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Identifying key influencing factors of cross-regional railway infrastructure interconnection: a fuzzy integrated MCDM framework

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Cross-regional railway infrastructure (CRI) plays an important role in promoting coordinated regional development. But current understanding on how to strengthen cross-regional railway infrastructure interconnection (CRII) and its influence mechanism is still very limited. This study constructed a conceptual model of CRII system to reveal the logic of CRII operation, and systematically identified 16 influencing factors. Meanwhile, an F-MCDM (F-Multi-criteria Decision Making) model was created to capture the interactions among the influencing factors, identifying eight key influencing factors and four possible countermeasures. The results revealed that *policy and institutional innovation*, *incentives and investment ecology*, *efficient implementation and coordination mechanisms*, and *supply chain and technology security capacity* are four crucial challenges for CRII. Among them, the *cooperation modes* between the central government and local governments, as well as among local governments, were identified as the most critical factors. Accordingly, a four-pronged framework of "policy alignment, cooperative incentives, operational excellence, and supply assurance" was developed to better promote CRII. This study contributes to a deeper understanding of CRII, enriches the body of knowledge on cross-regional transportation infrastructure interconnection, and provides theoretical support and decision-making references for policymakers to implement CRII.

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Introduction

Cross-regional railway infrastructure (CRI) plays a crucial role in fostering economic development, regional integration, and social cohesion. CRIs span across two or more provincial administrative regions, exerting significant and widespread influence on both national and regional economies, as well as social development (Xiang et al. 2023). The seamless interconnection of such infrastructure, referred to as cross-regional railway infrastructure interconnection (CRII) (Yang and Wu 2023; Yuan and Yang 2022), is vital for enhancing transportation efficiency and connectivity across diverse regions. CRII represents a complex system characterized prominently by cross-regional connectivity, necessitating a delicate balance of interests and coordinated development involving the central government, local governments, multiple jurisdictions, and associated regions. These dynamics encompass inter-regional considerations such as balancing interests among the central government, local governments, and multiple jurisdictions, and promoting coordinated development and social equity (Wan et al. 2022). CRII is influenced by policy, finance, technology, and environmental factors, as well as by multiple stakeholders (Sánchez-Silva et al. 2016; Wang and Yuan 2017; Wang and Xiang 2024). High-speed rail battles and inefficient cooperation by local governments are frequent (Wang and Xiang 2024). Therefore, unraveling the complex factors driving CRII is essential to optimize its potential and develop effective advancement strategies.

As the significance of CRII continues to expand, researchers have conducted extensive studies on its influencing factors. Much of this research focuses on the operational phase of CRII (Yang and Wu 2023; Yang et al. 2023b). Analytical efforts concerning CRII's influencing factors often concentrate on the micro-structural dimensions of CRI itself, assessing the accessibility of its physical structures (Yuan and Yang 2022). While this approach, which examines technical standards, operational procedures, and traffic indicators such as mileage and volume, provides valuable insights into CRII's influencing factors, it is limited by its narrow perspective. This limitation underscores the current scarcity of comprehensive research on CRII. Furthermore, the interrelated nature of factors influencing CRII complicates understanding its overall system behavior (Calatayud et al. 2017; Ji et al. 2019; Ruiz and Guevara 2020). Elements within complex infrastructure systems interact, establishing diverse causal relationships (Guevara et al. 2017). Therefore, it is crucial to comprehensively analyze these influencing factors and their relationships and to identify the key influencing factors for effective implementation of CRII (Reggiani et al. 2015; Yuan and Yang 2022).

Therefore, it is crucial to comprehensively analyze these influences and their relationships to effectively measure CRII's impact (Reggiani et al. 2015; Yang and Wu 2023; Yuan and Yang 2022).

To address the above research gaps, this study aims to systematically investigate and answer the following three research questions (RQs):

RQ1: What factors influence CRII?

RQ2: How do the influencing factors of CRII interact with each other?

RQ3: What are the key influencing factors of CRII?

This study contributes to improving the knowledge of cross-regional transportation systems in the area of interconnection, as well as providing a basis for decision-making to promote a better landing of the CRI. The specific contributions are in the following three areas:

Firstly, this study innovatively constructs a conceptual model of the CRII system and analyzes its elemental composition and interrelationships. By conducting a thorough literature review and expert interviews, it identifies a more comprehensive set of influencing factors for CRII, addressing the limitations of previous studies that had narrow perspectives and focused only on one phase. This enables policymakers to systematically understand the variables affecting CRII, facilitating its smooth implementation.

Secondly, an innovative F-DEMATEL-ISM-MICMAC composite model is developed by integrating Fuzzy Decision Making Trial and Evaluation Laboratory (F-DEMATEL), Interpretive Structural Modeling (ISM), and Matrices Impacts Croisés-Multiplication Appliquée a un Classement (MICMAC). This model quantifies the significance of these factors and elucidates their causal relationships, providing a clearer understanding of the factors influencing CRII. It addresses the current lack of consideration for the interactions between CRII influencing factors.

Lastly, using the F-DEMATEL-ISM-MICMAC composite model, a multi-layer recursive structural model of influencing factors is established. This model uncovers the intricate mechanisms among these factors and identifies the key influencers.

The remainder of this study is structured as follows: the "Literature review" section presents a literature review and identifies research gaps in CRII. The "Research methodology" section describes the research methodology. The "Results" section presents the results and analyses. The "Discussion" section comprehensively analyzes and discusses the key influencing factors and mechanisms of CRII with a comprehensive system of resolution strategies. The conclusions are presented in the final section.

Literature review

Identification of factors influencing CRII. CRII, as an emerging research field, is garnering widespread attention but is still in its initial exploration stage. Identifying the intricate web of factors influencing CRII is crucial for understanding its development dynamics. Previous research has typically examined these factors from a single perspective.

Firstly, the economic geography perspective evaluates CRII by analyzing the locational characteristics of the railway system. Variables such as total traffic mileage (Xu et al. 2018), daily routes (Li et al. 2021), traffic volume (Li et al. 2021), and fixed asset investment (Zhu et al. 2020) have been used for this purpose. Secondly, the physical system intrinsic property dimension was employed to analyze the CRI network. This involved studying macro flows of labor, information, and capital within the physical infrastructure. For example, a single case study identified the link between internal project controls and external stakeholders, while a large descriptive analysis identified barriers to public participation (Kivilä et al. 2017). GIS network representation was used to optimize connectivity for public transportation and population density (Kaplan et al. 2014).

Methods for analyzing CRII's influencing factors. Several analytical approaches have been utilized to understand the multifaceted influences on CRII. Case studies and content analysis were employed to reveal the roles of policy and institutional factors (Castanho et al. 2018). However, the complexity, uncertainty, and interdependence of CRII factors present new challenges (Lee and Song 2023). The Multi-criteria analysis (MCA) framework can integrate multidimensional factors and explore their deep interactions under uncertain development directions (Patni et al. 2023). Nonetheless, traditional MCA frameworks are better suited for independent evaluation criteria, making it challenging to accurately assess and improve CRII alternatives using conventional MCA techniques (Barak and Mokfi 2019; Labella et al. 2018).

In contrast, a systematic approach can address these difficulties by constructing internal and hidden interactions between influencing factors. This complex correlation is often described in transportation through dynamic complex models and structural modeling techniques. For instance, system dynamics approaches explore internal relationships in CRII (Yuan and Yang 2022), and complex network theory measures railroad system connectivity (Xu et al. 2020). Structural modeling techniques like FAISM and DFS can simplify topologies from integrated systems without losing functionality. Trivedi et al. (2021) used the DEMATEL-ISM approach to study interactions between barriers to inland waterways as sustainable transportation. Additionally, an integrated Case-Based Reasoning (CBR) and Fuzzy Adversarial Interpretive Structural Modeling (FAISM) framework was proposed to reveal microstructures in cross-regional road infrastructure operations, illustrated by the Hong Kong-Zhuhai-Macao Bridge (HZMB) case study (Yang et al. 2023b). A three-stage multi-criteria assessment framework, integrating the Best-Worst Method, FAISM, and Depth-First Search (DFS) with fuzzy linguistic terminology, was adopted to study post-epidemic demand shocks on CRII (Yang and Wu 2023). Their case study on the HZMB explored policy recommendations to enhance CRII.

Application of MCDM method. MCDM originated in the field of operations research and management science during the mid-to-late twentieth century (Qiu et al. 2019, 2024). It was developed to address the increasingly complex challenges of multi-objective decision-making processes, helping decision-makers make rational choices when faced with multiple conflicting or complementary evaluation criteria (Hasanzadeh et al. 2023; Zeng et al. 2022). MCDM methods include WSM (Weighted Sum Method) (Su et al. 2025), WPM (Weighted Product Method) (Chai et al. 2023), AHP (Analytic Hierarchy Process) (Farid and Riaz 2023), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) (Liu et al. 2023), DEMATEL (Decision-Making Trial and Evaluation Laboratory) (Zorlu et al. 2024), VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) (Dimitriou et al. 2025), and multi-objective programming. Each method has its own advantages, disadvantages, and specific application fields (Lee and Chang 2018).

Among the methods to analyze the correlation of factors are AHP, DEMATEL, and ISM. AHP allows decision-makers to analyze a decision problem by constructing a hierarchical structure that breaks down a complex problem into multiple levels of interconnectedness and determines the relative importance of each evaluation metric through pairwise comparisons (Ahmad and Tahar 2014). The DEMATEL method, based on graph theory, analyzes the logical correlations and direct influence relationships between factors in complex systems to reveal key factors (Chen 2021). The ISM approach identifies various factors affecting the system and their interrelationships, processing the information to clarify the correlations and hierarchies between these factors, thereby identifying the key factors and their internal relationships (Xie et al. 2023).

Combining different methods can provide more robust decision-making information, multiple mixed methods can be used to solve multi-criteria decision problems (Huo et al. 2023). For instance, many researchers have employed DEMATEL and ISM to identify key influencing factors and construct multi-level hierarchical models, yielding comprehensive information for decision-making. Some scholars first classify the hierarchy of influencing factors based on the ISM model and then adopt the MICMAC analysis method to categorize the attributes (Sharma et al. 2023). They analyze the states and functions of various factors by calculating the dependency and driving force between them, and subsequently propose appropriate countermeasures and suggestions.

Classical MCDM methods that consider deterministic or stochastic processes cannot effectively handle group decision-making problems that include imprecise linguistic information. Therefore, many scholars have integrated fuzzy set theories into MCDM methods, resulting in approaches such as fuzzy AHP and fuzzy TOPSIS (Dursun and Karsak 2010). Fuzzy set theory, introduced by Zadeh in (1965), addresses problems involving fuzzy sources by incorporating imprecise data into the decision-making framework (Zadeh 1965). Additionally, methods such as VIKOR, ELECTRE, and PROMETHEE are often used to solve multi-objective decision-making problems (Opricovic and Tzeng 2004).

Integrating fuzzy sets with composite MCDM models offers an effective means of reducing subjective judgment and accurately identifying factor relationships from both qualitative and quantitative perspectives (Cheng et al. 2023). Each method has distinct applicability. This study utilizes the F-DEMATEL-ISM-MICMAC model to investigate the influencing factors of CRII, with the following considerations: (1) the necessity of analyzing key factors by examining the interactions among them, prioritizing decision support over dynamic behavior simulation (Ebrahimi et al. 2024); (2) the reliance on expert knowledge and qualitative judgments for most CRII influencing factors, given the absence of substantial historical data. A combination of qualitative and quantitative methods is therefore essential to reduce subjectivity (Feng et al. 2023); (3) the importance of avoiding errors introduced by overly complex models while maintaining model robustness. The F-DEMATEL-ISM-MICMAC approach integrates multiple analytical methods, mitigating the subjectivity associated with single-method approaches and addressing the complex interrelationships among factors. This integration fosters methodological complementarity and cross-validation, enhancing the robustness of evaluation results (Vishwakarma et al. 2022). Additionally, it provides a structured framework for comprehensively understanding and analyzing the complex CRII system. By combining multiple methods, decision-makers can more accurately identify and prioritize critical issues, thereby improving decision quality.

Different methodologies each have their own strengths and weaknesses, and there is no universally "best" approach. However, it is crucial to select a method that aligns with the research objectives. This study employs the F-DEMATEL-ISM-MICMAC framework to analyze the complex interactions among the factors influencing CRII. Unlike standalone methods, this integrated model combines causal chain analysis, hierarchical structuring, and dynamic classification to offer a comprehensive view of the CRII system. Commonly used methods in existing CRII research, such as AHP-TOPSIS, FAISM, and System Dynamics, have some limitations. AHP-TOPSIS assumes independence among factors, neglecting the dynamic interactions that are crucial in CRII. FAISM is effective for analyzing single-structure relationships but fails to systematically uncover cross-dimensional and hierarchical dynamics. SD excels at long-term simulations but struggles to identify short-term key drivers in systems like CRII, where rapid optimization is necessary.

The F-DEMATEL-ISM-MICMAC framework addresses these limitations by integrating the unique strengths of its components. F-DEMATEL identifies causal relationships (Alshahrani et al. 2024), ISM constructs multi-layered structural models (Sharma et al. 2023), and MICMAC categorizes factors based on their driving and dependence powers (Agarwal et al. 2023). This integration facilitates the systematic identification of key drivers while addressing prior research gaps, such as the lack of holistic factor analysis and unclear causal mechanisms. In doing so, the approach combines causal analysis, hierarchical decomposition, and dynamic categorization of factors, offering a robust, multi-layered system solution for optimizing CRII and providing actionable insights for policymakers.

Research gaps. Upon reviewing the aforementioned studies, four main gaps persistently emerge:

Firstly, previous researches have failed to comprehensively address the factors influencing CRII due to the adoption of partial viewpoints. While the importance of the microstructure, pathways, and interactions of CRII is recognized, current research primarily focuses on microanalysis, neglecting a holistic understanding of CRII as a complex system. CRII is influenced by both its physical attributes and the broader system's external environment and stakeholder interactions, areas often overlooked in existing research. Additionally, the regional cross-influence on CRII has been inadequately explored.

Secondly, there is a lack of research elucidating the intricate causal relationships among factors influencing CRII. Evaluating CRII through a single indicator and ignoring interactions between influencing factors remains a significant gap. While dynamic and complex models like MCDM and system dynamics exist, the understanding of CRII influencing factors is insufficient, hindering a comprehensive analysis of CRII mechanisms. Current studies have not fully determined the relative importance of these factors, missing key elements necessary for accurate assessment.

Thirdly, prior researchers have identified certain influencing factors, but the understanding of the hierarchy structure of the complex interaction mechanisms and the key influencing factors remains unclear. This lack of clarity may hinder understanding of how factors exert their influence, impeding informed decision-making processes.

Fourthly, despite numerous studies on factors influencing Multi-Criteria Decision Making (MCDM) assessments, most have focused on industries such as manufacturing, mining, hospitality, and tourism. Few scholars have applied MCDM to the railway industry to analyze key parameters for sustainable development within railway transport organizations. Therefore, using the MCDM method to explore CRII influencing factors in the railway transport industry represents a novel contribution. Additionally, the combined use of F-DEMATEL-ISM-MICMAC for parameter evaluation is rare.

Therefore, this study presents a systematic conceptual framework for CRII, providing a comprehensive understanding of its components and identifying influencing factors. A complementary F-MCDM model is developed to investigate the interrelationships among CRII influencing factors and to identify the key influencing factors.

Research methodology

This study aims to provide a systematic perspective and conduct an in-depth analysis of the factors influencing CRII using the F-MCDM model. The first step involves identifying the influencing factors of CRII. By systematically deconstructing CRII through literature reviews and expert interviews, a comprehensive list of influencing factors is compiled. The second step entails analyzing the causal relationships among these factors. Utilizing the F-DEMATEL model, the relationships between factors are assessed, and centrality and causality measures are calculated to understand factor interactions and their significance. The subsequent step aims to elucidate the influence mechanism of these factors. Employing the ISM model, CRII influencing factors are categorized into hierarchical levels, forming a multivariate hierarchical diagram. The final step involves identifying key factors. Using the MICMAC model, drivers and dependencies among factors are analyzed to pinpoint key influencers. Based on the revealed influence mechanisms and key factors, targeted countermeasures are proposed. The research framework of this study is illustrated in Fig. 1.

System analysis of CMIP. CRII is a complex mega-system integrating personnel, facilities, processes, and technologies to manage cross-regional infrastructure (Prencipe 2000; Xiang et al. 2024). It functions as an integrated entity ensuring effective operation and interconnectivity throughout its lifecycle.

Involving diverse stakeholders with varying goals, responsibilities, interests, and operational mechanisms, successful CRII implementation hinges on: (1) Establishing reasonable goal constraints; (2) Facilitating multiple stakeholder interactions and negotiations; (3) Optimizing resource utilization within CRI; (4) Implementing rational safety measures. By systematically analyzing CRII, researchers can explore factors influencing its implementation. Based on these components and CRII's specific context, a system model was developed encompassing goal elements, actor elements, resource elements, and assurance elements, as depicted in Fig. 2. Each element will be further elaborated to elucidate the operational logic of the CRII system.

The actor element is crucial to the operation of the CRII system, determining its level and coordination among actors. It is categorized into governmental organizations, enterprises and institutions, and industry organizations or non-profit organizations and the public (Wu et al. 2019). The resource element forms the foundation of the CRII system, managing material flow, information flow, and technology flow effectively (Chen et al. 2022). It includes material, information, personnel, technology, funds, and policy categories, ensuring seamless coordination across these aspects. The goal element provides directional guidance influenced by internal and external environments, categorized into macro, meso, and micro goals (Yuan 2017). Macro goals emphasize CRII's contribution to national and societal development. Meso goals focus on intelligent, collaborative development aligned with industry trends, while micro goals address project-specific goals like safety, progress, cost, and quality. The assurance element supports the operation of the CRII system, encompassing external conditions and institutional environments such as support assurance, promotion assurance, constraint assurance, and emergency assurance (Xue et al. 2022).

Building on the implications of each element, we can further clarify the fundamental operational logic of the CRII system. During the operational process, the actor element utilizes decision support from the assurance element and dynamic support from the goal element. By managing the resource element based on feedback from these elements, the actor element promotes CRII. Influenced by the assurance element and constrained by the goal element, the actor element impacts the resource element within the CRII system through behaviors such as competition, cooperation, incentives, and supervision. A robust internal operating mechanism encourages the actor element to positively influence the resource element, while conversely, it can also create inhibitory effects.

Identification of influencing factors for CRII. Through the analysis of the CRII system, it was observed that CRII integrates various elements. Supported by assurance elements and guided by objectives, stakeholders establish interrelationships among these elements by managing resources, ultimately achieving CRII. The identification of factors influencing CRII began with a systems

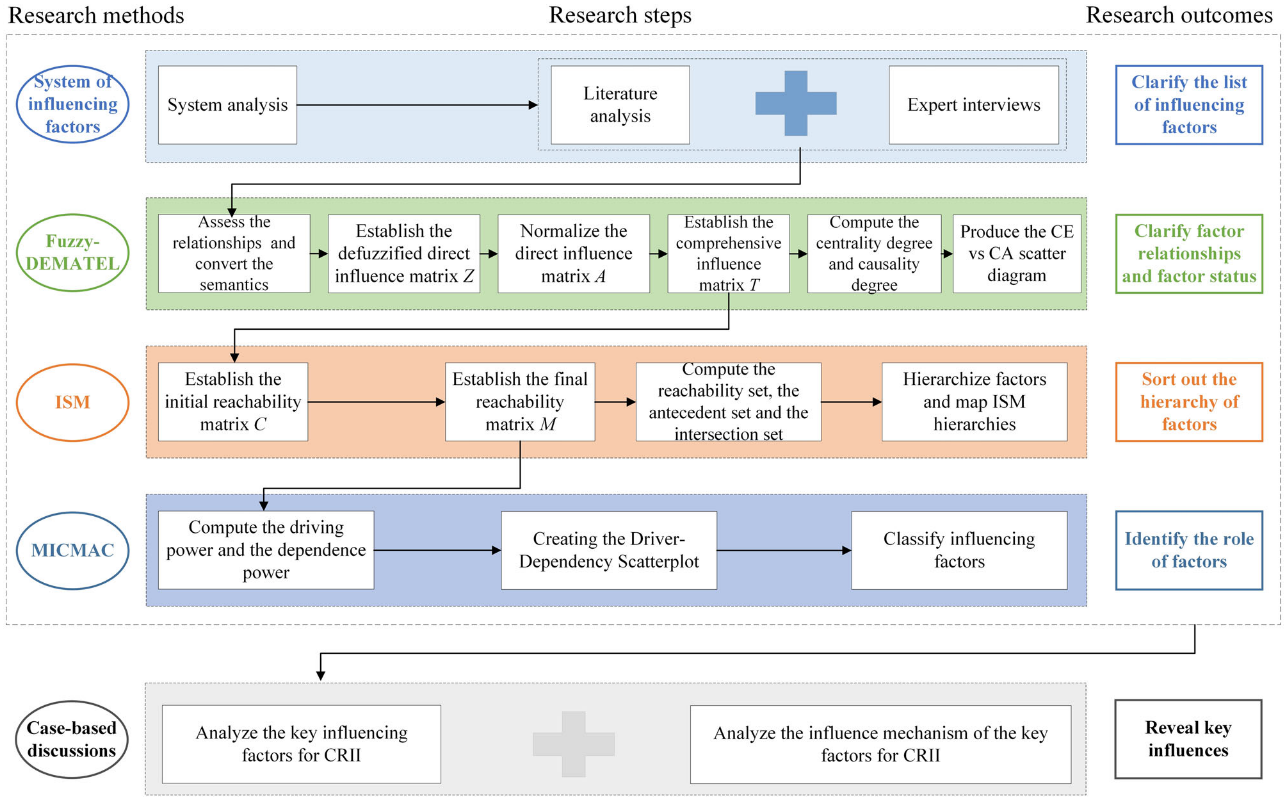

Fig. 1 Research framework.

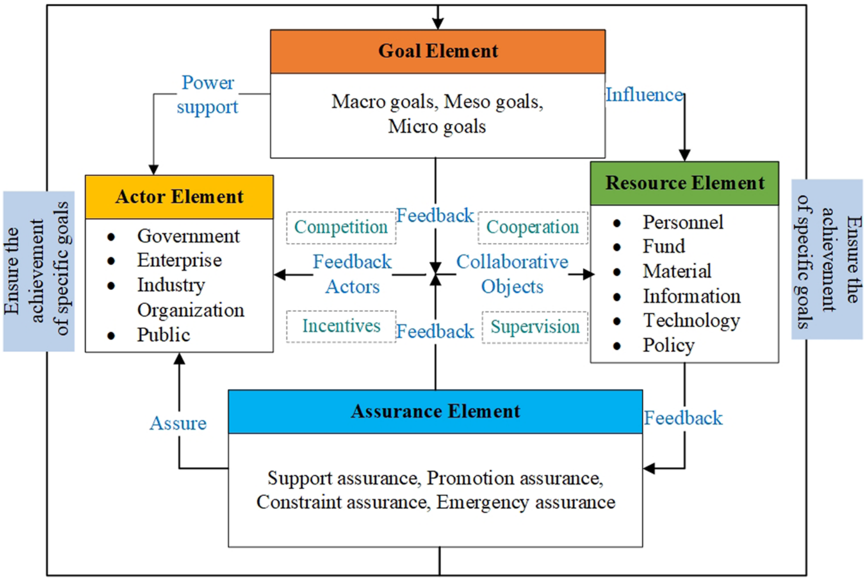

Fig. 2 CRII system model.

analysis approach. To ensure comprehensiveness and scientific rigor, this study employed two phases of identification methods: a systematic literature review and additional validation through expert interviews.

In the first phase, factors influencing CRII were initially identified through a systematic literature review following the PRISMA methodology (Jia et al. 2022). Scopus was used as the database, conducting an advanced search in the "Title, Abstract, and Keywords" fields using selected keywords such as "interconnection, cross-regional infrastructure projects, railway infrastructure projects, transportation infrastructure projects." Only English-language articles published between 2001 and 2023 were included, resulting in an initial set of 34 records to ensure the authority and relevance of factor identification.

Following the initial search, articles underwent further screening based on the following criteria: (1) Explicit mention or listing of influencing factors in text or charts; (2) Use of at least one factor identification method; and (3) Application of a specific classification method for factors. Subsequently, 13 representative and recent articles were selected for detailed review. Similar factors were consolidated and categorized to facilitate analysis. For instance, factors like "Multi-level government coordination

Table 1 The background information of the experts.

Demographic characteristic	Category	Frequency	Percentage
Gender	Male	17	85%
	Female	3	15%
Work unit	Research Institution	4	20%
	Owner Unit	4	20%
	Design Unit	1	5%
	Construction Unit	4	20%
	Supervision Unit	2	10%
	Government Construction Management Department	5	25%
Education level	Bachelor	5	25%
	Master	8	40%
	Doctorate	4	20%
	Other	3	15%
CMIP work experience	<5 years	5	25%
	5–10 years	6	30%
	11–20 years	8	40%
	>20 years	1	5%
Title	Junior title	5	25%
	Intermediate title	7	35%
	Senior title	7	35%
	Other	1	5%

mechanisms" and "Regional local government development partnership networks" were grouped under "Cross-regional local government cooperation model," reflecting their focus on cross-regional local government coordination. In total, ten influencing factors were identified through this literature review process.

In the second phase, the identified factors underwent validation through expert interviews. A focus group of 20 experts was selected, detailed in Table 1, possessing an average of 10.5 years of research experience in CRII. Experts responded to a questionnaire addressing three main questions: (1) What defines CRII? (2) What adjustments are warranted based on systematic analysis and literature review findings? (3) How can CRII realization be enhanced?

Guided by system analysis of CRII and supported by literature review and expert interviews, a total of 16 influencing factors were identified across actor dimensions, resource dimensions, and assurance dimensions. These factors are detailed in Table 3.

Fuzzy-DEMATEL method. The DEMATEL technique constructs a structural map of the system based on interrelations among cause-and-effect factors (Vishwakarma et al. 2022). Triangular fuzzy numbers in fuzzy set theory were introduced to quantify experts' subjective judgments, reducing fuzziness and subjectivity in scoring. This enhancement refines the DEMATEL method, leading to the development of the Fuzzy-DEMATEL model (Paul et al. 2023).

Step 1: Select the team of experts with CRII research experience.

A team of 20 experts with CRII experience was selected, and their information is shown in Table 1.

Step 2: Assess the relationships and convert the semantics.

A questionnaire evaluating the relationships among CRII influencing factors was distributed to 20 experts, who used a five-point Likert scale to rate the degree of influence between factors (Akyuz and Celik 2015; Luthra et al. 2022). The scale ranged from 0 to 4, where: 0: No influence; 1: Very low influence (VL); 2: Low influence (L); 3: High influence (H); 4: Very high influence (VH).

Table 2 Linguistic scales for the importance.

Linguistic terms	Linguistic values
No influence (NO)	(0, 0, 0.25)
Very low influence (VL)	(0, 0.25, 0.5)
Low influence (L)	(0.25, 0.5, 0.75)
High influence (H)	(0.5, 0.75, 1.0)
Very high influence (VH)	(0.75, 1.0, 1.0)

A linguistic variable gets values defined by linguistic terms which are words/sentences in a natural or artificial language. $\tilde{N} = (l, m, r)$ on X is a triangular fuzzy number (TFN) if its membership function. $\mu_{\tilde{N}}(x)$: $X \to [0, 1]$ follows Eq. (1):

$$\mu_{\tilde{N}}(x) = \begin{cases} (x-l)/(m-l) & l \leqslant x \leqslant m \\ (r-x)/(r-m) & m \leqslant x \leqslant r \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Where, l and r represent the lower limit and upper limit of the fuzzy number respectively, m is the most probable value, and the larger the value of $r-l$, the greater the fuzziness of the fuzzy number. Here, this study used five basic linguistics—"Very high", "High", "Low", "Very low", and "No" influence, with respect to a fuzzy level scale as in Table 2 to evaluate factors against each other.

Step 3: Establish the defuzzified direct influence matrix Z.

The fuzzy influence matrix obtained above underwent de-fuzzification. The process involved converting fuzzy data into crisp scores (CFCS) (Jangre et al. 2022; Mahmoudi et al. 2019). Initially, fuzzy values were transformed into crisp values using a method akin to calculating right and left scores using fuzzy max and min values, respectively. Subsequently, the total score was determined using membership functions in a weighted average approach.

Equations (2)–(4) are used while following the steps in CFCS technique:

$$xl_{ij}^{k} = (l_{ij}^{k} - \min l_{ij}^{k})/\Delta_{\min}^{\max} \tag{2}$$

$$\Delta_{\min}^{\max} = \max r_{ij}^{k} - \min l_{ij}^{k} \tag{3}$$

where xl_{ij}^{k} represents the normalized value of the left endpoint of the influence of factor i on factor j as assessed by the kth expert. l_{ij}^{k} represents the raw value of the left endpoint of the influence of factor i on factor j as assessed by the kth expert. $\min l_{ij}^{k}$ denotes the minimum value of the left endpoint of the influence of factor i on factor j across all experts. $\Delta_{\min}^{\max}$ represents the maximum range of the left endpoint values, i.e., the difference between the maximum and minimum left endpoint values as assessed by all experts:

$$xm_{ij}^{k} = (m_{ij}^{k} - \min l_{ij}^{k})/\Delta_{\min}^{\max} \tag{4}$$

where xm_{ij}^{k} represents the normalized value of the most likely value (peak) of the influence of factor i on factor j as assessed by the kth expert. m_{ij}^{k} represents the raw value of the most likely value (peak) of the influence of factor i on factor j as assessed by the kth expert.

$$xr_{ij}^{k} = (r_{ij}^{k} - \min l_{ij}^{k})/\Delta_{\min}^{\max} \tag{5}$$

where xr_{ij}^{k} represents the normalized value of the right endpoint of the influence of factor i on factor j as assessed by the kth expert. r_{ij}^{k} represents the raw value of the right endpoint of the influence of factor i on factor j as assessed by the kth expert.

Normalized values for lower boundary condition xls_{ij}^k and upper boundary condition xrs_{ij}^k are calculated by utilizing Eqs. (6) and (7) respectively:

$$\mathrm{xls}_{ij}^k = \mathrm{xm}_{ij}^k/(1 + \mathrm{xm}_{ij}^k - \mathrm{xl}_{ij}^k) \tag{6}$$

$$\mathrm{xrs}_{ij}^k = \mathrm{xr}_{ij}^k/(1 + \mathrm{xr}_{ij}^k - \mathrm{xm}_{ij}^k) \tag{7}$$

Crisp values are the result of the CFCS algorithm. Total normalized crisp values x_{ij}^k are derived using Eq. (8):

$$x_{ij}^k = [\mathrm{xls}_{ij}^k(1 - \mathrm{xls}_{ij}^k) + \mathrm{xrs}_{ij}^k \mathrm{xrs}_{ij}^k]/[1 - \mathrm{xls}_{ij}^k + \mathrm{xrs}_{ij}^k] \tag{8}$$

Calculate the defuzzification value of the kth expert evaluation z_{ij}^k using Eq. (9):

$$z_{ij}^k = \min l_{ij}^k + x_{ij}^k \Delta_{\min}^{\max} \tag{9}$$

Combine the evaluations of the p experts to obtain the defuzzified direct influence matrix Z using Eq. (10):

$$\mathrm{Z} = z_{ij} = \frac{1}{p}(z_{ij}^1 + z_{ij}^2 + \cdots + z_{ij}^p) \tag{10}$$

Step 4: Normalize the direct influence matrix A.

The row maximum method was used. Each row of the matrix Z was summed, the maximum value of which was taken, and all the elements of the matrix Z were divided by the maximum value to obtain the normalized influence matrix A using Eq. (11):

$$\mathrm{A} = \frac{x_{ij}}{\max\left(\sum_{j=1}^{n} x_{ij}\right)} \tag{11}$$

Step 5: Establish the comprehensive influence matrix T.

Matrix T is also sometimes referred as total relation matrix. “I” in Eq. (12) represents the identity matrix:

$$\mathrm{T} = \left(\mathrm{A} + \mathrm{A}^2 + \cdots + \mathrm{A}^k\right) = \sum_{k=1}^{\infty} \mathrm{A}^k = \mathrm{A}(\mathrm{I} - \mathrm{A})^{-1} \tag{12}$$

Step 6: Compute the centrality degree and causality degree.

Calculate the degree of influence, influenced, centrality, causality and weight of each factor in order to determine the status of the factors.

The degree of influence refers to the sum of the rows in the matrix T, which represents the value of the combined influence of the factors of each row on all other elements, denoted as D_i. The formula is shown in Eq. (13). Factors with a high influence are often seen as key forces that can significantly change or shape the state of other factors in the system:

$$D_i = \sum_{j=1}^{n} x_{ij}, (i = 1, 2, \ldots, n) \tag{13}$$

The degree of influenced refers to the sum of the columns in the matrix T and represents the combined influence value of the factors in each column on all other tones, denoted as C_i. The formula is shown in Eq. (14). In the system, highly influenced factors can be regarded as “followers” or “responders”, and their state tends to be adjusted according to the changes of other factors:

$$C_i = \sum_{j=1}^{n} x_{ji}, (i = 1, 2, \ldots, n) \tag{14}$$

The degree of centrality indicates the position of the factor in the evaluation system and the size of the role it plays, and the centrality of a factor is the sum of its influencing and influenced degrees, denoted as M_i. The formula is shown in Eq. (15). Any change of high centrality degree factors in the system may trigger extensive and far-reaching impacts, so they are the important pivot point of the stability and functionality of the system:

$$M_i = D_i + C_i \tag{15}$$

The degree of causality is obtained by subtracting the degree of influence and the degree of being influenced by a factor, denoted as R_i. The formula is shown in Eq. (16). The analysis of causality degree helps to identify dominant and subordinate factors in a system, thus providing a more accurate understanding of the system’s causal network. By adjusting the factors with high causality degree, it is possible to achieve guidance and optimization of the behavior of the whole system:

$$R_i = D_i - C_i \tag{16}$$

The degree of centrality is normalized to obtain the weights of the factors. When the degree of causality is greater than 0, it means that the factor has a greater influence on other factors, and is called the cause factor; when the degree of causality is less than 0, it means that the factor is influenced to a greater extent, and is called the effect factor (Bhatia and Srivastava 2018). In addition, the size of the degree of centrality of each factor represents the importance of the factor.

Step 7: Produce the centrality degree vs. causality degree scatter diagram.

Using the centrality degree (CE) as the horizontal axis and the causality degree (CA) as the vertical axis, the location of the factors was marked and the causality diagram was drawn.

ISM method. ISM, an MCDM method, analyzes the interrelationships among different criteria or elements in decision problems. The ISM approach involves the following steps:

Step 1: Establish the initial reachability matrix C.

In order to highlight the main influence relationship of each factor, it is necessary to determine the initial reachability matrix C. The adjacency matrix B amplifies the critical influence by eliminating the minor influence in the system through the threshold λ. Specific operations are as Eq. (17):

$$\mathrm{B} = b_{ij} = \begin{cases} 1 & b_{ij} \geq \lambda(i, j = 1, 2, \ldots, n) \\ 0 & b_{ij} < \lambda(i, j = 1, 2, \ldots, n) \end{cases} \tag{17}$$

The threshold λ calculated by Eq. (18) is determined based on the mean and standard deviation of the statistical distribution, and the relationship between the weak factors in the comprehensive influence matrix T is excluded to improve the objectivity of the calculation process and stratification results (Baiyegunhi et al. 2019):

$$\lambda = \beta + \theta \tag{18}$$

Where β is the mean value of the elements of matrix T, θ is the standard deviation, $\lambda \in [0,1]$. When elements b_{ij} and threshold λ in matrix B satisfy the relation $b_{ij} \geq \lambda$, the matrix element $b_{ij} = 1$ can be reached, and vice versa, $b_{ij} = 0$.

Since the matrix B fails to demonstrate the impact of factors on itself, it can be added by the unit matrix I to produce the connection matrix C as shown in Eq. (19):

$$\mathrm{C} = \mathrm{B} + \mathrm{I} = [\mathrm{c_{ij}}] \tag{19}$$

Step 2: Establish the final reachability matrix M:

$$\mathrm{C_1} = \mathrm{C} + \mathrm{I}, \mathrm{C_2} = (\mathrm{C} + \mathrm{I})^2, \ldots, \mathrm{C_i} = (\mathrm{C} + \mathrm{I})^{\mathrm{i}} \tag{20}$$

$$\mathrm{M} = (\mathrm{C} + \mathrm{I})^{\mathrm{i}+1} = (\mathrm{C} + \mathrm{I})^{\mathrm{i}} \neq (\mathrm{C} + \mathrm{I})^{\mathrm{i}-1} \tag{21}$$

In this step, C is first added with the unit matrix I to obtain the new matrix $(\mathrm{C} + \mathrm{I})$. The power operation is then performed on $(\mathrm{C} + \mathrm{I})$, as shown in Eq. (20). Finally, $\mathrm{M} = (\mathrm{C} + \mathrm{I})^{\mathrm{i}}$ can be obtained when the matrix operation satisfies Eq. (21) according to the Boolean operation rule.

Step 3. Compute the reachability set, the antecedent set and the intersection set:

$$R_i = \{f_i | F_{ij} = 1\} \tag{22}$$

$$S_i = \{f_i | F_{ji} = 1\} \tag{23}$$

$$R_i = R_i \cap S_i \tag{24}$$

The set of factors that are impacted by the factor i is denoted as the reachable set R_i. The set of factors that have influence on factor i is denoted as the prior set S_i. In accordance with the reachable matrix, R_i and S_i can be get with Eqs. (22) and (23), and it is verified whether the reachable set and the prior set meet Eq. (24). The corresponding factors i that satisfy Eq. (24) are the first level factors of the system. Then, the ith row and ith column of the reachable matrix are removed. Equations (22)–(24) are repeated to obtain the factors in the later levels until all factors are eliminated.

Step 4: Hierarchize factors and map ISM hierarchies.

By removing factors layer by layer, the factors are finally divided into different hierarchies. A multi-level recursive structural model is developed to investigate the action mechanism among the factors.

MICMAC method. MICMAC is a technique used to analyze interactions among elements within a complex system, specifically to identify key drivers or factors influencing a specific outcome. This method entails constructing a matrix that maps out relationships between elements, followed by matrix multiplication to determine the significance of each factor (Bagherian et al. 2024). MICMAC is closely associated with ISM and involves the following procedural steps:

Step 1: Compute the Driving Power and Dependence Power of the alternatives using Eqs. (25) and (26):

$$\mathrm{DrP}_i = \sum_{j=1}^{n} a_{ij}^{f} \tag{25}$$

$$\mathrm{DeP}_j = \sum_{i=1}^{n} a_{ij}^{f} \tag{26}$$

Step 2: Plot the driving power vs. the reliance power for each choice in the scatter diagram to identify the type of the factors and divide them into four separate quadrants as indicated below (Manjunatheshwara and Vinodh 2018).

- Autonomous enablers (Quadrant-I): these factors reside in the first quadrant and operate relatively independently within the system. Autonomous enablers exert minimal influence and primarily serve as transitional elements, influenced by constraints from lower factors and feedback from higher factors.
- Dependent enablers (Quadrant-II): positioned at the top of the ISM hierarchy in the second quadrant, dependent enablers exhibit low driving force and high dependence on lower-level components. They rely heavily on other factors for problem resolution and are strongly influenced by causal factors.
- Linkage enablers (Quadrant-III): located in the third quadrant, linkage enablers serve as connectors between ISM levels. These factors possess both high driving force and dependence, making them highly susceptible to influence from other factors and capable of reciprocally influencing them. They are often identified as key factors.
- Independent enablers (Quadrant-IV): predominantly found in the fourth quadrant, independent enablers occupy the lowest level in the ISM hierarchy and drive all parameters above them. They exert significant driving force with low dependency, acting as primary drivers within the system and profoundly impacting other factors and the overall system. They are also identified as key factors.

Results

This section presents the outcomes derived from the integrated MCDM tool applied in previous sections. Following this, it delves into the primary findings of the study, which seek to explore the factors influencing CRII through analyzing causal relationships, elucidating influencing mechanisms, and identifying key factors. These findings aim to provide managers with deeper insights into the factors that shape CRII. By understanding the causal relationships and dependencies among these factors, managers can identify those that significantly impact CRII and develop targeted strategies accordingly. Subsequently, the influencing factors of CRII and the results from F-DEMATEL analysis, ISM analysis, and MICMAC analysis are individually elaborated upon.

The list of CRII's influencing factors. Under the framework of systematic analysis, a total of 16 factors influencing CRII were identified across the actor dimension, resource dimension, and support dimension through a combination of literature review and expert interviews. Table 3 provides detailed insights into these factors. These factors underscore the multifaceted nature of enhancing CRII. Successful implementation requires not only physical infrastructure development but also robust institutional frameworks, operational excellence, and supportive policies and regulations. Each factor interacts with others, creating a complex network of dependencies and influences. Understanding these interactions and prioritizing areas for improvement will be crucial to fully harnessing the potential of CRII for economic growth, regional integration, and sustainable development.

Findings from F-DEMATEL analysis. Using Eqs. (1)–(10), we obtained the direct impact matrix Z after defuzzification, detailed in Table 4. The subsequent calculations using Eqs. (11) and (12) allowed us to derive the normalized direct influence matrix A and the comprehensive influence matrix T, presented in Tables 5 and 6, respectively. The comprehensive influence matrix T visualizes the relationships among influencing factors, depicted as a causality heatmap in Fig. 3. Equations (13)–(16) were applied to calculate the influence degree (D_i), influenced degree (C_i), centrality degree (M_i), and causality degree (R_i) of the CRII influencing factors. Following normalization of centrality degree weights, each influencing factor was categorized and ranked based on attributes, detailed in Table 7. Moreover, adhering to the "principle of taking half" (Yong et al. 2023), this study identified the top eight influential factors of centrality as key factors.

Based on F-DEMATEL analysis, A1 (Cross-regional local government cooperation model), A2 (Cross-regional enterprise coordination mechanism), C2 (Benefit-sharing mechanism), B3 (Information exchange platform), A5 (Central-local policy interaction model), C1 (Fiscal investment ecosystem), B6 (Policy incentive aggregation), and B4 (Material and technology supply chain) were identified as key factors influencing CRII.

F-DEMATEL analysis identified eight key factors and their interactions within the CRII system, uncovering the intricate dynamics among policy, resource, and operational dimensions. The influence degree revealed that A1 (Cross-regional local government cooperation model) is the most impactful factor,

Table 3 List of influencing factors for CRII.

Factor category	Influencing factors	Factor interpretation
Actor dimension (A)	Cross-regional local government cooperation model (A1)	Collaborative awareness, economic impact, and administrative efficacy exhibited by local governments.
	Cross-regional enterprise coordination mechanism (A2)	Collaboration among enterprises in railway construction, operations, corridor development, and logistics optimizes investment, improves market alignment, and enhances transport efficiency.
	Public interaction and feedback mechanism (A3)	Engagement, feedback, and open communication channels for communities and passengers in CRII
	Cross-industry collaboration pathways (A4)	Collaborative strategies and resource-sharing among the rail, road, aviation, energy, and ICT sectors across regions
	Central-local policy interaction model (A5)	Coordination between central and local governments in policy formulation and feedback
	Knowledge support system (A6)	Expertise from research and think tanks in technical consultation, strategic planning, and innovation.
Resource dimension (B)	Cross-regional talent allocation system (B1)	Talent cultivation, hiring strategies, and cross-regional talent mobilization for CRII
	Capital operation transparency mechanism (B2)	Effective cross-regional fund aggregation, transparency, and utilization
	Information exchange platform (B3)	The cross-domain information exchange network in CRII
	Material and technology supply chain (B4)	premium construction materials, advanced equipment, and a robust cross-regional supply chain
	Technological innovation system (B5)	Incorporating innovation and smart technologies into CRII
	Policy incentive aggregation (B6)	National and local cross-regional policy incentives, subsidy schemes, and tax relief measures
Assurance dimension (C)	Fiscal investment ecosystem (C1)	Robust fiscal backing, conducive cross-regional investment financing policies, and a healthy investment climate
	Benefit-sharing mechanism (C2)	The benefit -sharing mechanism is a catalyst for CRII, securing mutual gains for stakeholders.
	Legal regulatory framework (C3)	A robust legal framework coupled with stringent project approval and construction oversight
	Emergency response system (C4)	An all-encompassing cross-regional emergency preparedness plan and risk mitigation strategy

underscoring its central role in driving governance, resource allocation, and regional collaboration. Similarly, A5 (Central-local policy interaction model) and C2 (Benefit-sharing mechanism) exhibited high influence degrees, highlighting their significance in shaping institutional frameworks and ensuring fair resource distribution.

The analysis also emphasized the dependency of certain factors, such as A2 (Cross-regional enterprise coordination mechanism) and B3 (Information exchange platform), which displayed high influenced degrees. These factors are heavily reliant on upstream drivers like A5 and C1, making them susceptible to policy shifts or resource constraints. Furthermore, the centrality degree identified A1, A2, and C2 as pivotal nodes within the network, reflecting their crucial roles in maintaining the structural coherence of governance, resource allocation, and technical subsystems.

Causality analysis highlighted A5 (Central-local policy interaction model) and B6 (Policy incentive aggregation) as the primary root causes, demonstrating their foundational influence in initiating systemic changes. These factors significantly impact downstream elements like B3 and B4 (Material and technology supply chain), reinforcing their importance in maintaining system functionality and stability.

Collectively, these findings reveal a hierarchical and dynamic interplay among CRII factors, where policy alignment and incentive mechanisms serve as critical levers to enhance system efficiency and resilience. This analysis offers a systematic framework for prioritizing interventions, optimizing key drivers, and addressing system vulnerabilities to ensure the sustainable development of CRI projects.

Findings from ISM analysis. Through F-DEMATEL, initial insights into the relationships and influence degrees among influencing factors were gained. ISM was subsequently employed to analyze the hierarchical system of factors and their influence relationships systematically. Initially, the threshold λ from the F-DEMATEL model was set at 0.191443. Using Eqs. (17)–(19), the comprehensive influence matrix was processed to derive the initial reachability matrix C. Recognizing potential oversights in the initial reachability matrix regarding causal relationships among factors, the final reachability matrix M was obtained by validating these influence relationships. Table 8 presents the finalized reachability matrix M, calculated using Eqs. (20) and (21).

The final reachability matrix was used to form two sets for each factor: the reachable set and the prior set (using Eqs. (22) and (23)), and the intersection set of these two sets (using Eq. (24)). Once constructed, the factor whose intersection set equaled the reachable set was identified, assigned to the top level of the ISM hierarchy, and then removed from both sets for all factors. This process continued iteratively for the remaining factors until each was assigned an appropriate level, concluding with the establishment of a hierarchical directed graph. The iterative details are presented in Table 9, which

Table 4 The de-fuzzification matrix Z.

	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4
A1	0	0.96667	0.5	0.57361	0.81111	0.56667	0.57778	0.81111	0.81111	0.57778	0.5	0.81111	0.88889	0.88889	0.50278	0.47778
A2	0.57778	0	0.57778	0.72639	0.42222	0.56667	0.65556	0.81111	0.81111	0.73333	0.5	0.42222	0.5	0.73333	0.41667	0.56389
A3	0.65556	0.65556	0	0.49861	0.5	0.49444	0.42222	0.26667	0.42222	0.26667	0.26667	0.26667	0.42222	0.42222	0.71111	0.33056
A4	0.34444	0.5	0.42222	0	0.34444	0.49444	0.5	0.26667	0.57778	0.34444	0.34444	0.34444	0.5	0.34444	0.33889	0.26111
A5	0.88889	0.81111	0.34444	0.49583	0	0.26667	0.5	0.88889	0.57778	0.65556	0.57778	0.73333	0.73333	0.81111	0.71111	0.45556
A6	0.42222	0.5	0.42222	0.34306	0.34444	0	0.18889	0.26667	0.42222	0.11111	0.5	0.18889	0.18889	0.34444	0.19167	0.19167
B1	0.11111	0.5	0.26667	0.19028	0.18889	0.34722	0	0.11111	0.73333	0.73333	0.73333	0.11111	0.26667	0.42222	0.26944	0.49444
B2	0.57778	0.5	0.34444	0.42083	0.5	0.19167	0.42222	0	0.73333	0.57778	0.65556	0.26667	0.34444	0.73333	0.26111	0.19167
B3	0.5	0.81111	0.81111	0.64861	0.5	0.74028	0.5	0.57778	0	0.65556	0.57778	0.34444	0.26667	0.57778	0.64167	0.56389
B4	0.42222	0.5	0.26667	0.49861	0.34444	0.41667	0.34444	0.5	0.65556	0	0.65556	0.26667	0.26667	0.42222	0.33889	0.57222
B5	0.18889	0.5	0.26667	0.34306	0.26667	0.41389	0.42222	0.18889	0.42222	0.42222	0	0.26667	0.26667	0.5	0.34722	0.33889
B6	0.73333	0.73333	0.42222	0.57361	0.57778	0.56944	0.5	0.5	0.5	0.5	0.57778	0	0.57778	0.65556	0.64167	0.33056
C1	0.81111	0.73333	0.34444	0.49861	0.57778	0.41667	0.5	0.5	0.42222	0.57778	0.34444	0.5	0	0.57778	0.57222	0.33056
C2	0.96667	0.88889	0.57778	0.80694	0.65556	0.41667	0.5	0.57778	0.65556	0.65556	0.5	0.57778	0.5	0	0.425	0.40833
C3	0.5	0.34444	0.42222	0.42083	0.42222	0.33889	0.42222	0.5	0.42222	0.42222	0.34444	0.34444	0.42222	0.5	0	0.26111
C4	0.26667	0.18889	0.26667	0.19028	0.26667	0.18889	0.26667	0.26667	0.42222	0.42222	0.34444	0.18889	0.26667	0.42222	0.26944	0

Table 5 The normalized influence matrix A.

	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4
A1	0	0.09417	0.04871	0.05588	0.07902	0.0552	0.05628	0.07902	0.07902	0.05628	0.04871	0.07902	0.08659	0.08659	0.04898	0.04654
A2	0.05628	0	0.05628	0.07076	0.04113	0.0552	0.06386	0.07902	0.07902	0.07144	0.04871	0.04113	0.04871	0.07144	0.04059	0.05493
A3	0.06386	0.06386	0	0.04857	0.04871	0.04817	0.04113	0.02598	0.04113	0.02598	0.02598	0.02598	0.04113	0.04113	0.06927	0.0322
A4	0.03355	0.04871	0.04113	0	0.03355	0.04817	0.04871	0.02598	0.05628	0.03355	0.03355	0.03355	0.04871	0.03355	0.03301	0.02544
A5	0.08659	0.07902	0.03355	0.0483	0	0.02598	0.04871	0.08659	0.05628	0.06386	0.05628	0.07144	0.07144	0.07902	0.06927	0.04438
A6	0.04113	0.04871	0.04113	0.03342	0.03355	0	0.0184	0.02598	0.04113	0.01082	0.04871	0.0184	0.0184	0.03355	0.01867	0.01867
B1	0.01082	0.04871	0.02598	0.01854	0.0184	0.03382	0	0.01082	0.07144	0.07144	0.07144	0.01082	0.02598	0.04113	0.02625	0.04817
B2	0.05628	0.04871	0.03355	0.041	0.04871	0.01867	0.04113	0	0.07144	0.05628	0.06386	0.02598	0.03355	0.07144	0.02544	0.01867
B3	0.04871	0.07902	0.07902	0.06318	0.04871	0.07211	0.04871	0.05628	0	0.06386	0.05628	0.03355	0.02598	0.05628	0.06251	0.05493
B4	0.04113	0.04871	0.02598	0.04857	0.03355	0.04059	0.03355	0.04871	0.06386	0	0.06386	0.02598	0.02598	0.04113	0.03301	0.05574
B5	0.0184	0.04871	0.02598	0.03342	0.02598	0.04032	0.04113	0.0184	0.04113	0.04113	0	0.02598	0.02598	0.04871	0.03382	0.03301
B6	0.07144	0.07144	0.04113	0.05588	0.05628	0.05547	0.04871	0.04871	0.04871	0.04871	0.05628	0	0.05628	0.06386	0.06251	0.0322
C1	0.07902	0.07144	0.03355	0.04857	0.05628	0.04059	0.04871	0.04871	0.04113	0.05628	0.03355	0.04871	0	0.05628	0.05574	0.0322
C2	0.09417	0.08659	0.05628	0.07861	0.06386	0.04059	0.04871	0.05628	0.06386	0.06386	0.04871	0.05628	0.04871	0	0.0414	0.03978
C3	0.04871	0.03355	0.04113	0.041	0.04113	0.03301	0.04113	0.04871	0.04113	0.04113	0.03355	0.03355	0.04113	0.04871	0	0.02544
C4	0.02598	0.0184	0.02598	0.01854	0.02598	0.0184	0.02598	0.02598	0.04113	0.04113	0.03355	0.0184	0.02598	0.04113	0.02625	0

Table 6 The comprehensive influence matrix T.

	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4
A1	0.17106	0.28214	0.18311	0.21086	0.2186	0.1912	0.1986	0.22841	0.25716	0.21898	0.20453	0.19747	0.21846	0.25884	0.18811	0.16992
A2	0.19606	0.16506	0.16995	0.20003	0.16202	0.17104	0.18333	0.20299	0.23084	0.20736	0.18189	0.14275	0.16213	0.21738	0.15823	0.15942
A3	0.16961	0.18571	0.08881	0.14799	0.14013	0.13624	0.13363	0.12573	0.15829	0.13184	0.12686	0.1059	0.12963	0.15466	0.15685	0.11243
A4	0.12888	0.15788	0.1183	0.08992	0.11479	0.12671	0.12962	0.11265	0.15832	0.12684	0.12322	0.10217	0.12454	0.13376	0.11316	0.09734
A5	0.23828	0.25408	0.15872	0.19233	0.135	0.15402	0.18151	0.22459	0.22423	0.21425	0.19997	0.18239	0.19578	0.24002	0.19558	0.15879
A6	0.11707	0.13651	0.10318	0.10522	0.09908	0.06491	0.08559	0.09622	0.12398	0.08695	0.11877	0.07536	0.08211	0.11463	0.08402	0.07649
B1	0.09529	0.1443	0.09575	0.09877	0.09019	0.10491	0.07353	0.08823	0.16079	0.15196	0.14918	0.07184	0.09247	0.12863	0.09708	0.11238
B2	0.16628	0.17787	0.12456	0.14561	0.14324	0.11264	0.1371	0.10323	0.19072	0.16488	0.16682	0.10853	0.12454	0.18635	0.11967	0.10402
B3	0.18284	0.23043	0.18548	0.18725	0.16294	0.1813	0.16403	0.17696	0.14967	0.19293	0.18183	0.13108	0.13669	0.19691	0.17322	0.1545
B4	0.14114	0.16454	0.10966	0.14222	0.12014	0.12461	0.12124	0.13953	0.17299	0.10104	0.15777	0.09984	0.10864	0.14819	0.11762	0.13055
B5	0.10134	0.14175	0.09333	0.11015	0.09586	0.10798	0.11101	0.09344	0.13031	0.12105	0.07855	0.08511	0.09222	0.13321	0.10185	0.09478
B6	0.20488	0.22549	0.15069	0.18121	0.17124	0.16612	0.16484	0.17193	0.19614	0.18055	0.18186	0.10092	0.16617	0.20523	0.17372	0.13346
C1	0.20292	0.21525	0.13626	0.16626	0.16385	0.1448	0.15726	0.16477	0.18022	0.17931	0.15305	0.14129	0.10612	0.18946	0.16001	0.12723
C2	0.23784	0.25453	0.17532	0.21428	0.18945	0.16393	0.17653	0.19136	0.22488	0.20729	0.18716	0.16414	0.17073	0.15926	0.16585	0.15089
C3	0.14752	0.14884	0.12075	0.13302	0.12593	0.1148	0.12598	0.13778	0.14915	0.13777	0.12691	0.10604	0.1218	0.15245	0.08421	0.09973
C4	0.09539	0.09912	0.08207	0.08369	0.08517	0.07603	0.08529	0.08866	0.11544	0.10808	0.09834	0.06903	0.08177	0.11279	0.08424	0.05272

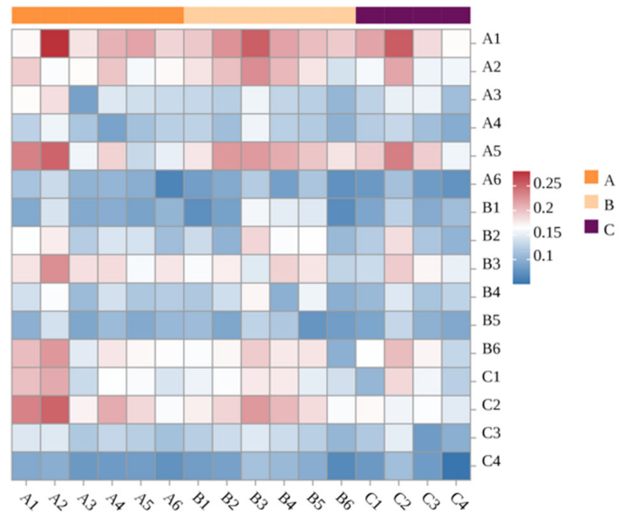

Fig. 3 Heat map of the influence relationship based on F-DEMATEL.

categorizes 16 factors influencing CRII into four levels. Specifically, Table 9 shows that the factors are distributed across four levels: $L_{1=}\{A_3, A_4, A_6, B_1, B_2, B_4, B_5, C_3, C_4\}$, $L_{2=}\{A_2, B_3, C_2\}$, $L_{3=}\{A_1, B_6, C_1\}$, $L_{4=}\{A_5\}$. Figure 4 illustrates the multi-level recursive structure model of factors influencing CRII. It decomposes the interactions among CRII influencing factors into a hierarchical framework. Levels 1 through 4 are categorized as surface, transition, deep, and essential levels, respectively.

The ISM analysis revealed a four-level hierarchical structure among the key factors influencing CRII, illustrating how foundational drivers propagate their influence to surface-level outcomes. This structure highlights the systemic interdependencies and the critical roles of various factors in shaping CRII's overall performance.

Level 4: Root cause. At the foundation of the hierarchy, A5 (Central-local policy interaction model) acts as the root cause, driving systemic changes across all levels. Its central role ensures alignment between central and local governments, establishing a unified policy framework critical for resource allocation and regional coordination. Any inefficiencies or misalignments at this level could destabilize the entire system, disrupting both fiscal and operational mechanisms. A5's position emphasizes the importance of maintaining consistent and effective policy directives to underpin the CRII framework.

Level 3: Deep-level drivers. Level 3 comprises A1 (Cross-regional local government cooperation model), C1 (Fiscal investment ecosystem), and B6 (Policy incentive aggregation), which collectively serve as deep-level drivers shaping the system's structural and financial stability. A1 facilitates intergovernmental cooperation, ensuring equitable resource sharing and coordinated decision-making, while C1 provides the fiscal backbone necessary for CRII projects, translating strategic policy into actionable financial support. B6 complements these factors by consolidating incentives that promote stakeholder engagement and enhance systemic participation. Together, these drivers act as the structural foundation for the effective implementation of CRII, linking high-level policy frameworks to operational subsystems.

Level 2: Transition layer. Level 2 includes A2 (Cross-regional enterprise coordination mechanism), B3 (Information exchange platform), and C2 (Benefit-sharing mechanism), which function as intermediaries bridging strategic drivers and operational outcomes. A2 facilitates enterprise-level collaboration, ensuring efficient resource utilization and

Table 7 Results and ranking of influence degree analysis.

Factor	D_i	Ranking	C_i	Ranking	M_i	Ranking	R_i	Factor attributes
A1	3.39747	1	2.5964	4	5.99387	1	0.80107	Cause factor
A2	2.91049	4	2.9835	1	5.89399	2	−0.07301	Effect factor
C2	3.03345	3	2.73176	3	5.76521	3	0.30169	Cause factor
B3	2.78806	5	2.82313	2	5.61119	4	−0.03507	Effect factor
A5	3.14955	2	2.21764	10	5.36719	5	0.93191	Cause factor
C1	2.58805	7	2.11383	13	4.70188	6	0.47422	Cause factor
B6	2.77446	6	1.88385	16	4.65831	7	0.89061	Cause factor
B4	2.09972	10	2.5311	5	4.63082	8	−0.43138	Effect factor
B2	2.27606	8	2.34647	8	4.62253	9	−0.07041	Effect factor
A4	1.95808	12	2.40883	7	4.36691	10	−0.45075	Effect factor
A3	2.20432	9	2.09592	14	4.30024	11	0.1084	Cause factor
C3	2.03271	11	2.17343	11	4.20614	12	−0.14072	Effect factor
B5	1.69194	14	2.43671	6	4.12865	13	−0.74477	Effect factor
B1	1.75527	13	2.22908	9	3.98435	14	−0.47381	Effect factor
A6	1.5701	15	2.14123	12	3.71133	15	−0.57113	Effect factor
C4	1.41782	16	1.93467	15	3.35249	16	−0.51685	Effect factor

Table 8 The final reachability matrix H.

	A1	A2	A3	A4	A5	A6	B1	B2	B3	B4	B5	B6	C1	C2	C3	C4
A1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	0	0
A2	1	1	0	1	0	0	0	1	1	1	0	0	0	1	0	0
A3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
A4	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
A5	1	1	0	1	1	0	0	1	1	1	1	0	1	1	1	0
A6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
B1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
B2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
B3	0	1	0	0	0	0	0	0	1	1	0	0	0	1	0	0
B4	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
B5	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
B6	1	1	0	0	0	0	0	0	1	0	0	1	0	1	0	0
C1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
C2	1	1	0	1	0	0	0	0	1	1	0	0	0	1	0	0
C3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
C4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table 9 Reachability set and antecedent set of each factor.

Factor	Reachability set	Antecedent set	Intersection set	Hierarchy
A1	A1, A2, A4, A5,B1,B2,B3,B4,B5,B6,C1,C2	A1,A2,A5,B6,C1,C2	A1,A2,A5,B6,C1,C2	L3
A2	A1,A2,A4,,B2,B3,B4,C2	A1,A2,A5,B3,B6,C1,C2	A1,A2,B3,C2	L2
A3	A3	A3	A3	L1
A4	A4	A1,A2,A4,A5,C2	A4	L1
A5	A1,A2,A4,A5,B2,B3,B4,B5,C1,C2,C3	A1,A5	A1,A5	L4
A6	A6	A6	A6	L1
B1	B1	A1,B1	B1	L1
B2	B2	A1,A2,A5,B2	B2	L1
B3	A2,B3,B4,C2	A1,A2,A5,B3,B6,C2	A2,B3,C2	L2
B4	B4	A1,A2,A5,B3,B4,C2	B4	L1
B5	B5	A1,A5,B5	B5	L1
B6	A1,A2,B3,B6,C2	A1,B6	A1,B6	L3
C1	A1,A2,C1	A1,A5,C1	A1,C1	L3
C2	A1,A2,A4,B3,B4,C2	A1,A2,A5,B3,B6,C2	A1,A2,B3,C2	L2
C3	C3	A5,C3	C3	L1
C4	C4	C4	C4	L1

technological sharing across regions. B3 plays a crucial role in enabling real-time communication and data exchange, fostering seamless coordination among stakeholders. C2 ensures equitable benefit distribution, mitigating potential conflicts and reinforcing stakeholder commitment. These factors collectively translate high-level strategic initiatives into tangible actions, ensuring the smooth functioning of CRII's operational layers.

Level 1: Surface-level outcomes. At the top of the hierarchy, A3 (Public interaction and feedback mechanism), A4 (Cross-industry collaboration pathways), B1 (Cross-regional talent allocation system), B2 (Capital operation transparency mechanism), B4 (Material and technology supply chain), B5 (Technological innovation system), A6 (Knowledge support system), and C3 (Legal regulatory framework) represent the system's immediate operational outcomes. These factors directly respond to changes driven by deeper levels and reflect the visible performance of CRII. For instance, B4 ensures the efficient flow of materials and technology, while B5 promotes continuous innovation and adaptability. Failures at this level typically signify deficiencies in higher-level factors, highlighting the need for robust coordination and foundational support.

Combining the results from F-DEMATEL and ISM, the root causes of CRII can be cross-checked: A5 (Central-local policy interaction model) emerges as the primary root cause, while A1 (Cross-regional local government cooperation model), C1 (Fiscal investment ecosystem), and B6 (Policy incentive aggregation) are identified as key causal factors with significant influence on other factors. Additionally, A2 (Cross-regional enterprise coordination mechanism), B3 (Information exchange platform), and B4 (Material and technology supply chain) are categorized as effect factors. These factors occupy upper levels in the hierarchy of CRII influencing factors and directly contribute to CRII problems, warranting attention.

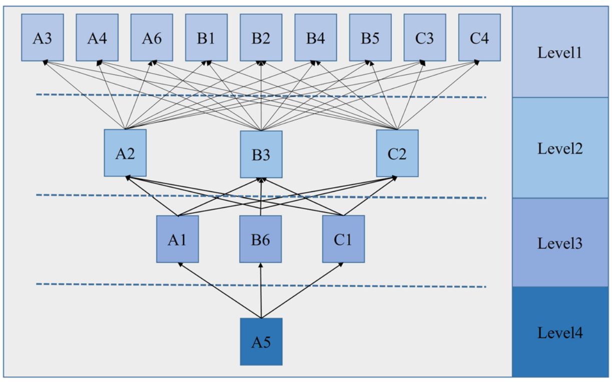

Fig. 4 Multi-level recursive structure model.

Findings from MICMAC analysis. The MICMAC analysis categorized the 16 influencing factors of CRII into four quadrants, based on their driving power and dependence power. This categorization highlights the systemic roles and dynamics of these factors within CRII, reinforcing insights from the ISM hierarchy. By integrating the final reachability matrix with Eqs. (25) and (26), the drive-dependence scores for each factor were computed. These results were then visualized in a drive-dependence scatterplot, depicted in Fig. 5.

In Quadrant I, B5, C1, B1, C3, B6, A3, A6, and C4 functioned as autonomous enablers. These factors exhibit low driving and low dependence, indicating limited connectivity with the core system dynamics. Despite their autonomy, they provide necessary support functions for CRII's operational stability.

In Quadrant II, B4, B3, C2, A4, and B2 were classified as dependent enablers. These factors display low driving power but high dependence, reflecting their reliance on upstream drivers like fiscal and policy mechanisms. Positioned in upper ISM levels, their effectiveness hinges on the performance of foundational drivers.

Quadrant III featured A1 and A2 as linkage enablers, characterized by "high drive and high dependence." These factors are pivotal in maintaining system coherence but are also vulnerable to disruptions. Their dual role as both influencers and dependents underscores their strategic importance in bridging policy, enterprise, and operational layers.

Quadrant IV housed A5 as the sole independent enabler, demonstrating high driving power and low dependence. As the system's primary root cause, it drives systemic changes across all levels while being minimally influenced by other factors. A5's strategic role in shaping governance and resource allocation highlights its prioritization in CRII optimization efforts.

The MICMAC analysis results highlight A1 (Cross-regional local government cooperation model), A2 (Cross-regional enterprise coordination mechanism), and A5 (Central-local policy interaction model) as key factors influencing CRII. This reinforces the findings of the F-DEMATEL-ISM analysis and

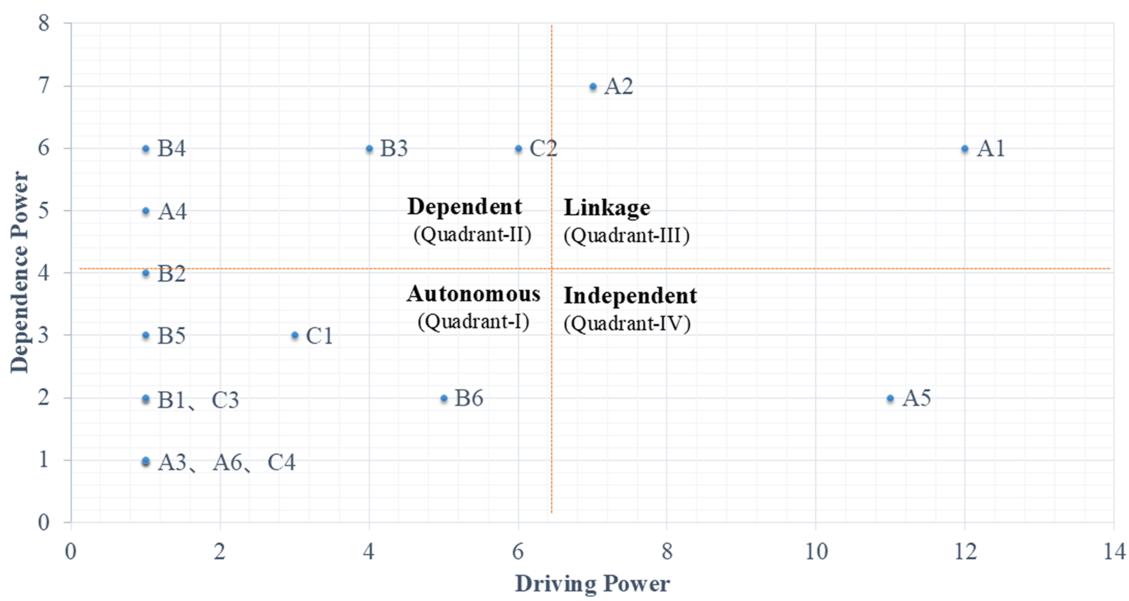

Fig. 5 Scatter diagram for MICMAC analysis.

underscores their pivotal role in addressing the challenges of promoting CRII.

Key influencing factors of CRII. By integrating the key influences identified through F-DEMATEL-ISM-MICMAC analysis, we identify A1 (Cross-regional local government cooperation model) and A5 (Central-local policy interaction model) as root causes influencing CRII, positioned at the top tier of key influencing factors ("key of keys"). Additionally, the analysis reveals that A2, B3, B4, B6, C1, and C2 are key factors impacting CRII, situated at the second tier. Figure 6 presents the key influencing factors of CRII derived from this integrated analysis.

Sensitivity analysis. Sensitivity analysis is used to test the robustness of the model results. Drawing on existing methodology (Guo et al. 2024), this study develops three distinct validation models. Model 1 removes factor A5 (Central-local policy interaction model) at the bottom of the ISM model, which has the largest impact on the other factors, as shown in Fig. 7a. The primary objective of Model 1 is to gauge the resulting changes in the driving power and dependence power of the remaining factors. The transition to Model 2 (as shown in Fig. 7b) removes the factor A2 (Cross-regional enterprise coordination mechanism), which is at the mid-level. A2, as a factor located at the mid-level, both influences as well as has an influence on the other factors. Finally, Model 3 (as shown in Fig. 7c) eliminates factor B4 (Material and technology supply chain) at the top level as a proxy, which can be influenced by other factors.

The exclusion of the central and local government collaboration model in Model 1 results in a significant downward shift in most of the factors. In this context, the dependence power of these factors shows a weakening trend, while the driving power remains almost the same. This result suggests that in the absence of central and local government collaboration, the interdependence of the factors will be significantly reduced, thus confirming the relevant findings.

In Model 2, both A1 and B6, which are located in Level 3, experience a shift to the left and downward. This shift indicates a decrease in driving power along with a decrease in dependence power. The dependence power of A5, which is located in the bottom level, also decreases, but the driving power stays the same. This suggests that the elimination of cross-regional enterprise cooperation weakens the impact of these factors. Meanwhile, most of the factors located in Level 1 move downwards, which indicates that the dependence power of these factors decreases significantly, but the driving power remains almost the same. It indicates that the influence of these factors on CRII is still maintained, but the dependence power is reduced.

In Model 3, the elimination of supply chain factor leads to a leftward shift of the factors in Level 2, Level 3 and Level 4. The driving power of these factors decreases while the degree of dependence remains almost the same. This indicates that factors at lower levels, either directly or indirectly, have an influence on the supply chain. Therefore, the three models effectively validate the robustness of the findings.

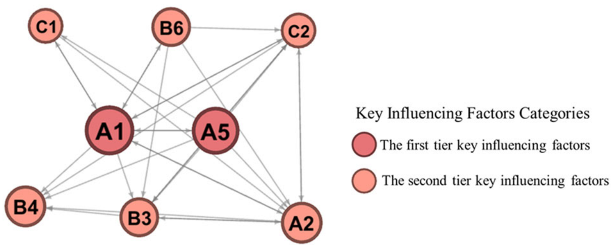

Fig. 6 CRII's key influencing factors.

Discussion

Surprisingly, this study finds that the key factors influencing the CRII mainly stem from the "cross-regional" nature of the CRI,

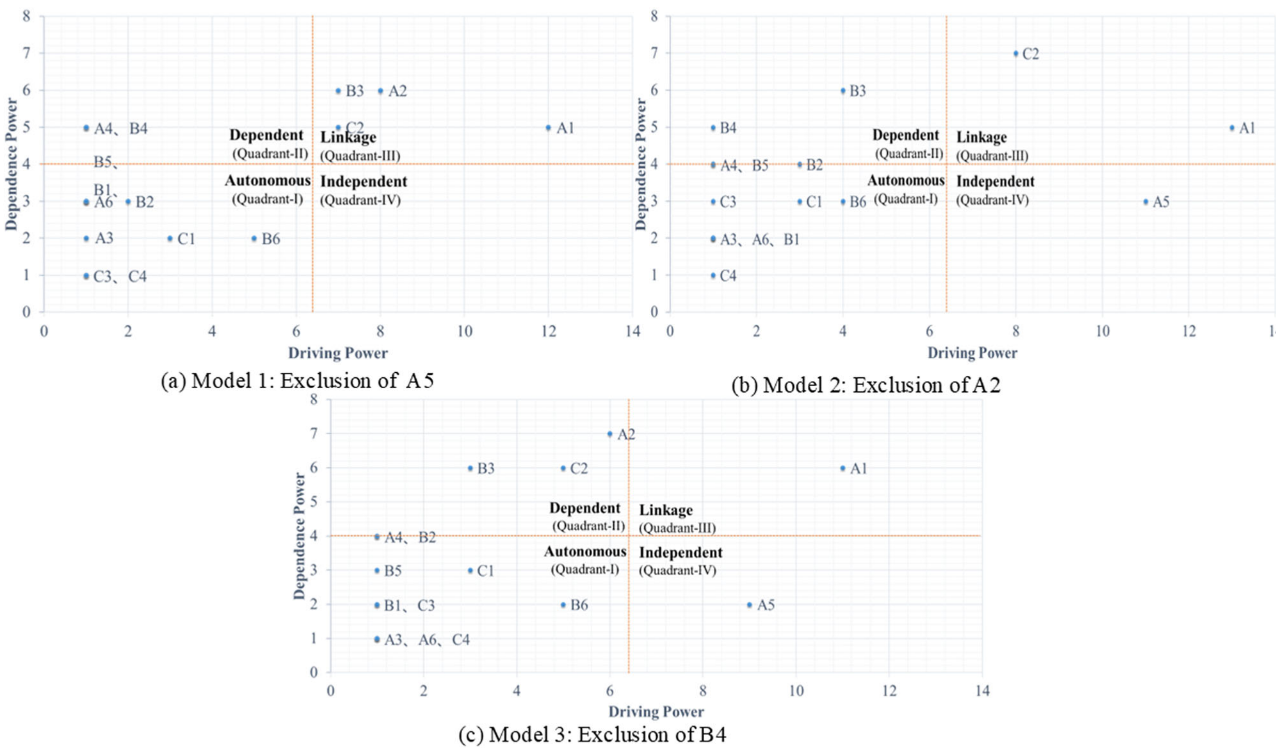

Fig. 7 Models employed for sensitivity analysis.

which has not been sufficiently emphasized in existing studies (Castanho et al. 2018; Wan et al. 2022; Xiang et al. 2023; Yang and Wu 2023; Yang et al. 2023a; Yuan and Yang 2022; Zhang et al. 2020). The central government-local government game and the local government-local government game brought by the "cross-regional" nature are the root causes affecting the CRII. The distribution of benefits, policy combinations, sharing platforms and other issues arising from the synergy of the main stakeholders will further affect the implementation of CRII. Next, the identified key influencing factors and their interactions will be further discussed and explained separately.

Discussions on the key influencing factors. Figure 6 accurately depicts the primary and secondary key influencing factors of CRII. Consequently, it is essential to separately explore how these two tiers of factors influence CRII.

Emphasizing the central role of first tier key factors. In the comprehensive strategy of CRII, A1 (Cross-regional local government cooperation model) and A5 (Central-local policy interaction model) serve as pivotal dual-wheel drivers, playing unparalleled roles as cornerstones with profound impacts on project planning, implementation, and outcomes. These factors have not been discussed in detail in previous studies (Wang and Yuan 2017; Yang and Wu 2023; Yang et al. 2023b; Yuan and Yang 2022). They are deemed "key of the key" because they fundamentally shape a synergistic and efficient policy and implementation environment (Toor and Ogunlana 2010), removing institutional barriers and establishing a robust institutional framework essential for advancing CRII.

A1 (Cross-regional local government cooperation model) is foundational for achieving CRII. China's decentralized administrative system provides local governments with substantial autonomy over areas such as infrastructure development, land approval, and financial expenditures. While this autonomy can foster local interests, it may also lead to conflicts that hinder the efficiency of CRI projects. Despite some informal collaborations, there is no clear, binding framework for long-term cross-regional cooperation. As a result, local governments often operate independently, which can cause inefficiencies, duplication of efforts, and delays. The lack of standardized cooperation processes further complicates CRI projects by introducing bureaucratic obstacles and slow decision-making. Financial disparities between regions exacerbate these challenges, with wealthier regions able to invest more in projects, while poorer areas struggle to secure funding. This imbalance leads to power discrepancies and potentially inequitable resource distribution, undermining the overall success of the CRII program. As regional economic integration accelerates, railway planning and construction increasingly extend beyond traditional administrative boundaries, requiring robust cooperation among neighboring local governments (Li et al. 2012). This model optimizes resource allocation, prevents redundancy, and ensures consistency in technical standards and safety protocols. Joint planning, unified approvals, and collaborative construction enable local governments to overcome geographical limitations, promoting regional synergy and advancing CRII. In the Yangtze River Delta urban agglomeration, the governments of Shanghai, Jiangsu, Zhejiang, Anhui, and other regions cooperate under the Yangtze River Delta regional cooperation mechanism. They plan railway networks, standardize construction practices, and share information resources, addressing challenges related to project approvals, funding, and land acquisition for inter-provincial projects (Lv et al. 2021). Key initiatives, such as the Shanghai-Suzhou-Nantong Railway and the Hangzhou-Huangshan High-speed Railway, have been completed at an accelerated pace, significantly enhancing regional transportation integration. Furthermore, Guangdong Province, the Hong Kong Special Administrative Region, and the Macao Special Administrative Region collaborate under the Greater Bay Area Construction Leading Group to integrate regional railway infrastructure, including the Guangzhou-Shenzhen-Hong Kong High-speed Railway.

A5 (Central-local policy interaction model) injects policy vitality and direction into CRII. The central-local policy interaction model is crucial for infusing policy vitality and direction into CRII. In China, CRI projects necessitate extensive collaboration between central and local governments. However, policy inconsistencies and variations in implementation often hinder progress. Local governments may not fully comply with central directives due to fiscal constraints, local protectionism, or political pressures, while the central government's lack of a clear policy framework for reconciling regional development with national objectives results in uneven practices across regions. Moreover, the allocation of central government funds and subsidies for infrastructure is often skewed toward regions with stronger political connections or better economic performance, putting less developed areas at a disadvantage and exacerbating regional disparities in project participation and development. The central government formulates macro-level policies and provides financial support for CRII construction, while local governments develop detailed implementation plans that align with central guidelines and local conditions. Effective interaction and policy coordination between central and local authorities are essential for ensuring consistent infrastructure development, preventing policy conflicts and resource fragmentation, and improving overall project efficiency (Adler et al. 2010). In the Beijing-Tianjin-Hebei urban agglomeration, the central government issued the "Outline of the Beijing-Tianjin-Hebei Coordinated Development Plan," which outlined strategic goals and policy support for regional development. Local governments have implemented these policies by prioritizing infrastructure projects. Guided by central directives, successful projects include the Beijing-Zhangjiakou High-Speed Railway and the Beijing-Xiong'an Intercity Railway, which have significantly improved connectivity and traffic efficiency between cities and fostered regional economic coordination.

The synergies between A1 (Cross-regional local government cooperation model) and A5 (Central-local policy interaction model) profoundly impact CRII. A1 supports micro-level policy execution, ensuring coherence, while A5 provides macro-level guidance, fostering trust and reducing uncertainties among all parties. This interplay strengthens policy implementation and local cooperation quality, driving steady CRII progress amidst complex governance. As the "key of keys," they unify markets, optimize resources, and enhance policy efficiency, crucial for CRII realization.

Capturing the supporting role of second-tier key factors. A2 (Cross-regional enterprise coordination mechanism) plays a pivotal role in CRII by facilitating resource flow and fostering technological innovation. It encourages enterprises from different regions to collaborate during the design, construction, and operation phases, thereby enhancing project efficiency and quality through the exchange of technology and management expertise (Shao et al. 2018). In China, state-owned enterprises play a crucial role in CRII, often receiving support from local governments in the form of land and capital. However, this relationship can foster local protectionism, which hinders cross-regional resource integration and impedes project execution. Moreover, the decentralized nature of Chinese enterprises can result in a lack of synergy and cooperation, leading to inter-enterprise competition and disparities in resource allocation. The influence of local governments on business operations and regulatory enforcement exacerbates these issues, creating regional disparities in policy, taxation, and environmental standards, which negatively impact the efficiency and success of cross-regional railroad projects. Effective communication and cooperation can accelerate technology adoption, reduce costs, and shorten construction timelines by pooling resources, thereby creating a dynamic market that supports the seamless implementation of CRII. For example, the Rail Net Europe (RNE) project brings together railway operators, infrastructure managers, and related firms across Europe to coordinate cross-border train scheduling, integrate ticketing systems, and standardize maintenance practices.

B3 (Information exchange platform) is pivotal in CRII by enhancing project transparency and responsiveness. It provides real-time updates on design changes, construction progress, and material needs, enabling swift decision-making. The lack of a unified digital platform for information sharing in CRII projects results in communication delays, data inconsistencies, and planning inefficiencies due to regional disparities in data management systems. This information asymmetry, exacerbated by varying digital infrastructure and technical capacity, particularly affects less-developed regions, potentially leading to project delays and inefficiencies. Moreover, the sensitivity of project-related data can hinder open information sharing, reducing trust and collaboration, especially in contentious projects. Efficient information flow minimizes asymmetry, fosters collaboration among stakeholders, and prevents conflicts and resource wastage caused by delayed or unclear communication (Ding 2020). For example, China Railway Corporation's railway engineering management platform exemplifies this approach, integrating standardized management, BIM technology, and cloud computing. This platform facilitates synchronized progress tracking, material management, and issue resolution across projects, significantly improving construction efficiency and management accuracy.

The stability and efficiency of B4 (material and technology supply chain) significantly impact CRII project quality and progress. A robust supply chain ensures the timely delivery of materials and services, minimizing disruptions. The material and technology supply chains for CRI projects are often complex, involving multiple provinces, industries, and stakeholders, which can result in coordination issues, inefficiencies, and delays. There are two main challenges associated with the material and technology supply chain in CRII. First, there is a reliance on specific regions for materials and technologies, such as specialized steel and advanced signaling systems, which are predominantly concentrated in China's eastern coastal areas. This geographic concentration can lead to logistical challenges and higher transportation costs, especially for remote or underdeveloped regions, potentially resulting in supply bottlenecks as infrastructure demands increase. Second, there is a dependency on foreign technologies and materials, particularly for high-speed rail and specialized components. Despite advancements in domestic capabilities, China still faces gaps in high-tech areas, exposing projects to external supply chain risks, including geopolitical tensions and global trade disruptions. Optimizing logistics and incorporating advanced technologies can reduce costs, enhance material traceability, and improve safety (Sheu and Chen 2014). This ensures stable support for railroad infrastructure construction, which is essential for the smooth execution of CRII projects. For example, in the "Sichuan-Tibet Railway" project, efficient supply chain management played a pivotal role. This included the deployment of advanced machinery and geological exploration technologies. Long-term partnerships secured critical material supplies, such as specialized steel and high-performance concrete. Advanced technologies like Beidou navigation and 3D scanning significantly improved construction efficiency and safety, ensuring the success of the project.

B6 (Policy incentive aggregation) consolidates policy and financial support for CRII projects by integrating resources from central and local governments. These incentives—such as tax breaks, subsidies, and loan concessions—lower the costs for corporate participation in infrastructure development and encourage private capital investment (Xu et al. 2024). China's policy landscape, which blends national strategies with localized implementation, creates both opportunities and challenges in aligning and consolidating incentives for CRII projects. The central government has introduced a variety of policies to foster infrastructure development, including tax incentives, funding subsidies, and preferential policies for Public-Private Partnerships (PPP). However, these incentives are often fragmented and may differ across regions, leading to inconsistent policy implementation and unequal levels of support for CRII projects. For example, some regions may offer more generous subsidies or tax breaks to attract investment, while others may face budget constraints, limiting their ability to provide sufficient incentives. Moreover, coordination between central and local policies is sometimes weak, resulting in misaligned incentives between the two levels of government. Aggregated policy incentives improve the investment climate, making projects more attractive and facilitating broader resource mobilization for faster implementation (Cheng et al. 2022). For instance, the China-Europe Railway Express, which links China and Europe, benefits from central government subsidies and tax incentives for logistics companies. Investment in railway infrastructure, such as hubs, container centers, and logistics parks, supports its operation. Local governments, including the Chongqing Municipal Government, supplement these incentives with additional subsidies and tax breaks for companies operating China-Europe trains, further promoting the growth of services like the "Yuxinou" train. Chongqing has also developed the Chongqing International Logistics Hub Park to optimize logistics services and enhance operational efficiency.

C1 (Fiscal investment ecosystem) has established a diverse and sustainable funding network for CRII, including government budgets, social capital, international aid, and other channels. This approach ensures continuous funding, reduces reliance on single sources, and enhances project resilience (Wong et al. 2022). The Chinese fiscal system, characterized by the decentralization of fiscal authority and reliance on local governments to finance infrastructure projects, presents both opportunities and challenges for CRII. Local governments often face significant fiscal constraints and depend heavily on central government transfers and subsidies to fund large-scale projects. However, the allocation of central funds is frequently influenced by regional priorities and may not always align with the urgent needs of CRII projects. Furthermore, the complexity of the central-local fiscal relationship can hinder the smooth allocation and efficient use of funds. By optimizing expenditure structures and utilizing models like public-private partnerships (PPP), the system ensures financial security and efficiency, both of which are crucial for the sustainability of projects (Bai and Qian 2010). For example, the Beijing-Shanghai High-Speed Railway, China's only profitable high-speed rail line, received both central and local government support, while also employing PPP models, bonds, and public listing to ensure efficient connectivity.

C2 (Benefit-sharing mechanism) ensures fair and transparent distribution of economic and social benefits among CRII stakeholders, promoting cooperation and stability (Minn et al. 2022). It helps mitigate conflicts, stimulates enthusiasm among local governments and investors, and encourages collaborative development (Nash et al. 2018). China's unique socio-political landscape, characterized by regional disparities in economic development and governance, presents both opportunities and challenges in ensuring the equitable distribution of CRI projects benefits among all stakeholders. The benefit-sharing mechanism must address the interests of multiple actors, including local governments, enterprises, and local communities, whose priorities and needs can vary significantly. For instance, economically developed coastal regions may expect higher economic returns from CRII investments compared to less-developed inland areas, leading to potential conflicts over resource allocation. Moreover, local governments may prioritize short-term economic gains from infrastructure development, while central government policies may focus on long-term, balanced regional growth. Effective benefit-sharing in CRII projects requires clear frameworks for allocating financial returns, addressing social and environmental concerns, and ensuring that all participating regions benefit from equitable development. For example, the Xi'an-Chengdu High-Speed Railway implemented a detailed mechanism to ensure the fair distribution of benefits, such as economic growth and land appreciation. Investment ratios, public expenditures, and risk-sharing strategies are considered, supporting a balanced framework that promotes regional synergy and project sustainability.

Discussions on the influencing mechanisms among the key factors. The key influencing factors in the CRII system are interconnected rather than independent, forming a complex network through interactions. This phenomenon is illustrated in Figs. 3 and 4. Using the results from key influences and the ISM hierarchy, we can identify significant influence paths. This study takes two paths as examples to illustrate how influencing factors interact to promote CRII.

Path 1: A5-A1-A2-A3. The Central-local policy interaction model (A5) provides the overarching guidelines that direct the Cross-regional local government cooperation model (A1). Local governments rely on these policies to navigate the complexities of cross-regional collaboration, ensuring that their efforts are aligned with national objectives (Yang and Wu 2023). This alignment is critical for the subsequent establishment of the Cross-regional enterprise coordination mechanism (A2), as businesses look to local governments for regulatory clarity and consistency when planning and executing projects across different regions (Witz et al. 2021). The coordination among enterprises is facilitated by the stability and predictability offered by coordinated local government policies, which helps to mitigate risks and fosters a conducive environment for investment and operation (Luthra et al. 2022). Finally, the Public interaction and feedback mechanism (A3) is influenced by the preceding factors, as it builds upon the cooperation and coordination established between governments and enterprises. With effective cross-regional cooperation and enterprise coordination, there is a greater likelihood of community engagement and the incorporation of public feedback into project design and execution (Castanho et al. 2018). This public involvement is essential for social acceptance and can help to identify and address potential issues early in the project lifecycle, leading to more efficient and effective CRI projects.

Path 2: A5-C1-C2-B2. The Central-local policy interaction model (A5) establishes the regulatory and financial parameters that govern the Fiscal investment ecosystem (C1), dictating how funds are allocated and managed for CRII projects (Cheng et al. 2022). These policies directly affect the Benefit-sharing mechanism (C2) by defining the rules for the equitable distribution of financial and operational benefits among participating regions, which is crucial for maintaining regional harmony and project support (Yang and Wu 2023). The clarity and fairness of benefit-sharing further enhance the Capital operation transparency mechanism (B2), as it creates an environment where stakeholders are more inclined to conduct and disclose financial operations openly, thereby ensuring accountability and fostering trust in the investment process (Xu et al. 2020).

This study expands on existing research by comprehensively analyzing factor interactions, thereby identifying critical factors and pathways. This approach enhances the understanding of CRII by providing insights into how various factors interrelate and influence the overall implementation process.

Strategies to enhance CRII. This study identifies that the key influencing factors of CRII originate from various dimensions, necessitating the development of a systematic strategy. In this context, a four-pronged framework of "policy alignment, cooperative incentives, operational excellence, and supply assurance" was formulated to effectively advance CRII.

Policy alignment. Policy alignment addresses the coordination challenges between central and local governments (A5), as well as among local governments (A1), to establish a unified and efficient CRI policy system.

Establishing a CRI Policy Coordination platform: A "CRI Policy Coordination Committee" should be established, led by the central government, with participation from local governments and enterprises (Xiang et al. 2023). This committee will oversee policy dissemination, resource allocation, conflict resolution, and project evaluation. Additionally, a real-time information-sharing platform should be developed to integrate data on approvals, progress, and resource allocation using blockchain technology, with strict permission management to ensure security and transparency (Wan et al. 2022). AI tools can further optimize decision-making by analyzing resource distribution and approval processes. For example, the Yangtze River Delta's joint mechanism has improved project efficiency. To ensure timely responses, the committee should implement rapid response mechanisms and hold quarterly meetings to resolve conflicts and adjust policies.

Developing a unified policy and planning framework: The central government should provide a national framework covering land approvals, environmental assessments, technical standards, and funding distribution for CRI projects (Guo et al. 2014). This framework must include clear guidelines on approval timelines, responsibilities, and performance standards. Early-stage policy planning should involve local governments, enterprises, and experts to build consensus on key areas such as funding, technology, and environmental impact. Periodic evaluations should align goals across stakeholders, supported by a centralized database for adjustments. Local governments should regularly report implementation feedback, such as resource utilization and approval timelines, to inform policy updates. For example, the Beijing-Tianjin-Hebei region used such a framework to reduce duplication and optimize resource allocation.

Establishing policy supervision and feedback mechanisms: A Policy Supervision Office should monitor CRI implementation through regular reports on key metrics, such as resource allocation, approval efficiency, and social impact. Automated tools can enhance monitoring efficiency and flag critical issues for priority resolution (Luthra et al. 2022). A digital feedback platform should enable local governments to report challenges and propose solutions in real time. Intelligent categorization can group issues, such as resource shortages or delays, and generate preliminary solutions for review. Pilot projects, such as the Beijing-Shanghai High-Speed Railway's pricing trial, should refine mechanisms before broader implementation to ensure effectiveness and scalability.

Cooperative incentives. Cooperative incentives aim to address benefit-sharing (C2), enterprise collaboration (A2), and policy incentives (B6) to foster regional cooperation and optimize resources.

Improving dynamic benefit-sharing mechanisms: The central government should establish a CRI benefit-sharing fund to ensure equitable resource allocation among regions (Yuan and Yang 2022). Allocation rules should reflect dynamic metrics such as GDP growth, tax contributions, and project participation, with quarterly adjustments. Priority should be given to underdeveloped areas to promote balanced growth. Independent audits and public reporting should be implemented to ensure transparency and foster trust. Additionally, quarterly regional meetings should be held to resolve disputes arising from benefit-sharing decisions. For example, the Yu-xin-ou Railway increased collaboration among stakeholders through transparent benefit-sharing rules.

Strengthening enterprise collaboration: An enterprise collaboration platform should facilitate resource sharing, technical cooperation, and R&D coordination (Xia and Xiang 2022). Real-time data and big data analytics can match firms with partnership opportunities. A joint R&D fund, co-financed by central and local governments, can support projects addressing critical technical challenges, with funding allocation based on criteria such as innovation potential and economic impact. Long-term cooperation agreements between enterprises should clarify roles and benefit-sharing arrangements to enhance stability. For example, CRRC's partnerships with local firms drove innovations in high-speed train technologies, strengthening competitiveness.

Optimizing policy incentives: Central and local governments should integrate resources into a unified incentive platform covering tax benefits, subsidies, and R&D funding. Policies should include clear eligibility criteria to reduce uncertainty. Optimized PPP models can clarify roles in benefit-sharing and risk allocation, supported by risk-sharing funds to encourage enterprise participation (Li et al. 2024). A dynamic evaluation mechanism should periodically assess policy effectiveness and refine incentives. For example, adjustments to the China-Europe freight train subsidy policy attracted more enterprises, boosting project success.

Operational excellence. Operational excellence focuses on addressing challenges related to information exchange platforms (B3) and operational management coordination, aiming to enhance project transparency and operational efficiency.

Building intelligent information management platforms: A unified CRI intelligent information management platform should be developed to integrate project progress, design changes, resource requirements, and financial data (Yang and Wu 2023). Blockchain technology with hierarchical permission management should be employed to ensure transparency and security. Additionally, AI modules should dynamically analyze construction progress and resource allocation to predict bottlenecks and offer optimization recommendations, such as adjusting construction schedules or reallocating resources. To improve management efficiency, a platform administrator team should monitor data updates and organize cross-departmental coordination meetings to resolve inconsistencies. The success of the China Railway Engineering Management Platform demonstrates that intelligent information management can significantly enhance project execution efficiency and transparency.

Improving cross-regional operational coordination mechanisms: A CRI Operational Coordination Committee should be established to oversee unified scheduling, ticketing system interconnectivity, and equipment maintenance standardization (Xiang et al. 2023). The committee should convene regular meetings to evaluate operational data and propose improvement measures. Furthermore, an interconnected electronic ticketing system with multilingual interfaces and multiple payment options should be developed to provide seamless ticketing experiences for passengers. This system should integrate regional discount policies and dynamic ticket price adjustment functions to attract more passengers to rail travel. Additionally, an intelligent scheduling system should optimize train operation plans, adjusting schedules in real time to meet passenger flow demands, while standardized maintenance procedures should ensure consistent quality across regions (Ojiako et al. 2015). For example, the centralized scheduling model of the Beijing-Shanghai High-Speed Railway significantly reduced train delays and improved overall operational efficiency.

Enhancing maintenance and emergency management: Regional maintenance centers should be established across the CRI network to centrally manage train inspection and maintenance tasks. These centers should be equipped with high-precision testing equipment and utilize IoT technology to monitor the condition of train components in real time (He et al. 2021). Furthermore, a comprehensive emergency management system should be developed to integrate emergency response processes, including resource allocation plans and personnel coordination mechanisms. The system should feature automated early warning functions, using AI to analyze train operation data and identify potential risks in advance. Cross-regional emergency drills should be conducted annually to simulate natural disasters and equipment failures, testing the effectiveness of emergency plans and refining them as necessary (Yang et al. 2023a). For example, the Sichuan-Tibet Railway significantly improved its emergency response capacity through multiple drills conducted in its complex geological conditions.

Supply assurance. Supply assurance aims to ensure the stable supply of materials and technology, focusing on the stability and security of material and technology supply chains (B4).

Establishing regional material reserves and allocation centers: Multiple regional material reserve centers should be established along the CRI corridor. These centers should develop reserve plans tailored to project scale and phase requirements, specifying material types (e.g., high-performance steel and track components) and inventory levels, with regular updates to inventory lists (Wong et al. 2022). An intelligent warehousing management system should be implemented, utilizing IoT technology for real-time inventory monitoring and big data analytics to optimize replenishment strategies, minimizing risks of surpluses or shortages. The system should include automated alerts to notify managers when inventory falls below safety thresholds. Additionally, multimodal transport resources should be integrated, and intelligent dispatching systems should dynamically plan logistics routes to enhance material transportation efficiency. For example, the Sichuan-Tibet Railway project employed a multi-node reserve and intelligent distribution model, significantly reducing logistics costs during construction.

Promoting localized production and R&D: Efforts should focus on encouraging the establishment of railway equipment manufacturing bases along the CRI corridor to reduce dependence on external markets. Fiscal subsidies and tax incentives could be provided to attract enterprises to locally manufacture core components for high-speed rail (Saleh et al. 2024). Moreover, special funds should be allocated to support critical technology R&D for CRI, fostering collaboration among universities, research institutions, and enterprises to drive innovation. Key areas of focus should include high-performance materials and signal control systems, reducing reliance on imported technologies. Strengthening industry-academia-research collaboration should involve establishing joint laboratories and technology transfer centers to accelerate the application of research outcomes (Qiu et al. 2024). For example, CRRC successfully advanced high-speed train technologies through joint R&D with universities, significantly enhancing domestic railway technologies.

Strengthening digital supply chain management: A blockchain-based supply chain management system should be developed to cover the entire process of procurement, transportation, storage, and distribution (Xue et al. 2024). This system should ensure transparency and traceability of material flows, reducing resource waste caused by information asymmetry. Additionally, a supply chain risk warning mechanism should be established, utilizing big data analytics and market trend predictions to identify potential disruptions in advance. This warning mechanism should integrate with the supply chain management system to provide real-time solutions, such as adjusting transport routes or introducing backup suppliers. Finally, smart logistics technologies should be promoted, leveraging AI to optimize transportation routes and dynamically allocate resources to prioritize critical materials during construction peaks (Stolbov and Shchepeleva 2020). For instance, the Sichuan-Tibet Railway's intelligent logistics system significantly improved material allocation efficiency.

Conclusion

In this study, we first systematically deconstructed CRII, and identified 3 categories and 16 influencing factors of CRII based on literature research and expert interviews; then we constructed an F-DEMATEL-ISM-MICMAC model to conduct an in-depth study on the influencing factors, which revealed the influencing mechanism of CRII and identified 8 key influencing factors, and finally constructed a four-pronged strategic framework for promoting CRII: policy alignment, cooperative incentives, operational excellence and supply assurance. The successful promotion of CRII requires multifaceted strategic support and institutional safeguards, each of which is indispensable, from policy guidance to technical implementation, and from financial investment to coordination of benefits. Cooperation between central and local governments and among local governments is the root cause of the influence of CRII. This leads to four major challenges for CRII: policy and institutional innovation, incentives and investment ecology, efficient implementation and coordination mechanisms, and supply chain and technology security capacity.

This study offers several notable contributions. Firstly, it innovatively offers a systemic analysis of CRII, providing a more comprehensive analytical framework that overcomes the current limitations of focusing solely on specific stages or isolated perspectives of CRII. This contribution enhances the existing body of knowledge on the subject. Secondly, adopting a systemic perspective, the study highlights the interactions among various factors, addressing the current issue of independently evaluating CRII influencing factors and contributing to a deeper understanding of CRII and its dynamics. Finally, the integrated F-DEMATEL-ISM-MICMAC analytical model developed in this study can be applied to explore and assess other factors and their interactions. The CRII influencing factors and their interrelationships identified in this study will serve to deepen policymakers' understanding and awareness of CRII. The key influencing factors and enhancement strategies identified in this paper will help guide policymakers to better target their policies.

This study has several limitations. Firstly, while it aimed to identify CRII influencing factors from a systemic perspective, there may have been inevitable omissions. Future research will focus on refining the list of influencing factors to deepen our understanding of CRII. Secondly, despite the introduction of fuzzy theory to mitigate subjectivity, further efforts are needed to reduce reliance on expert judgment through objective data or alternative methodologies. Additionally, the majority of experts involved in this study were from China, potentially introducing bias based on their backgrounds. Future research will seek broader international expert input to enhance the CRII influencing factor system and assessment outcomes. A comparative analysis of CRIIs across different countries will also be undertaken to identify universal and context-specific strategies for promoting CRIIs in various scenarios. This analysis aims to ensure that CRIIs are effectively tailored and applicable to diverse regional contexts. In addition, the strategies mentioned in this study still need to be further validated in the future to ensure applicability.

Data availability

Some data, models, or codes generated or used during the study are available from the corresponding author by request.

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Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

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Additional information

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