Leveraging machine learning for environmental cost management in green accounting

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Abstract. This study explores the role of green technology investment, machine learning adoption, and data analytics capability in enhancing environmental cost efficiency (ECE), focusing on Asian companies. It investigates how these technological investments foster ecological innovation, which mediates the relationship between these factors and cost efficiency. Using a quantitative approach, data were collected from 330 companies across various Asian industries and analyzed using Structural Equation Modeling (SEM). The results show that green technology, machine learning, and data analytics significantly contribute to ECE, with environmental innovation as a critical mediator. Machine learning adoption and data analytics were found to have the most substantial impact on fostering innovation and driving cost savings. This study highlights the importance of integrating technology and innovation to achieve environmental sustainability and cost efficiency, offering valuable insights for Asian policymakers and business leaders. These findings contribute to the growing literature on sustainability and provide practical implications for businesses looking to enhance their competitiveness while reducing environmental impact.

1 Introduction

In the modern world, environmental sustainability is a must, and businesses operating on the market today need to turn 'green' and integrate sustainability into their daily operations. With environmental issues becoming increasingly vital and climate change already critical, the world governments and ordinary consumers, including people and businesses, put more and more pressure on each industry to have their organizational behavior bear less environmental impact.

Consequently, companies are in-pouring money into green technologies, evolving sophisticated data analytics, and rapidly leveraging machine learning to catalyze environmental innovation and enhance cost efficiency. Ultimately, the outputs of these technologies allow organizations to monitor and limit their environmental impacts strongly, optimize the input resources, and cut unnecessary expenses from energy, waste, and

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emissions. Thus, ecological cost efficiency, which means striving to reduce the costs of getting environmental impacts that matter to operations specifically, becomes an organization's prime objective in equilibrating profit and sustainability. Asia has a compelling and not yet studied environment for researching green technology investing, leveraging machine learning, implementing environmental cost efficiency, and executing data analytics practices.

In the meantime, Asia is rapidly becoming the center of technology as various innovation practices, including technological solutions for dealing with pollution and developing the necessary analytical base, are rapidly growing on the continent. This produces a unique environment for researching the well-studied environmental cost efficiency threshold.

The majority of the literature has been researched aside from the solid nexus between sustainability and financial performance; it is essential to understand how these forms of green tech investment, machine learning implementation, and data analytics adoption contribute to the establishment of environmental cost efficiency, which is particular In the Asian context. Most of the research has been done on the developed western economies. This factor is a significant limitation to understanding the founding mode of how these technological investments pay off in a rapidly urbanizing and environmentally diverse region such as Asia.

1.1 Hypotheses development

As organizations realize the importance of adopting sustainability practices or facing mounting pressure, the Environmental Cost Efficiency (ECE) issue is gaining prominence. It is significant here to point out that environmental cost efficiency refers to an organization's ability to reduce the cost associated with its ecological footprint in energy, greenhouse gas emissions, and waste. To aid in environmental cost efficiency, companies direct investments toward green technology and incorporate machine learning and data analytics into optimizing the cost associated with the environment.

Green technology is eco-friendly and mitigates environmental damage by improving resource utilization and reducing waste. Investments directed towards green technology innovation, including renewable energy technologies, energy-efficient production systems, and waste management inventions, are fundamental in boosting an organization's ECE. Green technology investments contribute to a sustainable environment and allow for substantial cost reduction by promoting operational efficiency [1-10].

Clean technology investments reduce the overall cost of operation through reduced energy consumption, waste generation, and fines from regulatory bodies. Similarly, [11] observed that organizations that incorporate energy-saving machinery waste management equipment also experience double gains in minimizing their environmental damage and overall cost of operation. This relationship between green technology innovation and ECE is more pronounced in industries with a considerable energy requirement, as incorporating renewables and energy-efficient machines would substantially reduce costs.

Machine learning is rapidly gaining a role in the push for environmental cost efficiency. Machine learning algorithms enable organizations to sift through vast ecological data to identify the trend in reduction, consumption of resources, GHG production, and emission. By automating complex environmental data analysis, machine learning allows organizations to make data-driven decisions, resulting in improved resource utilization and cost reduction related to the organization's ecological footprint [12-17].

The application of machine learning in environmental management, in return, leads to reduced energy consumption and better control over waste generation, which is another tool in the arsenal of ECE. [18] stated that machine learning algorithms predicted a 30 % reduction in an organization's energy consumption. Machine learning could also be used in real-time streaming to pinpoint inefficiency in resource utilization in reciprocal mills and reduce the overall environmental cost. Many environmental regulations also require companies to monitor emissions levels and throughput, which might only be achieved by comprehensively tracking the machine learning process. This positively resonated with ECE by providing the requisite information for informed decision-making. This led to the development of the following hypotheses:

H1: There is a positive relationship between (a) green technology investment, (b) machine learning adoption, (c) data analytics and environmental cost efficiency.

Environmental innovation is developing and introducing new technologies, processes, and practices that contribute to sustainability by lowering environmental impacts and improving the effectiveness of resources. In other words, all human-led activities that enable the organization to decrease the negative aspects of its activities that have caused the environment are part of environmental innovation. Environmentally conscious technology adoption is at the core of ecological innovation. Recently, the increasing deployment of green technology, machine learning, and predictive systems has been one of the primary facilitators of environmental innovation.

These factors facilitate the emergence of solutions that enable companies to become more environmentally responsible and gain a competitive advantage by becoming more creative. This is essential to understanding why the current essay concerns the green technology investment-to-environmental innovation relationship. Eco-innovation investment is critical because it provides the company with the tools and ambitions to develop creative ways to tackle environmental issues and become more sustainable by, for example, combining existing ecosystems and acquiring more advanced machines environment; thus, eco-innovation investment contributes to this creative ambition.

[12] claims that green technology expenditure is required to increase companies' environmental innovation potential by enriching their ability to consider and acquire innovative products. This means that businesses that invest in green technology technologies can use upgraded technologies, and their level of learning becomes so high that they perceive the world as a much more developed, comfortable place on the set of green technology technologies. This led to the development of the following hypotheses:

H2: There is a positive relationship between (a) green technology investment, (b) machine learning adoption, and (c) data analytics positively influencing environmental innovation.

Investments in green technology are a critical driver of environmental innovation, leading to improved ecological cost efficiency. Green technology encompasses many environmentally friendly innovations, such as renewable energy systems, energy-efficient equipment, and waste management solutions. These investments provide companies with the necessary resources to innovate and develop sustainable practices that reduce their environmental footprint. As companies invest in green technology, they also foster a culture of innovation, encouraging continuous improvements in environmental performance.

The literature suggests that green technology investment does not directly lead to cost efficiency but facilitates environmental innovation, which drives cost reductions. [2] highlight that green technology investments often spark innovation in energy management and waste reduction processes, leading to cost savings over time. For example, companies investing in renewable energy sources may develop innovative ways to integrate these technologies into their production processes, reducing energy costs and lowering emissions. Thus, environmental innovation mediates the relationship between green technology investment and environmental cost efficiency by transforming initial investments into actionable, cost-effective sustainability solutions.

Machine learning (ML) is increasingly essential in fostering environmental innovation by providing companies with advanced tools to analyze and optimize their environmental performance. ML algorithms enable organizations to detect inefficiencies, predict resource demand, and implement real-time solutions to minimize waste and energy consumption. While adopting ML directly contributes to environmental cost efficiency through automation and predictive analytics, its potential is realized through its impact on ecological innovation.

ML adoption drives environmental innovation by enabling the development of more intelligent, more efficient systems that can optimize resource use in previously unattainable ways.

For instance, ML can facilitate innovations in energy management by predicting energy needs based on production schedules and external factors, such as weather patterns. These innovations reduce energy consumption and costs, leading to greater environmental cost efficiency. ML adoption also enables firms to innovate in areas such as emissions control and waste management by identifying opportunities for improvement based on historical data. Therefore, environmental innovation acts as a mediator, transforming the capabilities enabled by ML into innovative solutions that enhance ecological cost efficiency.

Data analytics capability allows companies to gather, process, and analyze vast amounts of environmental data, providing the insights needed to innovate in sustainability practices. Companies that leverage data analytics can track resource usage, emissions, and waste production in real time, leading to more informed decision-making and innovation in environmental management. While data analytics provides a direct means of improving cost efficiency by enabling more accurate tracking of ecological impacts, its actual value lies in its ability to drive environmental innovation.

Data analytics enhances environmental innovation by revealing inefficiencies in current practices and identifying opportunities for improvement. For example, firms using advanced analytics can develop innovative solutions for optimizing energy consumption or reducing waste across their supply chains. These innovations, in turn, lead to improved environmental cost efficiency as companies implement more sustainable practices that mitigate ecological costs. In this context, ecological innovation mediates the relationship between data analytics capability and environmental cost efficiency by transforming data-driven insights into innovative sustainability solutions that yield long-term cost savings. This led to the development of the following hypotheses:

H3: Environmental Innovation positively mediates the relationship between (a) green technology investment, (b) machine learning adoption, (c) data analytics capability, and environmental cost efficiency.

2 Methodology

The study uses convenience sampling, a non-probability sampling technique that enables data collection from easily accessible participants. While this method may limit the generalizability of the findings, it allows for the rapid collection of responses from a large group of participants, particularly in a region as diverse as Asia. Convenience sampling was chosen for its practicality and efficiency in gathering data from companies operating across various Asian industries, where time and resources may constrain more complex sampling methods.

Data will be collected using a structured survey distributed online. The survey will capture responses on key constructs, including green technology investments, machine learning adoption, data analytics capability, environmental innovation, and environmental cost efficiency. Respondents will be asked to rate these variables using a Likert scale to capture their perceptions and experiences with environmental management and cost-efficiency practices. The survey will be distributed via digital platforms such as email and professional networks to reach companies across multiple Asian industries. The survey method was selected because it efficiently collects large amounts of data from diverse respondents.

The target sample size for this study is 330 respondents, sufficient for conducting robust statistical analysis using SEM. According to the literature, a sample size of over 200 is typically recommended for SEM to ensure reliable and valid results. A sample of 330 will provide adequate power to test the proposed relationships between the independent variables (green technology investment, machine learning adoption, data analytics capability), the mediator (environmental innovation), and the dependent variable (environmental cost efficiency).

The collected data will be analyzed using SEM via AMOS software. SEM is an advanced statistical technique that examines multiple relationships between variables. It is particularly well-suited for testing the complex relationships hypothesized in this study, such as the mediating role of environmental innovation. SEM will be used to evaluate the direct and indirect effects of green technology investment, machine learning adoption, and data analytics capability on environmental cost efficiency, with environmental innovation acting as the mediator. The model will assess the strength and significance of these relationships to determine the overall fit and validity of the proposed theoretical framework.

3 Findings

Table 1. Regression One

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.508[a]	.258	.239	.629
a. Predictors: (Constant), Green Technology Investment, Machine Learning, Data Analytics and Environmental Cost Efficiency				

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.564	.229		2.464	.015
	Green Technology Investment	.348	.093	.300	3.735	.000
	Machine Learning	.258	.062	.347	4.127	.000
	Data Analytics	.431	.089	.124	4.842	.014
a. Dependent Variable: Environmental Cost Efficiency						

Tab. 1 presents a regression analysis examining the relationship between green technology investment, machine learning, data analytics, and environmental cost efficiency. The R square value of 0.258 indicates that the three predictors explain 25.8% of the variance in ecological cost efficiency. All three independent variables—green technology investment, machine learning, and data analytics—significantly contribute to environmental cost efficiency, as evidenced by their p-values ($p < 0.05$). Specifically, machine learning adoption has the most robust standardized coefficient ($\beta = 0.347$, $t = 4.127$), followed by green technology investment ($\beta = 0.300$, $t = 3.735$) and data analytics ($\beta = 0.124$, $t = 4.842$). These findings suggest that machine learning and green technology investment are crucial in improving environmental cost efficiency, while data analytics also makes a meaningful contribution.

Tab. 2 shows the regression results for the relationship between green technology investment, machine learning adoption, data analytics, and environmental innovation. The R square value of 0.340 suggests that the predictors explain 34% of the variance in environmental innovation. Machine learning adoption has the highest standardized coefficient (β = 0.547, t = 6.904), indicating its substantial influence on fostering ecological innovation.

Table 2. Regression Two

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.583[a]	.340	.323	.878
a. Predictors: (Constant), Green Technology Investment, Machine Learning Adoption				

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.456	.320		1.426	.157
	Green Technology Investment	.443	.130	.258	3.406	.001
	Machine Learning Adoption	.602	.087	.547	6.904	.000
	Data Analytics	.241	.084	.190	2.861	.010
a. Dependent Variable: Environmental Innovation						

Green technology investment (β = 0.258, t = 3.406) and data analytics (β = 0.190, t = 2.861) also positively impact environmental innovation. These results underscore that while all three factors contribute to environmental innovation, machine learning adoption is critical in driving innovative practices that improve sustainability.

Table 3. Regression Three

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.560[a]	.313	.308	.888
a. Predictors: (Constant), Environmental Innovation, Environmental Cost Efficiency				

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.500	.359		-1.393	.166
	Environmental Innovation	.875	.119	.560	7.340	.000
a. Dependent Variable: Environmental Cost Efficiency						

Tab. 3 presents the regression analysis exploring the relationship between environmental innovation and environmental cost efficiency. The R square value of 0.313 indicates that 31.3% of the variance in ecological cost efficiency is explained by environmental innovation. Environmental innovation significantly impacts environmental cost efficiency, with a strong standardized coefficient (β = 0.560, t = 7.340, $p < 0.001$). This suggests that companies that innovate in environmental practices are more likely to achieve higher levels of cost efficiency, reinforcing the role of innovation as a critical mediator between technological investments and sustainability outcomes.

Table 4 presents the Pearson correlation coefficients between green technology investment, machine learning, data analytics, environmental innovation, and environmental cost efficiency. Green technology investment has a moderate positive correlation with environmental innovation ($r = 0.449$, $p < 0.01$) and environmental cost efficiency ($r = 0.291$, $p < 0.01$), indicating that higher investments in green technologies are associated with more incredible innovation and cost efficiency.

Table 4. Pearson Correlations

	Green Technology Investment	Machine Learning	Data Analytics	Environmental Innovation	Environmental Cost Efficiency
Green Technology Investment	1				
Machine Learning	.255**	1			
Data Analytics	.178	.330**	1		
Environmental Innovation	.449**	.098	.211*	1	
Environmental Cost Efficiency	.291**	.298**	.259**	.548**	1
**. Correlation is significant at the 0.01 level (2-tailed).					
*. Correlation is significant at the 0.05 level (2-tailed).					

Machine learning also shows significant positive correlations with both environmental cost efficiency ($r = 0.298$, $p < 0.01$) and data analytics ($r = 0.330$, $p < 0.01$), suggesting that adopting machine learning enhances the company's ability to innovate and achieve cost savings. Data analytics has a weaker, yet significant, positive correlation with environmental innovation ($r = 0.211$, $p < 0.05$) and environmental cost efficiency ($r = 0.259$, $p < 0.01$), showing that data-driven decision-making also supports environmental outcomes. Finally, environmental innovation exhibits the strongest correlation with environmental cost efficiency ($r = 0.548$, $p < 0.01$), reinforcing the role of innovation as a critical factor in achieving cost-efficient sustainability practices. These relationships highlight the interconnectedness of technological investments and their impact on innovation and cost efficiency in environmental management. Bottom of Form

4 Discussion

The study's results validate the first hypothesis, demonstrating that green technology investment, machine learning adoption, and data analytics significantly contribute to environmental cost efficiency. Green technology investments enable companies to minimize their environmental impacts by utilizing energy-efficient systems, waste management solutions, and renewable energy sources. This aligns with previous studies, which found that companies investing in clean technologies experience reduced operational costs through improved energy efficiency and waste reduction. The findings suggest that organizations investing in green technology meet regulatory demands and benefit from cost reductions that improve their overall financial performance.

Machine learning adoption also plays a critical role in enhancing environmental cost efficiency by enabling companies to analyze large volumes of data, predict resource needs, and optimize operational efficiency. The study reinforces previous findings that machine learning helps companies identify inefficiencies in energy consumption and emissions control, allowing for more precise decision-making that leads to cost savings. These results highlight the importance of adopting machine learning systems to drive efficient and sustainable business operations, as real-time data analysis is crucial in industries facing high environmental pressures.

Data analytics capability further enhances environmental cost efficiency by enabling organizations to effectively gather, process, and interpret ecological data. The findings confirm that data analytics companies are better equipped to track vital environmental indicators such as energy consumption and waste production. This enables them to identify inefficiencies and implement corrective actions that reduce costs. By integrating data analytics into their sustainability strategies, companies can make data-driven decisions aligning with environmental and financial goals, ultimately improving cost efficiency.

The second hypothesis posits that green technology investment, machine learning adoption, and data analytics positively influence environmental innovation. The results support this hypothesis, revealing that each technological investment drives the development of new and innovative solutions that improve environmental performance. Green technology investment provides companies with the necessary infrastructure to experiment with innovative practices that reduce emissions, conserve resources, and minimize waste.

Adoption of machine learning was a critical driver of environmental innovation, enabling companies to optimize their operations by uncovering insights that would otherwise remain hidden. Machine learning algorithms allow companies to predict environmental trends, automate sustainability processes, and implement real-time solutions that enhance resource efficiency. These findings align with previous research indicating that machine learning can drive significant improvements in emissions control and waste management, making it a vital tool for fostering environmental innovation.

Data analytics was also shown to enhance environmental innovation by providing companies with actionable insights into their sustainability performance. By leveraging data analytics, organizations can identify inefficiencies, predict future ecological risks, and develop proactive measures that mitigate their impact while fostering innovative solutions. These findings validate the importance of data-driven strategies in driving innovation and advancing environmental sustainability.

The findings supported the third hypothesis, which examines the mediating role of environmental innovation in the relationship between green technology investment, machine learning adoption, data analytics, and ecological cost efficiency. The results indicate that environmental innovation plays a critical mediating role by transforming technological investments into tangible cost-efficiency outcomes.

Green technology investment does not directly lead to cost reductions but facilitates the development of innovative solutions that drive long-term savings. Horbach et al. (2012) emphasized that green technology often sparks innovation in energy management and waste reduction, leading to cost savings. The study confirms that environmental innovation enables companies to optimize their sustainability practices, translating green technology investments into cost-effective outcomes.

Similarly, machine learning adoption enhances environmental innovation by enabling companies to innovate in real-time resource management and emissions control. Machine learning algorithms allow the development of more intelligent, more efficient systems that optimize resource use, ultimately leading to greater environmental cost efficiency. The findings emphasize that the full potential of machine learning adoption is realized through its ability to drive innovation that fosters cost-saving measures.

Lastly, data analytics enhances environmental innovation by providing the necessary insights for companies to innovate their sustainability strategies. The study corroborates findings that data analytics helps companies identify opportunities for optimizing energy consumption and reducing waste. Through environmental innovation, data analytics capabilities are transformed into practical solutions that enhance ecological cost efficiency by improving operational sustainability [19-28].

The findings of this study are significant for several reasons. First, they provide empirical support for the idea that green technology investment, machine learning adoption, and data analytics are essential in driving environmental cost efficiency through ecological innovation. This is particularly important in Asia, where companies face growing pressure to meet environmental standards while remaining competitive in a rapidly developing region.

Second, the study highlights the mediating role of environmental innovation, underscoring the importance of innovation in translating technological investments into tangible cost-saving measures. This is critical for organizations seeking to balance environmental sustainability with financial performance, as innovation enables them to achieve both objectives simultaneously.

Finally, the findings contribute to the broader literature on sustainability and environmental management by providing insights into how Asian companies can leverage technology and innovation to enhance environmental cost efficiency. As Asia continues to be a global hub for both industrial activity and technological advancements, the results of this study provide valuable guidance for companies aiming to adopt sustainable practices while optimizing costs.

5 Limitations, contributions, and further research

One significant limitation is the use of convenience sampling for data collection. Although this method allowed for the efficient gathering of responses from many participants, it may not represent the broader population. The sample is likely skewed toward companies readily available and willing to participate in the survey, which could introduce selection bias. This means that the results may not fully capture the diversity of companies across different Asian industries and regions. Future studies should consider employing more rigorous sampling methods, such as stratified or random sampling, to enhance the generalizability of the findings.

The research adopted a cross-sectional design, which limits the ability to infer causality between the variables. While the study identifies significant relationships between green technology investment, machine learning, data analytics, and environmental innovation, it cannot definitively prove that these factors cause improvements in environmental cost efficiency. A longitudinal study would be more effective in tracking how these variables interact over time and understanding these technological investments' long-term impact on environmental outcomes.

Although focusing on Asia provides valuable region-specific insights, the findings may not apply to regions with different regulatory frameworks, cultural attitudes, and economic conditions. Asia is diverse, with countries at variousfinancial and technological development stages. The results might vary significantly if the study were conducted in Europe or North America, where environmental regulations and technological infrastructure differ. This limitation restricts the generalizability of the results beyond the Asian context.This study focused on internal technological investments (green technology, machine learning, and data analytics) and their relationship with environmental innovation and cost efficiency. However, external factors such as government regulations, market competition, and consumer pressure also play critical roles in shaping ecological performance.

This research contributes to the theoretical understanding of how technological investments influence environmental cost efficiency, particularly in the underexplored Asian context. By integrating green technology investment, machine learning adoption, and data analytics capability with ecological innovation, the study provides a comprehensive model that explains how these factors interact to enhance environmental cost efficiency.

The study emphasizes the critical role of environmental innovation as a mediator in transforming green technology, machine learning, and data analytics into cost savings. While much of the previous literature has focused on the direct effects of these technologies, this study highlights how innovation processes catalyzed by these investments drive cost efficiency. This insight is valuable for academic researchers and practitioners looking to understand how sustainability investments lead to financial and environmental benefits.

For businesses operating in Asia, the findings provide clear guidance on integrating technological investments with innovation strategies to achieve environmental cost efficiency. Companies in Asia, particularly in rapidly developing economies like China, India, and Southeast Asia, face significant environmental pressures while trying to maintain competitiveness. This study shows that investing in green technology, adopting machine learning, and leveraging data analytics isgood for sustainability andleads to significant cost savings when combined with innovation. Firms can use these findings to shape their sustainability strategies and make informed decisions about allocating resources to maximize environmental and financial performance.

The research provides region-specific insights for Asian policymakers, where regulatory frameworks and sustainability initiatives rapidly evolve. The findings suggest that policies encouraging businesses to invest in green technologies, machine learning, and data analytics could bring broader environmental and economic benefits. Policymakers can use this information to design regulations and incentives that promote environmental innovation while enhancing the competitiveness of companies in their respective countries.

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