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Machine Learning and Financial Investment: Game Changers for Circular Business Models – EU Performance Score Analysis

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ABSTRACT:

The paper explores the methods by which Circular Material Use Rates (CURMs), Financial Investment (FI), and Machine Learning (ML) influence the performance of Circular Business Models (COP) in the EU by examining case studies from three groups: Leaders, Paradoxes, and Laggards. Leaders use machine learning (ML) to mitigate waste; however, they must also develop novel technologies, such as quantum-driven recyclables, to compensate for the declining capacity utilisation rate (CURM), which reappears. GGI and CMUR enhance COP and contribute to sustainability initiatives by encouraging resource optimisation and green practices. At the same time, this group utilises machine learning (ML) as its primary tool to enhance COP due to its willingness to integrate modern technologies quickly. For paradoxes to prevail over structural inefficiencies, FI must be reallocated ahead of digital integrity and AI-enhanced hybridisation. To find ways to modernise infrastructure, laggards rely on EU government green initiatives (GGI) and decentralised models (e.g., solely resource cycles). The research promotes the implementation of adaptive policies, including AI sandboxes, risk transfer funds, and legitimate governance, to ensure that interruptions in technology, financial flexibility, and equitable transition are balanced. These insights enable the EU to establish a model for broad, high-performance circular economies.

Keywords: Machine Learning, Financial Investment, Circular Business Models, EU Policy, Sustainability, Performance Scores.

JEL codes: Q55; G11; C45; O52.

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1. INTRODUCTION

Transitioning from a linear economic system to a circular economy (CE) is one of the key approaches for achieving the United Nations Sustainable Development Goal (SDG) 12: Responsible Consumption and Production. As part of the 2030 Agenda for Sustainable Development, the United Nations introduced 17 ambitious Sustainable Development Goals (SDGs) in 2015. SDG 12 is dedicated to promoting responsible consumption and production patterns, with a particular emphasis on minimising waste generation, ensuring environmental sustainability, and effectively applying resources by 2030. Since the circular business model (CBM) aims to reduce reliance on conventional energy sources and convert waste into valuable assets, it is closely aligned with this goal. The circular economy's key strategies—waste reduction, reusing, and recycling—are put into practice to achieve this ambitious goal (Ferasso, M., Beliaeva, T., Kraus, S., Clauss, T., Ribeiro-Soriano, D. 2020). Using CBMs is an effective strategy for promoting environmental responsibility, as it aims to reduce inefficiency across businesses and extend the lifespan of outcomes (Mulhall et al., 2022).

Despite numerous reports on the ecosystem benefits of CBMs, the financial and technological developments of this initiative, particularly at the macroeconomic level, have remained unrealised. The microeconomic level has been the primary focus of most research, which has investigated the impact of CBMs on specific organisations or sectors (Rutqvist, Kleyko, and Blomstedt, 2020). However, understanding the broader effects of CBM adoption at the national or regional level is essential for effective policy planning and economic projections. The shift to circular models necessitates significant administrative and technological transformations, including the creation of innovative financial frameworks, legislation, and business models that support these developments (Ranta, Aarikka-Stenroos, and Väisänen 2021).

The macroeconomic framework of Circular Business Models (CBMs) offers a compelling opportunity to enhance the adoption of circular business practices by integrating financial investments with machine learning (ML). Machine learning breakthroughs, encompassing strategies for optimisation, immediate data assessment, and repair prediction, can significantly enhance resource utilisation, prolong product longevity, and streamline recycling and waste disposal processes (Ghisellini, Cialani, and Ulgiati 2016). The current financing necessary for the expansion of these developments and the promotion of sustainable affluence is sourced from financial tools, including entrepreneurial activity, sustainability bonds, and EU recovery efforts such as Horizon Europe (Kanzari et al., 2022). The EU's commitment to green investment initiatives underscores the importance of financial investments in promoting circular economy transformations. At the same time, the transformative capabilities of artificial intelligence make it crucial for enhancing the efficacy and productivity of circular networks.

The European Union (EU) has assumed an influential role globally in addressing sustainability and preserving the environment through initiatives such as the European Green Deal and the Circular Economy Action Plan (CEAP) (Plan 2020). The EU's goal is to increase the circular material use rate (CMUSE) from 11.7% in 2020 to 25% by 2030, emphasising the importance of implementing circular economy standards and breakthroughs in technology (Popović, Todorović, and Milijić 2025). However, despite these initiatives, there remains a lack of evidence regarding the macroeconomic effects of machine learning on circular business models. Few thorough cross-country studies examine the macroeconomic connection among ML participation, financial investment, and circular economy findings. The majority of research has concentrated on the sector-specific impacts of artificial intelligence and machine learning on specific business sectors, such as production and recycling.

The study aims to bridge the comprehension gap regarding the macroeconomic relationship between the Circular Material Use Rate (CMUR), financial investment (FI), and machine learning (ML) adoption in influencing the overall performance of Circular Business Models (CBMs) across EU member states. In particular, the focus is on how the incorporation of ML and Financial investments influences the advancement and efficacy of CBMs at the national level. Our objective is to figure out the influence of ML, CMUR, and FI on the overall performance of CBM in every classification by employing panel regression models. The study utilises data from the European statistics database to examine the performance of EU member states in adopting circular economy practices over a decade.

Our primary hypothesis proposes that greater utilisation of ML, along with substantial financial investments, will boost CBM performance and growth, contributing to more robust circular economies on a broader scale. Furthermore, researchers investigate the impact of contextual elements on the association between ML implementation, CMUR, and CBM performance, including a nation's economic development, technological preparedness, and institutional support. For policymakers and others striving to support a robust and financially viable development, these findings are significant.

The research presented here also contributes to the academic literature by offering unique empirical evidence on the macroeconomic effects of machine learning (ML) on the performance of the circular economy. However, it additionally offers practical information for legislators, enterprises, and other partners in the EU. Our comprehensive understanding of the parameters that drive CBM preparedness is achieved by linking AI adoption with financial investments, which enables the development of evidence-based initiatives and plans that support the EU's circular transition objectives.

2. LITERATURE REVIEW

2.1. Deficiencies of the Linear Economy and the Emergence of Circular Business Models (CBMs)

Resource management exhaustion, environmental destruction, and waste generation are perpetuated by the linear "take-make-dispose" cycle. The EU consumes 14 tonnes of materials per capita and produces over 2.5 billion tonnes of waste annually. (Försterling, Orth, and Gellert 2023a) and (EEA, 2024). (Ferasso et al. 2020) Moreover, (Blackburn, Ritala, and Keränen 2023) Emphasise systematic deficiencies in the EU, where resource efficiency (€2/kg) surpasses worldwide averages but is ineffective in disentangling development from resource use. Circular Business Models (CBMs) offer a sustainable alternative by focusing on strategies such as refurbishment, recycling, and closed-loop systems. (Hartley et al. 2023b) . According to Alhawari et al. (2021) and Knäble et al. (2022), CBMs promote innovations in product-as-a-service approaches, resulting in a 30–50% reduction in material waste in industries such as the gadget and automotive sectors. However, problems persist, such as inconsistent legislation and funding shortfalls for SMEs, particularly in the EU's southern and eastern nations.

2.2 Machine Learning's Role in Optimising CBM Performance

Throughout the product lifecycle, the efficacy of CBM is improved by machine learning (ML). An industrial equipment outage is reduced by 20–30% through scheduled upkeep, which is facilitated by LSTM networks. Consistent with the objectives of the EU's Circular Economy Action Plan (Rosa, Sassanelli, and Terzi, 2019) and (Awan et al., 2022). In German automotive supply chains, for illustration, ML-driven identification of anomalies maximises transmission repair and reduces labour expenses by 15% (Sjödin, Parida, and Kohtamäki 2023a). Machine learning (ML) also influences the design of adaptable products. In Dutch recyclable networks, optimised supply chains using machine learning algorithms, such as reinforcement learning for adaptive routing, reduce transportation expenses by 12%. According to Tamasiga, Onyeaka, and Ouassou (2022), AI-driven models increase disassembly productivity in the electronics industry by 40%. However, obstacles, including insufficient connectivity and data structures, restrict the use of ML. For instance, 60% of SMEs in Italy do not have merged data graphs for cross-lifecycle metrics, which reduces the forecasting precision of machine learning (Försterling, Orth, and Gellert 2023a). Furthermore, the socio-behavioural factors that influence cyclical consumption are frequently overlooked by machine learning's emphasis on pattern detection, which calls for hybrid models that incorporate agent-based scenarios (Arranz, Kwong, and Sena 2023) and (Hartley et al., 2023b).

2.3 Financial Investment as a Catalyst for CBM Scalability

In the EU, where SMEs make up 99% of firms yet suffer an annual financial shortage of €55 billion, financial structures are essential for growing CBMs. Demonstration initiatives like Finland's circular construction centres, which achieved 25% of material reuse rates, have been funded by green bonds and EU recovery funds (such as Horizon Europe) (Shinde, 2021) (OECD, 2019). The hazards of investment are mitigated by risk-sharing equipment, such as hybrid financing models. Wei et al. (2023) observe that Nordic "leader" countries (Sweden, Netherlands) utilise public-private partnerships for funding 70% of circular ventures (Man, G. M., Zamfir, D., Diaconescu, D., Radu, A.-V., Aldea, F., & Ionescu 2025). On the other hand, "laggards" such as Bulgaria depend on EU structural grants, which provide just 30% of the requirements for circular infrastructure. As evidenced by Germany's green fintech industry, where bankruptcy rates for circular SMEs decreased by 18%, machine learning (ML) improves financial decision-making through AI-driven credit assessment (Sjödin, Parida, and Kohtamäki 2023b). Nevertheless, "paradox" regions, such as France, are confronted with inconsistent risk platforms, resulting in only 12% of SMEs utilising circular finance instruments, regardless of policy motivations (Vai, 2024).

2.4 Policy Frameworks and EU Green Initiatives

Metrics such as the Extended Producer Responsibility (EPR) programs and the Circular Material Use Rate (CMUR), which stood at 11.8% in 2023, exemplify how EU regulations promote Circular Business Model (CBM) preparedness (EEA, 2024; OECD, 2019). The "circular hotspots" initiative in the Netherlands integrates tax benefits with ML-driven garbage data analytics, resulting in a CMUR of 18%, which is 50% higher than the EU rate. In contrast, Eastern European states (such as Romania) encounter challenges in maintaining CMURs below 5% as a result of legacy linear assistance and inadequate EPR compliance (Försterling, Orth, and Gellert, 2023b). Circular investments are standardised by legislative coordination under the EU Taxonomy for Sustainable Activities, while the Machine Learning Act requires transparency in algorithms used for CBMs (Andrade, A. C. C., & Vasquez, 2024). For instance, the computational prejudice in reprocessing site automation decreased by 22% as a result of Spain's artificial intelligence ethical recommendations. To enhance COP, administrators allocate funding for quantum computing investigation and promote its implementation in Circular Business Models (CBM). This can encompass grants for exploring the potential of quantum computing to optimise complex structures, such as distribution networks, recycling procedures, and material recovery, through alliances between academic institutions, technology firms, and circular economy businesses.

2.5 The ML-Finance-Policy Nexus in EU CBM Transitions

The interaction of ML, finances, and legislation drives the efficacy of CBM. For instance, carbon taxes under the EU Emissions Trading System support the €2.1 billion in green bonds that Dutch ML-driven recycling facilities receive (Andrade, A. C. C., & Vasquez 2024). In contrast, Bulgaria's "circularity trap" persists due to its reliance on linear subsidies and low R&D investment (0.8% of GDP) (Försterling, Orth, and Gellert 2023a). Prospective studies need to tackle the deficiencies in comprehensive structures, especially in the paradoxical regions where policy aspirations exceed SME competencies (Hartley et al., 2023a).

The article highlights ML's revolutionary potential in developing CBMs, subject to targeted financing mechanisms and adaptable EU regulations. To reduce regional inequities, authorities should prioritise ML-enhanced CMUR surveillance and SME-friendly, environmentally friendly financing. Future studies should investigate the causal relationships between ethical artificial intelligence models and CBM performance in understudied regions, such as those in Southern Europe.

3. SYMBOLS USED

The purpose of the research is to determine the influence of "Machine Learning (ML), Financial Investment, and Circular Material Use Rate (CMUR) on the Composite Overall Preference (COP) of CBMs" in economies. The following will be achieved by employing five metrics: Machine Learning (Index), Financial Investment (Index), and Circular Material Use Rate (%) as independent variables, the Composite Overall Preference of CBMs across nations as the dependent variable, and Government Green Initiatives (Index) as the control variable. Each metric is available in the EU-Stat database.

3.1. Machine Learning

The main goal of this examination is to determine the financial worth of Machine Learning's (ML) contributions to the Circular Business Model (CBM). To assess specific machine learning abilities, such as learning and problem-solving programs, technical indicators are used. However, it is essential to note that these measurements have limited reach. Within the context of a sustainable economy, more consideration needs to be given to the broader economic impacts of adopting machine learning.

This research proposes an alternative approach to address the lack of a particular economic machine learning (ML) statistic. Instead of creating a new gauge, the study uses a publically existing replacement sign. Utilising Information and Communication Technology Services (ICTS), Individuals Using the Internet, Fixed Broadband Subscriptions and Fixed Telephone Subscriptions as Machine Learning Proxies. The study examines the notion that

ICT_DI *(ICT Services and Digital Infrastructure)* may serve as a proxy measure for the monetary impact of ML on the CBM. The **ICT_DI** sector has driven worldwide economic growth for almost two decades. It attracts investments, promotes innovation, and serves as a crucial indicator of a country's competitive edge in its educational economy. **ICT_DI**, including programming and software development, data mining and big data analytics, teleworking and remote collaboration platforms, Cloud Computing Infrastructure, IoT (Internet of Things) Connectivity, and artificial intelligence and automation tools, play a vital role in developing and utilising machine learning (ML) systems.

ICT_DI Stats Accessibility: The EU member states register includes data on the percentage of GDP allocated to information and communication technology services by each nation. This freely available data enables precise study across several nations. Therefore, the research will use the **ICT_DI** (Index) metric from the EU member states database to measure the prevalence of ML in each nation's economy. Although there are disadvantages to adopting a proxy, this approach provides a practical option for evaluating the financial impact of machine learning within the central bank's methodology.

This research examines the impact of Machine Learning (ML) on Cost-Benefit Analysis (CBM) from an economic standpoint. The broader economic benefits of a sustainable economy cannot be fully quantified using technical metrics; however, they can be assessed through specific machine-learning skills, such as programming and problem-solving. **ICT_DI** is suggested as an alternative to a particular economic ML measure due to the significant time and resources required to develop such a metric. Three primary factors led to this choice. The **ICT_DI** sector significantly enhances both innovation and employment expansion.

Furthermore, the construction and utilisation of ML technologies significantly depend on components of **ICT_DI** → *(ICT Services and Digital Infrastructure)*, particularly in Programming and Software Development, Data Mining, and Big Data Analytics.

3.2. Financial Investment:

This study examines the impact of financial investments in circular business sectors as a distinct and independent variable. Gross Fixed Capital Formation (as a percentage of GDP), Foreign Direct Investment (net inflows as a percentage of GDP), Research and Development Expenditure (as a percentage of GDP), and Domestic Credit to the Private Sector (as a percentage of GDP) are the four main metrics used in the study. The data, which will be displayed as a percentage of each nation's total economic production, will cover the years 2010–2023. The study reveals significant differences in investment levels among EU member states. Projects for the circular economy have received relatively small investments from nations like Greece, Ireland, and Slovenia, which account for less than 0.4% of their total economic output. By allocating more than 0.7% of their GDP to circular economy initiatives, nations such as Austria, Belgium, France, Denmark, and Portugal have demonstrated a greater commitment. Throughout this period, Germany allocated approximately 0.6% of its GDP to investments related to the circular economy. The entire amount of money invested in the circular economy increased by more than €2.3 billion between 2010 and 2023, from €2.8 billion in 2010 to over €5.1 billion in 2023.

3.3. Circular Business Economy

The database of EU member states has exhaustively documented the circular business from 2011 to 2023, with more than 12 metrics available for various substances and operations. A new indicator, the Circular Materials Utilisation Rate (CMU rate), has been created to assess the effectiveness of EU economies. This rate determines the proportion of products that are reintroduced into the economic cycle. A higher rate suggests that resources are being utilised more effectively and recycled, thus decreasing the environmental impact.

The CMU rate in the EU increased progressively from 12.8% to 13.7% between 2010 and 2023, representing a 1.9 percentage point increase. By 2021, recycled or salvaged products comprised 14% of the materials used in manufacturing.

The CMURs of the majority of EU nations (20 out of 28) increased, with the Netherlands, Belgium, Italy, and Ireland demonstrating substantial gains, spanning from 5.9 to 9.9 percentage points. Between 2010 and 2021, the CMURs of countries such as Latvia, Croatia, and Bulgaria were quadrupled. Nevertheless, countries such as Luxembourg, Romania, and Finland witnessed a decrease in their circularity metrics.

3.4. Composite Overall Preference (COP)

The dependent variable in the present inquiry is the Composite Overall Preference (COP), which is a weighted index of four important factors affecting the performance of the circular economy in EU nations: the adoption of machine learning (30%), financial investment (20%), government green initiatives (GGI) (25%), and present management standards (CURM, 25%). The weights balance FI's function as an infrastructure promoter, GGI's policy-driven widespread structures (such as subsidies and regulations), and CURM's operational effectiveness in managing resources while also reflecting rigorous methodology and giving priority to ML's revolutionary potential in boosting circular systems (e.g., predictive waste models). This weighting ensures that financial and managerial elements are appropriately incorporated to capture comprehensive circular performance, aligning with empirical research that highlights technologies and regulation as key factors. In order to preserve the reliability of research and connection with EU circular economy objectives, the COP formula ($COP = 0.3\times ML + 0.2\times FI + 0.25\times GGI + 0.25\times CURM$) guarantees a robust, multidimensional assessment that is based on both numerical metrics (like investment levels) and qualitative evaluations (like policy effectiveness).

4. THE METHOD APPLIED TO THE CONCLUSIONS

4.1. Method

Investigated in the current article using a panel data model is the effect of Machine Learning (ML), Financial Investment (FI), and Circular Material Use Rate (CMUR) on the Composite Overall Performance (COP) of CBMs in the member countries of the European Union. The dependent variable in the present investigation is the Composite Overall Performance (COP), a weighted assessment of the four key variables that influence the attainment of the circular economy in EU countries.

The proportion of economic output associated with ICT_DI (ICT Services and Digital Infrastructure) will serve as a proxy independent variable to assess the impact of machine learning (ML) within a financial environment. A control parameter termed Financial Investment in Circular Business (Invest CB) will be established to thoroughly examine the potential impact of capital on a nation's recurrence. This variable will denote the proportion of manufacturing resources allocated to financial investment. Financial investment in the circular economy pertains to funding designated for sustainable practices, innovation, and infrastructure development. It advocates for critical areas, including waste management, environmentally friendly initiatives, and technological innovation. Metrics such as Gross Fixed Capital Formation, Foreign Direct Investment, Research and Development Expenditure, and Domestic Credit are utilised to quantify financial investment as an independent variable. These investments are crucial for facilitating the transition to a circular economy, promoting sustainable development, and ensuring a more environmentally friendly future. One control variable that represents how the administration promotes environmentally friendly growth in a circular economy is Government Green Initiatives (GGI). In addition, a country's level of circular business practices will be measured by the Circular Material Use Rate (CMUR%). It is measured using three key proxies: Government Effectiveness (the standard of public services), Regulatory Quality (the ability to develop and enforce effective regulations), and Environmental Tax (tax laws that promote environmentally friendly behaviour). GGI plays a crucial role in influencing the transition to a circular economy by fostering an environment that encourages sustainable practices and promotes effective laws.

The study will utilise a comprehensive dataset including all 28 applicable nations from 2010 to 2023. This panel data option offers numerous benefits. Initially, the accuracy of the results is improved by the fact that the number of observations exceeds that of conventional cross-sectional research. Additionally, panel data provides a more comprehensive understanding of the dynamic interaction of sections over time by incorporating multiple evaluations for each country. A broader understanding of the factors influencing the efficacy of the circular economy in EU countries can be achieved through the use of panel data analysis. It facilitates the investigation of complicated connections between variables.

As indicated in Equation 1, the regression model is a quantitative approach.

$$COP_{it} = \beta_1 + \beta_2 ML_{it} + \beta_3 FI_{it} + \beta_4 CUMR_{it} + r_0 GGI_{it} + u_{it} \qquad (1)$$

The symbol for the dependent variable is COP_{it}. The variables ML_{it}, $CURM_{it}$, and FI_{it} are independent. The real control is GGI_{it}. The equation's coefficients are denoted by the letters β_1, β_2, and β_3, as well as r_0, which stand for the intercept and slopes, respectively. The equation's error is denoted by the term "u_{it}". While the variable "i" denotes the intersecting component, particularly in the context of countries, the variable "t" denotes time.

This model is straightforward but may lack sophistication. It treats all nations as a single entity, disregarding the spatial and temporal aspects. The model used in this analysis is the Pooled panel model, which utilises the ordinary least squares (OLS) regression technique to assess the relationship for the whole group of 28 nations. This paradigm is beneficial for computing the entire EU area as a single entity.

The Pooled model is straightforward but imposes stringent limitations that may misrepresent the relationship between the dependent and independent variables. In this approach, it is crucial to identify a method that will effectively emphasise the distinct characteristics of each country under consideration or the impact of time.

One possible option is to enable the intercept to fluctuate for each nation while keeping the slope constant or to assume a constant intercept for all nations and allow the slope to vary for each country (Gujarati, 2003).
This article will use the initial choice. Equation 2 describes a model with a movable intercept for each cross-section and maintains constant slopes.

$$COP_{it} = \beta_1 + \beta_2 ML_{it} + \beta_3 FI_{it} + \beta_4 CUMR_{it} + r_0 GGI_{it} + u_{it} \qquad (2)$$

The collection of 28 nations represents the whole current population. These nations have identical laws and regulations surrounding the Circular business and the environment, making them homogeneous. This has significant implications for this model. A fixed effect model will be used if transferred sal effects are present. The Random Effect model applies when only a subset of the population is available for analysis. The entire population, comprising 28 nations (excluding Latvia due to a lack of ICT data), is considered in this scenario. The Fixed Effect Model will be used if any cross-sectional effects are identified.

4.2. Analysis and discovered

Initially, a test will be performed to determine whether the Pooled or Fixed Effect models are more appropriate for Eq. 1 in this specific case. As mentioned earlier, the FE model is more suitable because it considers the entire population. To accomplish this, one can implement the Redundant Fixed Effect--likelihood ratio test. Fixed effects are redundant and superfluous in this case, according to the null hypothesis (H0). The following are the results of the investigation.

Table 1 (Leaders Group, Paradoxes Group, Laggards Group) :

Leaders Group[4]

Test cross-section FIXED EFFECT			
Effects Test	Stat.	D.F.	Prob.
Cross-section F	6.84	(6, 87)	0.0000

Paradoxes Group[5]

Test cross-section FIXED EFFECT			
Effects Test	Stat.	D.F.	Prob.
Cross-section F	5.54	(11, 150)	0.0000

Laggards Group[6]

Test cross-section FIXED EFFECT			
Effects Test	Stat.	D.F.	Prob.
Cross-section F	2.80	(6, 85)	0.0155

[4] Leaders: Countries with the highest Composite Overall Preference, COP ≥ 40
[5] Paradoxes: Countries with the middle Composite Overall Preference 30 ≤ COP < 40
[6] Laggards: Paradoxes: Countries with the lowest Composite Overall Preference, COP < 30

Significantly substantial evidence of country-specific heterogeneity is shown by the findings of the Cross-Section F-test for all three groups: Leaders ($F=6.84$, $p<0.0001$), Paradoxes ($F=5.54$, $p<0.0001$), and Laggards ($F=2.80$, $p=0.0155$). As a result, the alternative hypothesis—that cross-section effects are not inapplicable—will be confirmed, and the null hypothesis (H0) will be rejected.

Consequently, the parameters of Equation 1 (Table 2) will be determined using the Fixed Effect model. The variable financial investment was assessed after a one-year time-lapse, as the full impact of the investment is not evident until the renovations are complete.

Leaders Group

Table 2. Main parameters of the Equ.1

Dependent Variable: Composite Overall performance (COP)					
Method: Panel EGLS (Cross-Sectional Time-Series)					
Variable	**Coefficient**	**Std. Error**	**z-value**	**p-value**	**[95% Conf. Interval]**
ln_ml	0.491***	0.029	16.88	0.000	[0.434, 0.548]
ln_fi_L1	0.164***	0.011	15.54	0.000	[0.143, 0.185]
ln_ggi	0.174***	0.014	12.75	0.000	[0.148, 0.201]
ln_curm	0.036***	0.008	4.42	0.000	[0.020, 0.052]
Constant	0.405**	0.171	2.37	0.018	[0.069, 0.741]

Paradoxes Group

Table 3. Main parameters of the Equ.1

Dependent Variable: Composite Overall performance (COP)					
Method: Panel EGLS (Cross-Sectional Time-Series)					
Variable	**Coefficient**	**Std. Error**	**z-value**	**p-value**	**[95% Conf. Interval]**
ln_ml	0.291***	0.025	11.54	0.000	[0.241, 0.340]
ln_fi_L1	0.151***	0.016	9.68	0.000	[0.121, 0.182]
ln_ggi	0.142***	0.020	7.20	0.000	[0.104, 0.181]
ln_curm	0.041***	0.012	3.56	0.000	[0.018, 0.064]
Constant	1.323***	0.163	8.14	0.000	[1.005, 1.642]

Laggards Group

Table 4. Main parameters of the Equ.1

Dependent Variable: Composite Overall performance (COP)

Method: Panel EGLS (Cross-Sectional Time-Series)

Variable	Coefficient	Std. Error	z-value	p-value	[95% Conf. Interval]
ln_ml	0.204***	0.024	8.69	0.000	[0.158, 0.250]
ln_fi_L1	0.088***	0.027	3.31	0.001	[0.036, 0.140]
ln_ggi	0.140**	0.055	2.54	0.011	[0.032, 0.247]
ln_curm	0.041	0.039	1.05	0.295	[-0.035, 0.117]
Constant	1.782***	0.246	7.24	0.000	[1.300, 2.264]

4.3. Interpretation

As already stated, all variables are represented as percentages. Equation 1 is described based on the calculated coefficients.

$$\mathbf{COP = 0.405 + 0.491*ML + 0.164*FI + 0.036*CURM + 0.174\ GGI} + u$$

(Leaders Group)

$$\mathbf{COP = 1.323 + 0.291*ML + 0.151*FI + 0.041*CURM + 0.140\ GGI} + u$$

(Paradoxes Group)

$$\mathbf{COP = 1.782 + 0.204*ML + 0.088*FI + 0.041*CURM + 0.142\ GGI} + u$$

(Laggards Group)

Equation 1 elucidates the impact of the four predictors on the final variable.

LG 1: Notable findings are shown by the regression analysis for the three groups. With a coefficient of (0.491 for ML, 0.164 for FI, 0.036 for CURM, and 0.174 for GGI), the model shows a positive correlation between the dependent variable (COP) and the predictors for the Leaders Group.[7]. The model indicates that the factors have a considerable impact, particularly ML, which has the highest coefficient among them, suggesting that it has a strong effect on COP. A constant of 1.323 is displayed in the Paradoxes Group equation, along with coefficients of 0.291 for ML, 0.151 for FI, 0.041 for CURM, and 0.140 for GGI. These findings highlight ML's beneficial contribution to COP but with considerably diminished effectiveness compared to the Leaders Group. With coefficients of 0.204 for ML, 0.088 for FI, 0.041 for CURM, and 0.142 for GGI, the Laggards Group proposes a constant of 1.782. The influence of the other variables remains constant in this group, although the impact of ML is less pronounced, yet still favourable.

[7] Leaders Group: Greece, Malta, Netherlands, France, Germany, Slovenia, Croatia.

A regression line with three slopes and one intercept is displayed in Equation 3. The coefficients in the regression model represent the intensity and direction of the link between the variables, as shown by the slopes. ML, the first independent variable, has a coefficient of 0.491. The dependent variable will rise in response to an increase in the regressor, as indicated by the positive value. For instance, the dependent variable will rise by 0.491% if the ML increases by 1%. Financial procedures are slower when compared to those recorded during the 2010–2023 period when ML increased by just 0.7 percentage points.

It is essential to note that the second dependent variable, regarding financial investments, is a lag variable. This suggests that the positive effects of increased financial investments in developing circular business performance may not be immediately apparent. A 1% increase in financial investment results in a 0.164% increase in the dependent variable, according to the coefficient of 0.164. However, compared to the ML variable, this influence is smaller and less significant, indicating that financial investments have a slower and more gradual effect on the development of circular businesses.

PG: The regression equation for the Paradoxes Group [8]Demonstrates a constant of 1.323, with coefficients of 0.291 for ML, 0.151 for FI, 0.041 for CURM, and 0.140 for GGI. These findings suggest that the dependent variable (COP) and all predictors are positively correlated, even though the influence of ML is less evident than in the Leaders Group. Specifically, a 1% rise in ML results in a 0.291% gain in COP, which suggests its impact on circular business performance, albeit at a lower level than that shown in the Leaders Group. With a 0.151% coefficient for financial investment, a 1% rise in financial investment will provide a 0.151% rise in COP. This has a positive impact, albeit slightly less than that of ML. In the same vein, CURM and GGI exhibit positive effects on COP, with coefficients of 0.041 and 0.140, respectively, indicating a moderate influence from these variables. In general, although machine learning (ML) continues to be a significant factor, its impact on the Paradoxes Group is marginally lower than that of the Leaders Group. Nevertheless, this underscores the beneficial impact of ML on the efficacy of circular businesses.

LG 2: The regression equation for the Laggards Group[9] shows a constant of 1.782, along with coefficients of 0.142 for GGI, 0.088 for FI, 0.041 for CURM, and 0.204 for ML. The dependent variable (COP) and all the predictors show a positive association, according to these results; however, the effects are not as significant as those observed for the Leaders and Paradoxes Groups. A 1% increase in ML is thought to result in a 0.204% increase in COP, according to the ML coefficient of 0.204. Although this effect is small, it nonetheless demonstrates how innovation and leadership enhance circular business outcomes in this group. A 1% rise in financial investment will result in a 0.088% increase in COP, according to the coefficient for financial investment, which is 0.088. This suggests a slower and more gradual influence than that of the other groups. With coefficients of 0.041 and 0.142, respectively, the effects of CURM and GGI are likewise favourable, confirming that these factors still support the expansion of the Laggards Group's circular business. Overall, even if the influence of the predictors is lower in this group, the findings nevertheless imply that COP benefits from

[8] Paradoxes Group: Portugal, Italy, Cyprus, Estonia, Luxembourg, Austria, Belgium, Ireland, Spain, Bulgaria, Latvia, Denmark, and Hungary.

[9] Laggards Group: Poland, Romania, Sweden, Lithuania, Czechia, and Finland

advancements in these domains, with circular business practices showing steady yet encouraging growth.

Table 5: Group-Specific Coefficients and Interpretations

Group	Variable	Coefficient	Interpretation
Leaders	ML	0.491	**Highest impact**: ML drives automation, waste reduction, and process optimisation. Leaders leverage ML to maximise efficiency gains.
	FI	0.164	**Secondary role**: FI supports scaling ML adoption but is less critical due to existing infrastructure.
	CURM	0.036	**Marginal impact**: CURM is already optimised; minimal direct gains from further improvements.
	GGI	0.174	**Strategic enabler**: GGI complements ML by funding green tech and aligning incentives.
Paradoxes	ML	0.291	**Moderate impact**: ML improves efficiency but struggles to overcome structural inefficiencies.
	FI	0.151	**Key driver**: FI addresses infrastructural gaps, enabling ML adoption and process upgrades.
	CURM	0.041	**Limited gains**: CURM improvements marginally reduce costs but require FI/GGI to unlock potential.
	GGI	0.140	**External catalyst**: GGI eases financial constraints and incentivises green transitions.
Laggards	ML	0.204	**Weak impact**: ML's effectiveness is limited by outdated systems; it requires FI/GGI for modernisation.
	FI	0.088	**Critical foundation**: FI modernises infrastructure, enabling future ML/CURM gains despite low ROI.
	CURM	0.041	**Foundational step**: CURM builds compliance and reduces long-term resource risks.
	GGI	0.142	**Essential support**: GGI provides funding and regulatory frameworks to incentivise sustainability.

5. DISCUSSIONS

5.1 Prospective Conditions: Understanding the Pathways for COP Optimization in Circular Business Models

The Leaders, Paradoxes, and Laggards groups each encounter distinct obstacles as well as opportunities in optimising their Composite Overall Performance (COP) through the incorporation of Machine Learning (ML), Circular Material Use Rate (CMUR%), and Government Green Initiatives (GGI), respectively. These three factors are crucial for enhancing the efficacy and environmental sustainability of the circular business model. The Leaders Group is in the best position to capitalise on the widespread use of machine learning, as it begins with a comparatively low baseline COP. The Leaders Group is capable of promptly adopting technological advances, utilising ML as the primary tool to drive significant improvements in operational effectiveness and cost reduction due to its previously established operational structure. The organisation may lead to the improvement of COP by automating processes, reducing waste, and optimising resource use through the use of machine learning (ML). The Leaders Group also benefits from GGI and CMUR%, alongside ML. GGI provides government incentives for green technologies to promote their endeavours, while CMUR% promotes the application of recycled or sustainable resources to reduce their ecological effects and expenditures. Consequently, the Leaders Group's transition is primarily driven by ML, while GGI and CMUR% serve to reinforce sustainability objectives and enhance COP in an overlapping way.

The Paradoxes Group, on the other hand, has more intrinsic deficiencies and organisational challenges despite having an elevated base COP. In this situation, a more sophisticated, combined strategy is needed because ML by itself is insufficient to produce noticeable benefits. To make significant progress, the Paradoxes Group has to implement ML, Financial Investment (FI), and CMUR% increases. Due to the Leaders Group's current impediments, the influence of machine learning (ML) on procedure optimisation is significantly diminished. In this group, financial investment (FI) is crucial for removing infrastructure obstacles and enabling the integration of machine learning technology. Enhancing CMUR%—by increasing the proportion of circular materials used—would also help reduce waste and lower manufacturing costs, supporting their businesses' sustainable future. GGI is particularly significant because legislative policies and incentives can provide the necessary external support, reducing financial barriers and facilitating the group's more efficient adoption of environmentally friendly technology. The ratio of ML, FI, and CMUR% is crucial in this group, and GGI offers a supportive atmosphere for environmentally conscious innovations.

The Laggards Group, which has the highest baseline carbon intensity of production (COP), encounters the most substantial obstacles to improvement. ML is solely unable to eradicate the profound inefficiencies that prevail in the processes of this group. The Laggards Group requires a broader approach that prioritises the optimisation of FI, GGI, and CMUR%. This group must prioritise financial investment to modernise outdated facilities, adopt environmentally friendly technologies, and enhance resource utilisation, as their baseline carbon footprint is higher. The impact of ML on operational enhancements will be limited unless it is supported by FI and GGI, which can provide the requisite capital and external assistance for the adoption of circular business practices. CMUR% optimisation is particularly critical for the Laggards Group, as it enables them to enhance the environmental performance of their products and services, reduce their dependence on virgin materials, and reduce costs. As they concentrate on optimising resources, GGI can assist them in overcoming financial obstacles and promoting the transition to more environmentally friendly innovations, thereby resulting in a decrease in CO2 emissions and a more environmentally friendly business model.

Table 6. Drivers, Constraints, and Strategic Implications Across Adoption Groups

Group	Primary Driver	Secondary Driver	Tertiary Driver	Key Constraint	Strategic Implication
Leaders	ML	GGI	FI	Diminishing returns from CURM	Reallocate resources from CURM to ML/GGI for sustained growth.
Paradoxes	FI	ML + GGI	CURM	Structural inefficiencies	Address organisational silos and process misalignment before scaling ML/FI.
Laggards	FI + GGI	CURM	ML	Outdated infrastructure	Prioritise infrastructure modernisation (via FI/GGI) to unlock ML/CURM potential.

6. POLICY REPERCUSSIONS

Legislators must utilise blockchain-enabled circular ledgers to address the structural deficiencies of Paradoxes, develop quantum-driven material discovery to tackle Leaders' declining CURM returns, and provide Laggards with decentralised C-DAOs for hyper-local resource loops, in order to move beyond traditional methods. Although AI-powered policy sandboxes model COP scenarios to prevent disparities, neuro-inclusive training initiatives can counteract ML-driven employment displacement in Paradoxes by matching FI with brain-diverse circular roles. To stimulate advancements on Earth, forward-thinking governance should apply circular economy (COP) principles to planetary circularity and require the reuse of materials in orbit. Governments may turn obstacles into opportunities for fair, planetary-scale circularity by aligning these tactics with group-specific COP levers—Leaders' ML proficiency, Paradoxes' FI harmony, and Laggards' GGI modernisation.

7. CONCLUSION

The study's conclusions indicate that to maximise Composite Overall Performance (COP) in circular business models, a customised strategy is required, tailored to the specific operating conditions of Leaders, Paradoxes, and Laggards. Leaders have recognised Machine Learning (ML) as the cornerstone of enhancing efficiency, enabling quick technology adoption, waste reduction, and automation. However, the decline in their yields from incremental improvements in material circularity (CURM) highlights a crucial juncture: maintaining progress requires new technologies, such as next-generation recyclable materials, rather than relying on conventional techniques. Paradoxes necessitate shifting financial investments (FI) away from profound structural flaws and toward blockchain-enabled transparency and AI-driven industrial collaborations to remove coordination restrictions. For Laggards, structural constraints must be addressed through government-led modernisation (GGI) and decentralised, community-centred initiatives, such as decentralised material iterations, since the fundamental barrier remains infrastructure degradation.

The complex connection of ML, CURM, and GGI underscores a common truth: COP optimisation is an ongoing adjustment of digital, financial, and governance factors rather than a uniform process. Laggards progress through community engagement bolstered by public-sector support; paradoxes thrive via institutional reforms that reconcile financial investment with circular practices; and leaders prosper when machine learning is integrated with inventive growth. To maintain sustainability benefits while preventing social inequalities, ethical imperatives, including equitable transfer of employment and algorithmic responsibility, must underpin these strategies for all stakeholders.

The circular economy requires regulations that emphasise systemic resilience and foster emerging technologies in the future. Quantum computing possesses the potential to transform materials science by enabling limitless recycling capabilities. Conversely, decentralised C-DAOs (Community-Driven Autonomous Organizations) possess the capacity to democratise efficiency via hyper-local resource management. To predict the ensuing consequences of efforts across businesses and communities, governments must build adaptable governance frameworks, such as AI-driven policy sandboxes. Policymakers can promote innovations with domestic impacts beyond global and economic constraints by implementing circular principles in the intergalactic management of resources, which necessitates the recycling of materials.

This study subsequently offers COP as an innovative framework for circular transformations that harmonises comprehensive equality with detailed business-model efficiencies. Legislators must strike a balance between attainable goals, such as eliminating circular standards, and practical precision, including modifying financial aid, incentives, and legislation to address the specific needs of various groups. To create collaborative design environments that promote equitable growth and inventive ethics, interdisciplinary research is essential. A circular economy, characterised by high performance, proportionality, flexibility, and resilience—a sustainable model transcending industries, boundaries, and generations—can be developed by participants through the recognition of this paradox.

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