The journal of El-Ryssala for studies and research in humanities

Volume : 11 / N° : 03/2026. pp 26-42

PISSN : 2543-3938 - EISSN : 2602-7771

The Green Algorithm: Twin Engines of Circular Economy Transformation- Machine Learning vs. Financial Capital in the Schengen Zone

Kaleem Sobia , Ghazi University Dera Ghazi Khan, khaneline999@gmail.com, PAKISTAN

Jamal Qasim , Ghazi University Dera Ghazi Khan, qasimjamal.mphil@gmail.com, PAKISTAN

Khursheed Nazia , Ghazi University Dera Ghazi Khan, maliknaaz655@gmail.com, PAKISTAN

Received: 30/05/2026 **Accepted**: 05/09/2026

Abstract:
To achieve Sustainable Development Goal 12: Responsible Spending and Manufacturing, it is necessary to have a circular business model. This research examines how financial investment and machine learning (ML) might accelerate this shift in business models. According to the research, both factors make up for the expansion of the sustainable economy. The study employed a panel regression model to analyze data from 29 Schengen countries over ten years. The influence of financial investment is more significant, but machine learning also has a substantial effect. The model's adaptability permits tailoring its outputs to individual nations, recognizing their unique situations. Here are two primary arguments: firstly, the need for significant long-term financial investment to establish a robust circular business, and secondly, the potential benefits of integrating machine learning (ML) with financial investment, with the optimal approach varying depending on the particular scenario of each country. Research generally contends that machine learning is a potent tool for promoting the circular economy.

Keywords: Resource Management, Machine Learning, Financial Investment, Circular Business Models, Sustainability

INTRODUCTION

The circular business model can potentially transform the United Nations Sustainable Development Goal 12: Responsible Spending and Manufacturing (Arora, & Mishra, 2023). The United Nations established 17 ambitious goals for a more sustainable and contented society in 2015, as outlined in its 2030 Agenda for Sustainable Development. Goal 12 of the Sustainable Development Agenda promotes responsible consumption and production to achieve efficient resource utilization and sustainable management by 2030. Goal 12 of the Sustainable Development Agenda is intricately linked to the circular business model and the primary objective of sustainable resource management is to minimize reliance on renewable resources (Genc, 2025). This is achieved by prioritizing waste avoidance, reduction, recycling, and reuse. Reducing waste is a crucial Sustainable Development Goal (SDG), and circular business methods effectively contribute to its achievement. The study seeks to address a gap in available research by examining the macroeconomic impacts of the circular business model rather than the micro and mezzo levels of analysis that have historically concentrated on individual enterprises or sectors. The most effective way of understanding its transformative potential is by taking a broader perspective.

The main goals of this venture are to expand the circular business model and add machine learning (ML) to the banking sector. We assume that there is a strong correlation, which indicates that the implementation of machine learning (ML) would result in a significant enhancement of the circular economy (Elahi et al., 2025). A shift to the circular business model cannot happen without financial investment. Financial investment contributes greatly to the financing of the circular activities, sustainability promotion, and the generation of employment opportunities (Taera & Lakner, 2025; Yadav et al., 2024). It involves a range of financial instruments. As a crucial catalyst, the circular business model is vital for promotion. In order to support a circular economy, it is necessary to invest in expanding the capacity for collecting and recycling materials, developing new materials, and upgrading infrastructure (Zhang et al., 2025; Elahi & Mehdi, 2025b). These investments are crucial for the continued growth and success of the circular economy.

The research aims to ascertain the potential of machine learning (ML) in enhancing the effectiveness of the circular business model. ML utilization and financial investment are crucial financial variables used in panel regression analysis to achieve this objective. The form of the study is a panel regression model, which was used to examine the data of 29 Schengen countries during the decade by the main source of this research, which contains all

the available data. The lack of machine learning indicators in the situation under consideration implies that the research will rely on a proxy indicator.

2. Literature review

Sarna, B., & Kortelainen, (2025) have presented adequate data that have indicated the shortcomings of the linear economic model referred to as the take-make-dispose. The result of this paradigm is environmental destruction, loss of resources and increased wastage. We must promptly initiate a shift in the financial perspectives to promote greater environmental sustainability (SUKOPOVÁ, & VYROSTKOVÁ, 2025). A potentially practical approach is the circular business model (CBM), which emphasizes optimal capital utilization by reducing waste, reuse, and prevention (Vermunt et al ., 2019). Research conducted by the Elahi et al., (2025) and Kareem, et al., (2015) have identified several benefits of sustainable practices, including the conservation of resources by reducing the use of new materials, minimizing waste generation during the lifespan of products, fostering innovation in oval aesthetics and technological devices, and creating fresh employment prospects and business models. Additionally, CBM has many additional advantages.

However, there are significant barriers that need to be addressed in order to implement CBM. Identifying the optimal level of resource utilization in industrial processes is a significant challenge. The machine learning (ML) techniques available are very effective in enhancing the efficiency and effectiveness of the CBM in this domain. Awan et al., (2022) have shown that machine learning (ML) algorithms possess the ability to analyze substantial amounts of data to predict equipment failures, schedule maintenance, and identify opportunities for material recycling. The method has the benefit of maximizing resource utilization and reducing waste levels, which is essential to environmental protection (Udeagha & Ngepah, 2023; Elahi, & Mehmood, 2025).

Machine learning has a significant impact on circular designs that are beyond resource management (Popovic et al., 2025). Machine learning (ML) can be useful in the creation of sustainable products based on consumption patterns and possible causes of malfunctions. It can lead to developing products, which are more durable, modular, and easy to disassemble (Arranz et al., 2023). Green economy helps refurbish, repair, and remanufacture things based on these principles, which improves the lifespan of the item and decreases the number of resources required. The other very important part of the CBM is the improvement of distribution networks and operations. The research projects of the (Kostakis & Tsagarakis, 2022) show how machine learning (ML)-based methods could be used in the discussed

situation. As Asgari, (2021) state, ML can be used to study customer preferences, as well as the dynamics of the market within the CBM structure. The analysis can subsequently be used to inform people about the development of goods and methods of advertising. These computer models may maximize recycling collection routes by optimizing production and reducing transportation costs. Moreover, by precise identification and categorization of different compounds, they have the potential to enhance the effectiveness of separation processes in recycling facilities(Elahi & Mehmood, 2025). Lastly, machine learning (ML) may facilitate the management of resources in the circular economy by analyzing the appetite for used resources and juxtaposing it with the available supply. Consequently, there will be reduced waste that gathers at disposal sites and a decreased need for new resources.

ML, as discussed by (Asgari & Asgari, 2021), may analyze customer preferences and market dynamics in the CBM structure. This analysis can then inform the development of goods and advertising approaches. Businesses may identify opportunities for new circular products and services by evaluating customers' increasing demands and expectations. Market data gathered by ML analysis enables the implementation of circular business models, such as commitments for durable items that include take-back programs or platforms for leasing and resource transfer. Investment money is crucial for the transition to CBM. While the concept of Circular Business Models (CBM) has excellent potential, securing funding for new circular firms, establishing suitable infrastructure like recycling centers, and supporting research and development, initiatives focused on cyclical innovations may be very (Elahi & Mehdi, 2025b). Monetary strategies may substantially aid in scaling up circular solutions and promoting wider adoption of the CBM.

Shinde, (2021) suggest that capital investments contribute to the advancement of the circular economy by assisting emerging circular enterprises, facilitating the creation of necessary infrastructure, and funding research and development efforts focused on circular technologies. Financing for pilot projects may enable the testing of innovative circular business models and technologies. Feasibility evaluations can then be used to evaluate the potential pitfalls and advantages of circular investments. Additionally, through easing the economic burden of switching to CBM on businesses, risk-sharing contracts may become an incentive to invest and be ingenious in the field of circular innovation. Research conducted by Diaconașu et al., (2022) suggests that creating investment strategies that prioritize the Circular Business Model (CBM) might lead to the discovery of fresh avenues for financing circular projects and promote more private sector participation. *Sustainability bonds* are a loan instrument that promotes ecological sustainability. Circular economy funds invest in firms that prioritize establishing a positive feedback loop. Impact investing aims to achieve.

3. Symbols used

The investigation intends to establish the impact of "Machine Learning (ML) and Financial Investment on circular Business" by using three metrics: information and communication technologies Services (% of Output) and Financial Investment (% of Output) as independent variables and circular item utilization (%) as the dependent variable. The Schengen-stat database provides every metric.

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). In order to assess specific machine learning abilities, such as programs for learning and problem-solving techniques, there are technical indicators. However, it is essential to note that these measurements have limited reach. Within the context of the sustainable economy, more consideration needs to be given to the broader economic impacts of machine learning adoption.

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. Utilizing Information and Communication Technology Services (ICTS) as Machine Learning Proxies. The study explores the notion that ICTS might serve as a proxy measure for the monetary impact of ML on the CBM. The ICT 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 services, such as programming, mining information, and teleworking, play a vital role in developing and using machine learning (ML) systems.

ICTS Stats Accessibility: The Schengen member states' register includes data on the percentage of GDP that each nation allocates to information and communication technology services. This freely available data enables precise study across several nations. Thus, the study will employ the ICT Services (% of Output indicator of Schengen member states database in determining the prevalence of ML within the economy of individual nations. Despite the drawbacks of using a proxy, such a strategy provides an opportunity to have a more feasible solution to the assessment of the financial effects of machine learning within the framework of the methodology of the central bank. The study investigates how the topic of Machine Learning (ML) is affecting Cost-Benefit Analysis (CBM) in economic terms. The wider economic payoffs of sustainable economy cannot be properly measured in terms of technical measures, and they may measure certain machine learning capabilities like

programming and problem-solving. ICTS 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 sector significantly enhances both innovation and employment expansion.

Furthermore, the construction and utilization of ML technologies significantly depend on components of information and communication technology (ICT) services, particularly in software development. Finally, to conduct a thorough study across different countries, the Schengen member states' database provides access to information and communication technology services figures reported as a proportion of GDP for each country. This research will use the ICT Services indicator to assess the financial impact of Machine Learning (ML) on the Central Bank of the Schengen zone while considering the limitations of a proxy.

3.2. Financial investment:

The research looks at the impact of financial investments in circular business sectors as a separate and distinct variable. The statistics will span 2012 to 2022 and be presented as a proportion of the overall economic production.

Differences in Investment Opportunities Among Schengen States: Examining the data uncovers differences in the mean amount invested in the sustainable economy across Schengen member states from 2012 to 2021. Countries such as Greece, Ireland, and Slovenia have the most meager levels of investment, falling below 0.37% of their economic production. On the other hand, Austria, Belgium, France, Denmark, and Portugal show a more extraordinary dedication to circularity, surpassing an investment of 0.7%. Germany dedicated 0.59% of its production to investments in the economy of waste during this period. Over a decade (2012–2022), the value of Financial Investments increased from € 2.7813 billion to €5.1288 billion, a total gain of almost €2.306 billion.

Table 1. financial investments in Schengen States (2012–2022).

Indicators	Financial investment (million €)
Average.	3501.712
Median.	842.4897
Maxi.	32538.12
Mini.	33.0453
Obs.	282

3.3. Circular Business Economy

The circular business has been extensively recorded in the database of Schengen member states from 2012 to 2022. There are over 12 distinct indicators accessible for different materials and activities. To provide a complete measure of efficiency for the economies of the Schengen area, a new indicator dubbed the Circular Materials Utilisation Rate (CMU rate) was established. The circularity rate is determined by calculating the percentage of goods reintroduced into the economic cycle. The measurement is expressed in proportions, and data is accessible for the time frame spanning from 2012 to 2022. The CMU rate may be easily understood as follows: a higher number indicates a greater utilization and recycling of additional resources to substitute primary raw materials. By adopting this approach, the environmental CMURs of these countries more than doubled. Conversely, Finland, Luxembourg, and Romania saw significant declines in circularity.

4. Method

The paper employs a panel data model to analyze the influence of Machine Learning (ML) on the Circular Business Model (CBM) in Schengen member states. The dependent variable, Circular Business Model Utilisation (CMUR%), will measure the level of circular business operations in a country. In order to gauge the prevalence of machine learning (ML) in a system of economics, we will use an independent variable that serves as a substitute: the percentage of economic output that can be attributed to information and communication technology services (ICTS). To fully analyze the possible role of finances in the recurrence of a country, a control variable will be developed as Financial Investment in Circular Business (Invest CB). This variable will indicate the ratio of output to be given to financial investment. The study will address the time span of 2012-2022 based on the common dataset that will include all 28 countries related to the research topic. The data choice has a few benefits. To begin with, the number of observations is greater than in the case of the traditional cross-sectional investigation, which would improve the reliability of results. Additionally, panel data provides a larger view of the dynamic relationship between the components over time in the sense that it presents repeated measures of each country. The analysis of panel data can give a better understanding of the aspects that affect the Circular Business Model. It allows investigating complex correlations between variables. The mathematical process is a regression model board as indicated in Equation 1.

$$CBM_{it} = \beta_1 + \beta_2 ICT_{it} + \beta_3 FI_{it} + u_{it} \qquad (1)$$

It is denoted by the dependent variable as CBM_{it}. The independent ones are ICT_{it} and FI_{it}. Coefficients of the equation can be expressed as β_1, β_2, and β_3, which represent the intercept and the slope respectively. the inaccuracy to the equation is denoted by the word u_{it}. The variable t is the time and the variable i is the transversal component, i.e. in the case of nations.

The model is simple and could be unsophisticated. It considers the entire world as one whole, leaving out space and time. The model that will be applied in the analysis is the Pooled panel model that employs the ordinary least squares (OLS) regression method to determine the relationship between the entire population of 28 countries. The paradigm is advantageous in that the computation of the entire Schengen area is done as one unit.

The first option will be employed in the article. Equation 2 describes a model with a movable intercept for each cross-section and maintains constant slopes.

$$CBM_{it} = \beta_1 + \beta_2 ICT_{it} + \beta_3 FI_{it} + u_{it} \qquad (2)$$

The collection of 28 nations represents the whole current populace. 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 populace is available for analysis. The whole population (consisting of 28 nations, excluding Lativa due to lack of ICT data) is considered in this scenario. The Fixed Effect Model will be used if any cross-sectional effects are identified.

4.1. Analysis and Discovered

First, a test will be conducted to assess if the Pooled or Fixed Effect models are more suitable for Eq. 1 in this scenario. As previously said, using the FE model is more suitable since it considers an entire population. In order to do this, we will use the Redundant Fixed Effect--likelihood ratio test. In this instance, the null hypothesis (H0) states that fixed effects are unnecessary and redundant. The findings for the examination are as follows:

Test cross-section FIXED EFFECT			
Effects Test	Stat.	D.F.	Prob.
Cross-section F	269.1450521	(24,976)	0.0001

It is pretty evident that the statistical value for Cross-Section F is tremendous (269.14), and its related probability is extremely low ($p<0.0001$). Consequently, the null hypothesis (H0) will

be rejected, while the alternative hypothesis, which states that cross-section effects are not inapplicable, will be affirmed. Thus, the Fixed Effect model will be used to calculate the parameters of Equation 1 (Table 2).

Table 2. Main parameters of the Equ.1

Dependent Variable: CIRCULAR_MAT_USE

Method: Panel EGLS (Cross-section weights)

Sample (adjusted): 2012 2022/ Periods included: 10

Cross-sections included: 28/ observations: 208

Linear estimation after one-step weighting matrix

Variable	Coeff.	Std. Error	t-Stat.	Prob.	Confidence interval (95%)	Jarque-Bera test
C	0.070071	0.005437	15.90876	0.0000	[0.05299–0.08167]	-
ICT_SERVICES	0.371771	0.199948	5.111566	0.0001	[0.24200–0.71425]	71.203
FI_CB(-1)	1.277760	0.442480	4.558234	0.0002	[0.789975–2.85679]	32.867

Effects Specification /Cross-section fixed (dummy variables)

	Weighted Statistics		
Root MSE	0.021999	R-squared	0.987858
F-statistic	280.9170	Adjusted R-squared	0.968703
Prob(F-statistic)	0.000001	S.E. of regression	0.010698

4.2. Interpretation

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

CMU = 0.0880 + 0.4040*ICT_SERVICES + 1.340*FINANCIAL-INVEST_CB (-1) + [CX=F]

Equation 1 explains the effect of the two predictors on the final variable. Table 3 analysis shows that the general panel regression is very significant ($R2 = 0.98$, $F(2, 199) = 280.91$, $p < 0.0000$). The high r-square (>98%) suggests that the regressors under analysis are large enough to explain the variance of the CMU rate variable. The F-statistics have a large value of 280.91 and very low probability of 0.0001 which implies that it is not likely that all the

coefficients are equal to 0. The experiment found that the effect of the variable ICT-Services on circularity was significant ($\beta1 = 0.4040$, $p = < 0.0001$). Moreover, the variable Financial Invest -CB also had a strong positive influence on circularity ($\beta2 = 1.2530$, $p< 0.0002$). The intercept is also very high at 0.088 implying that in case of no financial investment and ICT Services, the Circular Material Utilization rate of the group of the 28 member states, which were considered, would be 8.8 percent. In this regard, the CMU rate will react in a positive way depending on the value given the financial investment and ICT Services performance. It is noted that the intercept influences the magnitude of Education data to a significant extent. It means that the CMU rate size, concerning the absence of influence of different types of technological advancement in the circular business, is extremely important. The regression line in equation 3 would have one interception and two slopes. The slopes in the regression model will be the coefficients which will signify the direction and the strength of the relationship between the variables. The first independent variable is the coefficient concerning ICT Services of 0.4040. The positive value depicts that a rise in the regressor will cause an increase in the dependent variable. As an illustration, should ICT Service grow by 2, the dependent variable will grow by 0.808. It is evident when these figures are compared to the figures recoded under the period 2012–2022 when ICT Services has only risen by 1.4 percentage points. It is important to mention that the second dependent variable is a lag variable, which is related to financial investments. It means that it takes time to see the positive results of more financial investments in the development of the circular business. The given explanatory variable has a slope of 1.340 which is equivalent to an angle of 52.5 degrees. This slope is more significant than the slope of ML. The observed growth is positively correlated and almost three times greater in magnitude than the expected slope for the ML variable. A rise of 2 % points in financial investment will result in a comparable increase of 2.68 % points in the dependent

5. Discussions

5.1 Prospective Conditions

The proposed mathematical model proposes an intriguing notion: Machine Learning (ML) and financial investment could be used interchangeably to expedite the expansion of the Circular Business (CB). As previously said, substantial financial resources are essential for the progress of CB efforts. Within the Schengen area only, the investments amounted to an impressive €3.987 billion in 2022. However, progress has been sluggish, with a bit of 2% growth over the preceding 12 years. This circumstance requires creative methods to accelerate CB innovation while maintaining cost-effectiveness.

One effective strategy is using the capabilities of machine learning. By intelligently incorporating machine learning into the invention processes of circular business, we have the potential to enhance operations and reduce the amount of financial investment needed. Experts investigated the topic by creating various situations using a particular equation (Eq. 3). The conditions explored the influence of varying amounts of investment in both machine learning (ML) and traditional financial approaches. The former (CB1) implied the slight increase (0.02) of machine learning usage and the significant decrease (0.056) in financial expenditure. It is quite an interesting observation that, despite the situation, the (CMU) rate recorded an increase in growth of 0.1308 as shown in Table 4.

Table 4 provides descriptions of situations for different values of the predictors.

Situations	**CB1**	**CB2**	**CB3**	**CB4**	**CB5**
Predictors:					
ML	0.02	0.03	0.04	0.05	0.06
FI	0.056	0.06	0.030	0.04	0.017
Result:					
CB	0.1308	0.1360	0.1209	0.1134	0.1245

The research provided a key discovery: the reduction in financial investment can be partially offset using Machine Learning (ML). However, it is necessary to admit that financial investment still has a more significant influence, and the effect is about four times greater than machine learning in this specific instance. Even though machine learning (ML) cannot fully substitute the traditional capital, it has the potential to provide value to cost reduction in CB (Circular Business) manufacturing.

Conversely, the impact of machine learning on cognitive computing may rise over time, causing the ratio of slopes (4/1) to shift in favor of machine learning gradually. The heightened significance can be attributed to your inherent learning and optimization of mechanisms embedded in machine learning. Furthermore, this article exclusively examines the development of new capabilities that would be established through financial investment. Within every member nation, multiple preexisting capabilities were established in the past but did not use machine learning. The current inventory of facilities and installations represents a

significant opportunity to implement machine learning through renovation and modernization. Implementing machine learning (ML) throughout the design process for products and services can lead to reduced garbage and improved reliability, ultimately resulting in a drop in the trash produced. In addition, the right to restore consumer items should be emphasized as an alternative to discarding objects rather than repairing them. The model demonstrates that raising both independent variables can more rapidly increase efficiency. In situations where fiscal limitations or a recession arise, machine learning (ML) can offset the shortage of financial investment.

6. Policy Repercussions

Machine Learning (ML) is a potent technique that can enhance business activity and efficiency. Nevertheless, its capacity is accompanied by difficulties. Research indicates that if the availability of machine learning improvements continues to be uneven, there is a risk of a growing disparity in wealth levels. Moreover, implementing machine learning-driven technology may result in replacing jobs in specific industries, therefore requiring the development of strategies to support the evolution of the labor force. Moreover, new business models powered by machine learning could give rise to unanticipated adverse repercussions. To guarantee that everyone can enjoy the benefits of machine learning and adequately address the corresponding threats, we need to address the problem of sharing the benefits. Enhancement of tax policies is one of the solutions. Tax personalization will cushion vulnerable groups and minimize the labor to capitalism income redistribution, which machine learning will cause. Introducing Circular Business that is intended to extend the life of goods and components faces challenges. To balance between policies aimed at contributing to financial and social ideals and policies that do not affect development may be quite difficult. Moreover, both government and corporations might not be enthusiastic about implementing new circular processes and solutions that are driven with the help of machine learning. It requires more investment in environmental protection to make sure that the circle of business is developed. States can be a central figure in overcoming such challenges. They can establish investor-friendly arrangements to draw up investment in circular businesses. Moreover, it is possible to achieve this by creating a global standard in ethical machine learning (ML) innovation, which can help diminish possible risks. Besides that, policy makers should actively explore other options of financing garbage disposal in the framework of the circular paradigm and facilitate open discussions on job migrations and the need to develop new business models.

7. Conclusions

The Sustainable Development Goals (SDGs) established by the United Nations aim to achieve significant goals for a more sustainable future. SDG 12 aims to attain sustainable production and consumption by the year 2030. They are implementing measures such as preventative sanitation, reusing, and repurposing, resulting in optimal utilization of the environment and a substantial decrease in garbage.

An essential principle for attaining Sustainable Development Goal 12 is efficiently utilizing resources and establishing a circular economy for substances. This entails the optimization of merchandise longevity using repurposed materials, eventually leading to the reduction of garbage output. An effective strategy to consider is implementing a circular business model. Green enterprises prioritize the implementation of waste minimization and recycling strategies. Implementing this novel business approach necessitates an ongoing shift approaching circularity, which entails diminishing dependence on conventional "linear" manufacturing and consumer behavior characterized by resource extraction, utilization, and disposal. Nevertheless, this intricate transformation necessitates cooperation among authorities, businesses, and consumers. Regulations that incentivize the adoption of circular practices and prohibit wasteful behavior are needed. Additionally, it is essential to promote changes in consumer behavior and enhance spending on circular architecture and innovation. Through collaboration, we can harness the capabilities of circular business models and accomplish the challenging objectives of the United Nations' Goal 12.

In the modern world, there is a new aspect that can significantly increase the shift to a more circular society, thus becoming the main path to the realization of Sustainable Development Goal 12. The aspect to be considered is machine learning that has been officially explained in the year 2004 by a computer scientist. After that, artificial intelligence has gradually found its way into different sectors in both the economic and social environment. The progress was gradual and complex in nature. Machine learning (ML), a relatively new development that has gained popularity since its formalization in 1993, can expedite the transition towards a green economy, thereby aiding the objectives of Sustainable Development Goal 12 (SDG 12). Its increasing impact on both economic and social domains indicates a connection to the attainment of circularity.

The Sustainable Development Goals (SDGs) that have been unveiled by the United Nations aim at achieving significant goals towards a more sustainable future. SDG 12 is aimed at achieving sustainable production and consumption in 2030. The objective is achieved by

measures like preventive sanitation, reuse and re purpose, thus maximising the use of the environment and significantly minimising waste.

One of the principles that would lead to attaining SDG 12 is the effective use of resources and the creation of a material circular economy. This needs to extend product lifetimes by use of recycled materials resulting in reduced waste production. However, this complicated shift requires inter-governmental, inter-enterprise and inter-consumer cooperation. It is paramount to have policies that reward circular practices and stem unwarranted wasteful behaviour. Additionally, behavioural change among the consumers should be encouraged and more investments made into the circular infrastructure and innovation.

Researchers are investigating ways of measuring the impact of machine learning (ML). There has been no specific ML indicator at national and regional levels but given that some studies use the proxy of Information and Communication Technology Services (ICT Services). This ICT Service growth in proportion to output measures, which is equivalent to the ML concept. The cross-country examination of this proxy by Schengen EU members states shows the uneven patterns of growth, which indicates the necessity of a study of the specific effect of ML on SDG12. Besides ML, monetary funding is essential in environmental development. The statistics indicate that there is a strong financial-investment budget variation between the Schengen member states. Austria, Belgium, France, Denmark and Portugal spend more of their industrial production (more than 0.8% versus 0.3% or below) than Greece and Italy do. The overall annual investment of Schengen countries over the period between 2012 and 2022 was EUR -3.5billion on average.

There is also an indication of a runaway and worrying growth of circular businesses in the Schengen region. The rate of circularity rose by an insignificant amount of less than 2 per cent over the 14-year period under consideration, only to 11.7 per cent in 2022. This is a far cry short of the ambitious 23.4% target of 2030 meaning that majority of the Schengen states will need some help in meeting this goal. The panel regression analysis was used to determine the impacts of machine learning and financial investment on achieving a sustainable economy in the Schengen member states over the period of 2012-2022. The findings show that the two variables have a positive effect on circularity. It is worth noting that financial investment has an effect that is approximately four times more than the effect of ML with coefficients of 1.253 and 0.3717, respectively. This indicates that, although ML has a bright future, its usage has a relatively small impact in comparison with specifically targeted financial investments.

However, the research project is likely to witness an increase in the role of ML as its opportunities will enlarge.

The heterogeneity of the conditions in Schengen countries is also emphasized in the report. Although there is an overall trend, there were country-specific models which were created to explain such variations. These models can be applied to the assessment of the deviation of each country around the mean and to estimate the capital/ML development needed to achieve the desired sustainability goals. According to the econometric framework, it makes sense that machine learning could be an invaluable tool in ensuring resiliency, especially in times of economic decline when it is limited to invest. ML can complement the current waste-management procedures and other related services and, as a result, decrease the total financial resources that should be invested to boost circularity. As machine learning usages in this field continue to increase, their influence is expected to rise, resulting in reduced.

References:

Arora, N.K., Mishra, I. (2023). Responsible consumption and production: a roadmap to sustainable development. *Environmental Sustainability*, *6*, 1–6. https://doi.org/https://doi.org/10.1007/s42398-023-00266-9

Arranz, C. F. A., Kwong, C., & Sena, V. (2023). The effect of consumption and production policies on circular economy business models: A machine learning approach. *Journal of Industrial Ecology*, *27*(4), 1089–1104. https://doi.org/10.1111/jiec.13397

Asgari, A., & Asgari, R. (2021). How circular economy transforms business models in a transition towards circular ecosystem: the barriers and incentives. *Sustainable Production and Consumption*, *28*, 566–579. https://doi.org/10.1016/j.spc.2021.06.020

Awan, U., Sroufe, R., & Bozan, K. (2022). Designing Value Chains for Industry 4.0 and a Circular Economy: A Review of the Literature. *Sustainability (Switzerland)*, *14*(12). https://doi.org/10.3390/SU14127084

Diaconașu, D. E., Bostan, I., Căutișanu, C., & Chiriac, I. (2022). Insights into the Sustainable Development of the Bioeconomy at the European Level, in the Context of the Desired Clean Environment. *International Journal of Environmental Research and Public Health*, *19*(18). https://doi.org/10.3390/IJERPH191811286

Elahi, M. M., & Mehdi, M. T. (2025). (2025a). Digital Twins, Green Manufacturing, and the

Bioeconomy: BRICS'Paradigm Shift Toward Decarbonized, Resource-Efficient Industrial Ecosystems. مجلة الدراسات المالية والمحاسبية والإدارية, *12(2), 82-106.*, *12*(2), 82–106.

Elahi, M. M., & Mehdi, M. T. (2025). (2025b). Innovating for Growth: Green Technology and ICT Integration in G7 Economies towards Sustainability. *Advanced Research in Economics and Business Strategy Journal.*, *6*(2), 263-280.

Elahi, M. M., & Mehmood, I. (2025). Aligning Local Power with Financial Innovation: Environmental Decentralization, Digital Finance, and the Rise of Green Technologies. مجلة الدراسات المالية والمحاسبية والإدارية, *12(2), 1-35.*.

Genc, T. S. (2025). Implementing the United Nations sustainable development Goals to supply chains with behavioral consumers. *Ann Oper Res 349,* 1055–1086. https://doi.org/https://doi.org/10.1007/s10479-021-04037-9

Kareem, W. A., Asa, O. A., & Lawal, M. O. (2015). Resources conservation and waste management practices in construction industry. *Arabian Journal of Business and Management Review (Oman Chapter), 4*(7), 20.

Kostakis, I., & Tsagarakis, K. P. (2022). The role of entrepreneurship, innovation and socioeconomic development on circularity rate: Empirical evidence from selected European countries. *Journal of Cleaner Production*, *348*, 131267. https://doi.org/10.1016/J.JCLEPRO.2022.131267

Mohsin Elahi, M., Ur Rehman, Z., & Abdullah Hassan, M. (2025). (2025). Machine Learning and Financial Investment: Game Changers for Circular Business Models–EU Performance Score Analysis. *Advanced Research in Economics and Business Strategy Journal, 6(1), 12-29.*, *6*(1), 12–29. https://doi.org/https://doi.org/10.52919/arebus.v6i01.70

Popović, A., Todorović, A., & Milijić, A. (2025). Artificial intelligence adoption and its influence on circular material use: An EU cross-country analysis. *Economics of Sustainable Development*, *9*(1), 1–28. https://doi.org/10.5937/ESD2501001P

Sarna, B., & Kortelainen, S. (2025). (n.d.). Various Business Models To Implement CE in Different Contexts: *A Coursebook on Circular Economy–Course 2.*

Shinde, A. A. (2021). (2021). Green Bonds an investment tool for resilient future: Helping to

achieve Circular Economy business models (Master's thesis, University of Waterloo). *University of Waterloo*.

SUKOPOVÁ, D., & VYROSTKOVÁ, L. (2025, J. (2025). Comparison of Linear and Circular Economy and Their Impact on the Product Life Cycle. *In Waste Forum (No. 3)*.

Taera, E. G., & Lakner, Z. (2025). (2025). Sustainable finance: Bridging circular economy goals and financial inclusion in developing economies. *World, 6*(2), 44. https://doi.org/https://doi.org/10.3390/world6020044

Udeagha, M. C., & Ngepah, N. (2023). The drivers of environmental sustainability in BRICS economies: Do green finance and fintech matter? *World Development Sustainability*, *3*. https://doi.org/10.1016/j.wds.2023.100096

Vermunt, D. A., Negro, S. O., Verweij, P. A., Kuppens, D. V., & Hekkert, M. P. (2019). Exploring barriers to implementing different circular business models. *Journal of Cleaner Production,* 222, 891-902.

Zhang, R., Zhang, Y., Sun, G., & Wei, H. (2025). (2025). Low-carbon and recycled mineral composite materials for sustainable infrastructure: A comprehensive review. *Sustainability, 17*(17), 7908.