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Analysing Cause-and-Effect Relationships of Circular Economy Factors in Construction Megaprojects Using Fuzzy DEMATEL

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ABSTRACT: Circular economy (CE) practices have emerged as a pivotal approach for enhancing sustainability in construction megaprojects. However, their implementation is hindered by the complexity of interrelated drivers. This study investigates the relationships among CE drivers and categorizes them into cause-and-effect groups to support effective decision-making in construction megaprojects. A comprehensive literature review identified key CE drivers, followed by semi-structured interviews with 15 industry experts in China to validate and contextualize these drivers. To address the uncertainty and subjectivity in expert opinions, Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) was employed to analyze the interdependencies and hierarchical structure of the drivers. The analysis revealed that Policy and Regulation (PR), Business Model and Tools (BMT), and Market and Economic Incentives (MEI) are critical cause drivers, while Design and Construction Practices (DCP) and Education and Awareness (EA) are primary effect drivers. These findings offer actionable insights for practitioners and policymakers to prioritize strategic interventions that drive CE adoption. This research contributes to advancing CE implementation strategies, addressing sustainability challenges, and enriching the body of knowledge in construction management.

Keywords
Circular Economy, Sustainable Construction Megaprojects, Fuzzy DEMATEL, China

1. INTRODUCTION

Construction Megaprojects (CMPs) are large-scale, high-investment initiatives that significantly impact economies, societies, and the environment. These projects often exceed a billion dollars in cost and are characterized by their immense complexity, heightened risks, ambitious goals, and intense public scrutiny. Despite their potential benefits, managing CMPs presents formidable challenges, particularly in project execution, stakeholder coordination, and risk mitigation (Flyvbjerg, 2014).
A recurring issue with CMPs is their tendency to underperform across technical, financial, social, and environmental dimensions. This underperformance is frequently linked to inadequacies in project management strategies, governance structures, and decision-making processes. Persistent problems such as cost overruns, schedule delays, and scope creep further complicate their delivery, often leading to significant financial losses and diminished public trust (Nyarirangwe et al., 2019). For instance, Lusail City's CP5B in Qatar suffered from design inconsistencies and coordination failures, nearly doubling its projected

timeline (Luai et al., 2017). Similarly, Denver International Airport and the Channel Tunnel faced cost escalations and delays, highlighting systemic flaws in large-scale project delivery.

To address these challenges, a paradigm shift is needed. Traditional evaluation frameworks focusing solely on cost and schedule metrics are insufficient. Sustainability and stakeholder satisfaction must be prioritized, necessitating stable legal, financial, and political frameworks. Effective risk management and the integration of environmental and social considerations aligned with the Sustainable Development Goals (SDGs) are now imperative (Corazza et al., 2023; Meshref & Ibrahim, 2024).

This urgency has driven the emergence of *sustainable megaprojects,* which emphasize resource efficiency, environmental responsibility, and long-term resilience. However, transitioning from linear practices to sustainable models requires fundamental changes in planning, execution, and material lifecycle management. One promising approach is adopting circular economy (CE) principles, which minimize waste through recycling, reuse, and regenerative design, contrasting with the traditional “take-make-dispose” model.

Despite its transformative potential, CE adoption in megaprojects faces substantial barriers, particularly in developing economies. Regulatory gaps, limited institutional awareness, and fragmented supply chains hinder progress, as seen in regions like Saudi Arabia, where entrenched linear economic models persist due to insufficient incentives and technical expertise (Alotaibi et al., 2024). Overcoming these challenges requires collaboration among policymakers, industry leaders, and communities to design supportive frameworks and innovative solutions (Ncube et al., 2023). While prior studies, such as Mhatre et al., (2023) have used methods like DEMATEL to prioritize CE adoption barriers in emerging economies, critical gaps remain in understanding the interconnected drivers that enable CE integration especially within megaprojects, which are pivotal to sustainable development yet understudied in CE research.

Existing literature explores CE applications in construction but lacks systemic analysis of how drivers interact to influence adoption, particularly in emerging economies like China a global leader in infrastructure development. This study addresses this gap by analyzing cause-and-effect relationships among CE drivers to facilitate their integration into megaprojects. By focusing on systemic categories (e.g., policy, market dynamics), this research provides actionable insights for prioritizing interventions. While individual drivers play critical roles, their impacts are often amplified or constrained by the broader categories they belong to (e.g., regulatory frameworks or market dynamics). Analyzing categories thus provides a more coherent basis for understanding systemic barriers and opportunities in CE implementation. By addressing these relationships, this study seeks to pave the way for a more sustainable and resource-efficient future in the construction industry.

2. METHODOLOGY

This study employs a three-stage methodology to systematically identify Circular Economy Drivers (CEDs) in sustainable megaprojects. The approach consists of (1) an extensive literature review, (2) Data Collection (semi-structured interviews and Literature review), and (3) Fuzzy DEMATEL (FDEMATEL) analysis. Each stage is designed to build upon the previous one, ensuring a structured and sequential investigation into the factors influencing the adoption of CE principles. The methodology not only provides a comprehensive framework for understanding these drivers but also enhances the rigor and reliability of the research findings.

2.1 Stage 1: Literature Review

The literature review utilized the Scopus database for its extensive coverage of peer-reviewed literature and advanced citation-tracking features. A systematic search was conducted using the Boolean query: [(TITLE-ABS-KEY ("circular economy factors") OR TITLE-ABS-KEY (" circular economy enablers") OR TITLE-ABS-KEY (" circular economy drivers") OR TITLE-ABS-KEY ("circular economy adoption") OR TITLE-ABS-KEY (" circular economy critical success factors ") OR TITLE-ABS-KEY (" circular economy barriers") OR TITLE-ABS-KEY ("circular economy implementation") AND TITLE-ABS-KEY ("construction ") OR TITLE-ABS-KEY ("mega projects") OR TITLE-ABS-KEY ("projects"))] , yielding an initial 81 papers. Following Ibrahim et al. (2024), inclusion criteria focused on peer-reviewed articles and review papers explicitly addressing CE drivers, enablers, barriers, or adoption in construction/megaprojects, while excluding non-English papers, non-peer-reviewed content (e.g., books, editorials), and studies lacking empirical or theoretical relevance. After de-duplication and title/abstract screening, 74 papers remained. To complement the database search, a snowballing technique (Ibrahim et al., 2025; Ibrahim, Faris, et al., 2024) was employed to identify additional influential studies by cross-referencing citations and references from key papers, ensuring coverage of seminal works that may not have appeared in the initial search (Ibrahim, Zayed, et al., 2024). Full-text screening further refined the sample, culminating in 76 papers that met the study's scope of CE adoption in large-scale construction projects. This multi-stage approach balanced comprehensiveness with rigor, addressing potential database limitations while ensuring transparency and reproducibility. To gain deeper insights, semi-structured interviews were conducted with ten experienced practitioners specializing in megaprojects in China. These experts, with 11 to over 25 years of professional experience and advanced academic qualifications (master's or Ph.D.), provided valuable insights into the drivers and their impacts on CE implementation. Based on the interview findings, the list of practices was refined, some variables were modified, and new variables (e.g., BMT9 and DCP5) were introduced. Additionally, the drivers were reorganized into five main categories, as shown in Table 1.

Table 1. CEDs to adopting CE in Construction Megaprojects (Oluleye et al., 2023; Wuni & Shen, 2022)

Category	ID	CEDs
Policy and Regulation (PR)	PR1	Establish clear guidelines for adopting circular economy (CE) in construction and demolition waste management.
	PR2	Require stakeholders to use secondary materials to promote circularity.
	PR3	Conduct regular government inspections to ensure circularity in demolition projects.
	PR4	Enforce strict penalties and regulations to prevent illegal dumping.
	PR5	Promote waste classification and sorting practices.
	PR6	Mandate reporting and documentation to support planning for CE initiatives.
Education and Awareness (EA)	EA1	Integrate CE principles into university curricula and encourage related research.
	EA2	Educate decision-makers on CE benefits.
	EA3	Develop skills and roles necessary for CE adoption in the industry.
	EA4	Facilitate expert workshops on CE principles and implementation.
Business Model and Tools (BMT)	BMT1	Create circular business models and decision-support systems for waste management.
	BMT2	Develop metrics and indicators to measure CE performance.
	BMT3	Use BIM simulations to assess material reuse potential early in projects.
	BMT4	Build data management platforms to drive value creation in CE.
	BMT5	Apply life-cycle analysis during design stages to evaluate material reuse benefits.
	BMT6	Leverage material stock data to enable reuse in new buildings.
	BMT7	Encourage manufacturers to retain ownership of materials for future reclamation.
	BMT8	Develop material passports to document detailed information on materials used.
	BMT9	Use digital tools (e.g., BIM, IoT) to optimize processes, track materials, and improve resource management.
Market and Economic Incentives (MEI)	MEI1	Allocate budgets effectively to support CE principles in construction.
	MEI2	Build secondary markets for recycled materials and components.
	MEI3	Offer rewards and incentives to promote CE adoption and awareness.
Design and Construction Practices (DCP)	DCP1	Design structures for easy disassembly to maximize value recovery.
	DCP2	Conduct pre-demolition audits to identify and recover resources.
	DCP3	Ensure proper storage of waste to maintain the quality of recyclable materials.
	DCP4	Design buildings with adaptability to facilitate future reuse.
	DCP5	Choose materials based on durability, repairability, and recyclability.

2.2 Stage 2: Data Collection

The study aimed to validate a proposed model and achieve research objectives through an interview conducted in Mainland China and Hong Kong, regions chosen for their high number of CMPs and shared regulatory frameworks. To ensure the effective application of the proposed framework, the selection of qualified experts as the primary source of data was essential. Three strict criteria were applied during the expert shortlisting process. First, each expert was required to have at least ten years of relevant experience in construction megaprojects. Second, they needed to hold at least an undergraduate degree in a field related to building and construction. Third, they had to demonstrate a high level of awareness of circular economy practices and tools, resulting in the selection of 15 experts.

2.3 Stage 3: Fuzzy Concept

Fuzzy sets are characterized by elements with varying degrees of membership. Introduced by Zadeh (1971) as an extension of classical set theory, fuzzy sets differ from classical sets, where membership is strictly binary—an element either belongs to a set or it does not. The mathematical foundations used in this research are drawn from the works of Chou et al.(2012).
A fuzzy number A on R is defined as a triangular fuzzy number (TFN) if its membership function Ã (x): R→ [0,1] is given by the following equation (1):

[1]
$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-l}{m-l}, l \le x \le m \\ \dfrac{u-x}{u-m}, m \le x \le u \\ 0, \quad otherwise \end{cases}$$

In Equation (1), l and u represent the lower and upper bounds of the fuzzy number Ã while m denotes its modal value. A triangular fuzzy number (TFN) is expressed as Ã = (l, m, u).

2.3.1 Fuzzy DEMATEL (FDEMATEL)

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was developed to analyze structural relationships within complex systems (Liou et al., 2008). The mathematical concepts are based on the works of Liou et al. (2008) . The analysis was conducted at the category level to reflect the systemic nature of CE adoption, where drivers within categories (e.g., Policy and Regulation) collectively influence outcomes. This approach aligns with the study’s focus on strategic decision-making, enabling stakeholders to prioritize interventions at a level compatible with institutional and organizational capacities. The process of constructing the DEMATEL model is outlined below:

Step 1: Define Criteria and Establish the Fuzzy Linguistic Scale: A decision-making committee followed a structured approach, first defining decision goals and identifying relevant evaluation criteria. Linguistic variables were assigned values based on predefined term sets, which categorize influences as "Very High Influence," "High Influence," "Low Influence," "Very Low Influence," and "No Influence." These linguistic terms were then mapped to a fuzzy scale, as presented in Table 2.

Step 2: Generate Assessments from Decision-Makers: To evaluate the relationships between the drivers $F = \{F_i | i = 1,2, \cdots, n\}$, experts provided pairwise comparisons. From these comparisons, the fuzzy values $\tilde{Z}(1), \tilde{Z}(2), \cdots, \tilde{Z}(n)$ were obtained. The fuzzy matrix $\tilde{Z}(k)$ represents the initial direct-relation fuzzy matrix for expert K, as shown in Equation [2] .

Table 2. Linguistic Scales for Importance *(Chou et al., 2012).*

Linguistic terms	Scale of fuzzy number
Very high influence (VH)	(0.5,0.75,1)
High influence (H)	(0.25,0.5,0.75)
Low influence (L)	(0,0.25,0.5)
Very low influence (VL)	(0,0,0.25)
No influence (No)	(0,0,0)

[2]
$$\tilde{Z} = \begin{bmatrix} 0 & \tilde{Z}_{12}^{(k)} & \cdots & \tilde{Z}_{1n}^{(k)} \\ \tilde{Z}_{21}^{(k)} & 0 & \cdots & \tilde{Z}_{2n}^{(k)} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{Z}_{n1}^{(k)} & \tilde{Z}_{n2}^{(k)} & \cdots & 0 \end{bmatrix}; k = 1,2, \cdots, P$$
$$\tilde{Z}_{ij}^{(k)} = (\tilde{l}_{ij}^{(k)}, \tilde{m}_{ij}^{(k)}, \tilde{u}_{ij}^{(k)})$$

Step 3: Normalize the Direct-Relation Fuzzy Matrix: The values of $\tilde{\alpha}_i^{(k)}$ and $\beta^{(k)}$ are represented as triangular fuzzy numbers, as defined in Equations [3], [4] and.

[3] $$\tilde{\alpha}_i^{(k)} = \sum \tilde{Z}_{ij}^{(k)} = \left(\sum_{j=1}^{n} \tilde{l}_{ij}^{(k)}, \sum_{j=1}^{n} \tilde{m}_{ij}^{(k)}, \sum_{j=1}^{n} \tilde{u}_{ij}^{(k)}\right)$$

[4] $$\beta^{(k)} = max\left(\sum_{j=1}^{n} \tilde{u}_{ij}^{(k)}\right) \quad 1 \le i \le n$$

In addition, linear scale transformation is applied to convert the criteria scales into comparable ones. This process yields the normalized direct-relation fuzzy matrix $\tilde{X}^{(k)}$ as shown in Equation [5].

[5] $$\tilde{X} = \begin{bmatrix} \tilde{X}_{11}^{(k)} \tilde{X}_{12}^{(k)} \cdots & \tilde{X}_{1n}^{(k)} \\ \tilde{X}_{21}^{(k)} \tilde{X}_{22}^{(k)} \cdots & \tilde{X}_{2n}^{(k)} \\ \vdots \quad \vdots \quad \ddots & \vdots \\ \tilde{X}_{n1}^{(k)} \tilde{X}_{n2}^{(k)} \cdots & \tilde{X}_{nn}^{(k)} \end{bmatrix}; k = 1,2,\cdots,P$$

Where $\tilde{X}_{ij}^{(k)} = \left(\tilde{Z}_{ij}^{(k)}/\beta^{(k)}\right) = \left(\left(\frac{\tilde{l}_{ij}^{(k)}}{\beta^{(k)}}\right), \left(\frac{\tilde{m}_{ij}^{(k)}}{\beta^{(k)}}\right), \left(\frac{\tilde{u}_{ij}^{(k)}}{\beta^{(k)}}\right)\right)$

This research assumes that there is at least one i for which $\sum_{j=1}^{n} \tilde{u}_{ij}^{(k)} < \beta^{(k)}$. Furthermore, Equations [6] and [7] are used to calculate the average matrix $\tilde{X}$.

[6] $$\tilde{X} = \frac{\tilde{x}^{(1)} \oplus \tilde{x}^{(2)} \oplus \cdots \oplus \tilde{x}^{(p)}}{P}$$

[7] $$\tilde{X}^{k} = \begin{bmatrix} \tilde{X}_{11} \tilde{X}_{12} \cdots & \tilde{X}_{1n} \\ \tilde{X}_{21} \tilde{X}_{22} \cdots & \tilde{X}_{2n} \\ \vdots \quad \vdots \quad \ddots & \vdots \\ \tilde{X}_{n1} \tilde{X}_{n2} \cdots & \tilde{X}_{nn} \end{bmatrix}$$

Where $\tilde{x}_{ij} = \left(\sum_{k=1}^{p} \tilde{x}_{ij}^{(k)}/P\right)$

Step 4: Establish and analyze the structural model: After obtaining the normalized direct-relation matrix $\tilde{X}$, the total-relation matrix T can be calculated. It is essential to ensure the convergence of $\lim_{w \to \infty} \tilde{X}^{w} = 0$. The total-relation fuzzy matrix is presented in Equations [8] - [10].

[8] $$\tilde{T} = \lim_{w \to \infty} (\tilde{X} + \tilde{X}^2 + \cdots + \tilde{X}^{w})$$

[9] $$\tilde{T} = \begin{bmatrix} \tilde{t}_{11} \tilde{t}_{12} \cdots & \tilde{t}_{1n} \\ \tilde{t}_{21} \tilde{t}_{22} \cdots & \tilde{t}_{2n} \\ \vdots \quad \vdots \quad \ddots & \vdots \\ \tilde{t}_{n1} \tilde{t}_{n2} \cdots & \tilde{t}_{nn} \end{bmatrix}$$

Where $\tilde{t}_{ij} = (l_{ij}^{''}, m_{ij}^{''}, u_{ij}^{''})$

[10] $$Matrix\left[l_{ij}^{''}\right] = X_l \times (I - X_l)^{-1}$$
$$Matrix\left[m_{ij}^{''}\right] = X_m \times (I - X_m)^{-1}$$
$$Matrix\left[u_{ij}^{''}\right] = X_u \times (I - X_u)^{-1}$$

Step 5: Defuzzify the Total-Relation Matrix: Defuzzification methods are categorized based on vertical or horizontal representations of possibility distributions. The most used defuzzification method is the Centroid (Centre-of-Gravity) method (Pedrycz, 1995); however, it does not differentiate between two fuzzy numbers that have the same crisp value despite differing shapes. Therefore, the CFCS (Converting Fuzzy Data into Crisp Scores) defuzzification method is adopted for the fuzzy aggregation procedure, as it offers a more accurate crisp value compared to the Centroid method (Opricovic & Tzeng, 2003). Many scholars have also employed the CFCS method in defuzzification processes within fuzzy DEMATEL applications, highlighting its effectiveness in accurately translating fuzzy data into crisp scores (Li et al., 2023). The CFCS method, proposed by Opricovic and Tzeng (2003) is based on determining the left and right scores using fuzzy min and fuzzy max operations, with the total score calculated as a weighted average according to the membership functions. To defuzzify the total-relation matrix T. The CFCS method is described as follows in Equations [2] - [17]:

i. Normalization:

[2] $$xl_{ij}^{t} = \left(l_{ij}^{t} - minl_{ij}^{t}\right)/\Delta_{min}^{max},$$

[3] $$xm_{ij}^{t} = \left(m_{ij}^{t} - minl_{ij}^{t}\right)/\Delta_{min}^{max},$$

[4] $$xu_{ij}^{t} = \left(u_{ij}^{t} - minl_{ij}^{t}\right)/\Delta_{min}^{max},$$

Where $\Delta_{min}^{max} = maxu_{ij}^{t} - minl_{ij}^{t}$.

ii. Compute left (ls) and right (rs) normalized value:

[5] $$xls_{ij}^{t} = xm_{ij}^{t}/(1 + xm_{ij}^{t} - xl_{ij}^{t})$$

[6] $$xrs_{ij}^{t} = xu_{ij}^{t}/(1 + xu_{ij}^{t} - xm_{ij}^{t})$$

iii. Compute total normalized crisp value:

[16] $$x_{ij}^{k} = \left[xls_{ij}^{t}\left(1 - xls_{ij}^{t}\right) + xrs_{ij}^{t}xrs_{ij}^{t}\right]/\left[1 - xls_{ij}^{t} + xrs_{ij}^{t}\right]$$

iv. Compute crisp values:

[17] $$f_{ij}^{k} = minl_{ij}^{t} + x_{ij}^{k}\Delta_{min}^{max}$$

Step 6: Calculate the row and column sums from the defuzzified total relation matrix using the relevant Equations [18] - [19].

[18] $$\widetilde{D} = \sum_{j=1}^{n} f_{ij}$$

[19] $$\widetilde{R} = \sum_{i=1}^{n} f_{ij}$$

Step 7: Draw the cause–effect relationship diagram and analyze the results. The ($\widetilde{D}$+$\widetilde{R}$) values named "Prominence/cause" represent the overall influence of the drivers, while the ($\widetilde{D}$-$\widetilde{R}$) values named "Relation/effect" characterize their causal relationships. Based on above statements, when ($\widetilde{D}$-$\widetilde{R}$) is positive, the criterion belongs to the cause group. Otherwise, the ($\widetilde{D}$+$\widetilde{R}$) is negative, the criterion belongs to the effect group.

3. DATA ANALYSIS AND RESULTS

The adoption drivers of Circular Economy (CE) for construction megaprojects are systematically analyzed and structured using our proposed methodology. These drivers were first identified through an extensive literature review. To further investigate their interrelationships, we collected evaluation data via expert interviews, focusing on five key drivers. To capture the complex relationships among these drivers, we employed the Fuzzy DEMATEL method, which enables a nuanced assessment through linguistic terms.

Specifically, experts performed pairwise comparisons using five influence levels. These linguistic terms were mapped onto a fuzzy scale, as detailed in Table 2. The collected data were aggregated into a direct relation fuzzy matrix in Table 3. Next, we applied Equations [10] – [12] to normalize this matrix, with the results shown in Table 4. Once normalization was completed, the total relation matrix T was derived using Equations [13] – [15], as presented in Table 5. To obtain crisp values, CFCS defuzzification was applied [16] – [22], leading to the computation of R and D values [23] – [24]. Finally, a cause-effect relationship diagram (Figure 1) was developed, summarized in Table 6.

Table 3. Aggregated direct relation fuzzy matrix

	PR			**EA**			**BMT**			**MEI**			**DCP**		
	l	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**
PR	0	0	0	1.513	2.430	3.082	1.705	2.641	3.419	1.576	2.512	3.290	1.771	2.597	3.308
EA	1.500	2.437	3.152	0	0	0	1.714	2.539	3.254	1.446	2.271	3.174	1.767	2.593	3.308
BMT	1.383	2.209	3.112	1.591	2.619	3.334	0	0	0	1.869	2.806	3.396	1.678	2.705	3.421
MEI	1.546	2.573	3.351	1.662	2.578	3.293	1.521	2.549	3.260	0	0	0	1.513	2.450	3.227
DCP	1.835	2.862	3.515	1.278	2.306	3.209	1.585	2.410	3.250	1.504	2.421	3.136	0	0	0

Table 4. The fuzzy normalized direct-relation matrix

	PR			**EA**			**BMT**			**MEI**			**DCP**		
	l	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**
PR	0	0	0	0.101	0.162	0.205	0.114	0.176	0.228	0.105	0.167	0.219	0.118	0.173	0.221
EA	0.100	0.162	0.210	0	0	0	0.114	0.169	0.217	0.096	0.151	0.212	0.118	0.173	0.221
BMT	0.092	0.147	0.207	0.106	0.175	0.222	0	0	0	0.125	0.187	0.226	0.112	0.180	0.228
MEI	0.103	0.172	0.223	0.111	0.172	0.220	0.101	0.170	0.217	0	0	0	0.101	0.163	0.215
DCP	0.122	0.191	0.234	0.085	0.154	0.214	0.106	0.161	0.217	0.100	0.161	0.209	0	0	0

Table 5. The Fuzzy Total Direct relation Matrix

	PR			**EA**			**BMT**			**MEI**			**DCP**		
	l	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**	**l**	**m**	**u**
PR	0.072	0.299	1.237	0.161	0.434	1.391	0.177	0.450	1.427	0.168	0.441	1.407	0.182	0.453	1.428
EA	0.162	0.430	1.394	0.068	0.286	1.204	0.176	0.436	1.403	0.160	0.420	1.385	0.181	0.444	1.412
BMT	0.156	0.432	1.422	0.165	0.447	1.415	0.074	0.304	1.254	0.184	0.459	1.424	0.177	0.462	1.446
MEI	0.162	0.444	1.422	0.166	0.441	1.403	0.163	0.445	1.422	0.070	0.296	1.229	0.165	0.445	1.427
DCP	0.178	0.455	1.428	0.145	0.424	1.397	0.166	0.434	1.420	0.161	0.431	1.400	0.073	0.301	1.248

3.1 Identification of CE Drivers

By combining Figure 1 and Table 6, we can analyze the influence of each driver and assess its overall impact on the system. This analysis helps identify the key drivers of CE adoption for construction megaprojects. In the DEMATEL method, the degree of centrality (D + R) represents the total influence a criterion exerts and receives within the system. A higher D+R value indicates a more central role in the network of influences. Conversely, the difference (D - R) determines whether a criterion primarily acts as a cause or an effect. If D−R > 0, the evaluation criterion exerts more influence on others than it receives, classifying it as a causal driver. If D−R < 0, the criterion is more influenced by others than it influences them, making it an effect driver. The D−R values are reported in Table 6.

3.1.1 Cause drivers' analysis

Cause drivers have a net impact on the entire system, meaning their performance significantly influences the overall objective. Therefore, prioritizing these drivers is crucial to enhancing CE adoption. Unlike many studies that simply categorize cause drivers without further analysis, this paper thoroughly examines each one to determine its significance. The cause drivers, identified by their positive (D - R) values, include PR, BMT, and MEI. Among all cause drivers, 'Business Model and Tools' (BMT) has the highest D - R value (0.0266), indicating that it exerts a stronger influence on the system than it receives from other drivers. Additionally, as shown in Table 6, BMT has a high influence score of 2.8172, making it the most impactful cause driver. This suggests that implementing effective business models and tools—such as digital tracking systems and circular economy-based financial structures—can significantly enhance CE adoption in construction megaprojects. 'Policy and Regulation' (PR) follows closely with a net effect score (D - R) of 0.0130 and an influential impact score (D) of 2.7907. This highlights that well-defined policies and regulatory frameworks play a critical role in promoting circular economy adoption. Governments and regulatory bodies must establish clear policies and provide strong incentives to facilitate the transition.

3.1.2 Effect drivers' analysis

Effect drivers tend to be significantly influenced by other drivers. However, analyzing them is essential for understanding their unique role in the system. The effect group, characterized by negative (D - R) values, includes Education and Awareness (EA) and Design and Construction Practices (DCP). Among the effect drivers, 'Design and Construction Practices' (DCP) has the highest D + R score (5.5874), demonstrating its fundamental importance in CE adoption. As shown in Figure 1, the D - R score of DCP is -0.0546, slightly below zero, indicating that it is a net receiver. Its degree of influential impact (D) is 2.7664, while its received impact (R) is 2.8210. This suggests that although DCP is influenced by other drivers, it remains a critical component in achieving circular economy goals. Implementing innovative design strategies, modular construction techniques, and material reuse practices can significantly enhance the system's efficiency. Another effect driver, 'Education and Awareness' (EA), has a D + R score of 5.4788 but a negative D - R value (-0.0067), indicating its susceptibility to other drivers. While its direct influence is moderate, increasing education and awareness among stakeholders—including engineers, contractors, and policymakers—can lead to a more comprehensive adoption of CE principles. Training programs and knowledge-sharing initiatives should be prioritized to bridge the knowledge gap and foster an informed construction industry.

Table 6. Final output (Cause and Effect values).

Enablers/Drivers	D	R	D-R	D+R	Cause /Effect
Policy and Regulation (PR)	2.7907	2.7776	0.0130	5.5683	Cause
Education and Awareness (EA)	2.7361	2.7428	-0.0067	5.4788	Effect
Business Model and Tools (BMT)	2.8172	2.7906	0.0266	5.6078	Cause
Market and Economic Incentives (MEI)	2.7843	2.7626	0.0217	5.5469	Cause
Design and Construction Practices (DCP)	2.7664	2.8210	-0.0546	5.5874	Effect

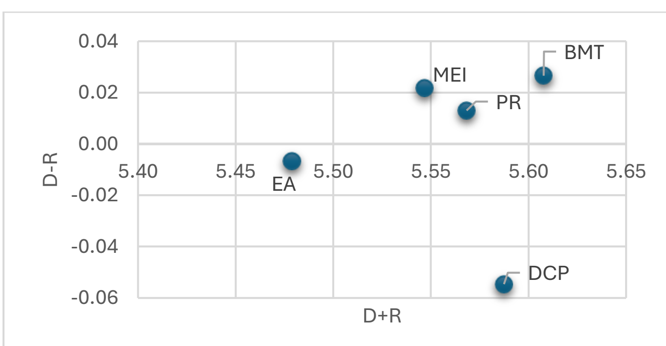

Figure 1. The cause–effect diagram.

The adoption of a circular economy (CE) in construction megaprojects is driven by three primary causal factors: Policy and Regulation (PR), Business Models and Tools (BMT), and Market and Economic Incentives (MEI). PR establishes foundational frameworks through government mandates, standards, and incentives that enforce resource efficiency and sustainable material use, as emphasized by AlJaber et al. (2024), who stress the role of clear regulations in fostering CE adoption. BMT provides practical frameworks and technologies, such as digital twins and material-tracking systems, which optimize design and resource management, aligning with Meng et al.(2023), who highlight how digital tools overcome barriers to CE implementation. MEI acts as a catalyst by offering financial motivations like tax breaks and green procurement policies, which align profitability with sustainability, as noted by John et al. (2023). These causal factors collectively influence two critical effects: Education and Awareness (EA), which addresses knowledge gaps among stakeholders through training and awareness campaigns, as Adams et al. (2017) argue, and Design and Construction Practices (DCP), which institutionalizes circularity via modular designs and recyclable materials, enabled by BMT innovations (Meng et al., 2023). Together, these cause-effect relationships underscore a systemic shift toward CE in construction megaprojects, where strengthening causal drivers amplifies downstream effects.

4. CONCLUSIONS

This study analyzed the cause-and-effect relationships among Circular Economy (CE) drivers in construction megaprojects using the Fuzzy DEMATEL approach. The findings highlight the complexity of CE adoption, emphasizing the critical role of Policy and Regulation (PR), Business Model and Tools (BMT), and Market and Economic Incentives (MEI) as primary cause drivers. These drivers exert significant influence over other factors, making them strategic priorities for enhancing sustainability in megaprojects. On the other hand, Design and Construction Practices (DCP) and Education and Awareness (EA) were identified as effect drivers, meaning their improvement is largely dependent on interventions targeting the cause drivers. The results provide valuable insights for policymakers, industry practitioners, and researchers seeking to facilitate CE integration into construction megaprojects. Strengthening regulatory frameworks, promoting innovative business models, and enhancing economic incentives can accelerate the transition from linear to circular construction practices. Furthermore, fostering education and awareness can enhance industry-wide adoption and long-term sustainability. By addressing the interdependencies among CE drivers, this research contributes to a more structured approach to decision-making in sustainable megaprojects. This study acknowledges several limitations that warrant consideration. First, the research focuses on China’s construction megaprojects, which may limit the generalizability of findings to other regions with distinct regulatory, economic, or cultural contexts. Second, the reliance on expert opinions within the Fuzzy DEMATEL framework, though valuable, inherently involves subjectivity in interpreting interdependencies among drivers, which could influence the robustness of causal relationships. Future research should explore the dynamic evolution of these drivers over time and their adaptability to shifting economic, regulatory, and technological landscapes. Additionally, applying the framework to real-world mega projects in developing countries will validate its practicality and scalability in diverse regional contexts. Comparative studies with multi-criteria decision-making (MCDM) models, such as AHP or TOPSIS, are also recommended to benchmark the framework’s effectiveness and identify synergies or gaps in addressing CE complexities. Expanding the dataset to include broader stakeholder perspectives, including informal waste sectors and local communities, will further refine CE adoption strategies. Finally, integrating risk management principles, such as supply chain vulnerability assessments or lifecycle uncertainty analyses, could enhance the framework’s robustness.

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