and difficult to perceive. With technological development, detecting weak signals masked by noise has received increasing attention, and weak signal research has gradually shifted from engineering to social management.

Three fields have extensively discussed weak signal concepts:

Market Economics Perspective: Signals are information sets that help rational people make value judgments, not necessarily tangible. American economist Spence first used "market signals" to explain how sellers reduce information asymmetry [49]. O. Heil and T. S. Robertson defined market signals as declarations and rehearsals of potential actions, distinguishing them from market behavior and classifying them as strong or weak based on information volume [50]. G. S. Day and P. J. H. Schoemaker noted weak signals are ambiguous, uncertain, and mixed with noise—neglecting them may cause companies to lose new markets [51].

Corporate Strategic Planning Perspective: H. Ansoff first proposed weak signals for strategic surprise issues in corporate strategic management, describing them as early signs with uncertain impacts on future development [52-53]. B. Coffman detailed specific types: ideas affecting corporate environment, threats or opportunities, and aids for growth [54]. J. S. Brown argued companies need to scan business environments to capture early weak signals for strategic insights [55].

Futures Studies Perspective: Finnish scholars discussed weak signals as early warnings of future change. O. Kuusi et al. identified two views: weak signals are early warnings whose importance depends on receiver cognition, or they are objective phenomena with fundamental future impacts [58]. E. Hiltunen interpreted weak signals from three dimensions: quantity, underlying information, and understanding, noting any dimension' s increase strengthens the signal [61].

3.2 Characteristics of Weak Signals

Researchers' descriptions of weak signals share commonalities: uncertain impact, fragmentation, interpretive complexity, evolution into trends, and guiding future change. Table 5 summarizes these characteristics: weak signals are incomplete, widely dispersed, small in quantity, difficult to understand, and rarely noticed; they persist from first appearance to strengthening or disappearance; they are ambiguous in information and future impact; they relate to potential phenomena with delayed but significant consequences; and they are objective but their utility is linked to receivers.

Weak signals are early manifestations of breakthrough innovation. As time passes, weak signals gradually strengthen and become more detectable. Therefore, focusing on early weak signal acquisition and analysis makes early identification possible.

3.3 Weak Signal Identification Methods

3.3.1 Environmental Scanning Method Weak signals mixed with noise have reduced detectability. H. I. Ansoff and E. J. McDonnell proposed a three-layer filter: monitoring layer (capturing weak signals), mental layer (iterative assessment of relevance and value), and propulsion layer (decision support) [53]. R. Wagner et al. proposed network-based scanning using information foraging theory and vector space models [74]. E. Amanatidou et al. suggested two phases: exploratory scanning with keywords, evaluation, and clustering; and issue-focused scanning for secondary weak signal identification [75].

3.3.2 Scenario Analysis Method This method amplifies weak signals through detailed reasoning to construct multiple future scenarios, gradually clarifying valuable signals and reducing cognitive bias [64]. However, it requires many reasoning steps, takes time, and is highly subjective. P. J. H. Schoemaker et al. combined scenario planning with business analysis to accelerate weak-to-strong signal conversion, designing a "strategic radar" tool [63]. V. Kaufmann and E. Ravalet used scenario planning to project French population mobility trends by 2050 [76]. P. Meissner et al. built a structured framework integrating expert judgment to monitor blind spots and weak signals in scenario planning [77].

3.3.3 Fuzzy Comprehensive Evaluation Method Based on fuzzy mathematics, this method quantifies incomplete information through: information screening, measurement (grading and weighting), and comprehensive evaluation [78]. It converts fuzzy judgments into quantitative analysis for rapid decision-making when information is limited. Deng Shengli et al. used this with AHP to quantitatively identify competitive weak signals [57]. Dong Yin and Liu Qianli applied fuzzy TOPSIS for supply chain risk weak signal observation [79]. However, weight assignment is subjective.

3.3.4 Catastrophe Theory Identification Method Catastrophe phenomena are universal in nature, and scientific development has gradual-to-sudden change characteristics [80]. Catastrophe theory uses mathematical models to describe qualitative changes from continuous action interruption, predicting complex system behavior [81]. When systems reach critical points, small disturbances may cause mutations—a phenomenon called critical slowing down with precursors like slower recovery, increased autocorrelation, and increased variance [82]. Wu Hao et al. used variance and autocorrelation to detect climate mutation precursors [83]. However, M. Scheffer noted critical slowing down only indicates increased possibility of transition, not specific warnings [84]. R. J. Perla and J. Carifio argued Kuhn' s incremental and revolutionary innovations correspond to continuous change and critical point mutations, making catastrophe theory logical for scientific epistemology frameworks [85].

3.3.5 Machine Learning Detection Methods In the big data era, weak signal identification increasingly relies on technical means like text mining, Bayesian networks, latent semantic analysis, and local outlier factors. J. Yoon proposed a keyword-based text mining method for weak signal topics [86]. D. Thorleuchter and D. P. Vanden used latent semantic indexing for clustering analysis [87-88]. Korea' s NEST model uses Bayesian network clustering with pattern recognition [89]. J. Kim and C. Lee combined text mining with local outlier factors to improve detection sensitivity [90]. G. Joanny et al. generated multi-word concept dictionaries for disruptive technology prediction [91].

3.3.6 Comparison of Weak Signal Identification Methods Table 6 compares the methods: environmental scanning (rich information but high professional requirements), scenario analysis (amplifies signals but subjective and time-consuming), fuzzy evaluation (quantifies qualitative information but subjective weighting), catastrophe theory (detects critical thresholds but low accuracy), and machine learning (handles large data volumes but requires expertise and resources). Weak signal identification is a complex, uncertain process requiring collection of incomplete information and selection of relevant signals. Breakthrough innovations exist as weak relationships between topics in their infancy, making weak relationship analysis crucial for early identification.

4 Weak Relationship Analysis and Its Application

4.1 Connotation of Weak Relationships

The term "weak ties"originated in sociology. M. S. Granovetter noted strong connections represent high interaction with homogeneous information, while weak ties are bridges between different groups, providing heterogeneous information for new opportunities and technological innovation [92]. Weak relationships are a relative concept, defined as network connections between nodes that fall below a certain threshold. As shown in Figure 2 [Figure 2: see original paper], core layer nodes have strong direct connections, while outer layer nodes require many intermediaries to connect, forming sparse network structures with weak relationships. Threshold determination is key and requires adjustment based on dataset characteristics and research purposes.

4.2 Application of Weak Relationship Analysis

Weak tie theory has evolved from sociology to corporate innovation, economic management, and scientific information fields. P. A. Julien et al. found weak ties better trigger technological innovation in SMEs [94]. J. Zenou et al. showed maintaining weak ties improves employment rates [95]. Liu Junwan et al. quantified weak, strong, and super ties in scientific collaboration networks [96]. S. H. Yoo and D. K. Won used agent-based simulation to explore weak relationships between non-keywords for nanotechnology trend identification [97].

4.3 Fusion and Convergence Analysis of Weak Relationships

This approach employs fusion algorithms to comprehensively analyze various types of weak associations, gradually strengthening them to obtain clearer information. Figure 3 [Figure 3: see original paper] shows the process: first converging same-type weak relationships, then using algorithms to mine cross-type associations, and finally fusing multiple enhanced weak relationships to identify breakthrough research topics. The process filters valueless relationships for more precise results.

Existing studies have explored multi-relationship fusion. Xu Haiyun et al. used PathSelClus algorithm to fuse co-occurrence, citation, and co-authorship relationships, improving topic clustering [98]. S. Jensen et al. used meta-path methods to associate literature, keywords, authors, and citations for topic evolution [99]. D. Zhang et al. designed meta-graph methods to capture more complex relationships [100]. Liu Tong et al. used meta-matrices with LDA for core patent identification [101]. C. Shi et al. proposed HERec model for community prediction [102].

4.4 Complex Dependencies in High-Order Networks

Real-world networks are increasingly complex, and traditional models struggle to capture complex dependencies and path information. High-order network models can capture weak relationships that traditional methods miss. Current research has three directions: multi-layer high-order models, combinatorial high-order models, and non-Markovian high-order models.

4.4.1 Multi-Layer High-Order Models These address complex relationships with multiple link types. Ma Mengzhou integrated homologous data into multi-layer networks for key gene identification, using random walk algorithms with probability transition matrices [103]. L. Gauvin et al. represented multi-layer networks as third-order tensors for community identification while preserving dimensional information [104].

4.4.2 Combinatorial High-Order Models These generalize pairwise links to arbitrary node sets. Luo Yongen et al. built a hypergraph model using shared entropy for clustering, achieving higher accuracy than linear SVM [105]. A. R. Benson et al. built a general framework based on high-order connectivity patterns, unifying topic analysis and network partitioning [106].

4.4.3 Non-Markovian High-Order Models These incorporate time series data to reveal indirect influence paths. J. Xu noted first-order Markov models ignore that state transitions may result from previous transitions, causing prediction bias [107]. R. Lambiotte et al. demonstrated non-Markovian models better reveal underlying connections in community detection and system dynamics [108].

5 Development Trends for Weak Signal Identification of Breakthrough Research

5.1 Capturing Effective Early Weak Signals of Breakthrough Innovation

Breakthrough innovations appear as weak associations between topics in early stages. Unlike strong signals like high-frequency words, weak signals contain more diversified information reflecting overall disciplinary structure. However, many scientific discoveries have few early detectable signs, and captured weak signals often mix with noise and fragmented information. Effective discrimination depends on researchers' knowledge and advanced technical support. Future research should focus on capturing effective weak signals to improve identification accuracy.

5.2 Emphasizing Dynamic Evolution of Breakthrough Research Topics

Breakthrough innovations develop from incremental innovations through quantitative to qualitative change. Existing methods mostly focus on static signals at specific time points, failing to observe overall knowledge diffusion. Clarifying topic generation, development, and decline patterns enables capturing themes with transformative potential. Future research should introduce time series analysis to analyze dynamic evolution patterns and achieve early identification.

5.3 Using High-Order Network Models to Analyze Weak Relationships

High-order network models in complex networks can capture multi-dimensional information: mutual influence between nodes and edges, different connection types, global impacts, and temporal sequences. These capture weak relationships that traditional methods miss. Using high-order models can better mine complex weak dependencies, discover knowledge development trends, track topic dynamic evolution, and achieve early identification of breakthrough research.

Conclusion

This paper compared existing breakthrough innovation identification methods, finding insufficient attention to weak signals and lack of deep exploration of dynamic topic evolution, making early identification difficult. It introduced weak signal concepts, characteristics, and identification methods, demonstrating feasibility for early breakthrough innovation identification. Since most identification focuses on relationship data like citations and semantics, the paper analyzed weak relationships as a special weak signal type. Single weak relationships provide limited information, but fusion algorithm models can integrate multiple weak relationships for clearer directional information. Future research should capture effective early weak signals, analyze dynamic evolution patterns, and use high-order network models to improve early identification accuracy.

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Author Contributions

Liu Yahui: Responsible for data collection, paper writing and revision; Xu Haiyun: Supervised paper writing and revision.

Note: Figure translations are in progress. See original paper for figures.