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AI-Driven Green Supply Chain Management: Assessing Adoption, Implementation Gaps, and Environmental Performance

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Abstract:
Artificial Intelligence (AI) is increasingly transforming Green Supply Chain Management (GSCM) by enabling intelligent decision-making, logistics optimization, resource efficiency, and environmental improvement. This study examines the role of AI adoption in GSCM among logistics-intensive organizations in Western Maharashtra. Specifically, the study assesses the level of AI adoption, examines the effect of technology investment on AI adoption and environmental performance, and investigates the mediating role of AI adoption in the relationship between technology investment and environmental performance. Primary data were collected from 131 organizations across major logistics-intensive sectors in Western Maharashtra. Descriptive analysis, cluster analysis, regression, mediation analysis, and moderated mediation analysis were employed. The findings identified three distinct levels of AI adoption: low (35.1%), medium (40.5%), and high (24.4%). AI adoption demonstrated a significant positive effect on carbon reduction, with carbon reduction increasing from 4.28% in low-AI organizations to 12.42% in high-AI organizations. Technology investment also increased significantly across AI-adoption levels, from 2.41% to 5.58%. Mediation analysis confirmed that AI adoption significantly mediates the relationship between technology investment and carbon reduction, with an indirect effect of 0.125 (95% CI: 0.068–0.192), indicating partial mediation. Further analysis showed that organizational readiness strengthens the translation of technology investment into AI adoption. The study concludes that AI adoption represents an important organizational capability through which technological investment can contribute to improved environmental performance and more sustainable GSCM practices.

Keywords: *Artificial Intelligence; Green Supply Chain Management; AI Adoption; Technology Investment; Environmental Performance; Carbon Reduction; Organizational Readiness; Sustainable Logistics.*

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1. Introduction :

The intersection of Artificial Intelligence (AI) and sustainability within the manufacturing supply chain has emerged as a significant area of interest for both researchers and industry practitioners in recent years (Haenlein & Kaplan, 2019; Mikalef et al., 2019). As global concerns about climate change and resource scarcity intensify, there is an increasing pressure on industries to reduce their carbon footprints while simultaneously enhancing operational efficiency (McCarthy et al., 2006). The manufacturing sector, which is a major contributor to global emissions, is under particular scrutiny (Min, 2009). AI-driven solutions have been identified as key enablers in addressing these dual objectives of reducing environmental impact and improving operational performance.

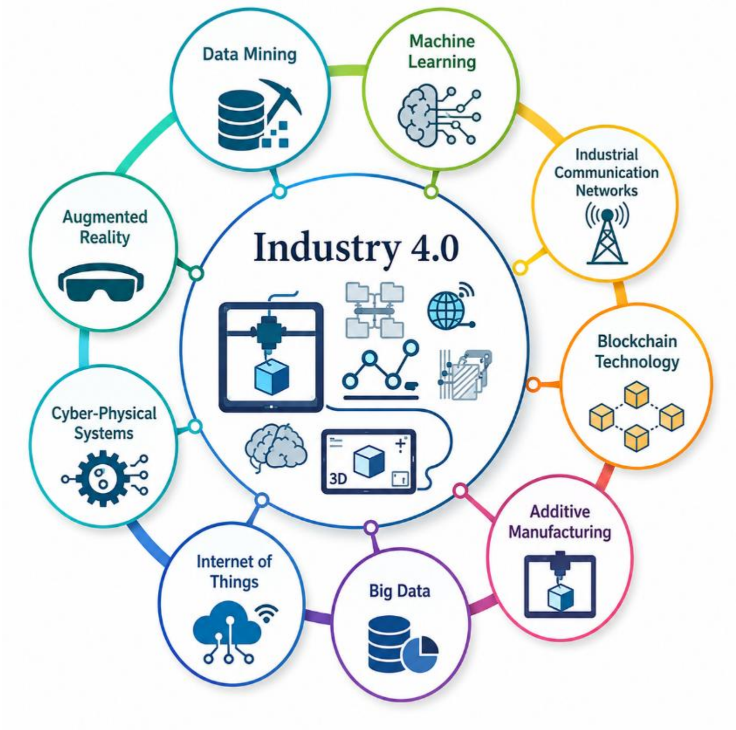

Figure 1: Major Digital Technologies Enabling Industry 4.0

According to a study by (Pontrandolfo et al., 2002), the integration of AI technologies within the supply chain is becoming essential for optimizing processes, minimizing waste, and enhancing overall sustainability. This burgeoning interest is reflected in a growing body of literature that highlights AI's capacity to tackle complex challenges within the manufacturing supply chain, particularly in relation to sustainability (O'Leary, 2013; Ramos et al., 2008).

1.1 Artificial Intelligence in Green Supply Chains:

AI has emerged as one of the most influential technologies transforming manufacturing supply chains by improving operational efficiency, decision-making, and environmental sustainability (Haenlein & Kaplan, 2019; Mikalef et al., 2019). Growing concerns regarding climate change, resource depletion, and increasing regulatory pressure have encouraged manufacturing organizations to adopt sustainable supply chain practices that minimize environmental impact while

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maintaining competitiveness (McCarthy et al., 2006). As one of the major contributors to greenhouse gas emissions and industrial waste, the manufacturing sector is increasingly integrating AI technologies to support sustainable operations and achieve long-term environmental objectives (Min, 2009).

The advancement of Industry 4.0 has accelerated the adoption of intelligent technologies such as Artificial Intelligence, Machine Learning, Big Data Analytics, IoT, cloud computing, and digital twins across manufacturing supply chains. These technologies enable organizations to optimize production planning, improve demand forecasting, automate warehouse operations, monitor energy consumption, reduce waste generation, and enhance resource utilization (Pontrandolfo et al., 2002; O'Leary, 2013). AI-driven decision-support systems also facilitate predictive maintenance, logistics optimization, and real-time supply chain visibility, thereby contributing to both operational excellence and environmental sustainability (Ramos et al., 2008).

Figure 2: AI-Enabled Green Supply Chain Management Cycle in Manufacturing

Despite the increasing adoption of AI technologies, many manufacturing organizations continue to experience challenges in converting technological investments into measurable sustainability outcomes. Differences in organizational readiness, digital infrastructure, employee capabilities, and supply chain integration often influence the effectiveness of AI implementation. Consequently, understanding the mechanisms through which AI contributes to environmental performance has become an important research concern (Mikalef et al., 2019).

Although previous studies have extensively examined AI applications, Green Supply Chain Management (GSCM), and sustainable manufacturing independently, limited empirical research has

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investigated the mediating role of AI adoption in linking technology investment with environmental performance. Furthermore, the influence of organizational readiness in strengthening AI adoption has received comparatively less empirical attention. Therefore, the present study develops and empirically examines a conceptual framework that investigates the mediating role of AI adoption and the moderating influence of organizational readiness on environmental performance. The findings are expected to contribute to both academic literature and managerial practice by providing evidence on how AI-enabled technologies can support sustainable manufacturing and Green Supply Chain Management.

Therefore this study aims to empirically examine the role of AI in strengthening GSCM practices within organizations in Western Maharashtra. Specifically, the study seeks to assess the current level of AI adoption across GSCM-related supply chain functions and to examine the extent to which technology investment contributes to the adoption of AI-enabled capabilities. Further, the study investigates the influence of AI adoption on environmental performance, with particular emphasis on carbon reduction outcomes, and examines whether AI adoption serves as a mediating mechanism through which technology investment translates into improved environmental performance. The study also considers the role of organizational readiness in determining the effectiveness with which technological investments are converted into AI capabilities. Through these objectives, the study seeks to provide empirical evidence on how AI-enabled technological transformation can support more environmentally sustainable and efficient supply chain practices in the regional industrial context of Western Maharashtra.

2. Literature Review :

2.1 Artificial Intelligence Adoption in Green Supply Chain Management

Recent literature increasingly identifies AI, Big Data Analytics, and related digital technologies as important enablers of GSCM and sustainable operational performance. Bag et al. (2021) demonstrated that AI-based technological dimensions positively influence GSCM strategies and processes, which subsequently contribute to environmental, social, and financial performance. Similarly, Allahham et al. (2023), based on evidence from UK hospitals, reported that Big Data Analytics and AI can improve demand forecasting, inventory management, logistics optimization, predictive maintenance, and carbon-emission reduction. Rashid et al. (2025) further showed that AI-powered Big Data Analytics strengthens green supply-chain collaboration, sustainable manufacturing, and environmental process integration, with green supply-chain collaboration acting as an important pathway towards sustainable performance. More recently, Zhang et al. (2025) demonstrated the potential of AI-IoT-enabled green supply chains for carbon reduction and operational efficiency in manufacturing. These studies collectively suggest that AI adoption is moving beyond a purely technological function and is increasingly becoming an organizational capability for improving green supply-chain outcomes.

The sustainability implications of AI are also evident in transportation and fleet-related applications. Reddy (2024) highlighted the contribution of AI-enabled electric vehicles to energy management,

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battery optimization, and reduction of greenhouse-gas emissions, while Macharia et al. (2023) emphasized the role of AI, Machine Learning, and IoT in improving EV performance and energy management, although infrastructure, cybersecurity, and interoperability remain important challenges. Goel et al. (2021) and Manzolli et al. (2022) similarly emphasized vehicle electrification and fleet-level optimization as important pathways towards lower-emission transportation. At the broader level, Roman (2022), through a review of 1,238 publications, identified transport emissions, sustainable supply-chain and logistics models, performance measurement, and future policy as major research streams in sustainable transportation. Overall, the literature establishes a strong link between intelligent technologies, sustainable transportation, and environmental performance; however, comparatively less attention has been given to how technology investment is translated into environmental performance specifically through different levels of AI adoption within logistics-intensive organizations. This provides the basis for examining AI adoption as a mediating mechanism in the present study.

2.2 Technology Investment, AI Adoption and Environmental Performance

Artificial Intelligence and machine-learning techniques are increasingly being applied to logistics optimization, particularly in vehicle routing, demand forecasting, fleet allocation, and real-time decision-making. Kunnapapdeelert et al. (2022) demonstrated that particle swarm optimization can support green vehicle routing by simultaneously reducing transportation costs and emissions, while Arora (2025) reported that an AI-enabled federated learning framework improved route optimization, fuel savings, delivery efficiency, and carbon-emission reduction. Similarly, Subramanian et al. (2023) found that advanced machine-learning models improved transportation demand forecasting, with GRU achieving the highest predictive accuracy. Fadda et al. (2021) further showed that integrating clustering, forecasting, and optimization techniques can improve demand prediction, fleet allocation, and logistics planning under uncertain demand conditions. These findings indicate that AI-enabled analytical and optimization capabilities can improve both operational efficiency and environmental outcomes in logistics.

The application of AI extends beyond routing and forecasting to integrated fleet management and intelligent logistics systems. Bnouachir et al. (2020) found that Big Data-based fleet management improved fleet utilization, resource allocation, and real-time decision-making, while Oyekanlu et al. (2020) highlighted the contribution of advanced communication and fleet-management technologies to coordination and logistics efficiency. Oran (2021) similarly identified AI and robotics as important technologies for improving logistics efficiency and supporting sustainable logistics systems. Tong et al. (2019) reported that AI-enabled transportation systems enhance predictive decision-making, traffic management, safety, and transportation efficiency. In a broader sustainability context, Makhdoom et al. (2025) found that green supply-chain management, green technology investment, waste management, and AI-powered big-data analytical capabilities positively influence sustainable performance. Collectively, these studies establish the operational

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value of intelligent logistics technologies; however, limited attention has been given to AI adoption as an organizational-level capability through which technology investment can translate into measurable environmental performance, particularly among logistics-intensive organizations in Western Maharashtra. This gap provides the basis for examining AI adoption and its mediating role between technology investment and environmental performance in the present study.

2.3 AI Adoption as a Mediating Mechanism in Sustainable Supply Chains

Recent research increasingly suggests that the environmental benefits of digital transformation do not arise solely from technology investment itself but depend on the organizational and supply-chain capabilities developed through its implementation. Le et al. (2024) found that digitalisation contributes to sustainable corporate performance through green innovation and Green Supply Chain Management, indicating that intermediate capabilities play an important role in translating technological resources into sustainability outcomes. Similarly, Gariba et al. (2024), using evidence from EU economies, reported that sustainable supply-chain practices mediate the relationship between digitalisation and Sustainable Development Goals. These findings suggest that digital technologies can create environmental value when they are embedded within appropriate supply-chain practices rather than being treated simply as technological investments.

Within this broader digitalisation–sustainability relationship, AI represents a more advanced capability because it enables organizations to analyse large volumes of operational data, improve prediction and decision-making, and optimize supply-chain processes in real time. Benzidia et al. (2021) demonstrated that big data analytics and AI can support green supply-chain process integration and improve environmental performance, thereby highlighting the importance of AI-enabled capabilities in achieving sustainability outcomes. More recent evidence also shows that AI-driven innovation can influence sustainable performance through green supply-chain integration, with internal and external integration acting as significant mediating mechanisms (Dong et al., 2026).

Despite these developments, the existing literature provides comparatively limited empirical evidence on AI adoption as the specific mediating mechanism linking technology investment with environmental performance, particularly within logistics-intensive organizations in emerging regional contexts. Much of the recent literature examines digitalisation, AI, GSCM, or sustainable performance as broader constructs, while the pathway through which organizational technology investment is converted into AI capability and subsequently into measurable environmental improvement remains insufficiently explored. The present study addresses this gap by examining AI adoption as a mediator between technology investment and environmental performance among logistics-intensive organizations in Western Maharashtra. This approach provides a more mechanism-oriented explanation of how technological resources can contribute to environmental improvement through AI-enabled GSCM capabilities.

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3. Materials and methodology

3.1 Research Design :

The present study **adopts a quantitative, cross-sectional research design** to empirically examine AI adoption within GSCM practices and its relationship with technology investment and environmental performance. The quantitative approach is appropriate because the study requires systematic measurement of AI adoption, technology investment, and environmental performance, along with statistical testing of the proposed mediation relationship. The study is conducted among logistics-intensive organizations operating in Western Maharashtra. Data are collected through a structured questionnaire and analyzed using descriptive and inferential statistical techniques, with mediation analysis employed to examine the indirect effect of technology investment on environmental performance through AI adoption. The conceptual framework of the study is as follow in figure 3 :

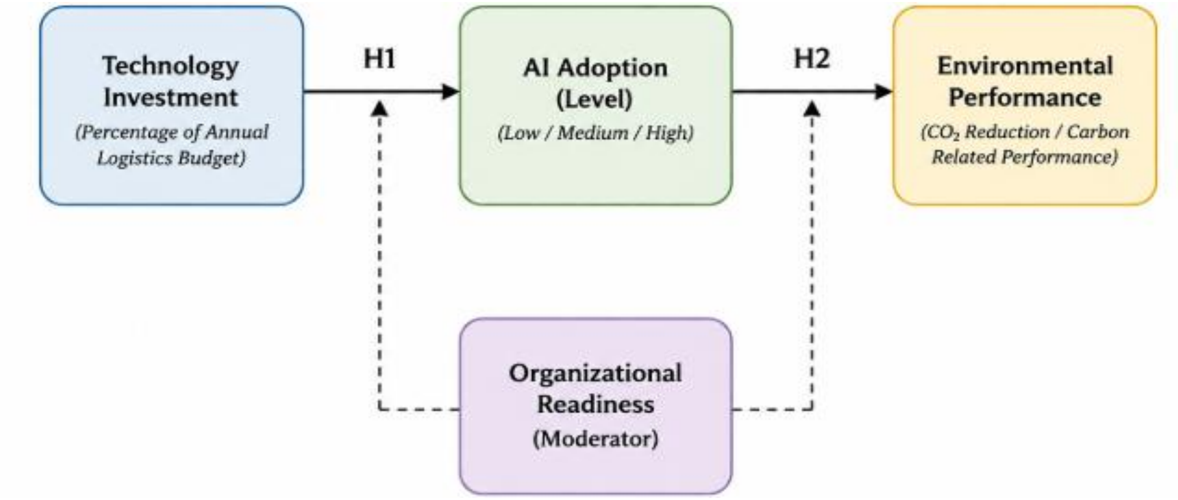

Figure 3 : Conceptual Framework of the Study

The conceptual framework proposes that technology investment contributes to improvements in environmental performance partly through enhanced AI adoption. Technology investment represents the organizational allocation of resources toward information technology, software, analytics, and related supply chain technologies. AI adoption represents the extent to which AI-enabled applications are implemented across supply chain and logistics functions, while environmental performance represents improvements associated with carbon reduction. The framework further considers organizational readiness as a contextual factor that may strengthen the conversion of technology investment into AI adoption.

Hypothesis :

H1: Artificial Intelligence adoption has a significant positive effect on Environmental Performance in Green Supply Chain Management practices among organizations in Western Maharashtra.

H2: Technology Investment has a significant positive effect on AI Adoption in Green Supply Chain Management.

H3: AI Adoption significantly mediates the relationship between Technology Investment and Environmental Performance.

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3.2 Study Setting and Population

The study is conducted in **Western Maharashtra, India**, a region characterized by substantial industrial, manufacturing, commercial, and logistics activity. The study setting covers major industrial and commercial centres, including **Pune, Mumbai, Thane, Nashik, and Kolhapur**. The geographical focus is selected because organizations operating in these locations undertake substantial transportation, logistics, distribution, and supply chain activities and are therefore directly exposed to the operational and environmental implications of technology adoption and green logistics practices.

The target population comprises medium- to large-scale industrial and commercial organizations with significant logistics and distribution functions. For the broader study, an organization is considered to have a significant logistics function when it maintains a dedicated fleet of at least 20 commercial vehicles for freight movement or last-mile distribution, incurs annual logistics expenditure exceeding ₹5 crore, and operates within a logistics-intensive sector relevant to the regional economy and environmental footprint.

The sampling frame developed for the broader study consists of organizations identified through multiple industry and business sources. "These include directories and databases associated with the **Confederation of Indian Industry (CII), Federation of Indian Chambers of Commerce & Industry (FICCI), Maharashtra Industrial Development Corporation (MIDC), listed companies on the Bombay Stock Exchange (BSE) and National Stock Exchange (NSE),** and verified industry reports relating to major logistics-intensive sectors in Maharashtra. The resulting multi-source sampling frame is intended to improve organizational coverage and reduce dependence on a single source of industrial listings".

3.3 Sampling Technique and Sample Size

A **stratified sampling approach is used** to ensure adequate representation of organizations from different industry sectors in Western Maharashtra. The industry sector serves as the primary stratification variable because the nature and extent of GSCM practices, technology investment, and AI adoption may vary across sectors. Within each stratum, organizations are selected using **simple random sampling**, giving eligible organizations an equal probability of selection.

The required sample size is determined using Cochran's formula for a finite population:

$$n_0 = \frac{Z^2 p(1-p)}{e^2}$$

where **Z = 1.96** represents a 95% confidence level, **p = 0.50** represents the maximum variability, and **e = 0.08** represents the acceptable margin of error. The finite population correction is subsequently applied as:

$$n = \frac{n_0}{1 + \frac{(n_0 - 1)}{N}}$$

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Based on the available sampling frame, the statistically required sample is estimated and a **final target sample of 125 organizations** is considered adequate for the quantitative analysis. The sample size provides sufficient observations for examining the relationships among technology investment, AI adoption, organizational readiness, and environmental performance.

Hence, respondents are selected from organizations involved in manufacturing, logistics, transportation, and related supply-chain activities in Western Maharashtra. The final sample is used to assess AI adoption in GSCM practices and test the hypothesized mediation relationship between technology investment, AI adoption, and environmental performance.

3.4 Data Collection Tools

Primary data are collected using a structured questionnaire administered to logistics-intensive organizations operating in Western Maharashtra. The questionnaire is designed to capture the variables required to assess AI adoption and its relationship with technology investment and environmental performance. For the present study, relevant information is drawn primarily from the sections covering organizational profile, AI and technology investment, and environmental performance.

The questionnaire includes organizational characteristics such as industry sector, fleet size, annual logistics expenditure, and geographical location to describe the study sample. Technology Investment is measured through the percentage of the annual logistics budget allocated to IT and technology, including software, hardware, and analytics.

AI Adoption is assessed through seven AI-enabled applications used in supply chain and logistics functions: demand forecasting/predictive analytics, route optimization, predictive fleet maintenance, driver behaviour monitoring, warehouse automation/robotics, computer vision for load optimization, and dynamic pricing/freight optimization. The number of applications adopted is used to classify organizations into Low AI (0–1 tools), Medium AI (2–3 tools), and High AI (4 or more tools) adoption levels.

Environmental Performance is assessed using carbon-related operational indicators, particularly average fleet CO_2 emission intensity and financial savings associated with emission reductions. Average CO_2 emissions are recorded in grams per kilometre, while annual financial savings resulting from emission reductions are recorded in ₹ lakhs. The measurement and operationalization of the variables included in the study are presented in Table 1.

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Table 1 : Measurement of Variables Used

"Variable	Role in Model	No. of items	Measurement/Indicators
Technology Investment	Independent Variable	1	Percentage of annual logistics budget allocated to IT and technology
AI Adoption Level	Mediating Variable	1	Seven AI applications; classified as Low, Medium, or High
Environmental Performance	Dependent Variable	2	CO_2-related performance and emission-reduction outcomes
Organizational Readiness	Moderator	3	Industry sector, fleet size, logistics expenditure and location"

3.5 Pilot Study :

The questionnaire is reviewed for content validity before its administration. The Content Validity Index (CVI) was calculated for each item:

$$CVI = \frac{Number\ of\ experts\ rating\ item\ as\ relevant\ (3\ or\ 4)}{Total\ number\ of\ experts}$$

An expert panel comprising five experts with academic and professional expertise in supply chain management and logistics evaluates the relevance, clarity, and appropriateness of the questionnaire items. The Content Validity Index (CVI) is calculated as the proportion of experts rating an item as relevant, with retained items meeting the acceptable CVI criterion of ≥ 0.80.

A pilot study is conducted with 15 organizations from the target population to assess the clarity, comprehensibility, and reliability of the instrument. Minor modifications are made to the wording and presentation of items based on the pilot feedback. For multi-item measures, internal consistency is assessed using Cronbach's alpha, with a coefficient of 0.70 or above considered acceptable. The validated questionnaire is subsequently administered to the final study sample.

3.6 Statistical Analysis :

The collected data are analyzed using IBM SPSS Statistics and Hayes' PROCESS macro to assess the level of AI adoption and examine its role in the relationship between technology investment and environmental performance. Initially, descriptive statistics are used to summarize the distribution of the major study variables, including AI adoption, technology investment, and carbon reduction. Frequencies and percentages are used to describe the adoption of individual AI applications, while means and standard deviations are used for continuous and composite measures.

To assess the level and pattern of AI adoption, K-means cluster analysis is applied to the seven AI application variables: demand forecasting/predictive analytics, route optimization, fleet maintenance predictive analytics, driver behaviour monitoring, warehouse automation/robotics, computer vision for load optimization, and dynamic pricing/freight optimization. The resulting clusters are interpreted as Low, Medium, and High AI adoption groups. Differences across the

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identified AI adoption groups in technology investment and carbon reduction are further examined using appropriate significance tests. This analysis provides an empirical basis for classifying organizations according to their level of AI adoption.

To examine the mediating role of AI adoption, mediation analysis is conducted using Hayes' PROCESS macro Model 4 (Hayes, 2018). In the mediation model, Technology Investment is specified as the independent variable, AI Adoption Level as the mediator, and CO_2 Reduction/Environmental Performance as the dependent variable. The analysis estimates the direct effect of technology investment on environmental performance, the effect of technology investment on AI adoption, the effect of AI adoption on environmental performance, and the indirect effect transmitted through AI adoption. The significance of the indirect effect is evaluated using bootstrap confidence intervals, where an interval that does not include zero indicates significant mediation (Hayes, 2018).

In addition, moderated mediation analysis using PROCESS Model 7 is employed to examine whether Organizational Readiness influences the strength of the relationship between technology investment and AI adoption. Organizational readiness incorporates dimensions related to IT infrastructure, digital culture, and change-management capability. Conditional indirect effects are estimated at low, mean, and high levels of organizational readiness. The Index of Moderated Mediation and its bootstrap confidence interval are used to determine whether the indirect effect of technology investment on environmental performance through AI adoption varies significantly according to organizational readiness (Hayes, 2018). Statistical significance is assessed at the 5% level ($p < 0.05$). The correspondence between the study objectives and the statistical analyses employed is presented in Table 2.

Table 2: Analysis–Objective Mapping

“**Objective**	**Analysis Used**	**Key Variables**
Objective 1: To assess the level of AI adoption in GSCM practices among organizations in Western Maharashtra.	Descriptive statistics + K-means cluster analysis	AI Adoption Level, Seven AI Applications
Objective 2: To examine the mediating role of AI adoption between technology investment and environmental performance.	PROCESS Model 4 + Bootstrap Mediation	Technology Investment → AI Adoption → CO_2 Reduction
Extended analysis of H4	PROCESS Model 7 (Moderated Mediation)	Technology Investment × Organizational Readiness → AI Adoption → CO_2 Reduction“

3.7 Outcome Measures

The study measures the following key variables in accordance with the proposed conceptual framework and hypotheses:

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- **AI Adoption Level (Mediator):** Measured based on the organization's use of seven AI-enabled supply-chain applications: demand forecasting/predictive analytics, route optimization, fleet maintenance predictive analytics, driver behaviour monitoring, warehouse automation/robotics, computer vision for load optimization, and dynamic pricing/freight optimization. The adoption pattern is subsequently classified into Low, Medium, and High AI adoption using K-means cluster analysis.

- **Technology Investment (Independent Variable):** Measured as the percentage of the organization's logistics/technology budget allocated to technology-related investments. This variable represents the level of organizational investment in technological capabilities.

- **CO_2 Reduction / Environmental Performance (Dependent Variable):** Measured as the percentage reduction in carbon dioxide emissions achieved through organizational logistics and supply-chain activities. Higher CO_2 reduction indicates better environmental performance.

- **Organizational Readiness (Moderator):** Measured as a composite construct reflecting the organization's readiness to implement and utilize AI technologies, incorporating IT infrastructure, digital culture, and change-management capability.

- **AI Application Adoption Indicators:** The seven individual AI applications are also examined separately to identify differences in adoption patterns across Low, Medium, and High AI adoption groups. These indicators provide the basis for validating the AI adoption classification and examining its relationship with technology investment and environmental performance.

4. Result & Data Analysis :

4.1 Participant Flow and Response Rates

The survey is administered to organizations operating in logistics-intensive sectors in Western Maharashtra. A total of 500 organizations are approached through the identified sampling frame. The survey response process and derivation of the final sample used for analysis are presented in Table 3.

Table 3 : Survey Response and Final Sample

"Category	Number	Percentage
Total survey invitations sent	500	100.0%
Undelivered/Invalid contacts	18	3.6%
Effective sample reached	482	96.4%
Responses received	152	31.5%
Incomplete responses	21	4.4%
Usable complete responses	131	27.2%
Final sample for analysis	131	100.0%"

The final dataset therefore comprises 131 usable organizational responses. The achieved sample exceeds the minimum target sample of 125 organizations specified in the study design and provides

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an adequate basis for examining AI adoption and its mediating role in the relationship between technology investment and environmental performance.

4.2 Sample Characteristics

The characteristics of the participating organizations and respondents are presented to establish the contextual profile of the sample. Since the present paper focuses specifically on AI adoption, technology investment, environmental performance, and organizational readiness, only the respondent and organizational characteristics relevant to these variables are considered.

4.2.1 Distribution of Organizations by Industry Sector

The participating organizations represent seven major logistics-intensive industry sectors in Western Maharashtra. The achieved distribution closely follows the proportional allocation planned during sampling, with representation from automotive and auto components, logistics and third-party logistics services, pharmaceuticals and chemicals, FMCG and consumer goods, engineering and heavy manufacturing, e-commerce and retail technology, and other manufacturing sectors. The distribution of the sample across the industry sectors is presented in Table 4.

Table 4 : Sample Distribution by Industry Sector

"Industry Sector	Target Sample	Achieved Sample	Achievement (%)
Automotive & Auto Components	21	22	104.8
Logistics & 3PL Services	11	12	109.1
Pharmaceuticals & Chemicals	16	17	106.3
FMCG & Consumer Goods	19	20	105.3
Engineering & Heavy Manufacturing	15	16	106.7
E-commerce & Retail Technology	14	15	107.1
Other Manufacturing	29	29	100.0
Total	125	131	104.8"

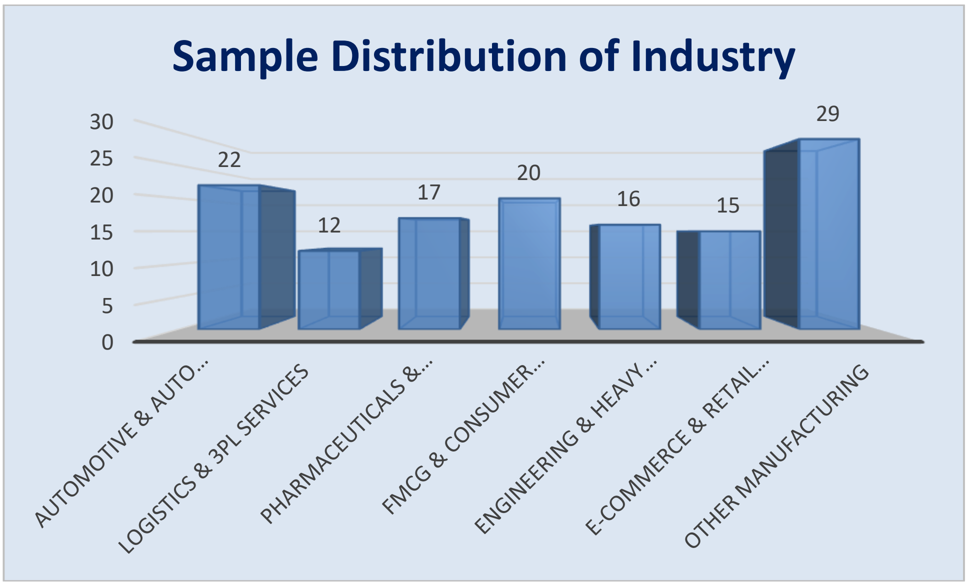

Figure 4 : Sample Distribution By Industry Sector.

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The sample demonstrates adequate representation across the major logistics-intensive sectors of Western Maharashtra. Other Manufacturing constitutes the largest share of the sample (22.1%), followed by Automotive and Auto Components (16.8%), FMCG and Consumer Goods (15.3%), Pharmaceuticals and Chemicals (13.0%), Engineering and Heavy Manufacturing (12.2%), E-commerce and Retail Technology (11.5%), and Logistics and 3PL Services (9.2%).

4.2.2 Organizational Characteristics in terms of Fleet Size &Annual Logistics Expenditure

The participating organizations represent a range of fleet sizes and logistics expenditure levels. In terms of fleet size, 21.4% of organizations operate 20–50 vehicles, 29.8% operate 51–100 vehicles, 25.9% operate 101–200 vehicles, 16.0% operate 201–500 vehicles, and 6.9% operate more than 500 vehicles. Thus, organizations operating 51–200 vehicles constitute the largest proportion of the sample (55.7%), indicating substantial representation of medium- and large-scale fleet operators. Regarding annual logistics expenditure, 23.7% of organizations report expenditure of ₹5–10 crores, 32.8% report ₹11–25 crores, 22.1% report ₹26–50 crores, 13.7% report ₹51–100 crores, and 7.6% report expenditure exceeding ₹100 crores. Overall, 21.3% of organizations incur annual logistics expenditure above ₹50 crores, reflecting considerable variation in the scale and intensity of logistics operations. This organizational diversity provides an appropriate basis for examining differences in technology investment and AI adoption across logistics-intensive organizations in Western Maharashtra.

4.3 Respondents Profile :

4.3.1 Respondent Designation and Functional Role

The survey responses are obtained from professionals directly involved in logistics, supply chain, fleet management, operations, sustainability, and organizational decision-making. Logistics and Supply Chain Managers constitute the largest respondent group (35.9%), followed by Fleet Managers (26.0%), Operations Coordinators (16.8%), Sustainability Officers (9.1%), and other senior management personnel (12.2%). The predominance of respondents occupying logistics- and supply-chain-related positions indicates that the collected responses are informed by individuals with direct knowledge of logistics operations, technology implementation, AI adoption, and sustainability-related practices.

4.3.2 Professional Experience in Supply Chain and Logistics

The respondents demonstrate substantial professional experience in the supply chain and logistics domain. Among the respondents, 13.7% have 0–5 years of experience, 32.1% have 6–10 years, 29.0% have 11–15 years, 16.8% have 16–20 years, 6.1% have 21–25 years, and 2.3% have more than 25 years of experience. Thus, 77.9% of the respondents have more than five years of professional experience, indicating that the majority possess adequate industry exposure to provide informed responses regarding technology investment, AI adoption, and environmental performance.

4.4 Descriptive Statistics of Study Variables

Descriptive statistics are used to summarize the distribution and central tendency of the principal variables included in the proposed mediation model. In accordance with the objectives of the present study, the analysis focuses on AI adoption, technology investment, and environmental performance among the 131 participating organizations. AI adoption is measured through the number of AI-enabled tools used by an organization and categorized into low, medium, and high adoption levels. Technology investment is measured as the percentage of the annual logistics budget allocated to technology, while environmental performance is represented through carbon-

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related indicators, particularly average CO_2 emission intensity and carbon-related savings. The descriptive results provide the empirical baseline for the subsequent mediation and moderated mediation analyses. The descriptive statistics of the principal study variables are presented in Table 5.

Table 5 : Descriptive Statistics of Principal Study Variables

"Variable	N	Minimum	Maximum	Mean	SD
AI Adoption Level	131	1	3	1.89	0.74
Technology Investment (%)	131	1.20	8.50	3.84	1.67
Average CO_2 Emission Intensity (g/km)	131	425.00	890.00	652.84	102.36
Carbon Tax Saved (₹ Lakhs)	131	0.00	48.50	12.64	11.28"

The descriptive results indicate that the organizations demonstrate an **early-to-moderate level of AI adoption**, with a mean AI adoption score of 1.89 (SD = 0.74) on the three-level scale. Technology investment ranges from 1.20% to 8.50% of the logistics budget, with a mean of 3.84% (SD = 1.67), indicating considerable variation in the extent to which organizations allocate resources towards digital and technology-enabled logistics. Environmental performance also varies substantially across organizations, with average CO_2 emission intensity ranging from 425 to 890 g/km and a mean of 652.84 g/km (SD = 102.36). Carbon-related savings range from zero to ₹48.50 lakhs, with a mean of ₹12.64 lakhs (SD = 11.28). These variations provide sufficient dispersion in the principal study variables for examining the proposed relationships among technology investment, AI adoption, and environmental performance.

4.4.1 Distribution of AI Adoption

The distribution of organizations according to their level of AI adoption is presented in Table 6.

Table 6 : Distribution of Organizations by AI Adoption Level

"AI Adoption Level	AI Tools Used	Number of Organizations	Percentage
Low	0–1 tools	46	35.1%
Medium	2–3 tools	53	40.5%
High	4+ tools	32	24.4%
Total	—	131	100.0%"

The distribution shows that 40.5% of organizations fall within the medium AI adoption category, followed by 35.1% with low adoption and 24.4% with high adoption. Thus, nearly three-fourths of the organizations (75.6%) remain within the low-to-medium adoption categories, while approximately one-fourth demonstrate relatively high AI integration. The mean AI adoption score

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of 1.89 further indicates that AI integration is progressing beyond the initial stage but has not yet become widespread across the entire sample. The types of AI tools deployed by the participating organizations are presented in Table 7.

Table 7: Types of AI Tools Deployed

"AI Tool/Application	Number of Companies	Percentage of Total Sample
Demand Forecasting/Predictive Analytics	58	44.3%
Route Optimization Algorithms	52	39.7%
Fleet Maintenance Predictive Analytics	41	31.3%
Driver Behavior Monitoring/Analytics	37	28.2%
Warehouse Automation/Robotics	29	22.1%
Chatbots/Customer Service Automation	24	18.3%
Computer Vision for Load Optimization	16	12.2%
Dynamic Pricing/Freight Rate Optimization	12	9.2%"

Demand Forecasting and Predictive Analytics (44.3%) and Route Optimization Algorithms (39.7%) are the most widely deployed AI applications, reflecting the availability of mature software solutions and clear ROI propositions. Fleet Maintenance Predictive Analytics (31.3%) and Driver Behavior Monitoring (28.2%) show moderate adoption, leveraging telematics data for operational improvements. More advanced applications such as Computer Vision for Load Optimization (12.2%) and Dynamic Pricing (9.2%) remain niche, adopted primarily by technology-forward organizations.

4.4.2 Technology Investment

Technology investment is measured as the percentage of the annual logistics budget allocated to IT and technology-related activities, including software, hardware, analytics, and related digital systems (see table 8) . Across the 131 organizations, technology investment ranges from 1.20% to 8.50%, with a mean of 3.84% (SD = 1.67). The distribution shows moderate positive skewness (0.52), indicating that a larger proportion of organizations operate at relatively lower investment levels, while a smaller group reports considerably higher technology investment.

Table 8 : Technology Investment by AI Adoption Level

"AI Adoption Level	N	Mean Technology Investment (%)	SD
Low	46	2.41	0.92
Medium	53	3.96	1.18
High	32	5.58	1.43
Total	131	3.84	1.67"

A clear increasing pattern is observed between technology investment and AI adoption level. Organizations classified as low AI adopters allocate an average of 2.41% of their logistics budget to technology, compared with 3.96% among medium adopters and 5.58% among high adopters. This progressive increase provides preliminary descriptive evidence of a positive association between technology investment and AI adoption, which is examined statistically in the subsequent mediation analysis.

4.4.3 Environmental Performance

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Environmental performance is assessed using two key indicators: Average CO_2 Emissions per Kilometer and Carbon Tax Saved. As result in table 9 , shows Average CO_2 emissions range from 425 to 890 g/km, with an overall mean of 652.84 g/km (SD = 102.36), indicating considerable variation in emission intensity across the participating organizations. This variation may reflect differences in fleet composition, vehicle age, fuel type, operational practices, and the extent of technology-enabled efficiency measures. Carbon Tax Saved ranges from ₹0 to ₹48.50 Lakhs, with a mean of ₹12.64 Lakhs (SD = 11.28). The relatively high positive skewness (1.12) indicates that carbon savings are concentrated among a smaller proportion of organizations, suggesting differences in the extent to which organizations have implemented emission-reduction initiatives.

Table 9. Environmental Performance Metrics by Industry Sector

"Industry Sector	N	Avg. CO_2 (g/km)	Carbon Tax Saved (₹ Lakhs)
E-commerce & Retail Technology	15	584.67 (94.32)	21.84 (12.46)
FMCG & Consumer Goods	20	612.35 (89.67)	17.52 (11.83)
Pharmaceuticals & Chemicals	17	638.24 (97.85)	14.38 (10.27)
Automotive & Auto Components	22	643.18 (105.42)	13.65 (11.04)
Logistics & 3PL Services	12	679.58 (108.76)	9.47 (8.92)
Engineering & Heavy Manufacturing	16	702.31 (96.58)	7.23 (7.85)
Other Manufacturing	29	714.52 (99.43)	6.81 (7.36)
Total	131	652.84 (102.36)	12.64 (11.28) "

Sector-wise results indicate noticeable differences in environmental performance. E-commerce and Retail Technology records the lowest average CO_2 emissions (584.67 g/km) and the highest carbon tax savings (₹21.84 Lakhs), followed by FMCG and Consumer Goods, with emissions of 612.35 g/km and carbon tax savings of ₹17.52 Lakhs. In contrast, Other Manufacturing reports the highest average emissions (714.52 g/km) and the lowest carbon tax savings (₹6.81 Lakhs), followed by Engineering and Heavy Manufacturing, with emissions of 702.31 g/km and savings of ₹7.23 Lakhs. The findings therefore demonstrate substantial variation in environmental outcomes across sectors. These differences provide an important baseline for examining whether differences in technology investment and AI adoption are associated with improved environmental performance in the subsequent mediation analysis.

4.X Data Screening and Preliminary Checks

Prior to hypothesis testing, the dataset was screened for completeness, outliers, distributional properties, and potential violations of regression assumptions. The final dataset comprised 131 usable organizational responses. Preliminary screening confirmed that missing data were minimal and did not materially affect the analysis. Univariate outliers were assessed using the interquartile range (IQR) approach, and extreme observations were treated through winsorization where

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required. The adequacy of the dataset for subsequent statistical analysis was further assessed through the following checks:

- **Missing Data:** Item-level missingness was below 3% and was appropriately addressed before analysis.

- **Outlier Detection:** The IQR method was used to identify univariate outliers, with extreme values winsorized at the 5th and 95th percentiles where necessary.

- **Multicollinearity:** Correlations among the principal variables remained within acceptable limits. The highest correlation was between AI Adoption and Technology Investment ($r = 0.67$, $p < 0.01$). VIF values ranged from 1.47 to 2.28, with a mean VIF of 1.85, confirming the absence of problematic multicollinearity.

- **Common Method Bias:** Harman's single-factor test was conducted because the study used self-reported organizational data. The first factor accounted for 28.12% of the total variance, which is below the commonly used 50% threshold, indicating that common method bias is unlikely to substantially influence the findings.

- **Sample Adequacy:** The achieved sample of 131 organizations exceeds the minimum requirement of 108 observations estimated for multiple regression with up to eight predictors and provides an adequate basis for the planned mediation analysis.

4.4 Hypothesis Testing and Mediation Analysis

To examine the proposed relationships among technology investment, AI adoption, and environmental performance, correlation and regression-based mediation analysis was conducted. In accordance with the study objectives, AI adoption is considered both an outcome of technology investment and a potential mechanism through which technology investment contributes to improved environmental performance. The mediation analysis follows the regression-based approach proposed by Hayes, where the indirect effect is evaluated using bootstrapped confidence intervals. This approach is particularly appropriate for examining whether the effect of technology investment on environmental performance operates partly through the development and use of AI-enabled supply chain capabilities. Recent research similarly highlights the importance of AI-enabled capabilities in translating digital and technological investments into sustainability outcomes (Makhdoom, 2025).

4.4.1 Effect of AI Adoption on Environmental Performance and Technology Investment on AI Adoption

The initial regression paths required for mediation are examined in table 10 before assessing the indirect effect. The results indicate that Technology Investment has a positive and statistically significant effect on AI Adoption ($\beta = 0.294$, $SE = 0.038$, $t = 7.74$, $p < 0.001$; 95% CI [0.219, 0.369]). This finding indicates that organizations allocating greater resources to technological infrastructure

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and digital capabilities tend to demonstrate higher levels of AI adoption within their supply chain operations. Therefore, the result provides support for H2.

AI Adoption also demonstrates a positive and statistically significant relationship with Environmental Performance, measured in terms of carbon reduction (β = 0.426, SE = 0.072, *t* = 5.92, *p* < 0.001; 95% CI [0.284, 0.568]). The finding indicates that greater adoption of AI-enabled supply chain applications is associated with improved environmental outcomes. AI-based demand forecasting, route optimization, predictive maintenance, driver behaviour monitoring, and other data-driven applications can improve resource utilization and operational efficiency, thereby contributing to emission reduction. Recent empirical research likewise reports that AI-enabled capabilities can contribute to sustainable supply-chain and environmental performance, although the strength of the relationship may vary across organizational and technological contexts (Makhdoom, 2025).

Thus, the result provides empirical support for H1, which proposes that AI adoption has a significant positive effect on environmental performance.

Table 10 : Regression Paths for Technology Investment, AI Adoption and Environmental Performance

"Relationship	β	SE	t	p	95% CI
Technology Investment → AI Adoption	0.294	0.038	7.74	<0.001	0.219–0.369
AI Adoption → Environmental Performance	0.426	0.072	5.92	<0.001	0.284–0.568
Technology Investment → Environmental Performance (Total Effect)	0.384	0.064	6.00	<0.001	0.258–0.510
Technology Investment → Environmental Performance (Direct Effect)	0.259	0.068	3.81	<0.001	0.125–0.393"

Note: Environmental Performance is represented by carbon reduction.

4.4.2 Mediating Role of AI Adoption

The mediating role of AI Adoption is examined using a bootstrapped mediation model, with Technology Investment as the independent variable, AI Adoption as the mediator, and Environmental Performance as the dependent variable. In table 11, the total effect of Technology Investment on Environmental Performance is positive and significant (β = 0.384, SE = 0.064, *t* = 6.00, *p* < 0.001; 95% CI [0.258, 0.510]). After AI Adoption is introduced into the model, the direct effect of Technology Investment remains significant but decreases to β = 0.259 (*p* < 0.001).

More importantly, the indirect effect of Technology Investment on Environmental Performance through AI Adoption is 0.125, with a bootstrap standard error of 0.032 and a 95% bootstrap confidence interval of 0.068 to 0.192. Since the confidence interval does not include zero, the indirect effect is statistically significant. This confirms that AI Adoption significantly mediates the relationship between Technology Investment and Environmental Performance.

The persistence of a significant direct effect alongside a significant indirect effect indicates partial mediation. Approximately 32.6% of the total effect of Technology Investment on Environmental

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Performance operates through AI Adoption (0.125/0.384). Thus, technology investment contributes to environmental performance both directly and indirectly by strengthening organizational AI capabilities.

Table 11 : Mediation Effect of AI Adoption between Technology Investment and Environmental Performance

"Effect	β / Estimate	Boot SE	Boot LLCI	Boot ULCI	Interpretation
Total Effect	0.384	0.064	0.258	0.510	Significant
Direct Effect	0.259	0.068	0.125	0.393	Significant
Indirect Effect through AI Adoption	0.125	0.032	0.068	0.192	Significant; partial mediation"

The findings are consistent with recent research emphasizing that AI can function as an enabling mechanism through which technological capabilities and digital transformation contribute to greener supply-chain processes and sustainability outcomes. For example, recent evidence identifies AI-powered analytics and green technology capabilities as important mechanisms linking GSCM practices with sustainable performance (Makhdoom, 2025). Similarly, recent research on AI-driven sustainability identifies supply-chain integration and operational improvements as mechanisms through which AI capabilities can be translated into environmental and sustainable performance (Dong , 2026).

Accordingly, **H3 is supported**, confirming that AI Adoption significantly mediates the relationship between Technology Investment and Environmental Performance.

4.4.3 AI Adoption Levels and Environmental Performance

To further examine Objective 1, AI adoption levels are assessed using the three AI-adoption categories derived from the organization's use of AI-enabled supply-chain applications (see table 12). The cluster analysis identifies three distinct groups: Low AI Adoption (n = 46; 35.1%), Medium AI Adoption (n = 53; 40.5%), and High AI Adoption (n = 32; 24.4%).

The groups demonstrate clear differences in technology investment and environmental performance. Mean Technology Investment increases from 2.41% of the relevant budget in the low-AI group to 3.96% in the medium-AI group and 5.58% in the high-AI group ($p < 0.001$). Similarly, mean CO_2 reduction increases from 4.28% among low-AI organizations to 7.86% among medium-AI organizations and 12.42% among high-AI organizations ($p < 0.001$).

The pattern provides additional evidence that higher levels of AI adoption are associated with stronger environmental performance. The application-level results also show progressively greater use of demand forecasting, route optimization, predictive maintenance, driver behaviour monitoring, warehouse automation, computer vision, and dynamic pricing/freight optimization across the three AI-adoption groups. These findings are consistent with recent literature identifying

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AI-enabled optimization, analytics, and supply-chain integration as mechanisms capable of supporting greener and more efficient supply-chain operations (Wang, 2026).

Table 12: AI Adoption Levels, Technology Investment and Environmental Performance

"AI Adoption Level	n (%)	Mean Technology Investment (%)	Mean CO_2 Reduction (%)
Low AI Adoption	46 (35.1%)	2.41	4.28
Medium AI Adoption	53 (40.5%)	3.96	7.86
High AI Adoption	32 (24.4%)	5.58	12.42
Significance	—	$p < 0.001$	$p < 0.001$"

4.4.4 Moderating Role of Organizational Readiness

Although the primary analysis focuses on the mediating role of AI adoption, the study further examines whether organizational readiness strengthens the conversion of technology investment into AI adoption. Organizational readiness is considered in terms of IT infrastructure, digital culture, and change-management capability. The moderated mediation analysis is conducted using Hayes' PROCESS approach, with Technology Investment as the predictor, AI Adoption as the mediator, Environmental Performance (CO_2 Reduction) as the outcome, and Organizational Readiness as the moderator. Moderating Effect of Organizational Readiness on Technology Investment–AI Adoption Relationship

Table 13: Moderating Effect of Organizational Readiness on Technology Investment–AI Adoption Relationship

"Effect	β	SE	t	p-value	LLCI	ULCI
Technology Investment → AI Adoption	0.294	0.038	7.74	<0.001	0.219	0.369
Technology Investment × Organizational Readiness → AI Adoption	0.186	0.058	3.21	0.002	0.072	0.300
Technology Investment → AI Adoption at Low Readiness (-1 SD)	0.142	0.052	2.73	0.007	0.039	0.245
Technology Investment → AI Adoption at Mean Readiness	0.294	0.038	7.74	<0.001	0.219	0.369
Technology Investment → AI Adoption at High Readiness (+1 SD)	0.446	—	—	<0.001	—	—"

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Conditional Indirect Effect

To further examine whether organizational readiness influences the indirect effect of Technology Investment on Environmental Performance through AI Adoption, the conditional indirect effects are estimated at low, mean, and high levels of organizational readiness. The conditional indirect effect of technology investment on environmental performance through AI adoption is presented in Table 14.

Table 14: Conditional Indirect Effect of Technology Investment on Environmental Performance through AI Adoption

“Level of Organizational Readiness	Indirect Effect	Boot SE	Boot LLCI	Boot ULCI
Low (-1 SD)	0.060	0.024	0.018	0.112
Mean	0.125	0.032	0.068	0.192
High (+1 SD)	0.190	0.045	0.108	0.284
Index of Moderated Mediation	0.079	0.028	0.028	0.138“

The conditional indirect effect of Technology Investment on Environmental Performance through AI Adoption increases with organizational readiness, from 0.060 at low readiness to 0.125 at mean readiness and 0.190 at high readiness. The Index of Moderated Mediation is 0.079 (Boot SE = 0.028, 95% Boot CI = 0.028–0.138), with the confidence interval excluding zero. This confirms that the indirect relationship varies significantly according to the level of organizational readiness. In practical terms, organizations with stronger readiness are better able to convert technology investment into AI capabilities and subsequently achieve greater environmental performance improvements (Dong , 2026).

This finding extends the mediation result by demonstrating that AI adoption is not only an important mechanism linking technology investment with environmental performance, but the strength of this mechanism also depends on organizational readiness. The result is consistent with the broader technology-adoption literature, which emphasizes that technological investment alone may not generate equivalent organizational outcomes unless adequate infrastructure, capabilities, and organizational preparedness are present (Tornatzky & Fleischer, 1990; Mikalef et al., 2019).

Discussion and Findings :

The results in study demonstrate that AI adoption has an important role in strengthening GSCM and environmental performance among logistics-intensive organizations in Western Maharashtra. The results corresponding to Objective 1 show that organizations differ considerably in their level of AI maturity, with 35.1% classified as low AI adopters, 40.5% as medium adopters, and 24.4% as high adopters. High-adoption organizations show substantially greater use of demand forecasting (84.4%), route optimization (81.3%), fleet maintenance analytics (71.9%), and driver behaviour

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monitoring (68.8%). This indicates that organizations are increasingly using AI for operational areas that directly support efficiency and resource optimization, while more advanced applications such as computer vision and dynamic freight optimization remain comparatively less adopted. This pattern is consistent with Ferreira and Reis (2023), who identify AI as an important enabler of forecasting, decision-making, visibility, and operational improvement in supply chains.

The findings further support H1, demonstrating a significant positive relationship between AI adoption and environmental performance. Mean carbon reduction increases from 4.28% in the low-AI group to 7.86% in the medium-AI group and 12.42% in the high-AI group ($p < 0.001$). Sector-level results also show variation in environmental outcomes, with E-commerce and Retail Technology reporting the lowest average CO_2 emissions (584.67 g/km) and highest carbon-tax savings (₹21.84 lakh), whereas Other Manufacturing reports 714.52 g/km and ₹6.81 lakh, respectively. These findings indicate that greater AI adoption is associated with more effective resource utilization and emission reduction and are consistent with Lin et al. (2024), who highlight the contribution of AI-enabled capabilities and green innovation to environmental performance.

The results also support H2, as technology investment increases consistently across AI-adoption levels, from 2.41% of the logistics budget among low-AI organizations to 3.96% among medium-AI and 5.58% among high-AI organizations ($p < 0.001$). More importantly, the mediation analysis provides support for H3. Technology investment significantly predicts AI adoption ($\beta = 0.294$, $p < 0.001$), while AI adoption significantly predicts carbon reduction ($\beta = 0.426$, $p < 0.001$). The indirect effect of technology investment on environmental performance through AI adoption is 0.125, with a 95% bootstrap confidence interval of 0.068–0.192, which excludes zero. The direct effect remains significant ($\beta = 0.259$, $p < 0.001$), confirming partial mediation, with approximately 32.6% of the total effect operating through AI adoption. Thus, the findings suggest that technology investment contributes to environmental improvement not only directly but also by enabling organizations to develop AI-based capabilities. This is consistent with evidence that digitalization and green supply-chain capabilities can strengthen sustainable organizational performance (Le et al., 2024).

The additional analysis of organizational readiness further strengthens this interpretation. The interaction between technology investment and organizational readiness is significant ($\beta = 0.186$, $p = 0.002$), while the conditional indirect effect increases from 0.060 at low readiness to 0.190 at high readiness. The index of moderated mediation is 0.079 (95% CI: 0.028–0.138), indicating that organizations with stronger technological infrastructure, digital culture, and change-management capability are better able to convert technology investment into AI adoption and subsequent environmental benefits. Overall, the findings establish that technology investment provides the resource base, organizational readiness facilitates its effective utilization, and AI adoption acts as the key mechanism through which these resources contribute to improved environmental performance in GSCM.

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Theoritical Implications :

The study contributes to the emerging literature on AI-enabled Green Supply Chain Management by establishing a technology–capability–performance relationship. The findings indicate that technology investment does not influence environmental performance solely through a direct pathway; rather, a substantial part of its effect operates through AI adoption. This supports a capability-oriented interpretation of digital transformation in which technological resources acquire environmental value when organizations develop the capabilities required to utilize them effectively. A second theoretical contribution is the positioning of AI adoption as a mechanism within the GSCM–environmental performance relationship. Existing literature has increasingly examined digitalization, AI, and sustainable supply chains, but the present findings provide empirical evidence that AI adoption can function as an intermediate organizational capability connecting technology investment with measurable environmental outcomes. This extends recent research that identifies AI and digital technologies as important enablers of sustainable supply-chain transformation.

Finally, the additional organizational-readiness analysis indicates that the effectiveness of technological investment depends partly on the organizational context in which it is implemented. This provides a more nuanced theoretical explanation of AI-enabled sustainability by showing that technological resources, organizational capability, and environmental outcomes are interconnected rather than independent phenomena.

Practical Implications for Industry

- Prioritize high-impact AI applications: Organizations should initially focus on demand forecasting, route optimization, predictive maintenance, and driver-behaviour monitoring because these applications show comparatively higher adoption and direct operational relevance.

- Link technology budgets with sustainability targets: Technology investment decisions should be evaluated not only in terms of productivity but also in terms of measurable outcomes such as fuel efficiency, emissions reduction, and carbon savings.

- Build AI capability progressively: Organizations with low AI maturity can adopt a phased approach, moving from basic predictive applications towards advanced automation, computer vision, and dynamic freight optimization.

- Strengthen organizational readiness: Investment in IT infrastructure, employee digital capabilities, and change-management capacity should accompany AI investment to ensure that technological resources are effectively converted into AI capabilities.

- Target high-emission sectors: The sectoral differences indicate greater improvement potential among sectors reporting higher emissions and lower carbon savings. Such organizations can prioritize AI-enabled logistics optimization as part of their GSCM strategies.

- Monitor environmental outcomes: AI implementation should be evaluated using measurable environmental indicators such as CO_2 emissions per kilometre and carbon savings rather than adoption level alone.

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Strengths & limitations :

Strengths

The study has several strengths. First, it focuses specifically on logistics-intensive organizations in Western Maharashtra, providing context-specific evidence from an important industrial and commercial region. Second, the study integrates AI adoption, technology investment, and environmental performance within a single analytical framework rather than examining these variables independently. Third, the use of mediation analysis provides evidence regarding the mechanism through which technology investment contributes to environmental performance. Fourth, the classification of organizations into low-, medium-, and high-AI adoption groups provides additional empirical evidence regarding differences in technological maturity and environmental outcomes. Finally, the study combines organizational characteristics and sector-level environmental indicators, strengthening the practical relevance of the findings.

Limitations

The study also has certain limitations. The cross-sectional design limits the ability to establish temporal causality between technology investment, AI adoption, and environmental performance. The study is geographically restricted to Western Maharashtra; therefore, the findings may not be directly generalizable to organizations operating in other Indian regions or different national contexts. In addition, several organizational measures are based on survey responses and may therefore be influenced by reporting or response bias. Environmental performance is represented primarily through carbon-related indicators, whereas other dimensions of environmental sustainability, such as water consumption, waste generation, and resource circularity, are not examined in detail. Future research can address these limitations through longitudinal studies, larger multi-region samples, and objective environmental performance data.

Conclusions of the study :

The study demonstrates that Artificial Intelligence has an important role in strengthening Green Supply Chain Management and environmental performance among logistics-intensive organizations in Western Maharashtra. The findings corresponding to the first objective show substantial variation in AI maturity, with organizations distributed across low-, medium-, and high-adoption categories. The high-AI group demonstrates considerably greater adoption of predictive analytics, route optimization, predictive maintenance, and other AI-enabled supply-chain applications.

The study further establishes a significant positive relationship between AI adoption and environmental performance. Carbon reduction increases from 4.28% among low-AI organizations to 12.42% among high-AI organizations, indicating that greater AI maturity is associated with stronger environmental outcomes. Technology investment also increases systematically across AI maturity levels, from 2.41% to 5.58%, supporting the role of technological investment as an important foundation for AI-enabled GSCM.

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Most importantly, the mediation analysis confirms that AI adoption significantly mediates the relationship between technology investment and environmental performance. The indirect effect is 0.125 (95% CI: 0.068–0.192), while the direct effect remains significant, establishing partial mediation. Approximately 32.6% of the total effect of technology investment on carbon reduction operates through AI adoption. The additional organizational-readiness analysis further shows that this pathway becomes stronger when organizations possess greater readiness to implement and utilize digital technologies.

Overall, the findings justify the central argument of the study that AI adoption is not merely a technological trend within GSCM but an important organizational capability through which technology investment can be translated into measurable environmental improvements. The study therefore contributes to the growing evidence that intelligent, data-driven supply-chain practices can support the transition towards more efficient and environmentally sustainable logistics systems.

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