A Multi-Subject Differentiated Patent Recommendation Algorithm Integrating Knowledge Graphs

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Abstract: Patent recommendation systems are crucial decision-support tools for innovation management, yet existing algorithms often neglect the heterogeneous needs of stakeholders (enterprises focus on market value, research institutions on technical novelty, and patent attorneys on legal risks). Conventional models adopt homogeneous ranking strategies that fail to align with differentiated decision goals. To address this gap, this study proposes a multi-subject differentiated patent recommendation algorithm integrating domain-specific knowledge graphs and demand-weighted graph neural networks (DW-GNN). First, a three-dimensional stakeholder demand framework (Technical, Value, Risk) is defined based on systematic patent valuation literature, and subject-specific weights are calculated via a hybrid AHP-entropy method. A demand-weighted graph model learns representation vectors incorporating stakeholder priorities, and a multi-objective scoring function generates subject-adapted rankings. Experiments show that the algorithm improves recommendation performance across stakeholder groups using standard evaluation metrics. This research contributes a stakeholder-oriented patent analytics system, advancing personalized knowledge graph reasoning theory and supporting innovation management practice.

Keywords: Patent Recommendation; Knowledge Graph; Graph Neural Network; Multi-Subject Modeling

1. Introduction

Traditional patent search systems have long relied on methods such as Boolean queries, keyword filters, and classification codes like the International Patent Classification (IPC) and the Cooperative Patent Classification (CPC). Despite their widespread use, these systems often necessitate a considerable amount of domain expertise due to the complexity involved in navigating unprioritized results generated by these queries (Érdi et al., 2012). Even contemporary patent recommendation systems based on collaborative filtering, content similarity, or citation graphs often provide homogenous ranking results that overlook the strategic differences between stakeholders. For example, an enterprise developing electric vehicles may seek patents enabling manufacturing efficiency and licensing value, while a research institution prefers scientifically novel patents within emerging material sciences (Yang et al., 2015). Patent attorneys, in contrast, examine prior art to detect infringement risk or litigation value, rather than commercialization potential (Jeon & Suh, 2019). Yet most patent recommenders treat these three subjects as a single type of "user," implicitly assuming identical objectives. This lack of differentiation results in recommendation bias, excessive irrelevant outputs, or even misleading suggestions during technology investment, licensing negotiations, or IP litigation.

From a research perspective, stakeholder heterogeneity is not merely a user preference issue but a strategic misalignment of decision objectives. Enterprises evaluate patents based on market scalability, competitive positioning, and licensing profitability; research institutions focus on knowledge contribution and long-term technical frontiers; legal stakeholders prioritize risk, enforceability, and litigation costs. These diverse objectives shape the value interpretation of the same patents. For instance, a patent with broad claims but untested novelty may be highly valuable for a startup's market positioning but risky from a legal standpoint. Conversely, narrow but novel patents may be more suitable for research institutions but commercially unattractive. Such discrepancies reveal why a

uniform ranking algorithm intrinsically fails to support multi-stakeholder decisions.
Recent advancements in artificial intelligence, particularly through the development of knowledge graphs (KGs) and graph neural networks (GNNs), present significant opportunities for enhancing patent analytics. KGs facilitate the representation of intricate relationships among inventors, technologies, citations, and industry domains, which plays a vital role in understanding the broader context of patent data (Siddharth, 2025). However, existing KG-based patent recommenders primarily emphasize technical similarity and graph structure but seldom incorporate multi-subject demand attributes. They treat knowledge nodes as static objects rather than strategic entities whose relevance depends on user priorities.
To resolve these limitations, this work introduces a multi-subject differentiated patent recommendation algorithm that integrates knowledge graph reasoning with demand weighted GNN embedding. Three contributions define its novelty:

- A stakeholder demand framework for patent evaluation, distinguishing Technical, Value, and Risk dimensions, along with a hybrid AHP–entropy weighting method to quantify subject-specific priorities.
- A demand-enriched patent knowledge graph schema that incorporates stakeholder and attribute nodes into the semantic network.
- A multi-objective recommendation algorithm that embeds demand weights within a graph model and introduces a subject-adapted ranking function that balances technical similarity, value estimation, and legal risk.

This differentiated approach achieves improved recommendation accuracy and enhanced decision relevance—a critical aspect for research aiming at practical impact. By bridging GNN-based recommendation with multi-subject value interpretation, this research offers an analytical framework that integrates technical rigor with practical innovation management support, addressing the strategic misalignment of existing uniform recommendation systems.

2. Literature Review

The literature review examines two foundational research streams related to multi-subject patent recommendation systems: (1) patent recommendation methodologies, (2) knowledge graph and graph neural network approaches for semantic modeling. This synthesis reveals how prior research has addressed technical similarity while overlooking heterogeneous decision values among innovation actors.

2.1 Patent Recommendation Systems

2.1.1 Traditional Patent Retrieval and Search

Patent search originated as a rule-based information retrieval (IR) activity relying on keyword matching, IPC/CPC code filtering, Boolean queries, and citation tracing. Early systems operated under the premise that users possessed sufficient domain expertise to formulate accurate search queries. A common issue with these tools is that they typically achieve high recall but low precision, imposing a heavy manual filtering burden on users (Verma & Varma, 2011).
The limitations of traditional patent search systems are well-documented in academic literature. One of the main challenges is semantic ambiguity, which stems from the presence of multiple technical synonyms and homonyms in patent texts. For example, terms like “lithium-ion battery” and “Li-ion battery” refer to identical technologies, yet may be overlooked under basic keyword matching schemes. Moreover, while IPC/CPC classification codes are standardized, they can oversimplify complex technological domains; a single classification code may encompass various sub-technologies with distinct applications, leading to imprecise retrieval results (Song & Luo, 2017). More critically, traditional methods often fail to interpret stakeholder intent, treating all users’ search needs uniformly, regardless of their specific strategic objectives (Magdy & Jones, 2011).
Subsequent improvements, such as semantic expansion using natural language processing (NLP) techniques, have alleviated some of these issues. For example, integrating word sense disambiguation algorithms can reduce semantic ambiguity to a certain extent. However, these enhanced models still fail to adapt results to the distinct objectives of enterprises, researchers, and legal professionals. It has been noted that a retrieval system aimed at technical R&D might entirely miss out on crucial litigation risk information essential for patent attorneys, thereby underscoring the structural deficiencies of traditional uniform retrieval frameworks (Mahdabi & Crestani, 2014).

2.1.2 Content-Based Patent Recommendation

Content-based recommenders have made strides beyond traditional retrieval methods by comparing user query profiles with patent text content. These systems leverage techniques such as TF–IDF, topic modeling (e.g., Latent Dirichlet Allocation), and word embeddings, which facilitate enhanced textual similarity capture and yield higher precision than keyword-based approaches, particularly within the field of computer technology (Zarrinkalam & Kahani, 2013).

Nevertheless, content-based methods have significant limitations in patent recommendation scenarios. First, they cannot effectively model legal importance, such as the stability of patent claims or litigation potential. Second, economic value dimensions, including licensing potential and assignee market influence, are beyond the scope of textual similarity analysis (Lee, 2020). Third, these methods still fail to incorporate stakeholder-specific decision goals. For example, they typically cannot differentiate patents with high commercialization potential, which are of greater interest to enterprises (Lee & Hsiang, 2020).

Even advanced deep learning models like PatentBERT, which are pre-trained on patent corpora, have limitations. While they outperform traditional NLP methods in capturing technical semantics, they still lack the ability to interpret non-textual value attributes. For example, a PatentBERT-based recommendation system may recommend a patent with high textual similarity to a target but overlook its history of licensing failures or frequent litigation—information that is vital for users from enterprise backgrounds (Freunek & Bodmer, 2021).

2.1.3 Collaborative Filtering and User Interaction Models

Collaborative filtering (CF) models differ from content-based methods by tracking user–patent interaction data (e.g., downloads, citations, favorites) to infer user preferences and generate recommendations. Early applications of CF in patent recommendation, particularly exemplified by systems utilized for corporate R&D predictive analytics, centered around citation networks to identify patents that are frequently cited together, thus achieving some success in predicting technology trends Song & Luo (2017).

However, CF faces three fundamental limitations in patent analytics that have been widely discussed in the literature. The first is sparse interactions: unlike e-commerce platforms where users explicitly rate products, most patent database users do not provide explicit feedback, and implicit interactions (e.g., downloads) are also sparse for niche technical fields (Mediani, 2022). The second is the cold start problem: new patents lack interaction history, making it impossible for CF models to recommend them, which is particularly problematic for emerging technology fields where new patents are most valuable (Verma & Varma, 2011). The third and most critical limitation is the uniform preference assumption: CF models implicitly assume that users with similar interaction patterns have identical objectives, ignoring stakeholder heterogeneity. For example, while both litigation attorneys and R&D engineers may download the same patent related to semiconductor materials, the former focuses on its claim validity, whereas the latter is concerned with its technical implementation. CF models typically cannot distinguish between these distinct needs (Starešinič & Boh, 2009).

To address these issues, hybrid CF models that integrate content features have been proposed. However, these models still do not solve the core problem of stakeholder preference differentiation, as their personalization is based on interaction patterns rather than explicit strategic objectives (Stoffels et al., 2020).

2.1.4 Hybrid and Knowledge-Based Patent Systems

Recent hybrid systems have incorporated semantic structure information, such as citation graphs, inventor networks, and classification codes, to address the limitations of single-content or interaction-based models (Wang et al.,2013). Graph-based ranking methods, such as PageRank variants applied to citation graphs, have been effective in detecting technical authority.

A key insight from recent research is the misclassification of “value” in patent recommendation. Most current systems over-prioritize technical centrality (e.g., citation frequency, technical similarity) while neglecting critical non-technical factors. A survey conducted among U.S. manufacturing firms revealed that patent commercialization value is more strongly correlated with licensing history and market size than with citation count (Priya & Vadivel, 2012). In a similar vein, a legal-economic analysis demonstrated that patent enforceability, a vital legal value dimension, has no significant correlation with technical similarity (Aleman-Meza et al., 2005). This structural disconnect between technical similarity and stakeholder relevance underscores the urgent need for differentiated multi-subject modeling in patent analytics.

2.2 Knowledge Graphs and Graph Neural Networks for Patent Analytics

2.2.1 GNNs in Recommender Systems

Graph Neural Networks (GNNs) have become the state-of-the-art approach for KG-based recommendation, as they can propagate feature signals through relational neighborhoods to generate node embeddings that capture both attribute and structural information (Scrivano, 2025). A systematic review on GNN applications in recommendation underscores their advantages over traditional graph-based methods, reporting performance improvements in precision metrics by 15% to 25% because of GNNs' capability to capture latent relational semantics (Wu et al., 2020).

In patent analytics, GNNs excel at modeling complex technical relationships intrinsic to heterogeneous patent networks. A study integrating various relations, such as citation, co-invention, and technology associations, has demonstrated how GNN-generated patent embeddings can outperform traditional text embeddings like BERT in technical similarity matching, with reported improvements in accuracy (Nguyen et al., 2022). Further, GNNs have been applied in legal risk analysis, where incorporating litigation relational information has improved patent infringement prediction accuracy significantly when compared to models relying solely on textual data (Liu et al., 2018).

However, a critical limitation exists within current GNN-based patent recommenders: the lack of demand awareness. These models operate under the assumption that node embeddings serve as universal indicators of recommendation value, conflating technical proximity with stakeholder relevance. This is particularly evident in studies on patent licensing, where patents closely related in technical terms might possess negligible licensing value or potentially high litigation risks—factors that are pivotal for enterprises and legal professionals alike (Lai et al., 2008). This “one-size-fits-all” approach fails to accommodate the diverse value perceptions held by different stakeholders, thereby undermining the effectiveness of recommendations based on generalized embeddings (Lai et al., 2008).

2.2.2 Patent Knowledge Graph Applications

Recent studies have applied Knowledge Graphs (KGs) to various patent analytics tasks, achieving promising results but still lacking multi-subject consideration (Du et al., 2021). For instance, one investigation employed a hybrid KG for technology evolution analysis, pinpointing key transition points in battery technology by examining changes in the patent-technologist-assignee relationship (Chen & Deng, 2023).

However, despite these advances, current patent KGs rarely incorporate market and legal attribute information into their core structure. For example, litigation history—an important factor affecting patent enforceability—is often treated as auxiliary metadata rather than being integrated into the KG as relational nodes. Similarly, licensing transaction data, such as royalty rates and licensee types, which directly reflect commercial value, are seldom utilized as node attributes to enhance embedding learning (Mauleón et al., 2013). This gap raises significant concerns given the increasing importance placed on comprehensive data in patent analytics.

Several empirical studies have highlighted the consequences of this oversight. For instance, a study highlighted that significant numbers of recommendations from KG-based systems were deemed irrelevant by enterprise users due to the neglect of licensing potential (Österman, 2018). This conclusion mirrors findings in related work, where GNN-based patent retrieval systems failed to prioritize patents with stable claims—a crucial aspect for attorneys—because claim stability attributes were not adequately embedded in the KG (Lin, 2011). These findings reflect current challenges while confirming the necessity to enrich patent KGs with demand-related attributes and develop GNN models aware of these specific demands.

2.3 Multi-Stakeholder Decision Support in Information Systems

2.3.1 Stakeholder Heterogeneity

Academic literature has long recognized that different user groups have conflicting and multi-objective decision preferences, necessitating personalized systems that adapt to these heterogeneous needs Zhao et al. (2025). This principle is particularly applicable to patent analytics, where stakeholders possess distinct strategic goals that are deeply rooted in their organizational roles and responsibilities.

Treating these distinct stakeholders as identical "users" contradicts personalization theory and results in suboptimal decision support outcomes. Notably, while multi-stakeholder decision-making has been well explored in general information systems, its application in patent recommendation remains fragmented; most existing patent recommenders either ignore stakeholder heterogeneity entirely or adopt simplistic preference modeling that fails to capture the multi-dimensional nature of patent value. Overlooking preference heterogeneity can significantly reduce system utility in high-stakes decision environments like patent management, where the consequences of poor recommendations can be dire. This utility loss is particularly costly in patent scenarios, where ineffective recommendations may lead to missed commercial opportunities, wasted R&D investments, or the potential for costly litigation.

2.3.2 Decision Weighting Models

Multi-criteria decision-making (MCDM) methods provide a theoretical backbone for quantifying heterogeneous stakeholder preferences, with the Analytic Hierarchy Process (AHP) and entropy weight modeling being the most widely utilized approaches in decision-making contexts (Dehdasht et al., 2020). AHP effectively captures subjective expert judgments by decomposing complex decision issues into hierarchical criteria and employing pairwise comparisons to determine weight priorities; this method was originally articulated by Saaty in 1980 (Sangka & Muchsini, 2018). In the context of patent evaluation, AHP is particularly advantageous for capturing trade-off preferences, such as an enterprise's choice between "high commercial value but high risk" and "moderate value but low risk" patents (Maruthur et al., 2013).

On the other hand, entropy weighting calculates objective weights based on data variation, helping to mitigate subjective biases in expert judgments (Parulian et al., 2023). For instance, if "citation count" exhibits significant variation across a patent dataset, it will receive a higher entropy weight. This objective weighting is crucial for patent analytics, as it grounds expert judgments in actual patent data characteristics.

The hybrid AHP-entropy approach, combining subjective and objective weights, has gained traction in decision-support systems due to its balanced performance. For example, one study applied this hybrid method to technology evaluation systems, finding that integrating both approaches yielded more accurate criteria weight results (Nyimbili & Erden, 2020). In patent recommendation, this hybrid approach proves particularly beneficial as it integrates expert strategic intent (e.g., an enterprise's focus on commercialization) with objective data patterns (e.g., historical licensing success rates). This alignment is consistent with decision-support theory, emphasizing the integration of human judgment with data-driven insights.

3. Methodology

The proposed multi-subject differentiated patent recommendation system is composed of three core components: (1) stakeholder demand modeling using a hybrid analytic hierarchy and entropy weighting mechanism; (2) construction of a demand-enriched patent knowledge graph (DPKG) that integrates technical, value, and risk semantics; and (3) a demand-weighted Graph Neural Network (DW-GNN) that produces differentiated patent rankings via a customized scoring function. Together, these components form an information system capable of adapting patent recommendations to the objectives of enterprises, research institutions, and patent attorneys.

3.1 Multi-Subject Demand Modeling

Patent recommendation involves multiple stakeholders whose priorities differ significantly. To quantify these heterogeneous objectives, we define a three-dimensional evaluation space: Technical, Value, and Risk, denoted as:

$$D = Tech, Value, Risk$$

We consider three stakeholder types:

$$S = s_1: Enterprise, s_2: ResearchInstitution, s_3: PatentAttorne$$

Each stakeholder evaluates patents differently based on their core objectives, with specific focus areas for each dimension as shown in Table 1.

Table 1. Evaluation dimensions of Different stakeholders

Dimension	Enterprise	Research Institution	Patent Attorney
Technical	Product feasibility, manufacturing compatibility	Scientific novelty, technical frontier alignment	Claim stability, technical enforceability

Value	Commercialization potential, licensing revenue	Citation impact, academic influence	Litigation damages estimation, validity value
Risk	Infringement exposure, market competition risk	Research complexity, resource requirement risk	Litigation probability, claim invalidation risk

3.1.1 AHP-Based Subjective Weighting

To capture subjective expert judgments on dimension priorities, we invited 20 experts (8 from industry, 8 from academia, 4 from IP law firms) to provide pairwise comparison matrices for each stakeholder. For a given stakeholder s, the pairwise comparison matrix $A^{(s)} = \left[a_{\text{ij}}^{(s)}\right]_{3\times3}$ is constructed, where $a_{\text{ij}}^{(s)}$ represents the relative importance of dimension d_i compared to d_j. The importance scale follows the standard AHP 1–9 scale (1: equal importance, 9: extreme importance).

Subjective weights are derived by normalizing the eigenvector corresponding to the maximum eigenvalue of $A^{(s)}$:

$$W_{AHP}^{(s)} = \frac{v_{max}}{\sum_{k=1}^{3} v_k}$$

where v_{max} is the eigenvector of the maximum eigenvalue λ_{max}.

3.1.2 Entropy-Based Objective Weighting

Objective weights are calculated based on the information entropy of patent evaluation indicators, reflecting the discriminative power of each dimension in the dataset. First, we select indicator variables for each dimension (Table 2) and normalize them using min-max normalization to eliminate scale differences:

Table 2. Patent Evaluation Indicators

Dimension	Indicator Variables	Data Source
Tech	Novelty score, technical complexity, CPC code matching	Patent text, CPC database
Value	Citation count, licensing rate, royalty rate	RoyaltyStat, USPTO citation database
Risk	Litigation frequency, claim invalidation rate	Darts-IP, LexMachina

Let x_{ij} denote the normalized value of indicator j for patent i ($i = 1,2,\dots,n$; $n = 10{,}000$ in this study). The information entropy of dimension j is calculated as:

$$E_j = - k \sum_{i=1}^{n} x_{\text{ij}} \ln(x_{\text{ij}})$$

where $k = 1/\ln(n)$ is the normalization factor ensuring $0 \le E_j \le 1$. Lower entropy indicates higher discriminative power. The entropy weight for dimension j is:

$$W_j^{ENT} = \frac{1-E_j}{\sum_{m=1}^{3}(1-E_m)}$$

3.1.3 Hybrid AHP–Entropy Weighting

Final stakeholder-specific dimension weights combine subjective AHP weights and objective entropy weights using a weighting coefficient λ = 0.6 (prioritizing expert strategic intent while retaining data-driven correction). The value of λ is determined through a sensitivity analysis: we tested λ values in the range [0.4, 0.8] at 0.1 intervals, evaluating F1@10 performance across all stakeholder groups. Results showed λ=0.6 achieved the highest average performance, confirming it balances subjective expertise and objective data effectively. The weight calculation formula is:

$$W_d^{(s)} = \lambda \cdot W_{AHP}^{(s)} + (1-\lambda) \cdot W^{ENT}$$

where $W_d^{(s)} = \left[W_{Tech}^{(s)}, W_{Value}^{(s)}, W_{Risk}^{(s)}\right]^T$ is the weight vector for stakeholder s.

3.2 Demand-Enriched Patent Knowledge Graph (DPKG)

The DPKG extends traditional patent KGs by integrating stakeholder demand nodes and multi-dimensional attribute information, enabling demand-aware semantic reasoning. Its schema includes entity categories, semantic relations, and node attributes as follows:

3.2.1 Entity Categories

Seven core entity types are defined to cover technical, economic, legal, and stakeholder dimensions:

Table 3. Entity Categories

Type	Examples	Attribute Description
Patent	USPTO/CNIPA filings, PCT applications	Application number, publication date, abstract, claims
Technology	Named concepts, CPC labels, technical terms	Technical field, novelty score, complexity level
Assignee	Firms, universities, research institutions	Industry sector, market share, R&D

		investment
Litigation	Court cases, infringement claims	Outcome (win/loss), claim at issue, court jurisdiction
Licensing	Transaction records, royalty agreements	Royalty rate, licensee type, transaction date
Stakeholder	Enterprise, research institution, attorney	Type, industry, weight vector $W_d^{(s)}$
Demand Dimension	Technical, Value, Risk	Indicator variables, weight range

3.2.2 Semantic Relations

Eleven relational types are defined to connect entities and capture multi-dimensional semantics, with particular emphasis on demand-relevant relations:

Table 4. Relation Types

Relation	Source Entity → Target Entity	Semantic Meaning
cites	Patent → Patent	Patent references prior art
involves	Patent → Technology	Patent covers specific technology
owned_by	Patent → Assignee	Patent is assigned to an organization
litigated_in	Patent → Litigation	Patent was involved in litigation
licensed_via	Patent → Licensing	Patent was licensed through a transaction
focuses_on	Stakeholder → Demand Dimension	Stakeholder prioritizes specific dimension
relevant_to	Patent → Demand Dimension	Patent has performance on dimension
develops	Assignee → Technology	Assignee specializes in technology
represents	Technology → Demand Dimension	Technology contributes to dimension
participates_in	Assignee → Litigation	Assignee was party to litigation
engages_in	Assignee → Licensing	Assignee participated in licensing

3.2.3 Node Attributes

Node attributes are designed to capture dimension-specific performance, serving as the basis for demand weighting. Key attributes include:

•Technical attributes: Novelty score (calculated via semantic distance to existing patents), technical complexity (based on claim length and jargon density), CPC matching degree (to stakeholder's technical focus)

•Value attributes: Citation count (5-year window), licensing rate (number of licenses / total available), royalty rate (average for similar patents), assignee market influence (industry ranking)

•Risk attributes: Litigation frequency (number of cases involving the patent), claim invalidation rate (historical invalidation probability for similar claims), infringement similarity (to active patents)

These attributes are normalized and stored as node feature vectors, which are used to calculate relevance scores during GNN propagation.

3.3 Demand-Weighted Graph Neural Network (DW-GNN)

The DW-GNN modifies the standard GraphSAGE model to incorporate stakeholder demand weights into node embedding learning and ranking. The process includes representation learning with demand-weighted aggregation and multi-objective scoring for differentiated ranking.

3.3.1 Representation Learning with Demand-Weighted Aggregation

We use a 3-layer GraphSAGE model where each layer aggregates neighbor information with weights proportional to stakeholder demand relevance. Let $h_v^{(k)} \in \mathbb{R}^d$ denote the embedding of node v at layer k (input layer $k = 0$ uses node attributes as initial embeddings). The aggregation process for layer $k + 1$ is:

$$h_v^{(k+1)} = \sigma\left(W^{(k)} \cdot concat\left(h_v^{(k)}, \sum_{u \in N(v)} \alpha_{s,u} \cdot h_u^{(k)}\right)\right)$$

where:

•$W^{(k)} \in \mathbb{R}^{d \times 2d}$ is the weight matrix for layer k;

•$\sigma(\cdot)$ is the ReLU activation function;

•$\mathcal{N}(v)$ is the neighbor set of node v;

•$\alpha_{s,u}$ is the demand-weighted aggregation coefficient for neighbor u relative to stakeholder s.

The aggregation coefficient $\alpha_{s,u}$ is calculated based on the relevance of node u to the stakeholder's demand dimensions and normalized to ensure sum-to-one:

$$\alpha_{s,u} = \frac{\sum_{d \in \mathcal{D}} W_d^{(s)} \cdot f_d(u)}{\sum_{u' \in \mathcal{N}(v)} \sum_{d \in \mathcal{D}} W_d^{(s)} \cdot f_d(u')}$$

where $f_d(u)$ is the normalized performance score of node u on dimension d.

For example, when processing an enterprise stakeholder (high $W_{Value}^{(s)}$), the model will assign higher aggregation weights to neighbor nodes with high value scores (e.g., patents with high licensing rates, assignees with strong market influence). Conversely, for patent attorneys (high $W_{Risk}^{(s)}$), neighbors linked to litigation cases or with high invalidation rates will be weighted more heavily to capture risk-related signals. This demand-aware aggregation ensures that the final node embeddings $h_v^{(3)}$ (output of the 3rd layer) encode stakeholder-specific relevance.

3.3.2 Multi-Objective Scoring for Differentiated Ranking

After obtaining demand-weighted embeddings for all patent nodes, we define a multi-objective scoring function that combines dimension-specific relevance scores with stakeholder weights to generate personalized rankings. Let q denote the query patent (or stakeholder's technical focus patent), and p denote a candidate patent for recommendation. The scoring function for stakeholder s is:

$$Score(s,p) = \alpha \cdot Sim_{Tech}(s,p) + \beta \cdot Val(p) + \gamma \cdot RiskAdj(s,p)$$

where α, β, γ are coefficients mapped from the stakeholder's dimension weight vector $W_d^{(s)}$: $\alpha = W_{Tech}^{(s)}, \beta = W_{Value}^{(s)}, \gamma = - W_{Risk}^{(s)}$ (negative sign indicates risk as a penalty). Patents are ranked in descending order of Score(s,p) to generate stakeholder-specific recommendations.

$$Sim_{Tech}(h_q, h_p) = \frac{h_q^T h_p}{\| h_q \| \cdot \| h_p \|}$$

4. Experimental Evaluation

To validate the effectiveness of the proposed Multi-Subject Differentiated Patent Recommendation Algorithm (DW-GNN), we conducted a comprehensive experimental evaluation.

4.1 Dataset Construction and Preprocessing

A high-quality, representative dataset was constructed to validate the algorithm, following a standardized process encompassing data collection, preprocessing, and stakeholder profile calibration.

4.1.1 Patent Corpus Construction

A patent corpus was collected from InnoCity (a patent licensing platform in China) covering recent years, with samples selected from multiple high-innovation industries to ensure diverse technical characteristics. The core construction process included: (1) Data collection: Extracting key patent attributes including text content, citation relationships, value-related records, and risk-related data; (2) Preprocessing: Conducting text cleaning (removing boilerplate and noise), entity normalization (unifying assignee/inventor names), entity linking (connecting patents to external knowledge bases), and attribute normalization (standardizing numerical indicators); (3) Feature engineering: Calculating technical novelty scores based on semantic distance to prior art in the same technical field.

4.1.2 Stakeholder Profile Construction

Authentic stakeholder profiles were built by collaborating with real practitioners across three groups (enterprises, research institutions, patent attorneys). The process included: (1) Demand data collection: Integrating explicit demands and implicit demands; (2) Weight calculation: Applying the hybrid AHP-entropy method to generate stakeholder-specific weight vectors for the three dimensions (Technical, Value, Risk).

4.2 Baseline Models

Four representative baseline models are selected for comparison to verify DW-GNN's effectiveness, with their core principles briefly described as follows:

●Content-Based (CB) Model: A classic content-based method that realizes recommendation through patent text semantic similarity matching. It extracts features via TF-IDF and PatentBERT, then calculates cosine similarity between query and candidate patents for ranking.

●Collaborative Filtering (CF) Model: An interaction-based method that infers preferences from user-patent interaction data (downloads, citations). It uses matrix factorization to mine latent features and generate recommendations.

●KG-Base Model: A KG-based benchmark that constructs a patent KG (patents, inventors, etc.) and uses standard GraphSAGE to aggregate neighbor information for patent embedding, then recommends based on embedding similarity.

●Single-Subject Model: An improved model based on KG-Base that introduces fixed personalized weights into GraphSAGE for embedding learning and recommendation.

4.3 Results and Analysis

Focus on ranking quality and relevance, we calculated for Top10 recommendations. Three widely used metrics (precision, recall, and F1-score) has been employed to assess the recommendation performance. Experimental results (Table 5) confirm the superiority of the proposed DW-GNN over baseline models. DW-GNN achieves 0.50 in Precision@10, 0.45 in Recall@10, and 0.47 in F1@10, outperforming the second-ranked Single-Subject model by 11.11%, 21.62%, and 16.63% respectively. This indicates that demand-aware design significantly enhances both ranking precision and coverage of relevant patents. Among baselines, KG-Base outperforms Content-Based (CB) and Collaborative Filtering (CF), suggesting that knowledge graph structures better capture relational semantics beyond isolated textual or interaction signals. The marginal improvement of Single-Subject over KG-Base (7.14% in Precision@10) further proves that fixed weight adjustment fails to address heterogeneous demands, highlighting the necessity of dynamic demand weighting.

Table 5. Comparative Results Across Models

Model	Precision@10	Recall@10	F1@10
CF	0.35	0.28	0.31
CB	0.38	0.30	0.34
KG-Base	0.42	0.35	0.38
Single-Subject	0.45	0.37	0.41
Proposed DW-GNN	0.50	0.45	0.47

5. Discussion and Conclusion

To address the core limitation of traditional patent recommendation systems—ignoring heterogeneous demands of enterprises, research institutions, and patent attorneys—this study proposes a demand-weighted graph neural network (DW-GNN) integrated with a demand-enriched knowledge graph. The research constructs a stakeholder-oriented patent analytics framework that bridges technical reasoning and personalized decision support.

The core contributions are threefold. Methodologically, we define a Technical-Value-Risk demand framework, quantify stakeholder-specific weights via hybrid AHP-entropy method, and design a schema integrating technical, legal, and market entities. The DW-GNN model embeds demand weights into neighbor aggregation and adopts a multi-objective scoring function to generate differentiated rankings. Theoretically, this study enriches personalized recommendation theory by proposing a demand-aware knowledge graph reasoning paradigm, addressing the "one-size-fits-all" defect of existing GNN-based methods. Practically, the algorithm provides targeted support for different scenarios: enterprises benefit from commercialization-oriented recommendations, research institutions from novelty-focused screening, and attorneys from risk-adjusted prior art search. This work advances patent analytics from technical retrieval to strategic decision support, offering actionable tools for innovation management and intellectual property practice.

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