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Unveiling optimal SDG pathways: an innovative automated recommendation approach integrating graph pruning, intent graph, and attention mechanism

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ABSTRACT

The recommendation of Sustainable Development Pathways (SDPs) is crucial for achieving the United Nations Sustainable Development Goals (SDGs) at regional level. However, traditional recommendation algorithms struggle with two key challenges: spatial heterogeneity and sparse historical interaction records between regions and SDPs. To address these issues, we introduce the Regional Graph-Based Explainable Recommendation (RGB-ER) method. RGB-ER leverages a pruned Regional Graph (RG) to capture regional spatial heterogeneity, incorporating environmental, economic, and social factors into the recommendations. In addition, an Intent Graph models regional preferences across various attributes, bridging historical interactions with the RG and mitigating data sparsity. This dual approach significantly improves recommendation accuracy and interpretability. Extensive experiments show that RGB-ER outperforms state-of-the-art graph-based models, with a maximum improvement of 9.61% in Top-3 recommendation accuracy. A case study in Fujian Province – a region characterized by its mountainous terrain, complex socio-economic landscape, and significant sustainability challenges – illustrates RGB-ER's practical applicability, aligning well with local government strategies for sustainable development. Furthermore, we assess SDPs at the county level across China, highlighting the

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method's potential for guiding region-specific sustainable development planning. In conclusion, RGB-ER provides a robust, explainable framework for data-driven decision-making in sustainable development.

1. Introduction

Sustainable Development Pathways (SDPs) are strategic frameworks adopted by regions to achieve the United Nations Sustainable Development Goals (SDGs) (Arora-Jonsson 2023; Norman 2018). In China, these pathways are often referred to as Ecological Civilization Models, which aim to balance economic growth with environmental preservation and enhancement (Hansen, Li, and Svarverud 2018; Wang et al. 2021; Zhang et al. 2022).

A prominent example of such a model is the national park system. In Pengzhou, Sichuan Province, for instance, the establishment of the Giant Panda National Park has spurred the development of a panda-themed tourism industry. This initiative has significantly boosted local incomes, stimulated the growth of tourism and hospitality sectors, and contributed to regional economic development, all while maintaining the ecological integrity of the region. These examples underscore the critical role of region-specific SDPs in achieving SDGs, emphasizing the integration of economic development with environmental sustainability and offering replicable models for other regions to follow (Norman 2018; Nyangchak 2024; Yang, Yang, and Wang 2020).

Recognizing the value of these replicable models, researchers have explored various approaches to identify and recommend suitable SDPs tailored to regional contexts. Early efforts have primarily relied on expert-driven, geography-based assessments, including literature reviews, field investigations, data collection, and SWOT (Strengths, Weaknesses, Opportunities, and Threats) analyses (Ghorbani et al. 2015; Kaymaz, Birinci, and Kızılkan 2022; Palomares et al. 2021; Wan, Wang, and Wu 2024). While these qualitative methods capture valuable domain knowledge, they often rely heavily on expert judgment, which limits their objectivity, reproducibility, and applicability to large-scale comparative analyses.

Inspired by advancements in fields such as personalized product recommendation, researchers have increasingly explored data-driven computational techniques to enhance SDP recommendation (Guo 2019). These methods leverage historical data, regional attributes, and relational similarity to structure the recommendation process more systematically (Bachmann et al. 2022; Porciello et al. 2020; Sarker et al. 2019; Zeng et al. 2022). Although these approaches are promising in other domains, they remain at a preliminary stage within the context of SDP recommendation. Many of the algorithms adapted from commercial systems – such as collaborative filtering, matrix factorization, or deep learning models – have not yet been directly deployed in sustainable development planning. Nevertheless, their underlying principles offer valuable insights for developing scalable and objective recommendation frameworks.

Despite their potential, existing computational methods still face critical limitations when applied to the complexities of SDP recommendation. First, the ability to identify meaningful similarities across regions is constrained by spatial heterogeneity and diverse development contexts. Second, a lack of causal transparency in the recommendation process hinders their usefulness in policy settings, where explainability and stakeholder interpretability are essential. Third, these models often fail to capture the full complexity of regional development due to the absence of mechanisms for integrating heterogeneous and context-specific knowledge sources, which particularly limits their effectiveness with sparse historical interaction records.

Effective SDP recommendation thus requires more than algorithmic optimization; it demands the meaningful synthesis of diverse information types to support evidence-based and transparent decisions (Fotopoulou et al. 2022; Vinuesa and Sirmacek 2021; Yao and Li 2023). As illustrated in Figure 1, this entails integrating three interrelated forms of knowledge: case expertise knowledge, which draws on past regional successes; regional factor knowledge, which accounts for current socio-economic and environmental conditions; and causal intent knowledge, which grounds the recommendations in scientifically interpretable development rationales. Without this multi-dimensional integration, SDP recommendations risk becoming either overly generic or misaligned with regional realities.

To bridge these gaps, this study proposes an automated, knowledge graph-based framework – Regional Graph-Based Explainable Recommendation (RGB-ER) – tailored specifically for sustainable development planning. By integrating graph pruning

Figure 1. Types of knowledge essential for sustainable development pathways recommendation.

strategies, intent modeling, and attention mechanisms, RGB-ER connects spatially and semantically similar regions, enhances causal interpretability, and synthesizes diverse knowledge sources to improve recommendation quality and transparency.

This research offers three primary contributions. First, it introduces a new automated framework for SDP recommendation that integrates case-based, regional, and explanatory knowledge. Second, it presents a regional graph pruning strategy that categorizes and ranks attribute nodes to reduce spatial heterogeneity during graph convolution. Third, it introduces an intent graph mechanism that uncovers interpretable development pathways, enabling more robust, actionable, and scientifically grounded recommendations for regional sustainability strategies.

2. Related works

2.1. Traditional approaches to SDP recommendation

The field of SDP recommendation has traditionally relied on qualitative, expert-driven approaches. Among these, SWOT analysis has been widely used to assess regional development strategies based on the subjective judgment of domain experts (Ghorbani et al. 2015; Kaymaz, Birinci, and Kızılkan 2022; Palomares et al. 2021; Wan, Wang, and Wu 2024). While these approaches provide context-sensitive insights, they are inherently limited in scalability, consistency, and reproducibility.

To overcome these limitations, there has been growing interest in adapting computational techniques from fields such as e-commerce and personalized recommendation. Recommender system methods – such as collaborative filtering and content-based filtering – model user-item interactions and have demonstrated strong performance in commercial domains (Koren, Rendle, and Bell 2022; Thorat, Goudar, and Barve 2015). Although not yet directly applied to SDP recommendation, these mechanisms offer conceptual inspiration for developing models that account for historical patterns and contextual similarity.

Subsequent developments in machine learning, including ensemble methods (e.g. random forests) and deep neural networks, have further enhanced predictive capability in recommendation tasks (Wu et al. 2018; Zhang and Min 2016). However, the applicability of such black-box models to sustainability planning remains limited. Their lack of transparency and reliance on post-hoc explanations constrain their utility in policy environments, where explainability, stakeholder trust, and integration of domain knowledge are crucial.

2.2. Knowledge graph-based recommendation systems

Recognizing the need for both accuracy and interpretability, knowledge graph-based methods have emerged as a promising direction for complex decision-making tasks such as SDP recommendation. Unlike traditional recommender systems, knowledge graphs explicitly represent semantic relationships among entities – such as regions, environmental conditions, and development pathways – enabling structured reasoning, contextual understanding, and visual traceability (Cao et al. 2019). This approach is particularly well-suited to sustainable development scenarios, as it accommodates multidimensional interdependencies across economic, ecological, and social factors. By modeling these as interconnected entities, knowledge graphs allow for richer and more explainable recommendation processes.

Recent advances in graph neural networks (GNNs), such as Knowledge Graph Convolutional Networks (KGCN), Knowledge Graph Attention Networks (KGAT), and Knowledge Graph-based Intent Networks (KGIN), have demonstrated how relational learning on knowledge graphs can improve recommendation performance, even with relatively sparse training data (Wang et al. 2019; Wang et al. 2019; Wang et al. 2021; Zhou et al. 2020). Although these models have been primarily developed for consumer-oriented applications, they offer valuable design principles for sustainability-related tasks. However, existing implementations – originally developed within computer science for product recommendation – are often not directly applicable to SDP recommendation tasks and tend to inadequately address spatial heterogeneity.

The RGB-ER framework builds upon these foundations while addressing their limitations through several key innovations. By incorporating a domain-specific graph pruning mechanism and enhancing intent modeling specifically for sustainability contexts, our approach achieves superior performance while maintaining the interpretability advantages of knowledge graph methods. This combination of capabilities positions knowledge graph-based recommendation as uniquely suited to the complex, multidimensional challenges of sustainable development planning, where both accuracy and transparency are essential for practical implementation.

3. Methodology

3.1. Basic idea and problem formulation

The primary objective of this research is to identify optimal SDPs for target regions by integrating historical development experiences with local contextual conditions. We frame this as a recommendation problem, where the task is to uncover historical interactions – representing past development experiences – between target regions and SDPs. The key challenge lies in generalizing these interactions to uncover potential preferences among similar regions or SDPs, thereby enabling the generation of meaningful and actionable recommendations.

To measure the inherent similarities among regions, we utilize a knowledge graph, which facilitates the representation of interconnections between regions and SDPs. Historical interaction records from successful case studies and their corresponding SDPs offer valuable insights into the underlying intentions driving the adoption of these development models. Based on this, we propose a recommendation method that integrates an Intent Network with a Regional Graph (RG). This method effectively leverages prior knowledge, enabling us to generate reasonable and interpretable recommendations even when training data is limited.

In our framework, let T represent the set of target regions and P denote the set of SDPs. As shown in Figure 2, the interaction matrix $Y \in \mathbb{R}^{|T| \times |P|}$ captures the historical interactions between regions and SDPs. If $y_{t,p} = 1$, it indicates that target region $t \in T$ has previously adopted SDP $p \in P$; conversely, $y_{t,p} = 0$ signifies no historical interaction between target region t and SDP p. Furthermore, the RG serves as the knowledge graph for the regions, comprising a set of entities $\mathcal{V}$ and relationships $\mathcal{R}$ (for specific examples,

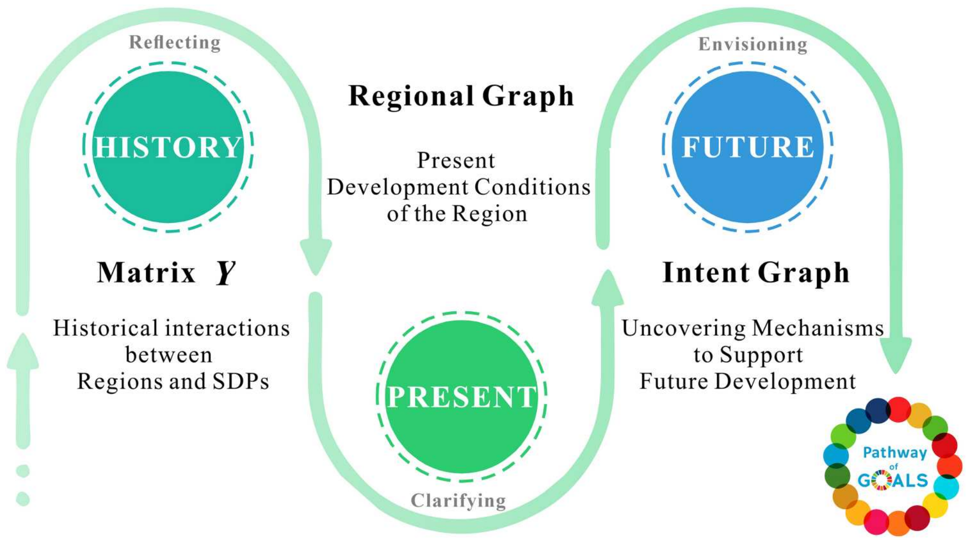

Figure 2. The conceptual framework and key components of the Sustainable Development Pathway (SDP) recommendation system.

please refer to Section 3.3.1). The Intent Graph (IG), derived from historical interaction records, connects regions to the SDPs they have previously adopted, allowing us to explore the deeper intentions behind these interactions.

Our goal is to learn a function $\mathcal{F}$ that predicts the score $\hat{y}_{t,p}$ for a region t and an SDP p, based on the provided RG, IG, and interaction matrix Y. The prediction is expressed as follows:

$$\hat{y}_{t,p} = F(t, p|RG, IG, Y) \tag{1}$$

By comparing these predicted scores, the top-K SDPs for each target region can be derived, forming a robust recommendation system tailored to the region's unique characteristics.

3.2. Regional graph-based explainable recommendation method

Building on the problem formulation outlined in Section 3.1, we propose the RGB-ER method. The technical workflow of RGB-ER, depicted in Figure 3, consists of three main stages:

- **Data Preparation and Collection:** This stage involves collecting comprehensive county-level geographic attribute data, encompassing spatial locations, economic indicators, natural resource distributions, environmental characteristics, and socio-cultural variables. Concurrently, a set of mature SDPs is collected from official directories and web-based data mining.
- **Construction of Regional and Intent Knowledge Graphs:** The collected data is preprocessed to construct the RG and IG, which serve as the foundation for subsequent

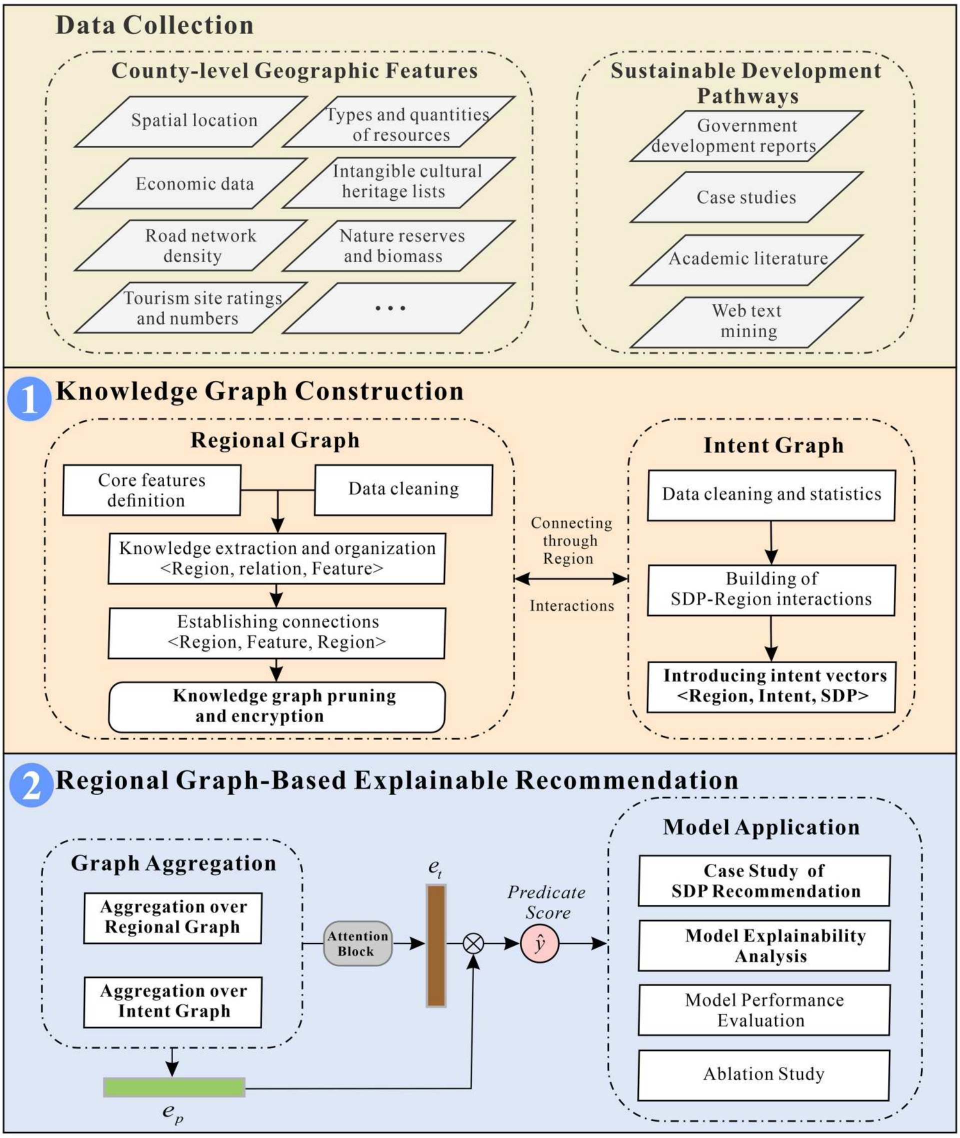

Figure 3. Technical workflow of the Regional Graph-Based Explainable Recommendation Method.

model operations. The detailed construction process and methodologies for these graphs will be discussed in Section 3.3.1.

- **Vector Representation and Recommendation Scoring:** The Graph Aggregation method using GNNs is employed to obtain vector representations of regions and SDGs. The recommendation score is then calculated through the dot product of these vectors. Comparing the model-generated scores allows for identifying the optimal SDP recommendations for each region.

The following provides a detailed explanation of the logic behind the calculation of recommendation scores.

The regional SDP recommendation task focuses on identifying optimal matches between regions and SDPs. This is accomplished by calculating the inner product of the region's embedding vector and the SDP's embedding vector, which serves as a scoring function to assess their similarity. The mathematical formulation for this scoring function is given by:

$$\hat{y}_{t,p} = e_t^T e_p \tag{2}$$

Here, $\hat{y}_{t,p}$ represents the recommendation score between target region t and SDP p, while e_t and e_p denote the embedding vectors for region t and SDP p, respectively.

To derive the embedding representations of e_t and e_p, we adopt a methodology inspired by the KGIN algorithm (Wang et al. 2021). We construct both the RG and IG to capture the intrinsic characteristics of regional development and the historical interaction patterns between regions and SDPs. The embeddings e_t^{RG} and e_t^{IG} are obtained through graph convolution techniques.

It is important to note that while our approach draws from the KGIN framework in capturing intent pathways, our method differs in the construction of the knowledge graph. As illustrated in Figure 4a, the original KGIN algorithm constructs its knowledge graph around items (which correspond to SDPs in this study), with embeddings aggregated sequentially from the knowledge graph and intent pathways. In contrast, our method constructs the knowledge graph around regions (analogous to users in KGIN), as illustrated in Figure 4b. Thus, the embedding for region e_t is computed by aggregating information from both the RG and IG, yielding e_t^{RG} and e_t^{IG}. These embeddings are then combined using an attention mechanism, as shown in Equation 3 (the specifics of this

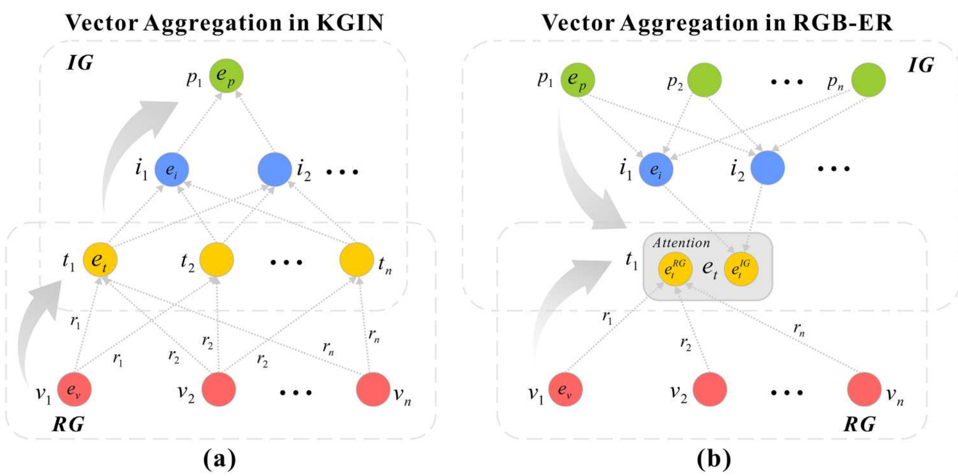

Figure 4. Comparison of vector aggregation processes between KGIN and the proposed RGB-ER method. (a) Illustration of vector aggregation in the KGIN method, and (b) illustration of vector aggregation in the RGB-ER method proposed in this study. In these illustrations, p represents SDPs, i denotes intents, t represents regions, v stands for feature nodes in the RG, and r indicates relationships within the RG.

process will be detailed in Section 3.3.2):

$$e_t = Attention(e_t^{RG},\ e_t^{IG}) \tag{3}$$

Once the embedding e_t is obtained, the embedding e_p can be directly utilized since it is already established during IG aggregation. By substituting e_t and e_p into Equation 2, we can compute the scores for different regions against various SDPs. The dominant intent vectors derived from this process can help explain the rationale behind the recommended SDPs, offering interpretability to the model's outputs. In the subsequent sections, we will evaluate the model's performance using standard metrics such as Precision, Recall, and F1 Score. Additionally, we will validate the model's practical SDP recommendation effectiveness using the development planning of counties in Fujian Province as a case study.

Notably, our experiments revealed that the large number of discrete numerical attribute nodes in the RG, which often lack direct interconnections, results in a sparse graph structure that limits the model's learning capacity and its ability to mitigate the effects of spatial heterogeneity. To address this issue, we introduce a pruning strategy that categorizes and ranks these discrete numerical attributes. This approach not only enhances the density of the RG and the model's ability to capture geographical heterogeneity but also improves overall computational efficiency. Details of this pruning strategy are discussed in Section 3.3.3.

Table 1. Data information in regional graph (RG).

Category	Attributes	Type of Attribute	Relation in RG
Geographic Information	Annual Precipitation	numerical	Has.AnnualPrecipitation
	Soil Type	categorical	Has.SoilType
	Climatic Zone	categorical	Has.ClimaticZone
	Elevation	numerical	Has.Elevation
	Landform Type	categorical	Has.LandformType
	Province	categorical	LocatedIn.Province
	City	categorical	LocatedIn.City
	Region	categorical	LocatedIn.Region
Resource Abundance	Agricultural Land Area	numerical	Contains.AgriculturalLandArea
	Vegetation Coverage	numerical	Has.VegetationCoverage
	Water Resources per Capita	numerical	Has.WaterResourcesPerCapita
	Forest Area Coverage	numerical	Has.ForestAreaCoverage
Economic Indicators	Total GDP	numerical	Has.TotalGDP
	GDP per Capita	numerical	Has.GDPPerCapita
	Urban Residents' Savings per Capita	numerical	Has.UrbanSavingsPerCapita
	Share of Secondary Sector	numerical	Has.SecondarySectorShare
	Share of Tertiary Sector	numerical	Has.TertiarySectorShare
Environmental Quality	Surface Water Quality Index	numerical	Monitors.SurfaceWaterQuality
	Soil Erosion Rate	numerical	Measures.SoilErosionRate
	Number of Biodiverse Habitats	numerical	Hosts.BiodiverseHabitats
	Nature Reserve Area Proportion	numerical	Contains.NatureReserveProportion
	Overall Natural Disaster Risk	numerical	Assesses.NaturalDisasterRisk
Infrastructure and Services	Transport Network Density	numerical	Has.TransportNetworkDensity
	Medical Facility Bed Count	numerical	Has.MedicalFacilityBedCount
	Number of Tourist Sites Rated AAA and Above	numerical	Contains.HighRatedTouristSites
Cultural Attributes	Ethnic Composition	categorical	Has.EthnicComposition
	Dialect	categorical	Has.Dialect
	Count of Intangible Cultural Assets	numerical	Has.IntangibleCulturalAssetsCount
	Types of Intangible Cultural Heritage	categorical	Lists.TypesOfIntangibleHeritage

3.3. Key algorithms in the RGB-ER method

3.3.1. Construction of the regional graph and intent graph

Regional Graph Construction: The RG is constructed at the county level in China by aggregating publicly available official statistical data. The RG functions as a semantic network composed of region-attribute-region pairs, wherein regional nodes are interconnected via shared attribute nodes. This network structure effectively captures spatial heterogeneity among regions.

To build the RG, we define 6 categories of indicators that represent the geographical attributes of the target regions, using a total of 29 specific indicators as outlined in Table 1. For each region, we collect various geographical attributes, such as meteorological data, hydrological information, and soil characteristics. These attributes are used to link each regional node with corresponding attribute nodes, following the relationships defined in Table 1. By establishing diverse paths between regions – each enriched with unique semantic information – we aggregate attribute data from related nodes to the regional node. This aggregation process helps to establish spatial correlations, improving our understanding of the interrelationships between regions.

Intent Graph Construction: The IG is constructed based on historical interaction records between regions and SDPs. To identify representative SDPs, we consult development planning documents issued by Chinese government departments, such as the 'National Nature Reserve Directory', 'National Forest Park Directory', and 'National Characteristic Town Directory'. Additionally, we employ web scraping and text analysis techniques to collect information on typical development models across county-level

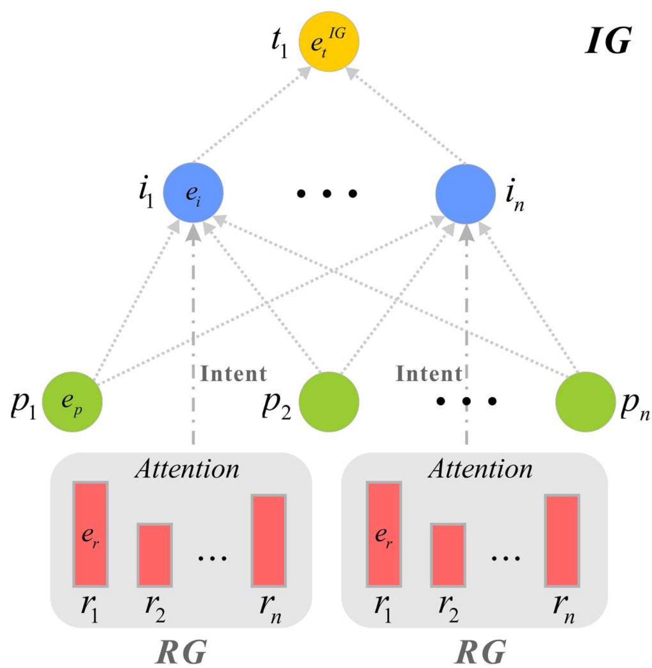

Figure 5. Schematic representation of the composition of the Intent Graph. In the figure, *t* represents regions, *i* denotes intents, *p* represents SDPs, and *r* indicates relationships within the RG.

regions in China (Wang et al. 2022). Through this process, we identify a total of 94 distinct SDPs (detailed in Appendix A), categorized into three levels, and compile 7,830 historical interaction records between regions and SDPs.

As illustrated in Figure 5, the IG consists of region nodes t, corresponding SDP nodes p, and a set of intent nodes i. These intent nodes are derived using attention-based operations applied to the relationships within the RG, forming triplets of the form $<t, \ i, \ p>$. The introduction of intent nodes mitigates the sparsity of interactions between regions and SDPs, enhancing the interaction density and providing greater interpretability to the model. The inclusion of multiple intent nodes facilitates richer intent representations.

The embedding representation of the intent vector i is denoted as e_i, which is computed as follows:

$$e_i = \sum_{r \in \mathcal{R}} \alpha(r, p) e_r \tag{4}$$

Here, $\mathcal{R}$ represents the set of all relationships in RG, $\alpha(r, p)$ indicates the importance of relationship r to intent vector i, and e_r is the embedding of relationship r within the RG. Further details on the construction of the IG can be found in Wang et al. (2021).

3.3.2. Attention-based regional embedding vector generation

As described in Section 3.2, the regional embedding vector e_t is derived by applying an attention mechanism to both e_t^{RG} and e_t^{IG}. Figure 6 illustrates this process in detail.

The vector e_t^{RG} is generated through multi-hop aggregation of the neighboring nodes of region t in the RG. We employ a graph convolution approach similar to RippleNet to aggregate information from the attribute nodes surrounding region t, thus enhancing its expressive power (Wang et al. 2018). This results in the intermediate vector $e_t^{RG(l)}$, which captures information from progressively distant nodes. The final regional embedding e_t^{RG} is computed as:

$$e_t^{RG} = \sum_{l \in L} e_t^{RG(l)}, \quad e_t^{RG(l)} = \frac{1}{|N_t^{RG}|} \sum_{(r,v) \in N_t^{RG}} e_r \odot e_v^{(l)} \tag{5}$$

Here, N_t^{RG} denotes the set of relation-entity pairs $(r, \ v)$ directly connected to region t in

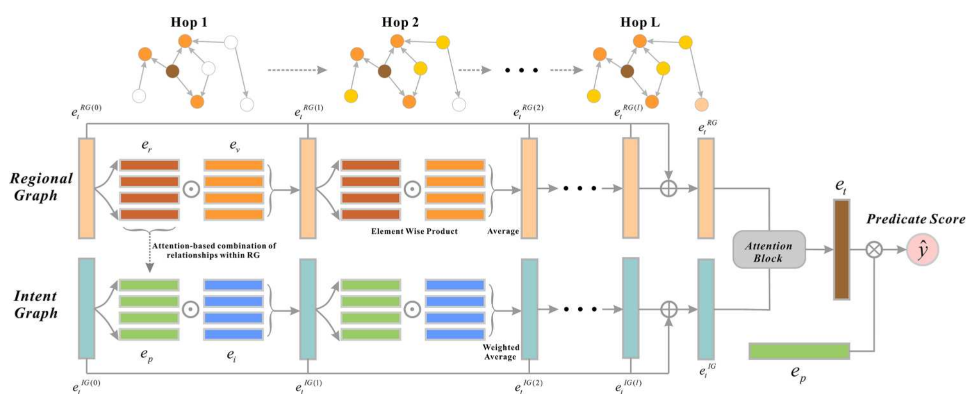

Figure 6. Structural diagram of the RGB-ER model proposed in this study. The upper and lower parts illustrate the process of vector aggregation over the RG and IG, respectively.

the RG, with e_r representing the embedding of relationship r, and $e_v^{(l)}$ the embedding of the neighbor node v during the l-th aggregation phase. The symbol $\odot$ indicates element-wise multiplication between two vectors.

The vector e_t^{IG} is derived by aggregating the SDPs p that have historically interacted with region t, along with a set of intent vectors i that link the two, as shown in the following equation:

$$e_t^{IG} = \sum_{l \in L} e_t^{IG(l)}, \quad e_t^{IG(l)} = \frac{1}{|N_t^{IG}|} \sum_{(i,p) \in N_t^{IG}} \beta(t, i)^{(l)} e_i \odot e_p \tag{6}$$

Here, N_t^{IG} represents the set of SDPs p and intent vectors i associated with target region t based on past interactions. The term e_i is the embedding of intent vector i, and e_p denotes the embedding of the SDP p. The weight $\beta(t, i)$ indicates the importance of intent vector i for region t, with further computational details available in the KGIN paper (Wang et al. 2021).

After obtaining e_t^{RG} and e_t^{IG}, the final regional embedding vector e_t is computed using an attention-based mechanism for weighted summation:

$$e_t = \sum_{n \in (RG,IG)} \gamma(n) e_t^n \tag{7}$$

Here, $\gamma(n)$ represents the importance of e_t^n in contributing to the final embedding vector e_t. The weight $\gamma(n)$ is computed as:

$$\gamma(n) = ReLU\left(\frac{\exp\left(We_t^n\right)}{\sum_{n \in (RG,IG)} \exp\left(We_t^n\right)}\right) \tag{8}$$

In this equation, the weight matrix W is a trainable parameter of the model that maps e_t^{RG} and e_t^{IG} into a shared semantic space, enabling the integration of the two semantic networks. The *ReLU* function is adopted as the activation function due to its widespread effectiveness in neural network training. It is important to note that the use of graph convolution and attention mechanisms increases the model's complexity, which in turn raises the training cost. However, as demonstrated in the subsequent experimental section, the attention mechanism significantly enhances the recommendation performance of the model, making this additional computational cost justifiable.

3.3.3. Pruning method for enhancing the regional graph

Although the initial construction of the RG has proven effective, we observe a limitation in the spatial correlation between regions. Specifically, around 69% (20 out of 29) of the regional attributes are numerical. Numerical attributes generally only connect to their corresponding target regions within the RG, which limits the overall spatial correlation across regions.

To address this issue, we propose a pruning method that removes numerical entity nodes from the RG and reintroduces them through a categorization process. This approach, illustrated in Figure 7, uses the attribute 'Number of Tourist Sites Rated AAA and Above' for Hexi and Xiaonan Districts as a case study. The pruning process consists of three stages:

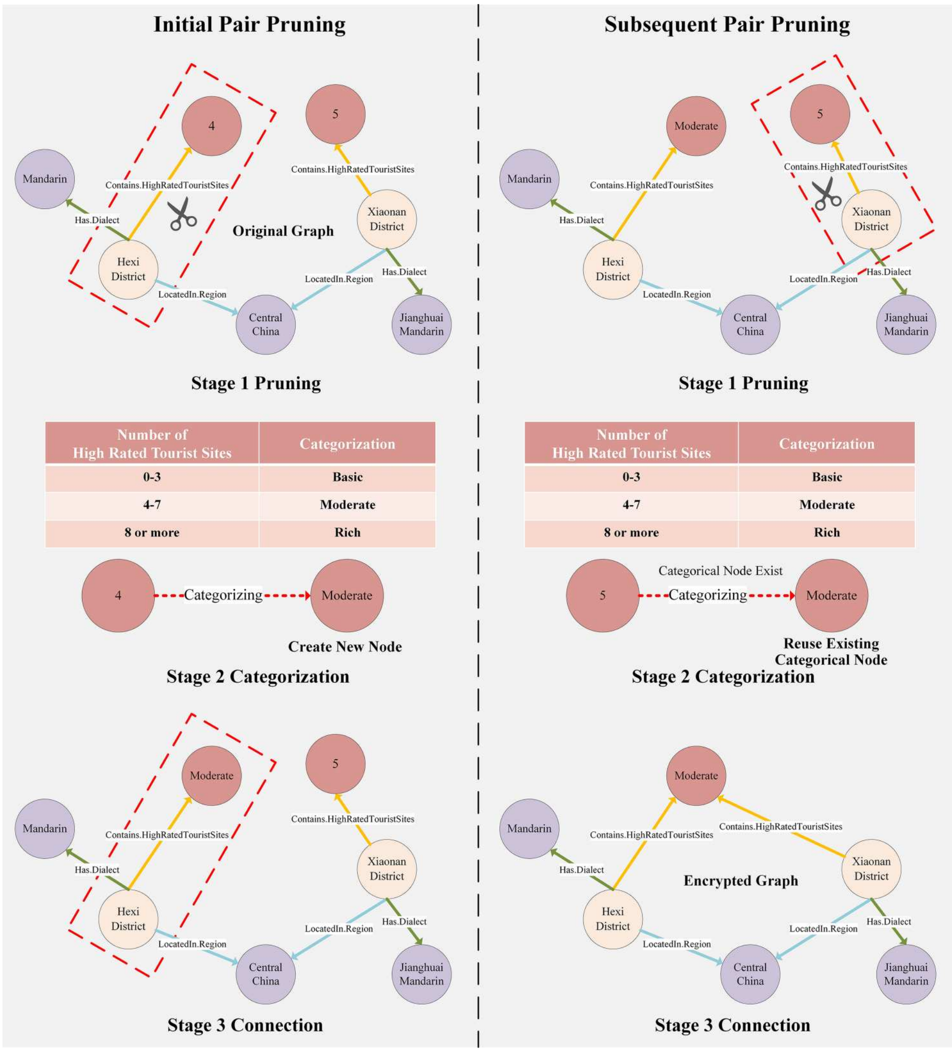

Figure 7. Pruning process in the Regional Graph.

(1) **Pruning Stage:** Identify and remove numerical nodes from the graph. This step helps to reduce the influence of sparse numerical values that do not contribute significantly to spatial relationships.

(2) **Categorization Stage:** Categorization is a straightforward method, but the process can be cumbersome. First, we gather widely recognized classification criteria for specific attributes and use these standards to categorize numerical attributes. For example, China's annual precipitation is classified into four categories:

- Arid regions: Annual precipitation < 200mm
- Semi-arid regions: Annual precipitation between 200 mm and 400mm
- Semi-humid regions: Annual precipitation between 400 mm and 800mm
- Humid regions: Annual precipitation > 800mm

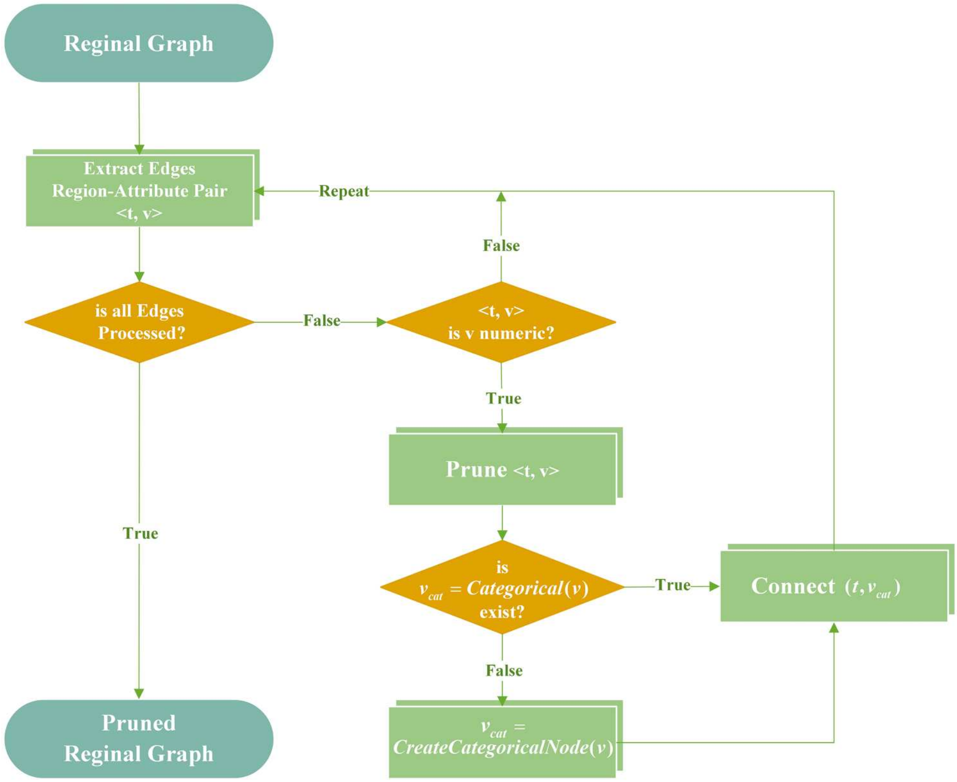

Figure 8. Flowchart of the pruning method for enhancing the Regional Graph.

For attributes without clear classification standards, we apply the natural breaks method to manually define categories (Chen et al. 2013). Once the categorization criteria are established, we check if the corresponding categorical node for each numerical attribute already exists. If it does, no new node is created; otherwise, a new categorical node is introduced. For instance, the categorical node 'Moderate' for both Hexi and Xiaonan Districts helps avoid redundancy.

(3) **Connection Stage:** After categorization, we establish connections between the categorical nodes and their respective regions. In Figure 7, after pruning and categorizing, both regions are connected via the 'Moderate' node. This process is consistently applied to all numerical nodes, thereby enhancing spatial correlation and improving the representation of spatial heterogeneity across the regions.

Detailed steps of the pruning algorithm are illustrated in the flowchart in Figure 8. The algorithm begins by extracting all edges of the form $\langle t, v \rangle$ from the RG. For each pair consisting of a region node t and its associated attribute node v, the algorithm first checks if v is numerical. If so, the corresponding edge $\langle t, v \rangle$ is pruned by removing v from the graph. If v is non-numerical, the algorithm checks whether a corresponding categorical node $v_{cat} = \text{Categorical}(v)$ exists. If present, a direct connection is established between region t and the categorical node. If not, the algorithm invokes the function

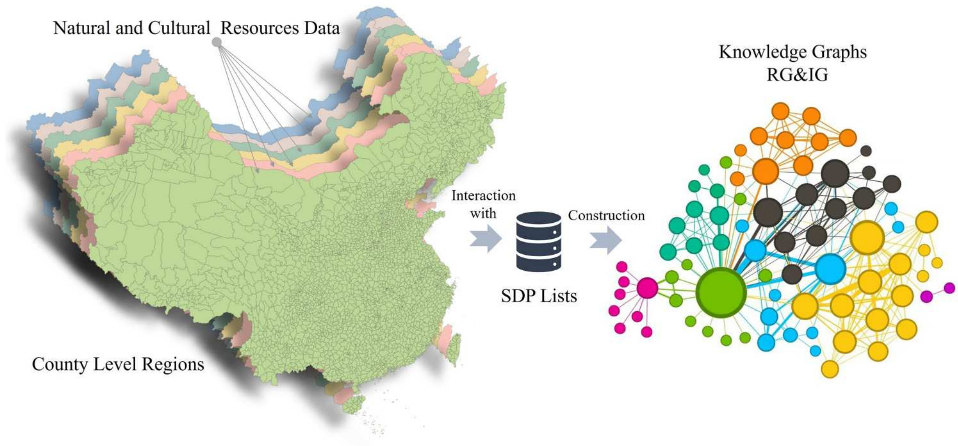

Figure 9. Illustration of development condition indicators, SDPs, and the corresponding Regional Graph (RG) and Intent Graph (IG) at the county level in China.

CreateCategoricalNode(v), which discretizes the numerical data into predefined intervals, assigns categorical labels, and creates the corresponding categorical node. Once all edges and nodes are processed, the pruned RG is output, ensuring that all attribute nodes are either categorized or removed.

4. Experiments and results

4.1. Dataset

SDPs represent development strategies that integrate economic growth with ecological conservation tailored to local conditions. As shown in Figure 9, to provide a comprehensive basis for recommending SDPs, we collected a dataset across 2596 counties in China, consisting of development indicators in 6 categories: Geographic Information, Resource Abundance, Economic Indicators, Environmental Quality, Infrastructure and Services, and Cultural Attributes (as aforementioned in Table 1). These data served as the basis for constructing the RG, as detailed in Section 3.3.1. In addition, we compiled a directory of 94 SDPs (detailed in Appendix A), categorized into three levels, and gathered 7830 historical interaction records between regions and SDPs from publicly available directories and web scraping (Wang et al. 2022). These interactions were used to construct the IG, which captures the relationships between regions and the SDPs they have previously adopted.

4.2. Experimental setup and evaluation criteria

4.2.1. Dataset preparation and training parameters

Following the construction procedures for the RG and IG described in Section 3.2, we generate the dataset as outlined in Section 4.1. For the experimental split, we use 80% of the historical interactions from the target regions as the training set and the remaining 20% as the test set. Within the training set, 20% of the data was further sampled as a validation set for hyperparameter tuning.

The embedding dimension was set to 64, the batch size to 128, and the initial learning rate to 1e-3. Additional hyperparameters – such as the number of intent vectors and the number of aggregation layers in the RG – were optimized through grid search over predefined ranges. For example, the number of layers was searched within {2, 3, 4, 5}, and the number of intents within {3, 4, 5}. Early stopping was applied based on validation loss with a patience of 10 epochs. Details of the selected configurations and their performance impact are discussed in Section 4.3.3.

4.2.2. Evaluation metrics and baseline models

To evaluate the Top-K SDP recommendations for each target region, we adopt an all-ranking strategy (Krichene and Rendle 2020), as opposed to the user subset extraction approach used in previous studies (Wang et al. 2019; Wang et al. 2019). Specifically, we recommend SDPs that have not been previously interacted with for each target region, and select the Top-K SDPs that best align with the region's development needs. The following metrics are used to evaluate recommendation accuracy.

Precision@K quantifies the proportion of recommended SDPs in the Top-K list that are actually relevant to the target region:

$$Precision@K = \frac{|R^K(t) \cap T(t)|}{K} \tag{9}$$

Recall@K measures the proportion of the true relevant SDPs (from the test set) that are captured within the Top-K recommendations:

$$Recall@K = \frac{|R^K(t) \cap T(t)|}{|T(t)|} \tag{10}$$

F1@K provides a harmonic mean of *Precision@K* and *Recall@K*, serving as an overall performance measure:

$$F1@K = \frac{2 \times Precision@K \times Recall@K}{Precision@K + Recall@K} \tag{11}$$

To evaluate the effectiveness of the proposed method, RGB-ER is compared with three state-of-the-art knowledge graph-based recommendation models – KGCN, KGAT, and KGIN – that serve as baselines.

4.3. Results

4.3.1. SDP recommendation results

After training and fine-tuning the RGB-ER model, we computed recommendation scores for each region across the 94 SDPs, ranking them to generate tailored lists of recommended SDPs. These recommendations consider the unique development conditions of each region while incorporating insights from development experiences in similar regions. This approach provides valuable guidance for policymakers aiming to balance economic growth with environmental sustainability. The model's interpretability, facilitated by intent vectors, further enhances understanding of the factors influencing recommendation outcomes.

Table 2. Top-5 relationship for each intent vector.

Intent	1^{st} relationship	2nd relationship	3rd relationship	4th relationship	5th relationship
i_1	Contains.AgriculturalLandArea	Measures.SoilErosionRate	Has.SecondarySectorShare	Has.ForestAreaCoverage	Has.TertiarySectorShare
i_2	Assesses.NaturalDisasterRisk	Has.ClimaticZone	Monitors.SurfaceWaterQuality	LocatedIn.City	LocatedIn.Province
i_3	Has.ForestAreaCoverage	Monitors.SurfaceWaterQuality	Has.WaterResourcesPerCapita	Has.UrbanSavingsPerCapita	Has.IntangibleCulturalAssetsCount
i_4	Has.VegetationCoverage	Has.UrbanSavingsPerCapita	Contains.NatureReserveProportion	Has.Dialect	Hosts.BiodiverseHabitats

The RGB-ER model identifies key attributes for each SDP by considering a broad spectrum of ecological, cultural, geographical, and economic factors. As illustrated in Figure 5, each intent vector i within the intent vector group I assigns varying weights to the relationships within the RG. Table 2 presents the top five relationships with the highest weights for each intent vector after model training.

An analysis of Table 2 reveals that the first intent vector (i_1) places significant weight on relationships related to resource abundance, with a marked preference for factors such as agricultural land area and forest coverage. The second intent vector (i_2) emphasizes geographical factors, such as climatic zones and city-level attributes. The third intent vector (i_3) reflects a more balanced approach, incorporating environmental quality, geographic information, economic indicators, and cultural aspects. Conversely, the fourth intent vector (i_4) is predominantly focused on environmental quality, with relationships highlighting nature reserve area proportion and biodiversity. These diverse weights reflect the complex nature of SDPs, which involve a multifaceted interplay of ecological, economic, and cultural factors. The RGB-ER model underscores the need for region-specific SDPs tailored to each area's unique characteristics.

To illustrate the recommendation process, we present a case study of Pengzhou City in Sichuan Province. Pengzhou is a mountainous, rainy region with a mild climate. As shown in Figure 10, the city has already implemented several SDPs, including the National Parks Pattern, Nature Reserves Pattern, and Agricultural Innovation Parks Pattern. After excluding these existing models, the RGB-ER model recommends the following top three SDPs for Pengzhou: Ecotourism Pattern, Beautiful Countryside Pattern, and Orchard Livestock Pattern. These recommendations aim to leverage the region's rich natural resources to boost economic development through tourism and rural revitalization. The Ecotourism Pattern and Beautiful Countryside Pattern emphasize sustainable tourism and rural development, which align with Pengzhou's goal of promoting environmental protection and economic growth through the establishment of the Giant Panda National Park. This alignment suggests that the model effectively identifies suitable

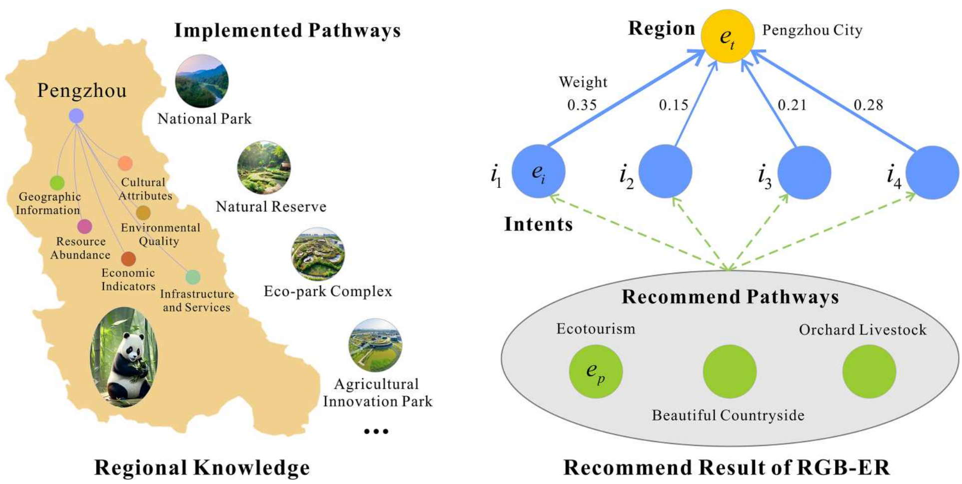

Figure 10. SDP recommendation results for Pengzhou based on the RGB-ER method.

SDPs by learning from historical development experiences in similar regions, thereby providing valuable insights for policymaking.

After obtaining the recommended SDPs, we analyzed the importance scores of the intent vectors in Pengzhou. As shown in Figure 10, the importance scores for the four intent vectors in Pengzhou are 0.35, 0.15, 0.21, and 0.28, respectively, with the highest scores assigned to i_1 and i_4, reflecting the model's focus on resource abundance and environmental quality. This result aligns with prior findings, confirming that the recommended SDPs for Pengzhou are predominantly influenced by environmental considerations. Although i_1 holds the highest weight, the recommendations for Pengzhou also illustrate the cumulative impact of all four intent vectors. This finding suggests that the RGB-ER model adopts a holistic approach to SDP recommendations by integrating multiple factors to produce comprehensive, region-specific recommendations. Thus, the RGB-ER model is capable of identifying SDPs that are in line with the overarching development goals of the target region, incorporating both environmental and economic dimensions.

4.3.2. Comparison of recommendation performance

To assess the recommendation performance of RGB-ER, we compared it with KGCN, KGAT, and KGIN across *Precision@K*, *Recall@K*, and *F1@K* metrics for both Top-3 and Top-5 recommendations. The experimental results, as shown in Figure 11, demonstrate that RGB-ER consistently outperforms the baseline models.

For *F1@K* and *Recall@K*, the RGB-ER method exhibited a substantial improvement. Since the average number of historical interactions for each region in the IG is three, we first evaluated the model with $K = 3$. In the Top-3 recommendations, RGB-ER achieved an *F1@3* improvement of 9.61% over KGCN, 7.02% over KGAT, and 3.47% over the best baseline model, KGIN. Additionally, RGB-ER showed the largest improvement in *Recall@3*, with an increase of 15.14%, surpassing KGIN by 8.86%.

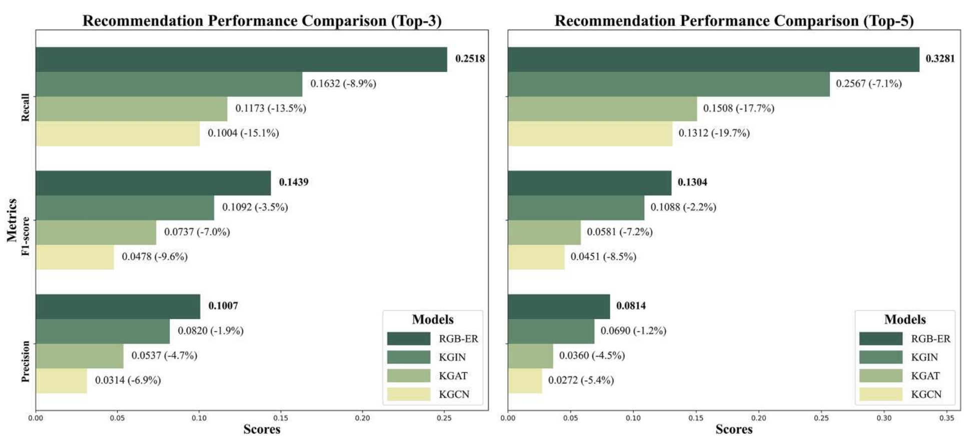

Figure 11. Performance comparison of Top-3 and Top-5 recommendations between RGB-ER and baseline models.

For a broader set of recommendations, we also evaluated Top-5 recommendations by setting $K = 5$. Here, RGB-ER outperformed KGCN, KGAT, and KGIN with an $F1@5$ improvement of 8.53%, 7.23%, and 2.16%, respectively. Notably, the improvement in $Recall@5$ was even more pronounced, with RGB-ER achieving a 19.06% improvement, surpassing KGIN by 7.14%. These results underscore the superior performance of RGB-ER, regardless of the number of recommendations.

4.3.3. Impact of model parameters

In this section, we examine how various hyperparameters affect the performance of RGB-ER. For consistency, we focus on $F1@3$ for Top-3 recommendations and evaluate the impact of each parameter in isolation. In addition, we report the corresponding training time, inference speed, and memory consumption under each configuration.

Impact of Neighbor Aggregation Size: The number of aggregation layers L in the RG was varied to investigate its effect on recommendation performance. As shown in

Table 3. Impact of neighbor aggregation size.

L	2	3	4	5
$F1@3$	0.1393	0.1375	**0.1439**	0.1403
Training Time (S)	175.8857	253.9536	297.6985	349.2970
Memory (GB)	0.3022	0.2838	0.3124	0.3225
Inference Speed (S)	0.0305	0.0640	0.0637	0.0699

Table 4. Impact of number of intent vectors.

$\|P\|$	3	4	5
$F1@3$	0.1337	**0.1439**	0.1405
Training Time (S)	253.7963	297.6985	358.2998
Memory (GB)	0.2651	0.3124	0.3462
Inference Speed (S)	0.0538	0.0637	0.0720

Table 5. Statistics of the RG with/ without pruning.

	Regions	Attributes	Relationship types	Density
RG	2596	39,744	29	0.009%
RG after Prune	2596	1669	29	0.863%

Table 6. Impact of graph pruning.

	$RGB-ER_{\text{w/o GP}}$	RGB-ER
$F1@3$	0.1312	**0.1439**
Training Time (S)	404.1434	297.6985
Memory (GB)	0.2889	0.3124
Inference Speed (S)	0.0596	0.0637

Table 7. Impact of attention block.

	$RGB-ER_{\text{w/o Att}}$	RGB-ER
$F1@3$	0.1277	**0.1439**
Training Time (S)	308.0988	297.6985
Memory (GB)	0.3733	0.3124
Inference Speed (S)	0.0543	0.0637

Table 3, an aggregation size of 4 layers maximizes spatial correlation among regions, improving the model's ability to account for spatial heterogeneity.

Impact of Number of Intent Vectors: Increasing the number of intent vectors beyond 4 resulted in diminishing returns. Table 4 shows that the performance begins to degrade when $|P|$ exceeds 4, likely due to the granularity becoming too fine and diluting useful information.

Impact of Graph Pruning: Table 5 shows statistics of the RG with and without pruning. Graph pruning improved the model's recommendation performance by removing redundant geographic attribute nodes, leading to higher graph density and more efficient path calculations. Table 5 and Table 6 show that pruning increased the graph density by 0.854%, resulting in a 1.27% improvement in $F1@3$.

Impact of Attention Block: We also evaluated the role of the attention block used to fuze features from the IG and RG. As shown in Table 7, the inclusion of the attention block facilitated a more effective integration of the two semantic spaces, resulting in a 1.61% improvement in F1@3.

5. Discussion

5.1. Regional sustainable development pathways in Fujian province

To further explore the practical applications of the RGB-ER model, we analyze the alignment between the Top-5 recommendations for regions in Fujian Province, China, and the governmental plans of SDPs in the region. The accuracy of the Top-5 recommendations is calculated as follows:

$$Accuracy = \frac{\sum_{d \in D} |Top(d) \cap Gov(d)|}{5 * |D|} \tag{12}$$

Here, D represents the set of 78 counties in Fujian Province, $Top(d)$ is the set of Top-5 recommendations for county d, and $Gov(d)$ is the set of SDPs included in the government's plans for that county.

The resulting accuracy of 79% demonstrates that the RGB-ER model aligns well with government priorities for sustainable development, suggesting its potential to support policy decision-making and enhance the efficiency of regional resource allocation. A selection of representative examples comparing the model's recommendations with government planning documents is provided in Appendix B.

To further assess the rationality of the current development directions across counties in Fujian Province, we analyze the alignment between the Top-5 recommended SDPs (excluding those already implemented) and the historical implementation of SDPs in the region. As described in Section 4.1, the 94 third-level SDPs can be grouped into six second-level categories. We evaluate the consistency between the current implemented SDPs in the region and the model-recommended SDPs by comparing their match in these second-level categories. The match was classified into four categories based on the degree of coincidence:

- Clearly Oriented (100% match)

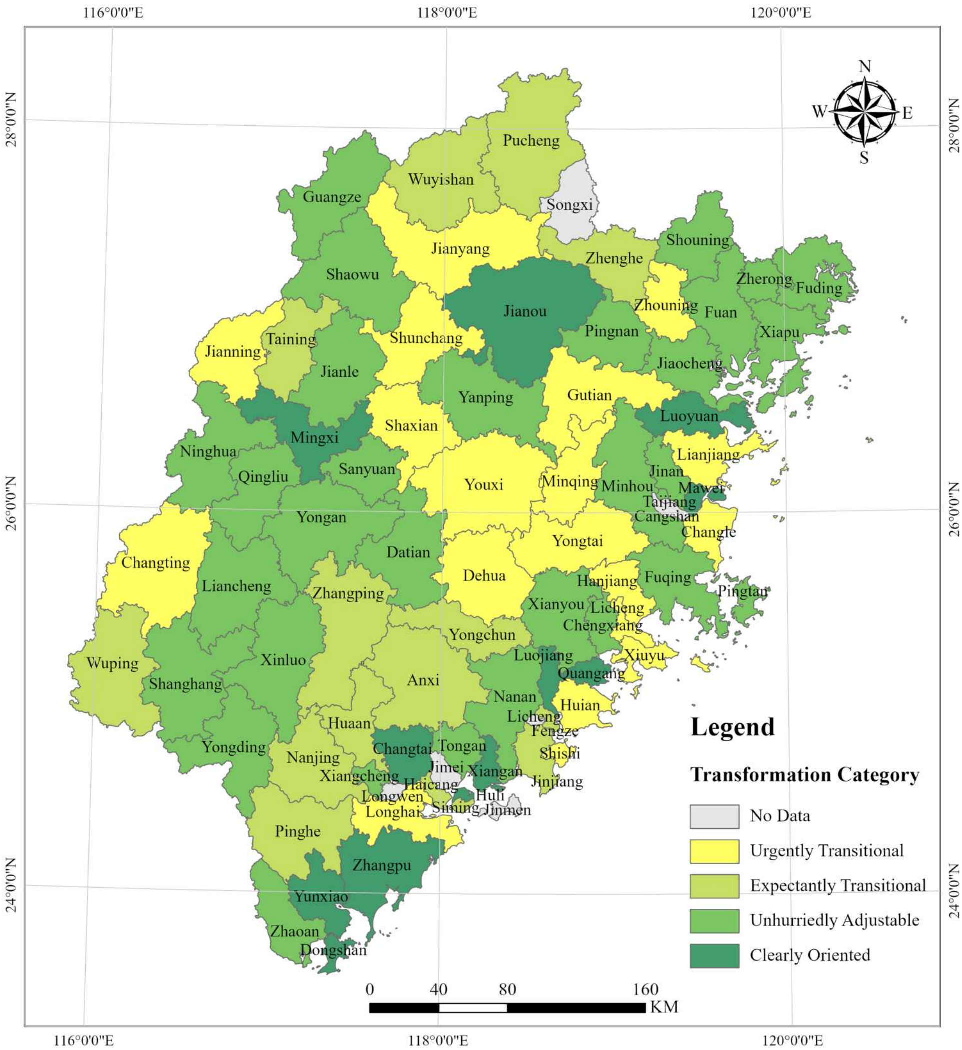

Figure 12. Sustainable development direction assessment for counties in Fujian province.

- Unhurriedly Adjustable (> = 50% match)
- Expectantly Transitional (< 50% match)
- Urgently Transitional (0% match)

The degree of match was quantified as:

$$coincidence\ degree = \frac{|E(t) \cap \mathrm{R}(t)|}{|E(t)|} \tag{13}$$

Here, $E(t)$ is the set of historical SDPs for region t, and $\mathrm{R}(t)$ is the set of recommended SDPs for the same region. Figure 12 shows that out of the 78 counties with historical SDP data, 56% were classified as 'Clearly Oriented' or 'Unhurriedly Adjustable', indicating that most regions follow established development principles and account for local geographic factors.

However, discrepancies were evident in northern Fujian, where the geography presents significant challenges, such as mountainous and rain-prone regions prone to natural disasters and ecological degradation. For instance, 56% of counties in Nanping were classified as 'Transitional', and 30% of counties in Sanming were in the 'Urgently Transitional' category. These findings indicate that although many regions align with historical development principles, notable gaps remain in ecological resilience and policy adaptation, particularly in vulnerable areas.

In the 'Transitional' regions, the most frequently recommended SDPs were the Natural Park Pattern and Eco-Park Complex Pattern. The Natural Park Pattern focuses on ecological protection and sustainable utilization through the management of natural parks, while the Eco-Park Complex Pattern integrates ecological protection with economic development by creating multifunctional parks that foster resource recycling, ecological conservation, and industrial growth. These SDPs are particularly appropriate for ecologically sensitive areas, effectively balancing environmental protection with economic growth, and in alignment with the growing recognition of innovation's crucial role in enabling progress towards the SDGs (Dzhunushalieva and Teuber 2024).

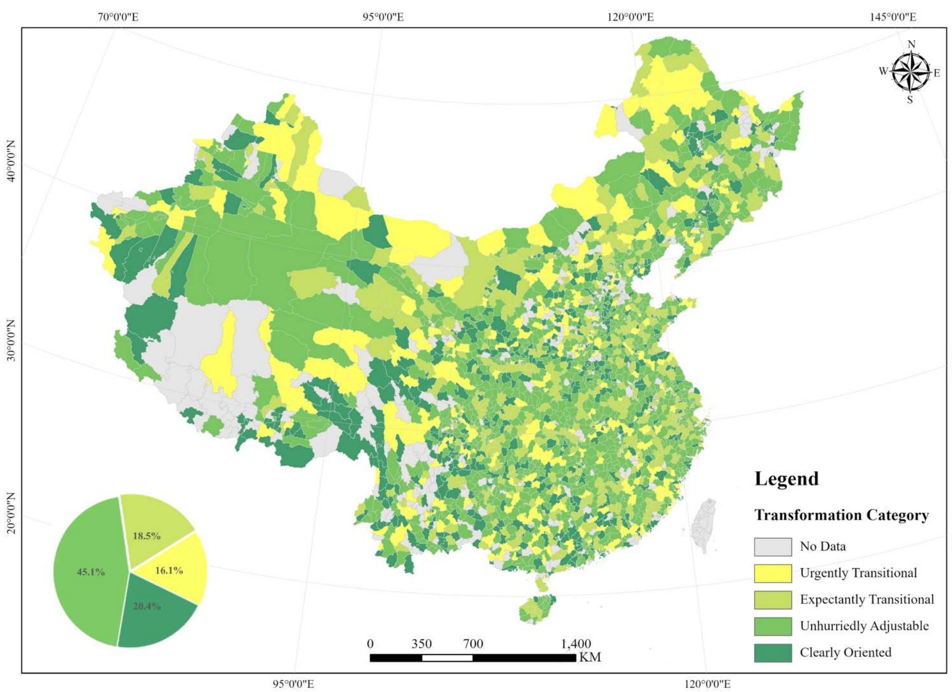

Figure 13. Assessment of sustainable development directions for counties in China.

5.2. Assessing county-level sustainable development pathways in China

After confirming the model's reliability in Fujian, we expanded the analysis to counties across China, as shown in Figure 13. The results revealed that 66% of regions fell into the 'Clearly Oriented' and 'Unhurriedly Adjustable' categories, a 10% improvement over Fujian. This increase can be attributed to the diverse geographical and environmental challenges across regions, such as the coastal mountainous areas in Fujian and the high-altitude, arid regions of Tibet and Xinjiang. These areas face more severe obstacles to sustainable ecological development, leading to a higher proportion of regions in the 'Transitional' categories. Additionally, regions marked as 'No Data' were primarily located in the western part of China, likely due to sparse population density and limited resources for collecting relevant SDP data in these areas.

In analyzing the SDPs recommended for the 'Transitional' regions across China, we found notable differences compared to Fujian. The most frequently recommended SDPs were the Agro-Pastoral Integrated Pattern and Ecotourism Pattern. The Agro-Pastoral Integrated Pattern merges crop farming with livestock breeding, creating a sustainable agricultural system where each sector supports the other. The Ecotourism Pattern encourages interactions between visitors and the natural environment while delivering economic and social benefits to local communities. These recommendations underscore the necessity of tailoring SDPs to the specific ecological, economic, and cultural contexts of each region, especially those with favorable natural resources.

Moreover, some regions in the 'Transitional' categories had limited historical SDP data (1-2 SDPs), which may have contributed to a lower match between the model's recommendations and past implementations. This limited data could result in an overestimation of the proportion of regions in the 'Transitional' category. Nevertheless, the model effectively captures the underlying relationships between SDPs and regional development contexts, offering valuable insights for policymaking. This represents an innovative application of knowledge, utilizing computational model recommendations to potentially advance progress towards the SDGs (Li et al. 2023).

5.3. Limitations and future directions

While the RGB-ER framework advances SDP recommendations by integrating spatial heterogeneity and interpretable intent modeling, its real-world applicability faces three fundamental challenges that warrant further investigation.

First, the current framework implicitly treats policy-making as a purely objective, data-driven process, thereby overlooking complex human and institutional dimensions such as stakeholder preferences, political constraints, and inter-regional governance dynamics – all of which critically shape the adoption and effectiveness of SDPs (Lafont-Torio et al. 2024; Lyulyov et al. 2024). Future extensions should aim to develop hybrid recommendation models that couple data-centric inference with mechanisms to capture policy-maker preferences and institutional coordination. This could be achieved through preference learning algorithms, multi-agent modeling, or collaborative network analysis, thereby improving the alignment between algorithmic outputs and actual governance priorities without sacrificing scientific rigor.

Second, the model's static design limits its capacity to reflect the dynamic feedback loops that characterize sustainable development interventions. In practice, policy decisions trigger evolving social, environmental, and economic responses that recursively influence the suitability of future strategies (Majumder et al. 2023; Roy et al. 2024). To address this, future research should explore dynamic graph representation learning and reinforcement learning-based sequential decision models, enabling adaptive recommendations that evolve in response to simulated impacts and changing regional contexts. Such capabilities would transform RGB-ER from a one-time recommender into a forward-looking policy planning engine capable of supporting long-term strategic scenario development.

Third, while the RGB-ER model incorporates interpretable intent vectors, the translation of these technical outputs into actionable policy insights remains limited. Enhanced causal inference frameworks are needed to better understand how regional characteristics interact to produce sustainable outcomes. This could be complemented by user-facing decision-support interfaces, integrating visual scenario exploration, policy impact simulation, and trade-off visualization to facilitate policy adoption (Hernandez 2017). In parallel, the model's feature space should be expanded to include underrepresented yet critical factors such as disaster resilience, social equity, climate vulnerability, and corporate sustainability performance, informed by systematic reviews of interdisciplinary sustainability literature (Gallego-Nicholls et al. 2025; Roy et al. 2021; Roy et al. 2023; Roy et al. 2024; Roy et al. 2024; Suárez Giri and Chaparro 2023).

6. Conclusion

This study introduces RGB-ER, a novel graph-based framework for SDP recommendation that integrates regional characteristics via interpretable knowledge structures. By incorporating graph pruning and attention mechanisms, RGB-ER captures spatial, cultural, and historical heterogeneity, achieving superior performance over existing baseline models. The model demonstrates strong practical value as a data-driven decision-support tool, facilitating the design of regionally adaptive strategies aligned with global SDGs and local policy priorities. In the case study of Fujian Province, RGB-ER achieved a 79% alignment with government planning documents, underscoring its potential to inform resource allocation and guide sustainable regional transformation.

Looking ahead, further research should aim to enhance RGB-ER's capacity to reflect policy dynamics and real-world complexity. Key directions involve incorporating stakeholder preferences and institutional dimensions, extending to dynamic and adaptive planning through reinforcement learning, and enhancing interpretability via causal analysis and scenario-based decision support. By integrating technical innovation with governance awareness, RGB-ER contributes to the advancement of intelligent, adaptive, and context-sensitive tools for sustainable development planning.

Author contributions statement

Qiang Wang: Conception and design of the study, methodology, software development, investigation, formal analysis, data curation, and writing of the original draft. Zhihang

Yu: Conception and design of the study, methodology, software development, and writing – review and editing. Shu Wang: Conception and design of the study, funding acquisition, supervision, and writing – review and editing. Yunqiang Zhu: Funding acquisition, supervision, and writing – review and editing. Xiaoliang Dai: Visualization and writing – review and editing. Zhiqiang Zou: Supervision and writing – review and editing. Weiming Huang: Methodology and writing – review and editing. Christophe Claramunt: Methodology and writing – review and editing. All authors contributed to critical revisions for intellectual content and approved the final manuscript. They are fully accountable for all aspects of the work, ensuring its accuracy and integrity.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Geolocation information statement

This study focuses on regions within China (35.0000°N, 105.0000°E), specifically Fujian Province (26.2500°N, 118.0000°E) and Pengzhou City in Sichuan Province (31.1139°N, 103.9217°E).

Data and codes availability statement

The data and materials used in this article are available upon request by the correspondence author.

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