Identifying Transferable Patents in Universities: A Postprint Based on Bayesian Theory and Combined Weighting Method

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Date: 2023-04-01T16:02:47+00:00

Abstract

[Purpose/Significance] Research on identifying transferable patents in universities is of positive significance for improving patent recommendation quality and facilitating the integration of university research with socio-economic development.

[Method/Process] First, based on literature review, quantifiable patent identification indicators were examined and established, and Bayesian theory was employed for preliminary screening of university transferable patents. Subsequently, a combination weighting method integrating multiple correlation coefficient and coefficient of variation was utilized to calculate indicator weights, and the weighted comprehensive transfer probability of remaining patents was computed. Finally, transferable patents were identified based on comprehensive probability values, with empirical validation conducted using university patents in the medical preparation domain characterized by high transfer volumes.

[Results/Conclusion] By leveraging Bayesian theory and combination weighting through preliminary screening and secondary identification, this method achieves effective calculation of comprehensive probabilities for university transferable patents. This approach ensures result accuracy while accounting for limited university patent management resources, thereby establishing a solid foundation for improving patent recommendation quality.

Full Text

Identification of University Transferable Patents: Based on Bayesian Theory and Combination Weighting Method

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Abstract: [Purpose/Significance] Research on the identification of university transferable patents is of positive significance for improving the quality of patent recommendations and promoting the integration of university research with socioeconomic development. [Method/Process] First, based on literature review, we tested and determined quantifiable patent identification indicators, and conducted preliminary screening of university transferable patents using Bayesian theory. Then, we employed the multiple correlation coefficient-coefficient of variation combination weighting method to calculate the weights of each identification indicator, and computed the weighted comprehensive transfer probability of remaining patents. Finally, we identified transferable patents according to their comprehensive probability values, and empirically tested our method using university patents in the high-transfer-volume field of medical configuration products. [Result/Conclusion] This method utilizes Bayesian theory and combination weighting to effectively calculate the comprehensive probability of university transferable patents through preliminary screening and secondary identification. It ensures result accuracy while accounting for limited university patent management resources, laying a solid foundation for improving patent recommendation quality.

Keywords: patent transfer; identification method; Bayesian theory; combination weighting

Classification Number: G255.53
DOI: 10.13266/j.issn.0252-3116.2021.05.012

University patents can only demonstrate their value when transferred. As a crucial entity for technological innovation, universities produce substantial patent output annually: in 2019 alone, they obtained more than 90,000 invention patents. However, despite this large accumulation, the patent transfer situation is not optimistic, with a transfer rate of merely 3.2% in 2019. This not only wastes significant human and material resources but also fails to leverage the role of university technological innovation in serving socioeconomic development. Many factors contribute to this outcome, with a particularly important one being that universities are not market competition entities. Most university patents are not outcomes of horizontal research projects and have low market relevance, making it unclear whether they can be accepted by the market or have recommendation value. If universities were to evaluate the transfer attributes of each patent individually, the cost would be enormous—an impractical and non-operational solution given the large volume, wide technological distribution, and limited management resources. Meanwhile, the national innovation system demands strengthened patent transfer efforts from universities. The Ministry of Education's 2020 Document No. 1, "Opinions on Improving Patent Quality and Promoting Transfer and Utilization in Higher Education Institutions," explicitly states that the orientation should highlight transformation and application, with patent quality and transfer/implementation rates in some universities reaching world-class levels by 2025. In summary, facing the massive volume and uneven quality of university patents, how to effectively identify their transferability and selectively promote those with market transfer potential has become a practical necessity for revitalizing university patents, promoting the integration of university research with market demand, and achieving innovation-driven development.

2 Literature Review

University patent transfer typically refers to the process where university patents are diffused and transferred to enterprises or individuals through patent right transfers. Compared with patent commercialization that focuses on practical transformation of technological forms, universities emphasize more on the transfer process where patent ownership changes hands. However, in research on transferable patent identification, academia has not made a clear distinction between the two concepts, often equating university patent transfer with patent commercialization. Current identification methods for transferable (or commercializable) patents mainly fall into three categories: identification based on patent characteristics, identification based on high-value assessment, and identification based on comprehensive patent analysis.

2.1 Identification Based on Patent Characteristics

Qiao Yongzhong et al. proposed that transferable patents can be identified by examining patent claims, arguing that the content and scope of patent rights must be fully governed by the claims, with specific and reasonable technical descriptions, to facilitate transfer. F. Schettino et al. found that patent transferability is also influenced by inventors' personal characteristics such as age, gender, and education level. X.Y. Ma et al. empirically demonstrated that university patent transferability correlates with technological innovation level—the higher the innovation, the greater the transfer potential. L.J. Olson suggested that legal stability and protection scope also affect patent transfer. Li Xiaotong et al. found that patents capable of satisfying human physiological, spiritual, and material needs are more likely to have transfer potential. Shu Hui et al. also noted that the higher the alignment between patented technology and market technical standards, the stronger the transferability. P. Dan et al. proposed that patent transferability is influenced by national and local policy support—the stronger the support, the higher the transferability. Although these studies cover a wide range and employ diverse assessment methods, they suffer from single-dimensional evaluation, low accuracy, difficulty in quantifying indicators, and susceptibility to subjective influences, making them lack operational feasibility.

2.2 Identification Based on High-Value Assessment

This approach explores patent transferability from the perspective of patent value assessment, positing that high-value patents are more transferable. By identifying high-value patents, transferable patents can be recognized. Specifically, F. Schettino et al. empirically demonstrated that remaining patent lifespan positively affects patent value—the longer the remaining life, the higher the value. Zhao Rongying et al. suggested that patent commercializability can be identified by the amount of attention information received, with more attention indicating core patents with higher transformation potential. A.C. Marco et al. found a linear relationship between the number of independent claims and patent value—patents with broader protection scope have higher value. J. Putnam et al. empirically showed that patent value also correlates with bibliometric indicators such as inventor count, examination duration, and family size. M. Squicciarini et al. proposed using the number of classification codes to identify patent value. Other scholars have suggested measuring patent value through citation counts and litigation numbers. While these studies have achieved 阶段性成果 and examined patent attributes from multiple angles, their exploration of patent value remains partial and insufficiently detailed. Moreover, using patent value alone to assess transferability has limitations and fails to comprehensively reflect university patent transferability, requiring further refinement.

2.3 Identification Based on Comprehensive Patent Analysis

This category employs common patent analysis methods for identification, including: Jin Xiaodong et al. used intangible asset evaluation methods (cost, market, income, and real options approaches) to determine transferability. Ran Congjing and Y. Zhang et al. used comprehensive indicator assessment, constructing multi-angle evaluation systems based on technology, market, and legal perspectives, and employing AHP, principal component analysis, and entropy methods to determine indicator weights. Y. Park et al. used patent citation analysis to quantify citation relationships from a knowledge flow perspective, revealing technology-industry relationships to calculate transfer probabilities. C. Jaehyun et al. used social network analysis to examine correlations between bibliometric indicators (citations, family size, inventor count, claims) and patent transfer, calculating network centrality measures and using multiple regression to build a transfer potential identification model. P. Hyunseok et al. used TRIZ evolution trends as technology assessment criteria, employing SAO text mining to process patent data and semantic analysis between patents and TRIZ trends to identify transferable patents. While methodologically diverse, these studies suffer from unsatisfactory evaluation effects, inaccurate weight determination, high computational complexity, and demanding technical requirements, necessitating further enrichment and expansion.

In summary, this paper proposes a university transferable patent identification method with low computational difficulty, strong operability, objective combination weighting for indicator values, and direct measurement of patent transferability. This approach aims to overcome current research limitations, enrich perspectives, and more objectively and accurately identify university transferable patents to assist universities in properly managing patent transfer.

3 Research Methods

Bayesian theory is a probability theory widely applied in mathematics and engineering. It involves estimating subjective probabilities for partially unknown states under incomplete information, then using Bayes' formula to revise occurrence probabilities, and finally making optimal decisions using expected values and revised probabilities. This theory considers both the probability of various reference populations and the loss from misjudgment, offering stable classification efficiency, diverse application scenarios, and strong robustness. It is particularly suitable for solving linear correlation classification problems, meeting the needs of transferable patent identification. Based on this, we adopt the research philosophy that patent indicators can classify and measure patents to identify university transferable patents: first, selecting and verifying quantifiable identification indicators through literature review; then using Bayesian theory to calculate prior probabilities of patent transfer for relevant bibliometric indicators, applying Bayes' formula to compute posterior probabilities for preliminary screening; next employing objective combination weighting for comprehensive weighting; and finally calculating weighted comprehensive transfer probabilities for remaining patents to achieve identification. The overall process is shown in [Figure 1: see original paper].

3.1 Selection and Verification of Identification Indicators

3.1.1 Preliminary Selection of Identification Indicators Scientific and reasonable indicator selection is the key prerequisite for transferable patent identification. University patent transferability is closely related to legal, technical, and market factors. Building on previous research and to enhance authority and objectivity while reducing arbitrary human intervention, we followed these principles: indicators should be objectively and quantitatively obtainable from patent texts; indicators should comprehensively reflect technological, legal, and market dimensions. Through literature review and expert consultation, combined with the Patent Navigation Manual issued by the National Intellectual Property Administration, we ultimately selected 11 quantifiable patent transferability identification indicators, detailed in .

3.1.2 Verification and Finalization of Identification Indicators The point-biserial correlation method is a common and effective approach for analyzing correlations when one variable is continuous and the other is binary {0,1}. To test the correlation between different patent identification indicators and patent transferability, we employed this method. The specific calculation formulas are as follows:

$$r_{pb} = \frac{\bar{Y}_p - \bar{Y}_q}{S_y}\sqrt{pq} \quad \text{(Formula 1)}$$

$$S_y = \sqrt{\frac{\sum(Y-\bar{Y})^2}{n}} \quad \text{(Formula 2)}$$

Where p is the proportion of one category in the binary variable, q is the proportion of the other category, $\bar{Y}_p$ is the mean of the continuous variable for category p, $\bar{Y}_q$ is the mean for category q, and S_y is the standard deviation of the continuous variable Y.

Based on significance test results, we selected indicators significantly correlated with patent transfer to construct the patent transferability identification indicator system.

3.2 Calculation of Identification Indicator Transfer Response Probability

To overcome the data deficiency and lack of quantification in previous qualitative research, we used Bayes' formula to calculate patent transfer probability for quantitative evaluation. For each indicator, we linearly sorted patents by indicator value, identified the top S patents as potentially transferable (where S is the predicted annual transferable patent count), counted actual transfer responses T_i, calculated prior probability $P(B_i)$, and used Bayes' formula to compute the transfer response probability $P(B_i|A)$:

$$P(B_i|A) = \frac{P(A|B_i)\cdot P(B_i)}{\sum_{j=1}^{i} P(A|B_j)\cdot P(B_j)} \quad \text{(Formula 3)}$$

$$P(B_i) = \frac{T_i}{S} \quad \text{(Formula 4)}$$

Where event A represents patent transfer, event B represents meeting transfer requirements, $P(B|A)$ is the conditional probability of B given A, and $P(A|B)$ is the conditional probability of A given B. The S value can be obtained through time series forecasting based on historical transfer data in the target technology field.

3.3 Preliminary Screening of Transferable Patents

Preliminary screening can eliminate non-transferable university patents, retaining only high-potential patents for secondary identification. The procedure involves: substituting each indicator's transfer response probability into the comprehensive probability calculation formula (Formula 5), sorting results inversely, and eliminating low-probability patents (with the threshold being the comprehensive probability when all indicators show low values). This step refines the research process, improves identification efficiency, and accommodates limited university patent management resources.

$$P(B|A) = \sum_{i=1}^{n} P(B_i|A) \quad \text{(Formula 5)}$$

3.4 Combination Weighting Calculation Method

Formula 5 assumes complete independence and equal weighting of feature vectors, which deviates from reality where different indicators contribute differently to transfer probability. To eliminate this bias, we employ an objective combination weighting method using multiple correlation coefficients and coefficients of variation.

3.4.1 Initial Weight Calculation

(1) The multiple correlation coefficient method reflects information redundancy and examines indicator independence:

$$\rho_i = \sqrt{r_i' R_{i-1}^{-1} r_i} \quad \text{(Formula 6)}$$

$$\omega_i' = \frac{1-\rho_i}{\sum_{i=1}^{n}(1-\rho_i)} \quad \text{(Formula 7)}$$

Where ρ_i is the multiple correlation coefficient of indicator i with other indicators, R_{i-1} is the correlation matrix of other indicators, and $r_i = (r_{1i}, r_{2i}, ..., r_{n-1,i})'$ is an $(n-1)$-order column vector.

(2) The coefficient of variation method reflects value dispersion and examines indicator variability:

$$v_i = \frac{S_i}{\bar{X}_i} \quad \text{(Formula 8)}$$

$$\omega_i'' = \frac{v_i}{\sum_{i=1}^{n} v_i} \quad \text{(Formula 9)}$$

Where v_i is the coefficient of variation, S_i is the standard deviation, and $\bar{X}_i$ is the mean of indicator i.

3.4.2 Determination of Identification Indicator Weights We combine the two weighting methods through weighted averaging based on their influence:

$$\omega_i = \alpha\omega_i' + (1-\alpha)\omega_i'' \quad \text{(Formula 10)}$$

Where α is the proportion of the multiple correlation coefficient method, and $(1-\alpha)$ is the proportion of the coefficient of variation method. This approach considers both data independence and variability, yielding more accurate and reasonable weighting results.

3.5 Patent Transfer Probability Calculation and Transferable Patent Identification

After determining combination weights, we calculate the weighted comprehensive transfer probability for remaining patents using the improved formula:

$$P(B|A) = \sum_{i=1}^{n} P(B_i|A) \cdot \omega_i(B_i, A) \quad \text{(Formula 11)}$$

Where $\omega_i(B_i, A)$ represents the weight of indicator i in measuring patent transferability. Patents are then sorted by comprehensive transfer probability, with the top S patents identified as transferable.

4 Empirical Study

4.1 Data Acquisition

PatSnap is a global patent database with timely updates and comprehensive data. Using PatSnap as our data source, we selected 32 universities with high patent transfer volumes from 2012-2017 (including Tsinghua University, Shanghai Jiao Tong University, etc.), focusing on the "A61K" (medical configuration products) field where transfer activity is high. Patents were granted through the end of 2019, with a search date of March 11, 2020, yielding 8,477 patents. After eliminating those with missing or incomplete information, we obtained 8,437 valid patents for empirical analysis.

4.2 Construction of Identification Indicator System

We extracted indicator features from the 8,437 patents and tested correlations using the point-biserial method, with patent transfer status as the binary variable and other indicators as continuous variables. Results are shown in .

Among the 11 proposed indicators, eight (patent citation count, family size, classification count, etc.) showed significant correlation with patent transfer at the 0.01 level and were retained. However, examination duration, inventor count, and litigation count were not significant (Sig > 0.05) and were excluded.

Examination duration is affected by multiple complex factors (technology field, examiner efficiency, national policies) and doesn't correlate with transferability. Inventor count is influenced by administrative incentives and university management models, lacking actual correlation. Litigation count lacks universality as most patents have no litigation history.

Based on this analysis, we constructed the transferable patent identification indicator system shown in [Figure 2: see original paper].

4.3 Preliminary Screening of Transferable Patents

We organized the data to count annual patent numbers (excluding expired and transferred patents) and transfer volumes, as shown in [Figure 3: see original paper]. The annual stock of valid patents in the medical configuration field shows overall growth, with the pace slowing in recent years, indicating a mature stage suitable for transfer research. Annual transfer volumes initially increased, slightly decreased, and now fluctuate around 65 patents.

As described in Section 3.2, the S value can be calculated via time series forecasting. Since this study uses 2019 transfer data for empirical testing, we directly used the actual 2019 transfer count of 63 patents as the threshold. We extracted the top 63 patents for each indicator, counted actual transfers, calculated prior probabilities $P(B_i)$, and computed transfer response probabilities $P(B_i|A)$ using Formula 3, as shown in .

Using Formula 5, we conducted preliminary screening, eliminating 4,343 low-potential patents and retaining 242 with initial transfer potential for secondary identification.

4.4 Calculation of Comprehensive Indicator Weights

We imported the patent data into SPSS to calculate multiple correlation coefficients and coefficients of variation for each indicator. Using Formulas 6 and 8, we computed initial weights, and Formula 10 for combination weights (with $\alpha = 0.5$ based on expert opinion). Results are shown in .

4.5 Comprehensive Transfer Probability Calculation and Identification

For the 242 preliminarily screened patents, we calculated weighted comprehensive transfer probabilities using Formula 11, standardized the results, and obtained final probability values. Using the 2019 transfer count (63) as the threshold, we selected the top 63 patents as the identification result. Partial results are shown in .

4.6 Results Verification and Discussion

We evaluated results using recall (R), precision (P), and their harmonic mean ($F1$):

$$R = \frac{\text{Actual hits}}{\text{Total actual transfers}}$$

$$P = \frac{\text{Actual hits}}{\text{Identified transferable patents}}$$

$$F1 = \frac{2PR}{P + R}$$

Comparing identified patents with actual 2019 transfers, we achieved 99.26% recall, 73.02% precision, and 84.13% $F1$ score, demonstrating that our method correctly identifies most transferable patents with good performance.

To further validate effectiveness, we compared our method with reference [22]: (1) **Methodology**: While existing methods use patent indicators for classification, they employ machine learning with high technical barriers, unobservable processes, and black-box operations. Our method uses mature Bayesian theory with transparent, objective combination weighting, moderate computational difficulty, and better suitability for university contexts. (2) **Research object**: Existing methods focus on patent commercialization, neglecting actual university transfer needs, which our study addresses. (3) **Accuracy**: Our method achieves comparable accuracy but uses complete field data, providing greater persuasiveness and objectivity than partial data approaches.

Conclusion

Enabling university patents to play a vital role in national economic structural optimization is a key issue for innovation-driven development. Addressing low transfer rates, limited management resources, and identification difficulties, we developed a transferable patent identification method based on Bayesian theory and combination weighting. The method: (1) selects and verifies quantifiable indicators through literature review; (2) calculates transfer response probabilities using Bayes' formula for preliminary screening; (3) applies multiple correlation coefficient-coefficient of variation combination weighting to account for differential indicator contributions; and (4) precisely identifies transferable patents through comprehensive probability ranking. Empirical results demonstrate significant effectiveness and reliability while accommodating resource constraints, providing a solid foundation for efficient patent promotion.

Limitations include insufficient integration of market domain indicators, which represents a direction for future research.

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