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Exploring the role of data-driven decision tools in integrating circular economy principles into supply chain networks: A UK local authority waste data study (2018–2023)

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Abstract

The circular economy (CE) offers a pathway toward efficient and sustainable resource utilisation, yet its principles remain poorly integrated into supply chain networks, partly because of insufficient digital tools for data-driven decision-making (DDDM). This study develops and empirically tests an approach for integrating CE principles with DDDM in United Kingdom (UK) waste management and supply chain networks. Secondary data published by the Department for Environment, Food and Rural Affairs (DEFRA) covering waste collection, recycling and reuse performance across UK local authorities between 2018 and 2023 were processed and analysed using Microsoft Excel, Power BI, Minitab and MATLAB. Descriptive, correlational and predictive analyses revealed clear patterns in circularity performance and its relationship with operational efficiency. National circularity increased steadily from 42.5% in 2018 to 47.1% in 2023, with a strong positive correlation between circularity and operational efficiency ($r = 0.78$, $R^2 = 0.67$, $p < 0.05$). Predictive modelling projects national circularity could approach 50% by 2025 under current policy trajectories. The study culminates in a Circular Economy–Data-Driven Decision-Making (CE–DDDM) framework that demonstrates how circular supply chains can be conceptualised, monitored and governed using analytics. The findings contribute to scholarship on circular supply chain integration with digital analytics and offer practical decision-support guidance for industry stakeholders, local authorities and policymakers.

Keywords: Circular Economy; Data-Driven Decision-Making; Supply Chain Management; Waste Management; Predictive Analytics; United Kingdom

1. Introduction

Historically, resource management in most economies has followed a linear "take-make-dispose" model in which raw materials are extracted, transformed into products, consumed and ultimately discarded as waste (Geiss et al., 2017). This pattern drives resource depletion, emissions and waste accumulation. In response, the circular economy (CE) has emerged as a system that seeks to eliminate waste and keep resources in continuous use through reuse, remanufacturing and recycling (Ellen MacArthur Foundation, 2019). Adoption of CE principles promises cost savings, improved environmental performance and greater organisational resilience (Kirchherr et al., 2017). However, organisations continue to struggle to operationalise CE concepts, in part because of a lack of reliable circularity metrics and limited use of data-driven decision-making (DDDM) tools (Kazancoglu et al., 2020).

Advances in DDDM and business analytics — including statistical predictive modelling, visualisation software and business intelligence platforms — now offer new opportunities to embed CE principles into supply chain management (Choi et al., 2018). By leveraging tools such as MATLAB, Minitab and Power BI alongside credible secondary datasets, organisations and policymakers can generate evidence-based insight into circularity performance and its operational implications.

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1.1. Problem Statement

Despite growing CE awareness, an empirical link between CE practices and key performance indicators (KPIs) such as resource efficiency and operational cost remains underexplored (Kazancoglu et al., 2020). There is similarly limited evidence on how DDDM tools can practically facilitate CE integration within supply chains, with most existing work either conceptual or confined to small-scale pilot studies in large, technologically advanced firms.

1.2. Aim and Objectives

This study aims to examine how DDDM tools can support the integration of CE principles within UK supply chain networks, and how this integration affects sustainability performance and organisational resilience. The specific objectives are to: (1) review the literature on CE adoption in supply chain management; (2) investigate the role of DDDM tools in supporting circular strategies; (3) analyse secondary waste-management datasets to assess the relationship between CE adoption and sustainability KPIs; (4) develop a structured CE–DDDM framework; (5) validate the framework through statistical, comparative and predictive testing; and (6) provide recommendations for managers and policymakers.

1.3. Contribution

The study contributes a structured, analytics-based framework linking circular practices to strategic KPIs (resource efficiency, waste diversion and operational cost), tested against a national, multi-year secondary dataset. This bridges a recognised gap between conceptual CE scholarship and the practical, quantitative application of digital analytics in circular supply chain governance.

2. Literature Review

The redesign of linear supply chains into CE-driven networks is increasingly necessary in response to global pressure for resource efficiency (Ellen MacArthur Foundation, 2019). CE practice emphasises reuse, remanufacturing, recycling and regeneration, replacing the conventional take-make-dispose model (Geissdoerfer et al., 2017). Embedding CE within supply chain management requires rethinking product design, distribution, consumption and recovery to create closed-loop systems that minimise waste and maximise resource value.

2.1. The Concept of Circular Economy

The Ellen MacArthur Foundation (2019) frames CE around three pillars: designing out waste and pollution, keeping products and materials in use, and regenerating natural systems. Its theoretical roots lie in industrial ecology and cradle-to-cradle thinking, which promote closed-loop production and eco-efficiency (Stahel, 2016). CE adoption also supports progress toward the UN Sustainable Development Goals, particularly Goal 9 (Industry, Innovation and Infrastructure) and Goal 12 (Responsible Consumption and Production) (Kirchherr et al., 2018). Nonetheless, CE adoption remains constrained by high implementation costs, limited digital capability and regulatory uncertainty (Rizos et al., 2016).

2.2. Supply Chain Networks and Sustainability Integration

A supply chain network (SCN) comprises the organisations, entities and activities involved in producing, distributing and delivering goods and services (Christopher, 2016). External environmental and social pressures have driven a shift toward Sustainable Supply Chain Management (SSCM), which balances economic, environmental and social performance (Carter & Rogers, 2008). Circular integration requires redesigning product flows, logistics and end-of-life management through reverse logistics, remanufacturing and closed-loop resource recovery (Genovese et al., 2017). However, data fragmentation across complex global supply networks continues to hinder circular integration (Gupta et al., 2021).

2.3. Data-Driven Decision-Making and Digital Transformation

DDDM prioritises decisions grounded in data analysis over intuition (Milla, 2025), proceeding through data collection, cleaning, analysis and decision stages that convert raw data into actionable insight (Gandomi & Haider, 2015; Provost & Fawcett, 2013). The digitalisation of supply networks — often termed the digital supply network — is transforming traditional chains into intelligent, connected ecosystems that enable circular practices such as remanufacturing and service-based production (Schoemaker et al., 2020).

2.4. Circular Economy and Data Analytics Integration

Integrating analytics with circular design supports lifecycle data analysis, predictive maintenance, material flow optimisation and circular supply planning (Pagoropoulos et al., 2017; Bag et al., 2021; Genovese et al., 2017). Machine learning models can forecast waste-generation trends and better match waste producers with recyclers (Chauhan et al., 2021; Lopes de Sousa Jabbour et al., 2019). However, interoperable data systems linking sustainability indicators across supply networks remain scarce, and many firms struggle to convert data into actionable insight, especially smaller enterprises constrained by cost (Garcia-Muiña et al., 2018; Tura et al., 2019; Rizos et al., 2016).

2.5. Decision-Support Tools and Theoretical Models

Decision-support systems (DSS) have evolved from spreadsheets toward real-time, AI-enabled platforms such as Power BI, Python and Minitab that link technical, economic and environmental criteria to support circular decisions (Charnley et al., 2019; Pieroni et al., 2019). Theoretically, the Resource-Based View (RBV) positions digital tools and circular practices as strategic resources that enhance competitive advantage (Hart, 1995); the Triple Bottom Line (TBL) framework argues that economic, environmental and social outcomes are interdependent (Elkington, 1998); and Industrial Symbiosis (IS) theory highlights how data-sharing platforms can identify symbiotic opportunities between industries (Chertow, 2000; Bocken et al., 2016).

2.6. Research Gaps

Three gaps recur in the literature. First, there is little empirical evidence of how specific analytical tools directly contribute to CE outcomes in supply networks, with most studies conceptual or limited to large, technologically advanced firms (Centobelli et al., 2020). Second, application of CE–DDDM models in resource-constrained or developing contexts is underexplored (Tura et al., 2019). Third, theoretical work rarely links data-driven decision models to measurable, longitudinal sustainability performance (Gupta et al., 2021). This study addresses these gaps by empirically testing a CE–DDDM framework against a six-year national dataset.

3. Methodology

3.1. Research Design and Philosophy

The study adopts a pragmatic, mixed-methods design combining descriptive and correlational quantitative analysis with qualitative interpretation of patterns against established theory (Saunders et al., 2019; Creswell & Plano, 2017). The quantitative strand statistically examines relationships between measurable CE indicators and supply chain performance metrics; the qualitative strand interprets these results in light of CE and SSCM theory.

3.2. Data Sources and Sampling

Secondary data were obtained with ethical clearance and written permission from data-owning organisations, principally the UK Department for Environment, Food and Rural Affairs (DEFRA, 2023), supplemented by Ellen MacArthur Foundation circularity benchmarks, corporate ESG reports and peer-reviewed literature. Datasets cover annual waste-management and recycling statistics reported by over 50 UK local authorities between 2018 and 2023, including total waste collected, recycling/reuse tonnage, resource efficiency and supply chain performance measures (cost, productivity and energy use). Purposive sampling selected approximately 40–50 local authorities and organisations representative of UK recycling and supply chain practice, drawn from twelve sourced datasets.

3.3. Data Cleaning and Pre-Processing

Data cleaning was conducted in Microsoft Excel, comprising consolidation of annual sheets into a single quarterly database, unit standardisation, treatment of missing values through imputation and cross-verification with DEFRA annual reports, and computation of derived metrics, including the Circularity Rate, calculated as:

Circularity Rate (%) = [(Total Waste Collected + Reused) / Total Recycled] × 100 (Equation 1)

All cleaned datasets were validated against official DEFRA summary statistics before being exported for statistical analysis and visualisation.

3.4. Analytical Tools and Techniques

Four complementary tools were used. Microsoft Excel supported baseline descriptive statistics, pivot-table analysis and simple visual trend reporting. Minitab 21 was used for correlation, multiple regression and significance testing (α =

0.05) to determine whether CE adoption levels relate to supply chain performance. MATLAB was used to train a feed-forward neural network (Levenberg–Marquardt algorithm, ten hidden neurons, 70/15/15 train–validation–test split) and to fit a polynomial regression model for predictive simulation of circularity under alternative scenarios (e.g. a 10% increase in recycling rate). Power BI produced interactive dashboards enabling dynamic filtering of circularity data by year, region and waste-stream type.

3.5. Framework Development and Validation

A CE–DDDM framework was developed comprising a Data Layer (CE performance inputs from DEFRA, WRAP and local authorities), an Analytical Layer (Excel, Minitab, MATLAB and Power BI processes such as correlation analysis, simulation and pattern recognition) and a Decision Layer (KPI dashboards and action recommendations), closed by a continuous Feedback Loop. The framework was validated through (i) statistical validation using regression significance (R^2 and p-values), (ii) comparative benchmarking against published DEFRA and Ellen MacArthur Foundation targets, (iii) MATLAB sensitivity testing of circularity parameters, and (iv) visual cross-checking of Power BI dashboards against source data.

3.6. Ethical Considerations

The study complied with the University of Greater Manchester's Research Ethics Policy (2024). Data were obtained through official written authorisation from DEFRA, WRAP UK and Bolton Council; only non-personal, aggregate data were used; processing and reporting followed principles of integrity, transparency and replicability; and all software was used under institutional or open-access licence.

4. Results

4.1. Descriptive and Trend Results

National circularity performance improved steadily and consistently across the six-year period, with a brief deceleration during the COVID-19 pandemic (2020–2021). Table 1 summarises the descriptive statistics.

Table 1 Summary statistics of UK circularity performance, 2018–2023 (author's analysis of DEFRA secondary data).

Year	Mean Circularity Rate (%)	Minimum (%)	Maximum (%)	Std. Dev.	National Waste Total (tonnes)
2018	42.5	28.3	57.9	8.4	23,650,000
2019	43.2	30.0	58.4	8.2	24,100,000
2020	44.6	31.1	60.3	8.5	24,350,000
2021	45.7	32.0	61.5	8.1	24,890,000
2022	46.2	33.4	62.7	8.0	25,120,000
2023	47.1	34.1	63.9	7.8	25,500,000

Circularity rose from 42.5% in 2018 to 47.1% in 2023 — a net gain of 4.6 percentage points. Regional disaggregation showed persistent disparities: the South East and South West consistently outperformed other regions, while densely populated urban authorities, including parts of London and the West Midlands, lagged behind with circularity below 40%. Authorities using digital waste-tracking systems achieved circularity rates above 50%, consistent with Pagoropoulos et al. (2017), who link data transparency to improved CE outcomes.

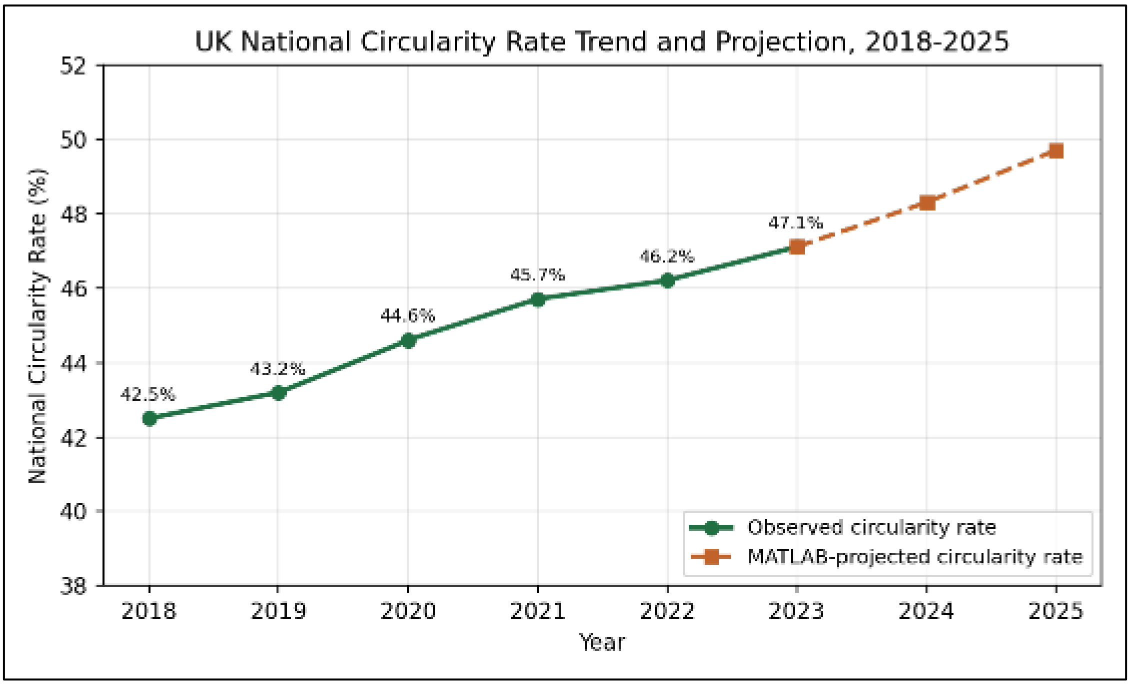

Figure 1 UK national circularity rate trend, 2018–2023, with MATLAB-projected trajectory to 2025.

4.2. Correlation and Regression Analysis

Pearson correlation analysis (Minitab) examined relationships between circularity rate and three supply chain performance indicators: waste reduction efficiency, residual waste, and operational cost efficiency (Table 2).

Table 2 Pearson correlation matrix between circularity and supply chain performance indicators.

Variables	Circularity Rate	Waste Reduction Efficiency	Residual Waste (%)	Operational Cost Efficiency
Circularity Rate (%)	1.00	0.78	–0.72	0.65
Waste Reduction Efficiency	0.78	1.00	–0.68	0.59
Residual Waste (%)	–0.72	–0.68	1.00	–0.61
Operational Cost Efficiency	0.65	0.59	–0.61	1.00

Circularity rate showed a strong positive correlation with waste reduction efficiency ($r = 0.78$), a moderate positive correlation with operational cost efficiency ($r = 0.65$), and the expected negative correlation with residual waste ($r = -0.72$). A simple linear regression model (Equation 2) was fitted to predict operational cost efficiency from circularity rate:

$Y = 22.31 + 0.41X$ *(Equation 2)*

where Y is predicted operational cost efficiency index and X is circularity rate (%). Regression diagnostics are summarised in Table 3.

Table 3 Regression output for circularity rate predicting operational cost efficiency ($R^2 = 0.67$, adjusted $R^2 = 0.65$, $p < 0.01$).

Predictor	Coefficient	SE Coefficient	t-value	p-value
Constant	22.31	1.52	14.68	0.000
Circularity Rate	0.41	0.07	5.86	0.002

The model indicates that circularity rate explains 67% of the variance in operational cost efficiency ($R^2 = 0.67$, $p < 0.01$), and that a one-percentage-point increase in circularity is associated with an approximate 0.41-point increase in operational cost efficiency, supporting the hypothesis that data-driven CE integration enhances economic and environmental performance simultaneously.

4.3. Predictive Modelling

A MATLAB neural network (ten hidden neurons, Levenberg–Marquardt training) achieved a strong overall fit (R = 0.78 across all data partitions), while a complementary second-order polynomial regression — $Y = 0.06X^2 + 1.24X + 42.3$, where X denotes year index (1 = 2018) — produced an excellent fit ($R^2 = 0.93$) and was used to project circularity for 2024 and 2025 (Table 4).

Table 4 MATLAB-projected national circularity rates, 2024–2025.

Year	Predicted Circularity Rate (%)	Year-on-Year Change (%)
2024	48.3	+2.6
2025	49.7	+2.9

Figure 1 illustrates the observed circularity trend (2018–2023) alongside the MATLAB-projected trajectory to 2025, suggesting national circularity could approach 50% under current policy and behavioural trends — an 8.2% cumulative increase since 2018, though with diminishing marginal gains as the rate approaches the 50% threshold.

4.4. The CE–DDDM Framework

Figure 2 presents the validated Circular Economy–Data-Driven Decision-Making (CE–DDDM) framework. The Data Layer captures CE performance inputs; the Analytical Layer applies statistical, visual and predictive analytics; the Decision Layer translates outputs into KPI dashboards and action recommendations; and the Feedback Loop enables continuous model refinement as new data and stakeholder input become available.

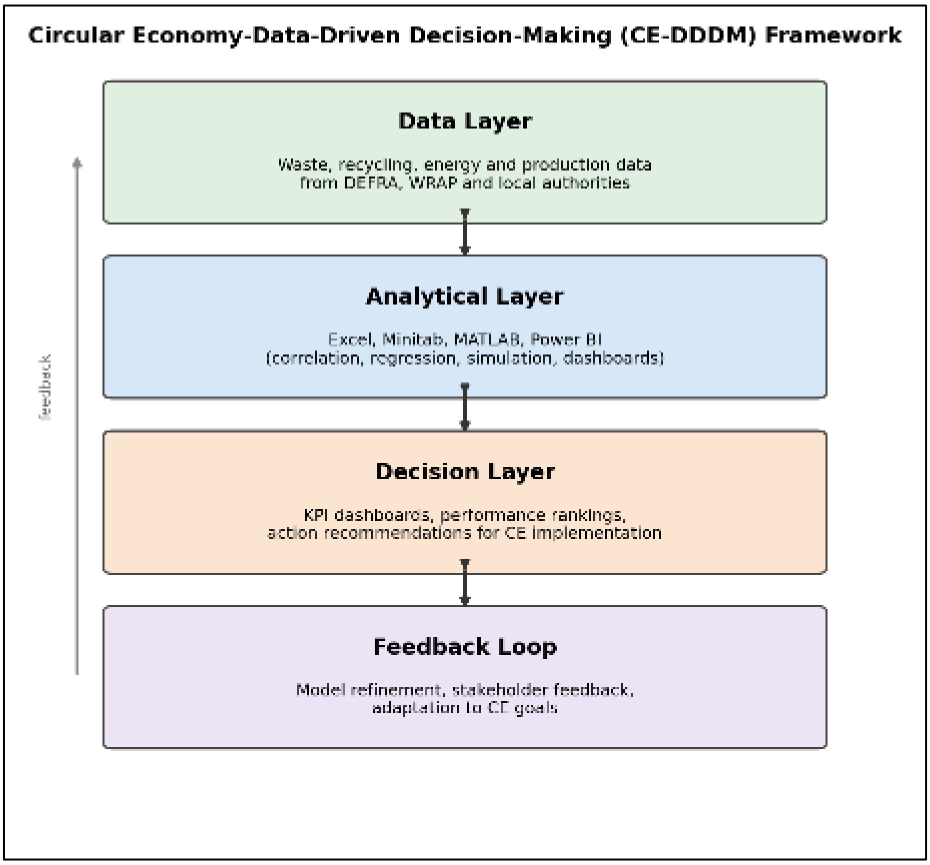

Figure 2 The Circular Economy–Data-Driven Decision-Making (CE–DDDM) framework, comprising Data, Analytical and Decision layers closed by a continuous Feedback Loop (author's framework)

4.5. Summary of Results

Table 5 Summary of research results across analytical methods.

Analysis Type	Tool	Key Finding	Interpretation
Descriptive statistics	Excel & Minitab	Circularity rose from 42.5% (2018) to 47.1% (2023)	Progressive, nationwide CE adoption
Visualisation	Power BI	Persistent regional disparities; South East/South West lead	Digital visualisation enables targeted policy response
Correlation	Minitab	r = 0.78 (circularity vs waste reduction efficiency)	Strong positive link to operational performance
Regression	Minitab	$R^2 = 0.67$, $p < 0.05$ (circularity predicts cost efficiency)	67% of cost-efficiency variance explained by circularity
Predictive modelling	MATLAB	Projected circularity ≈50% by 2025	Supports evidence-based sustainability planning
Framework validation	CE–DDDM model	Effective integration of analytics into CE decisions	Supports national data-driven CE transformation

5. Discussion

The results confirm a statistically significant, positive relationship between circularity and operational performance across UK local authority supply chains, consistent with Genovese et al. (2017) and Dubey et al. (2020), who link circular supply chain practices to measurable environmental and economic benefit. The 4.6-percentage-point improvement in national circularity over six years is real but modest relative to the UK Government's longer-term Resources and Waste Strategy targets (DEFRA, 2023), suggesting that early, easily captured gains are giving way to a plateau that will require more advanced digital enablers — such as IoT-based waste tracking and AI-driven matching of waste producers with recyclers — to sustain momentum (Pagoropoulos et al., 2017; Lopes de Sousa Jabbour et al., 2019).

The strong inverse relationship between circularity and residual waste (r = −0.72) corroborates the theoretical premise of closed-loop systems: as recycling and reuse rise, the residual fraction destined for landfill correspondingly falls. The moderate positive correlation with operational cost efficiency (r = 0.65) lends empirical support to Carter and Rogers' (2008) sustainable competitive advantage argument that environmental and economic performance need not trade off against one another.

Persistent regional disparities — with the South East and South West consistently outperforming urban authorities in London and the West Midlands — echo Rizos et al.'s (2016) observation that governance capacity, infrastructure maturity and digital readiness materially shape CE outcomes. This reinforces the Resource-Based View (Hart, 1995): authorities that have invested in digital waste-tracking infrastructure appear to convert that investment into a genuine circularity advantage, suggesting analytics capability itself functions as a strategic, rare resource.

The validated CE–DDDM framework demonstrates that fragmented local-authority waste data can be transformed into strategic, actionable intelligence, consistent with Centobelli et al. (2020). Its four-layer, closed-loop design operationalises the Triple Bottom Line and Industrial Symbiosis perspectives discussed in the literature review by linking real-time data capture to decision-making and continuous feedback, rather than treating analytics as a one-off reporting exercise.

Methodologically, triangulating Excel, Minitab, MATLAB and Power BI strengthened the robustness of the conclusions, though the study's reliance on secondary, aggregate local-authority data limits its granularity; sector-specific (e.g. manufacturing, construction, logistics) dynamics could not be examined. The predictive models, while exhibiting strong statistical fit, are extrapolations from a relatively short six-year series and should be interpreted as indicative trajectories rather than firm forecasts.

6. Conclusion

This study examined how data-driven tools and frameworks can support the integration of circular economy principles into UK supply chain networks, using secondary DEFRA data on local authority waste management (2018–2023).

National circularity increased from approximately 42.5% to 47.1% over the period, with projections suggesting rates near 50% by 2025. Correlation and regression analysis demonstrated a strong positive relationship between circularity and operational efficiency ($r = 0.78$; $R^2 = 0.67$, $p < 0.05$), supporting the hypothesis that data-enabled circular adoption strengthens both environmental and operational outcomes. The resulting Circular Economy–Data-Driven Decision-Making (CE–DDDM) framework offers a scalable model for integrating analytics with circular governance, bridging theoretical CE concepts and practical, evidence-based decision-making across UK supply chains.

6.1. Recommendations

Six directions are recommended for policy, practice and future research:

- Sector-specific application: Test the CE–DDDM framework in manufacturing, construction and energy sectors using primary data to strengthen its operational validity beyond waste management.
- Advanced digital technologies: Incorporate AI, machine learning and IoT for automated waste tracking, predictive material-flow modelling and real-time decision support.
- National data infrastructure: Establish a centralised, interoperable circular-data infrastructure with standardised formats to enable robust national-scale KPI monitoring.
- Policy and capacity building: Invest in digital sustainability training for council and industry staff, supported by policy incentives such as tax credits, to accelerate adoption.
- Longitudinal and cross-national research: Extend multi-year comparative studies across regions and countries to identify structural and cultural enablers of circularity.
- Social and ethical dimensions: Examine how data-driven CE frameworks affect community participation, employment and inclusive policymaking to ensure equitable transitions.

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