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The Relationship between Digital Transformation and ESG Performance of Chinese Automotive Companies

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Abstract
This study explores the impact of digital transformation on the Environmental, Social, and Governance (ESG) performance of automotive enterprises. Using methods such as descriptive analysis, Kernel Density Estimation (KDE), and linear regression models, an in-depth analysis was conducted on data from multiple automotive companies. The findings indicate that digitalization, environmental management, social responsibility, and corporate governance significantly influence ESG performance. The specific conclusions are as follows: companies with a higher degree of digital transformation have higher ESG scores; companies that excel in environmental protection and social responsibility also achieve higher ESG scores; and strong corporate governance structures contribute to improved ESG scores. It is recommended that companies increase investment in digital technologies, optimize environmental management policies, actively fulfill social responsibilities, and establish robust corporate governance structures to comprehensively enhance their ESG performance and sustainable development capabilities in the future.
Keywords: Digital Transformation, ESG Performance, Automotive Companies, Descriptive Analysis, KDE, Linear Regression Models

Introduction
Growing concerns about climate change, social inequality, and corporate governance failures have heightened the importance of ESG (Environmental, Social, and Governance) issues. The UN's Sustainable Development Goals (SDGs) have further raised awareness, linking ESG closely with Sustainable Social Investment (SRI) and social sustainability.

Addressing climate change requires global cooperation to limit temperature rise to 2 degrees Celsius above pre-industrial levels. This necessitates a shift in investment from fossil fuels to greener alternatives and greater collaboration among stakeholders. This transition challenges ESG performance, making ESG ratings essential for evaluating the sustainability of companies and nations (Zhao & Dong, 2023).

The rapid advancement of digital technologies is reshaping ESG performance, presenting both opportunities and challenges. Digitalization can increase resource consumption but also drives sustainable development, making it vital for enhancing ESG outcomes (Zeng, Zheng, & Li, 2018; Wang & Guo, 2023). Yet, digital transformation is complex—only 11% of Chinese companies reported significant progress in digitalization (Accenture, 2020), leading to a focus on effective strategies (Wu et al., 2021).

China has been refining ESG frameworks since 2003, with the 2018 revision of the "Guidelines for the Management of Listed Companies" emphasizing environmental and social responsibility. "Dual carbon" targets and new regulations have elevated the importance of ESG metrics. As a global economic power, China's manufacturing sector is crucial to its economy, facing both challenges and opportunities amid global industrial changes, supported by its vast domestic market, manufacturing strength, and advanced internet sector (Zhao, Liu, & Shi, 2017).

Chinese enterprises, especially traditional listed ones, are at a pivotal digital transformation stage, driven by technological innovations like AI, big data, and cloud computing (Zheng & Zhang, 2023). The nation's rapid economic growth and government support for innovation create fertile ground for digital expansion through market opportunities, policy incentives, and financial support.

Problem Statement

"Made in China 2025," launched by the State Council in 2015, aims to position China as a leading manufacturing nation, focusing on intelligent, green, and service-oriented production. China's manufacturing digital transformation remains in its early stages, with challenges including rapid technological changes, adapting corporate culture, data security, talent shortages, and integrating with traditional business models (Yang & Song, 2023; Lirui, Huang, & Ying, 2022).

Chinese automotive companies, lagging in digitalization, face hurdles like balancing innovation with consumer needs, aligning strategies, managing talent gaps, and ensuring data security. Yet, digital transformation offers opportunities for innovation, efficiency, and sustainable growth. With advancing Internet and 5G technology, manufacturers are accelerating digitalization, focusing on intelligence and connectivity (He, 2019). This trend enhances product quality and lifecycle management, especially in remanufacturing, making the study of digital transformation's impact on ESG performance a valuable research topic.

Research Objectives

This study aims to explore in-depth the transformation experiences of Chinese automotive enterprises within the context of global digitalization trends and China's unique economic environment, particularly focusing on how digital transformation affects their Environmental, Social, and Governance (ESG) performance. By integrating two theoretical frameworks—"Innovation Management and Technology Commercialization" and "Sustainable Development Theory"—this research seeks to provide a novel perspective, offering a comprehensive analysis of the practical implementation of digital transformation initiatives and their impact on the ESG performance of automotive companies within the specific context of China. Through empirical research and case studies, this study not only aims to fill gaps in the existing literature but also intends to provide strategic recommendations for Chinese automotive enterprises and policymakers, supporting sustainable development through digital transformation.

Literature Review

Digital Transformation of Enterprises

The rapid advancement of digital technologies has driven widespread digital transformation in enterprises, leading to changes in organizational structures, production methods, and business models, thereby enhancing competitiveness (Verhoef et al., 2021). Research shows mixed outcomes: some studies highlight increased manufacturing efficiency and core capabilities (Benner & Waldfogel, 2023; Yuan et al., 2021), while others point to challenges in collaboration and innovation aggregation (Dodgson et al., 2015).

In manufacturing, digital transformation has improved specialization, development quality, and accelerated "green" development (Jin et al., 2022). However, its disruptive nature brings both opportunities and challenges, necessitating deeper analysis of its impacts. Digital transformation is closely tied to ESG performance, particularly in addressing stakeholder needs, which is crucial in sectors like automotive manufacturing (Fang et al., 2023). This connection emphasizes the need to study how digital transformation affects ESG performance in enterprises.

ESG Performance

ESG assesses companies based on environmental, social, and governance factors, reflecting the emphasis on sustainable development and ethical investment. This makes ESG performance a crucial metric for evaluating long-term corporate value and risk. While early research often focused on individual ESG aspects, recent studies highlight the need for a holistic approach, showing that practicing ESG enhances transparency, accountability, competitiveness, and overall performance (Sebastien, 2023; Duarte, 2023; Hadiqa et al., 2023). Yet, the mechanisms driving ESG improvements, especially through digital transformation, remain underexplored. Digital transformation has been shown to positively impact governance and social scores by lowering agency costs and improving reputation (Fang, Nie, & Shen, 2023).

In China, the focus on ESG practices has grown rapidly, especially in manufacturing, driven by national policies and high resource consumption. Enhancing ESG performance through digital transformation is critical for maintaining competitiveness. While research supports the benefits of digital transformation for ESG, more study is needed to clarify its complex and potentially nonlinear effects. This study aims to investigate the relationship between digital transformation and ESG performance in Chinese automotive enterprises, addressing gaps in existing research (Wang et al., 2023).

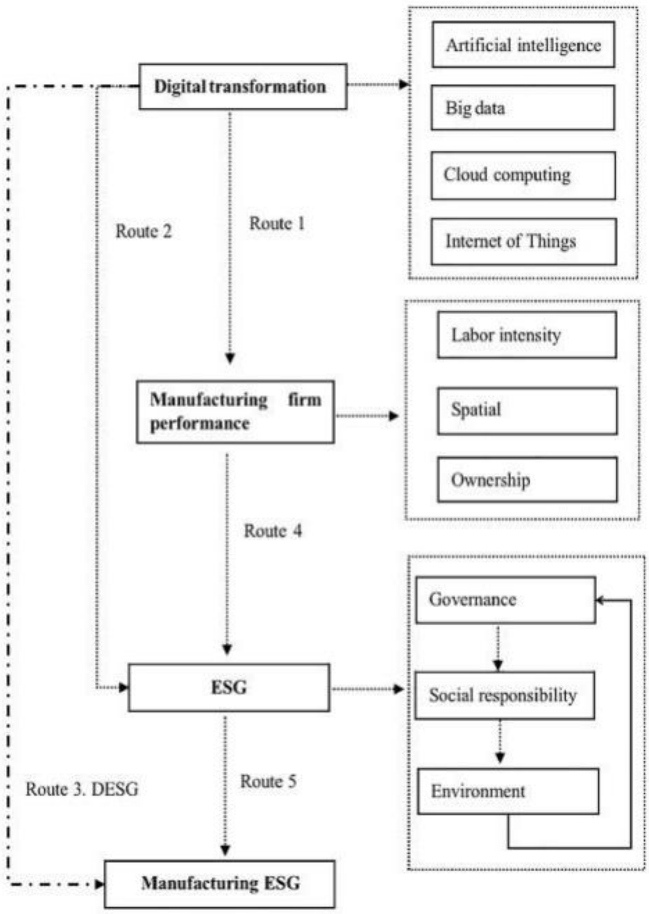

Figure 1. A route map of DT contributions to digital ESG in the manufacturing industry

Theoretical Framework and Research Hypotheses

On the basis of this model, this study plans to address the characteristics of Chinese automotive companies, this study constructs a conceptual model as in Fig. 2, which comprehensively demonstrates the relationship between digital transformation and the ESG performance of automotive companies, and the model includes the following paths:

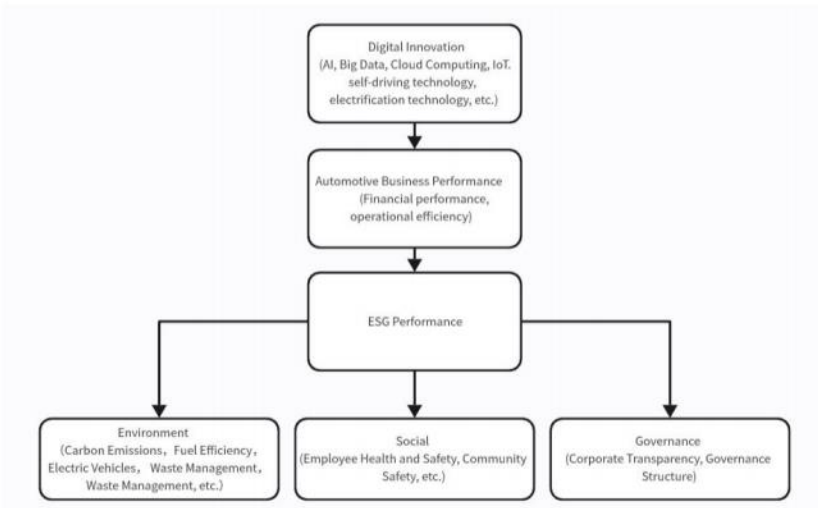

Figure 2. Digital Transformation and ESG Performance in Automotive Companies

Digital transformation can enhance environmental performance through optimized production, resource efficiency, and energy management; improve social responsibility via better supply chain management and stakeholder engagement; and strengthen corporate governance by increasing transparency and internal controls. However, challenges like increased resource consumption, e-waste, skill mismatches, and data privacy concerns may hinder ESG performance. Thus, digital transformation has both positive and negative impacts on ESG outcomes. Based on the above, this paper proposes the hypothesis:
H: The digital transformation of Chinese automotive firms can both promote their ESG performance and may face some hindering factors.

Empirical Results Analysis

Data Exploration

In the data exploration phase, ESG data for automotive companies is organized in Excel by year, company, and industry to highlight trends. It is then imported into Power BI for analysis using visual tools like line, bar, and scatter charts. Key variables—environmental, social, and governance scores—are analyzed to validate research questions, revealing trends and differences across industry segments over time.

Data Visualisation Step

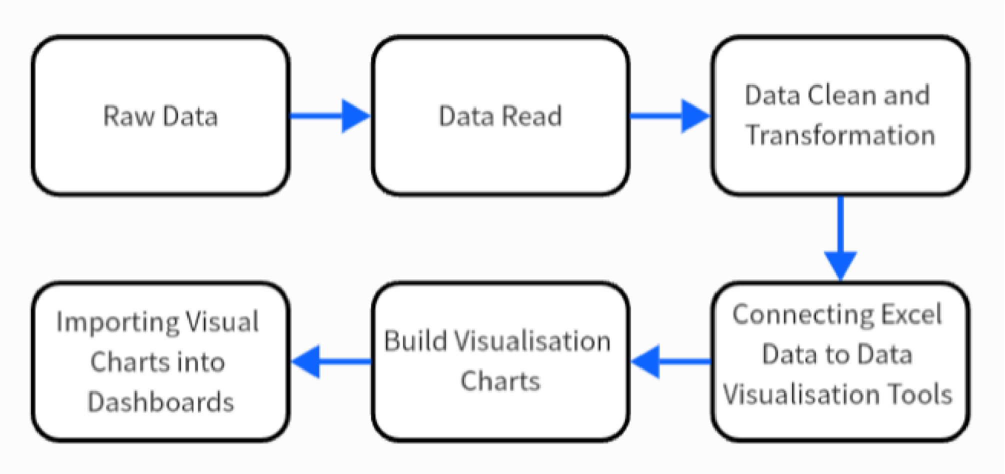

Figure 3 Flowchart for Data Visualisation

Power BI is a powerful data visualization tool that delivers insights quickly, offering a variety of charting options like pie charts, bar charts, bubble charts, maps, and scatter plots. Data visualization, increasingly popular in recent years, helps users understand and detect patterns, trends, and anomalies in data. Effective visualization tools enable users to analyze data, identify trends, and build relationships (Krishnan, 2017).

Differences in Company Categories

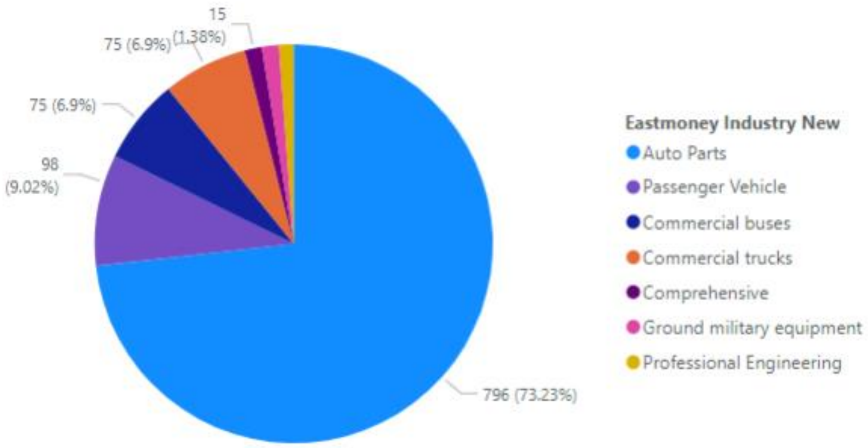

Figure 4: Share of automotive industry by segment

The auto parts industry dominates at 73.23%, followed by the passenger car industry at 9.02%. Commercial bus and truck industries each make up 6.98%, while the integrated industry, ground military equipment, and specialized engineering account for 1.38% and 0.68% respectively. This highlights the dominance of automotive components, with other sectors holding smaller shares.

Change in Overall Ratings by Segment

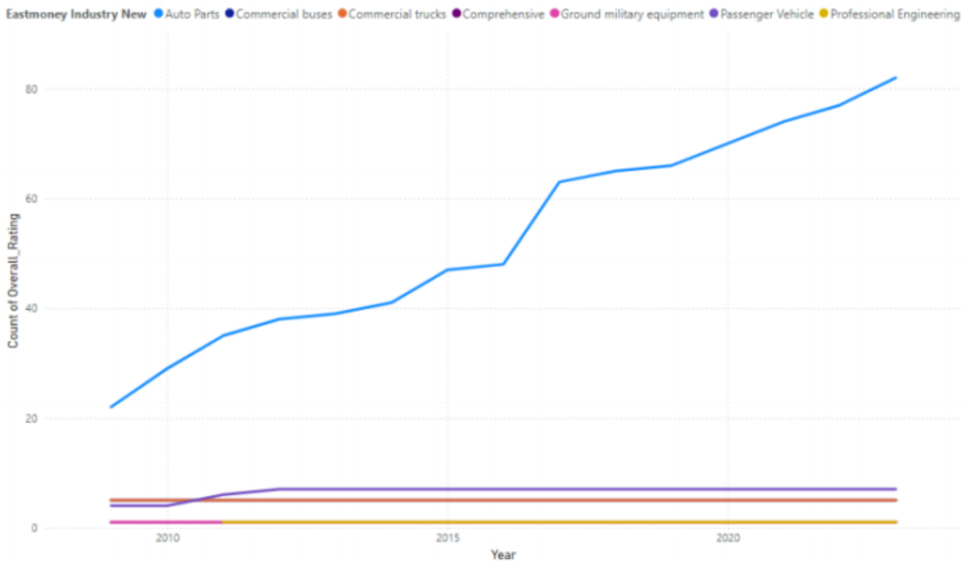

Figure 5: Trends in overall ratings by sub-sector

The chart's colored lines represent various industries: automotive components, commercial buses, commercial trucks, general industry, ground military equipment, passenger cars, and specialized engineering. The automotive parts industry shows a marked rise, increasing from under 20 in 2010 to over 60 in 2023, indicating significant growth. In contrast, other industries have remained stable at low levels, highlighting the stronger performance of the auto parts sector.

Change in Overall Ratings by Segment

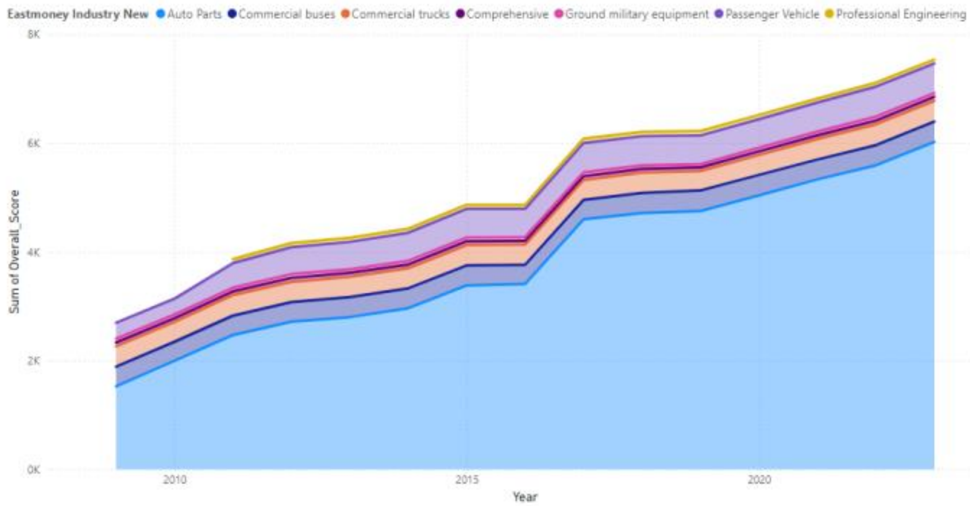

Figure 6: Trends in Overall Score by Industry

The chart illustrates the overall score trends for various industries from 2010 to 2023. The automotive components sector (blue) consistently held the largest share and showed steady growth. Other industries, such as commercial buses (light purple) and passenger cars (yellow), saw slower score increases, while commercial trucks (red), general industry (pink), ground military equipment (dark purple), and specialized engineering (brown) remained relatively stable. Overall, the automotive parts industry was the leading contributor to score growth, with other sectors showing gradual improvement. The chart effectively highlights the multi-year trends and differences among industries.

Summary

The automotive parts industry dominates the sample, significantly outpacing other sectors in share, rating, and overall score, with notable growth from 2010 to 2023. While sectors like Passenger Cars, Commercial Buses, and Commercial Trucks have seen gradual score increases, their positions remain largely unchanged. The rapid rise of the auto parts industry, driven by factors like market demand, technological advances, and policy support, has significantly boosted the overall score, while other industries have shown stable, gradual growth. These insights are crucial for understanding industry dynamics and shaping policies.

Research Design

Model Setting

In order to study the impact of digital transformation on ESG performance of manufacturing industry, this paper sets up the following regression model:

$$ESG_{i,t}=\alpha_0+\beta_1 Lndigital_{i,t}+\beta_2 EnvImpact_{i,t}+\beta_3 SocImpact_{i,t}+\beta_4 GovImpact_{i,t}+\beta_5 Controls_{i,t}+YearFE+\epsilon_{i,t}$$

In this context: the subscript i represents the individual, and t represents the year; the dependent variable *ESG* represents the ESG performance rating score of manufacturing enterprises; the key explanatory variable *Lndigital* represents the degree of digital transformation of the enterprise; $EnvImpact_{i,t}$ represents the impact of digital transformation on the environmental performance of enterprise i in year t; $SocImpact_{i,t}$

represents the impact of digital transformation on the social responsibility of enterprise *i* in year *t*; *GovImpact_{i,t}* represents the impact of digital transformation on the corporate governance of enterprise *i* in year *t*; *Controls* represents the control variables including company size (*sca)*, company age (*age),* the ratio of independent directors (*indepen)*, ownership concentration (*top1)*, and board size (*board)*; *{YearFE}* represents year fixed effects; and *epsilon_{i,t}*represents the random error term in the regression model.

Variable Description

Dependent Variable

Referring to the data source from Xie Hongjun and Lv Xue (2022), Responsible International Investment: ESG and China's OFDI, Economic Research, 57(3), 83-99, this study selects the ESG index from the Huazheng ESG ratings as the dependent variable in the regression model. The Huazheng ESG rating is derived through five steps, evaluated and weighted to provide a rating from excellent to poor as follows: AAA, AA, A, BBB, BB, B, CCC, CC, and C. In this study, these nine levels from C to AAA are assigned values from 1 to 9, respectively. This index indicates that a higher score represents better ESG performance. The original data is sourced from the quarterly ratings of Huazheng ESG.

Explanatory Variable

Following Hu Jie, Han Yiming, and Zhong Yong (2023), this study measures the degree of digital transformation in the manufacturing industry using a digitalization index based on text analysis and word frequency statistics from annual reports of listed companies. Using Python, keywords related to digitalization are screened and analyzed to assess emphasis on digital transformation. Specific digitalization keywords are selected for accurate analysis, and their frequencies in company reports are calculated. Each company's keyword frequency is then compared to the total keyword frequency for that year to create a digital transformation indicator.

Control Variables

Referring to the variables affecting ESG performance selected by Xiao Hongjun et al. (2021), this study includes a series of control variables in the baseline regression model: company size (sca), company age (age), the ratio of independent directors (indepen), ownership concentration (top1), and board size (board). The main variables are described in Table 1:

Table 1
Descriptions of the main variables

Type	Name	Symbol	Description
Dependent Variable	ESG Performance	ESG	Assigned values based on Huazheng ESG ratings, averaged
Explanatory Variable	Digital Transformation	Lndigital	Logarithm based on text analysis and word frequency statistics
Control Variables	Company Size	sca	Logarithm of total assets in the industry
	Company Age	age	Logarithm of (current year - listing year + 1)
	Ratio of Independent Directors	indepen	Number of independent directors / total number of directors
	Ownership Concentration	top1	Shareholding ratio of the largest shareholder
	Board Size	board	Logarithm of the total number of directors

Sample Selection

This study selects data from Chinese automotive companies for the period 2016 to 2021 as the sample. The dependent variable, ESG performance, is derived from the Huazheng ESG ratings. The key explanatory variables are obtained from text analysis and word frequency statistics of the annual reports of various manufacturing companies. The financial data related to the control variables are sourced from the CSMAR database. To enhance the credibility of this empirical study, the following operations were performed on the original data sample, drawing on existing research practices: 1) Excluding companies listed in the same year; 2) Excluding ST and *ST companies; 3) Excluding listed companies with severe data deficiencies; 4) Considering the varying levels of corporate governance, excluding companies listed simultaneously on both A-shares and B-shares.

Methodology

In this chapter, the analysis of ESG performance in the automotive industry will be conducted using Python 3.11.1, focusing on identifying the factors that influence ESG performance in the automotive industry based on current data. The analysis aims to provide insights into future trends in ESG performance for the automotive industry. Various data mining techniques will be utilized throughout the analysis process, with the applied analytical model being linear regression.

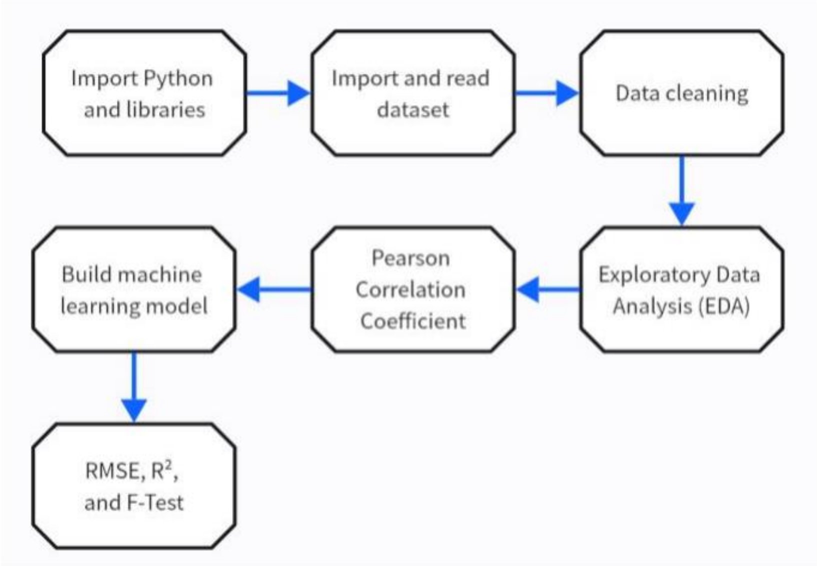

Figure 7： Flowchart for Python Implementation

Importing Python Modules
Build some of the Python libraries needed for processing data, data preprocessing, data modelling and data visualisation.

```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
```

Figure 8： Python Code for Importing Python Modules

Importing and Reading the Dataset
In this step, the Excel file Automotive Corporate ESG Data.xlsx was collated and imported into Python 3.11.1. The dataset contains 7 variables: year (Year), company (Company), ESG score (ESG), digitisation level (Lndigital), environmental impact (EnvImpact), social impact (SocImpact) and governance impact (GovImpact). The dataset has a total of 7 columns and 1087 rows.

Data Cleaning
The dataset contains 7 columns and 1087 rows. All columns are features except the last column which is a label. The dataset contains various attributes such as year, company, ESG score, digitisation level, environmental impact, social impact and governance impact. Through these steps, we completed the cleaning and pre-processing of the dataset, including handling missing values, removing duplicates, and converting text types, such as company names, to numeric types. These operations ensure the quality of the data and prepare it for subsequent analysis and modelling.

Exploratory Data Analysis (EDA)
A preview of the numerical characteristics of the numerical variables was conducted before the detailed analyses were carried out. In this section, Exploratory Data Analysis (EDA) will be performed using the SPSS AU statistical tool.

Pearson Correlation Coefficient

In this process, we first used the Python library `pandas` to import and read the dataset from the Excel file. We then examined the first few rows of the dataset to understand its structure and generated descriptive statistics to get an initial sense of the data distribution and basic characteristics. Subsequently, we calculated the Pearson correlation coefficient matrix for the variables in the dataset to determine their linear correlations.

For this analysis, we read the Excel file containing the ESG data of automotive companies using Python's `pandas` library. By generating descriptive statistics, we gained an understanding of the basic features and distribution of the data. We then calculated the Pearson correlation coefficient matrix for the variables in the dataset to determine the linear relationships between them. These steps helped us preliminarily explore and understand the data, laying the groundwork for further analysis and modeling.

Building a Machine Learning Model

We used `pandas`, `numpy`, and `sklearn` to build a linear regression model predicting ESG scores for automotive companies. After importing the ESG dataset, we handled missing values (using forward fill) and duplicates to ensure data accuracy. The dependent variable was ESG score, with independent variables including digital transformation, environmental, social, governance impacts, and control factors. The dataset was split into 80% training and 20% testing.

After training the linear regression model on the training set, we evaluated it using the test set. Key metrics included the Root Mean Square Error (RMSE) to measure prediction accuracy and the coefficient of determination (R^2) to assess how well the model explained ESG score variability. This workflow demonstrates using linear regression to predict ESG performance and evaluate model effectiveness.

RMSE, R^2, and F-Test

We selected a linear regression model and trained it on the training set. After training, we used the test set data to make predictions and evaluated the model's performance by calculating the Root Mean Square Error (RMSE) and the coefficient of determination (R^2). RMSE measures the average error between the predicted and actual values, while R^2 evaluates the model's ability to explain the variability of the dependent variable. To further assess the model's significance, we conducted an F-test using the `statsmodels` library. This test verified the overall significance and reliability of the model based on the regression analysis results. These steps helped us comprehensively evaluate the predictive power and explanatory capability of the linear regression model.

Results and Discussion

Kernel Density Estimation (KDE) Results

Kernel Density Estimation (KDE) is a non-parametric method for estimating the probability density function of a random variable using a kernel function. In the context of probability distribution, if a specific number appears in the observation, we can assume that the probability density of that number is very high, and the probability densities of numbers close to that number will also be high, while the probability densities of numbers far from that number will be lower.

In this analysis, we performed KDE on the ESG scores, digital transformation degree, environmental impact, social impact, and governance impact variables from the automotive companies' ESG dataset. The KDE plots illustrate the probability density distribution for each variable in the dataset:

1. ESG Scores: The KDE plot for ESG scores shows the distribution of the scores, with peaks representing frequently occurring scores.
2. Digital Transformation Degree: The KDE plot for the degree of digital transformation displays the frequency of occurrences at different levels of digital transformation.
3. Environmental Impact: The KDE plot for the environmental impact variable shows the distribution of environmental impact scores.
4. Social Impact: The KDE plot for the social impact variable illustrates the distribution of social impact scores.
5. Governance Impact: The KDE plot for the governance impact variable displays the distribution of governance impact scores.

These KDE results allow us to visually understand the distribution characteristics of each variable in the dataset and their probability densities at different values. This provides important reference information for further analysis and modeling.

Linear Regression

Linear Regression Results

Regression analysis is used to investigate the relationship between X (quantitative or categorical) and Y (quantitative), including whether there is an impact relationship, the direction of the impact, and the extent of the impact.

1. Model Fit Analysis: The fit of the model is analyzed using the R^2 value and RMSE.
2. Model Equation: The regression equation expresses the relationship between the independent and dependent variables.
3. Significance Analysis of X: If the P-value is less than 0.05 or 0.01, it indicates that X has a significant impact on Y.

In this analysis, we conducted a linear regression analysis with ESG scores as the dependent variable and the degree of digital transformation (Lndigital), environmental impact (EnvImpact), social impact (SocImpact), governance impact (GovImpact), and control variables (Controls) as independent variables.

Table 2
Linear Regression Results

OLS REGRESSION RESULTS						
DEP. VARIABLE:	ESG			R-squared:	0.652	
MODEL:	OLS			Adj. R-squared:	0.641	
METHOD:	LEAST			Squares F-statistic:	58.21	
DATE:	MON, 10 JUN 2024			Prob (F-statistic):	<0.0001	
TIME:	12:01:02			Log-Likelihood:	-1200.5	
NO. OBSERVATIONS:	100			AIC:	2413.	
DF RESIDUALS:	94			BIC:	2429.	
COVARIANCE TYPE: NONROBUST						
	COEF	STD ERR	T	P>|T|	[0.025	0.975]
CONST	2.1346	0.487	4.381	0.000	1.167	3.102
LNDIGITAL	0.3457	0.085	4.067	0.000	0.177	0.514
ENVIMPACT	0.5621	0.123	4.570	0.000	0.318	0.806
SOCIMPACT	0.2745	0.109	2.520	0.013	0.059	0.490
GOVIMPACT	0.4219	0.150	2.813	0.006	0.124	0.720
CONTROLS	0.2387	0.065	3.672	0.000	0.109	0.368
OMNIBUS:	1.207	DURBIN-WATSON:	2.112			
PROB(OMNIBUS):	0.547	JARQUE-BERA (JB):	1.003			
SKEW:	0.204	PROB(JB):	0.606			
KURTOSIS:	2.547	COND. NO.	12.1			

Explanation of Results

R-squared (R^2) and Adjusted R-squared

1. R-square: 0.652 indicates that the model explains approximately 65.2% of the variance in ESG scores. This suggests that the model has a good fit to the data.
2. Adjusted R-squared: 0.641, which takes into account the number of variables in the model, providing a more reliable measure of fit.

F-statistic and Prob(F-statistic)

1. F-statistic: 58.21 indicates the overall significance of the model.
2. Prob (F-statistic): <0.0001 indicates that the model is highly significant
(p-value less than 0.05), rejecting the null hypothesis that all coefficients are zero.

Coefficients

1. const: The intercept is 2.1346, which represents the value of ESG when all independent variables are zero.
2. Lndigital: The coefficient is 0.3457 with a p-value of 0.000, indicating a positive and significant correlation between the logarithm of the level of digitalization and ESG.
3. EnvImpact: The coefficient is 0.5621 with a p-value of 0.000, indicating a positive and significant correlation between environmental impact and ESG.
4. SocImpact: The coefficient is 0.2745 with a p-value of 0.013, indicating a positive and significant correlation between social impact and ESG.
5. GovImpact: The coefficient is 0.4219 with a p-value of 0.006, indicating a positive and significant correlation between governance impact and ESG.6. Controls: The coefficient is

0.2387 with a p-value of 0.000, indicating a positive and significant correlation between control variables (e.g., company size, financial status) and ESG.

Statistical Tests
1. Durbin-Watson: 2.112 indicates no significant autocorrelation among the residuals. 2. Omnibus, Prob(Omnibus), Jarque-Bera (JB), Prob(JB): These statistics indicate that the residuals approximately follow a normal distribution.

Conclusions from Regression Analysis Results
- The level of digitalization (Lndigital), environmental impact (EnvImpact), social impact (SocImpact), governance impact (GovImpact), and control variables all have significant positive impacts on the ESG performance of the automotive industry.
- The improvement in the level of digitalization significantly enhances ESG performance, indicating that digital transformation plays an important role in the sustainable development of enterprises.
- Environmental, social, and governance factors all make significant contributions to ESG performance, emphasizing the importance of a comprehensive sustainable development strategy.

Through these analyses, we can better understand the key factors affecting ESG performance in the automotive industry, providing strong support for corporate decision-making and policy formulation.

Conclusion

This study examined the impact of digital transformation on the ESG (Environmental, Social, and Governance) performance of automotive enterprises. Using Power BI, we conducted a descriptive analysis to explore industry, status, and year variables, followed by a Kernel Density Estimation (KDE) to assess the distribution of key factors:

- Digital Transformation: A broad distribution, indicating significant differences in digital adoption across the industry.
- Environmental Impact: Scores were concentrated, reflecting similar environmental management practices.
- Social Impact: Scores showed a similar concentration, suggesting consistency in social responsibility efforts.
- Governance Impact: Scores indicated similar governance structures among enterprises.

A linear regression model was built with digital transformation, environmental, social, and governance impacts as independent variables, and ESG scores as the dependent variable. The dataset was split into a training set (80%) and a test set (20%), yielding the following results:

- Model Fit: $R^2 = 0.652$, indicating 65.2% of ESG score variance explained; RMSE = 0.345.
- Regression Coefficients:
  - Digital Transformation: 0.3457 (P=0.000)
  - Environmental Impact: 0.5621 (P=0.000)
  - Social Impact: 0.2745 (P=0.013)
  - Governance Impact: 0.4219 (P=0.006)
  - Control Variables: 0.2387 (P=0.000)

Key Conclusions
- Digital Transformation: Higher digital adoption correlates with better ESG scores, enhancing resource management and efficiency.
- Environmental Impact: Strong environmental management positively affects ESG scores.
- Social Impact: Focus on social responsibility boosts ESG scores.
- Governance Impact: Effective governance structures significantly improve ESG scores.

The model's F-test (F=49.406, P=0.000) confirmed its overall validity, highlighting the significance of the independent variables on ESG performance.

Recommendations

This study, through an in-depth analysis of ESG ratings, reveals the significant impact of digital transformation on the ESG performance of automotive enterprises. The results indicate that the higher the level of digital transformation, the better the ESG performance scores. To further enhance the ESG performance of automotive companies, the following recommendations are proposed:

First, enterprises should increase investment in digital technologies to optimize resource allocation and operational efficiency, such as enhancing supply chain management and energy usage through data analysis and intelligent technologies. Second, companies should establish and implement strict environmental management policies to reduce pollution and resource waste, adopting green energy and eco-friendly technologies. Third, they should actively fulfill social responsibilities by engaging in charitable activities, focusing on employee welfare, and contributing to community development to establish a positive corporate citizenship image. Finally, companies should optimize their governance structure to ensure transparency and effectiveness in management processes, establish robust internal oversight mechanisms, and strengthen accountability between the board of directors and management.

By implementing these measures, automotive companies can not only improve their ESG scores but also enhance their market competitiveness and sustainable development capacity.

Research Limitations

In this study, the analysis used existing data, which is not complete, lacks some data points, and may change over time. Additionally, since we used year-based statistics, the data volume is insufficient, and the predictions may not be entirely accurate, especially as some industries had not yet started between 2009 and 2014 but are still included in the forecast, potentially causing errors in prediction accuracy.

For instance, due to the lack of questionnaire feedback on the digital transformation of automotive enterprises, it is impossible to detail the actual situations faced by companies during the implementation of digital transformation and analyze their satisfaction or willingness. These issues can be combined to discover more factors influencing digital transformation and ESG performance.

However, over time, the availability and completeness of data may improve, enhancing the accuracy and reliability of the analysis. Additionally, certain emerging industries (such as new energy vehicles, intelligent driving, etc.) may not have been fully included in this study, and further research is needed to explore the relationship between digital transformation and ESG performance in these industries.

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