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OPTIMIZING DELIVERY ROUTES, ENHANCING SUPPLY CHAIN EFFICIENCY, AND INVESTING IN INFRASTRUCTURE: A STRATEGIC APPROACH TO REDUCING CARBON EMISSIONS FROM THE TRANSPORT SECTOR

Summary. The main objective of this research is to get a better understanding of the carbon emissions produced by last-mile delivery, the impact of various vehicle types on these emissions, effective route efficiency, the role of urban infrastructure, and the optimization strategies in reducing emissions in Pakistan's transportation sector by using data from 1996 to 2022. It examines economic and environmental benefits. The ARDL results show that distribution route optimization reduces emissions over time, while alternative energy consumption, distribution density,

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and infrastructure investment reduce transportation emissions. Optimizing delivery routes reduced transportation emissions over time, demonstrating the importance of sustainable logistics in environmental issues. Granger causality estimations show that delivery density affects route optimization, infrastructure investment, supply chain efficiency, and alternative energy use. This shows how environmental sustainability methods rely on one another. A variance decomposition analysis indicates that alternative energy consumption, distribution density, and infrastructure investment will likely affect transport emissions variance over time. The research recommends that logistics businesses, governments, and politicians improve last-mile delivery operations and dramatically cut carbon emissions. The study provides practical solutions to environmental issues in urban goods transportation in Pakistan and advances sustainable logistics management.

Keywords: transport emissions, last mile delivery, route optimization, delivery density, supply chain efficiency, infrastructure investment, ARDL technique

1. INTRODUCTION

In the current age of environmental concerns and climate change, the transport sector is under more scrutiny because of its greenhouse gas emissions. Energy efficiency and transport emissions are major challenges for this business [1]. The global transportation network powers the modern economy. Thus, delivery routes must be efficient. [2] argue that this optimization is essential to reduce the transportation sector's environmental impact and make logistical operations more profitable. Studies suggest that feeder buses and their rapid transit systems reduce oil and traffic, improving energy efficiency. Predictive algorithms and smart meters can optimize delivery routes and reduce redelivery, saving time and energy. [3] found that energy-saving strategies for automated guided vehicles, hybrid optimization algorithms for vehicle routing problems, and non-intrusive energy optimization for industrial robots could reduce energy consumption and increase efficiency. Deep reinforcement learning systems also optimize delivery paths and efficiency [4]. In the long term, optimal transportation distribution routes may enhance Asian energy efficiency.

Vehicle pollution is substantially impacted by urban transportation density. [5] found that longer work trip travel times and urban density-induced traffic congestion increase emissions. Although denser cities have lower emissions per capita, population density reduces emissions. Another purpose of urban planning and design is to reduce car usage, transport, and greenhouse gas emissions. In regions with high job and residential density and good public transit, commuters may travel less and use fewer cars. Higher urban transport density has positives and downsides for transportation emissions [6]. Addressing these positives and downsides requires sustainable urban planning and transportation strategies. A "bottom-up" theoretical computation of transport carbon emissions and a basic distribution model of intermodal land use near rail transit stations may boost urban transport density and reduce emissions [7]. A linear model based on a complex network approach can predict how emissions would affect urban street network air pollution. Innovative urban space management, such as UAVs with mobile vision systems, will enhance transport management and reduce emissions. [8] suggests adding freight-specific data to transport models and imposing regulatory limits to reduce urban freight CO_2 emissions. When combined, these strategies may reduce trip emissions and increase urban transportation density.

Hydrogen technologies, energy-efficient, low-emitting cars, and their electrification or hybridization reduce transportation emissions. [9] suggests that these decisions may reduce local emissions and global warming. Non-coal fuels should be utilized to reduce emissions and improve public health. Emissions control and carbon pricing may decrease air pollutants, including CO_2. Due to the impact of economic development and energy consumption on goods movement, comprehensive energy and environmental restrictions are needed [10]. Emerging countries reduce emissions by increasing public transport usage. The rapid adoption of electric vehicles (EVs), standardized charging infrastructure, and government promotions may reduce tailpipe emissions.

Supply chain efficiency reduces carbon emissions in city delivery's final stages. A well-managed supply chain allows stakeholders to cooperate, resulting in optimal routing, reduced congestion, and improved logistical performance [11]. Carbon emissions decrease due to more efficient vehicle utilization and less damaging delivery routes. Supply chain efficiency is essential for reducing urban carbon emissions during late delivery. Smart transport systems and sophisticated logistical equipment may enhance road safety, traffic management, and real-time tracking [12]. Energy-efficient products and flexible production may reduce supply chain environmental impacts and energy consumption. A carbon emissions taxation scheme that considers supply chain power structures and cost efficiency is needed to meet sustainability targets. The manufacturer's contract design may reduce carbon abatement knowledge asymmetry losses [13].

The interaction prompted these research questions. First, *how do distribution density-optimized supply routes affect carbon emissions?* Efficient routes and increasing delivery density led to more condensed deliveries, which decreases emissions. This might reduce the environmental impact of each delivery to its utmost. Secondly, *how do the utilization of alternative energy sources and investments in infrastructure affect the efficiency of the supply chain, and subsequently, how do they influence the carbon emissions associated with last-mile delivery?* The reduction of carbon emissions in the final mile of delivery might be achievable through supply chain efficiency enhancements brought about by strategic infrastructure investments and the adoption of alternative energy sources. Lastly, *how does the level of investment in urban infrastructure influence the connection between vehicle type and carbon emissions?* Strategic infrastructure investments, especially those supporting alternative energy usages, may influence the effectiveness of different vehicle types in achieving sustainable last-mile delivery practices, considering the unique urban environments in Pakistan. The study has the following research objectives, i.e.,

I. Analyze the impact of delivery route optimization and density on carbon emissions in last-mile delivery in Pakistan.
II. Investigate the influence of alternative energy consumption and infrastructure investment on supply chain efficiency and carbon emissions in last-mile delivery in metropolitan areas of Pakistan.
III. Examine the effects of urban infrastructure investment on vehicle types and carbon emissions in Pakistan, focusing on alternative energy consumption.

After the introduction, Section 2 presents the literature review. Methodology is outlined in Section 3. Results are detailed in Section 4. Finally, Section 5 concludes the study.

2. LITERATURE REVIEW

Delivery route optimization is essential for lowering carbon emissions and other environmental issues. [14] found that improving express delivery station distribution routes may minimize carbon emissions. It can minimize pollutants and carbon emissions while delighting consumers and maximizing economic profits by improving cold-chain vehicle distribution patterns. Optimizing trash collection routes may reduce operational costs and carbon emissions. Environmental expenses and delivery delay penalties must be considered while optimizing low-carbon logistics delivery routes. This reduces delivery costs and carbon emissions [15]. Optimizing routes can save costs and emissions in carbon tax programs. This applies notably to delivery and pickup trucks working together. For these reasons, improving delivery routes reduces carbon emissions. It has many other positive effects on cold-chain distribution, express delivery stations, and waste management systems, which promote economic growth and ecological stability. According to [16], electric bus charging stations may be strategically located to minimize operating costs and emissions. [17] examines whether direct measurement technology can monitor port emissions for accurate carbon accounting and regulatory compliance. It investigates novel monitoring techniques to reduce carbon emissions. The first hypothesis of the study is as follows:

H1: Delivery route optimization is anticipated to result in a reduction of carbon emissions.

Delivery density considerably impacts carbon emissions. Delivery vehicle carbon emissions may be reduced by increasing road density or reducing warehouse distance. The CO_2 efficiency of delivery services compared to personal transport depends on the emissions ratio and customer density. Personal travel is best for a few consumers and has low emissions, whereas delivery services are best for many customers and have low emissions. More customers per car are needed to build more prosperous routes. Ground vehicles become more energy-efficient as deliveries grow [18]. A Chinese study reveals a U-shaped relationship between per capita express delivery volumes and transportation sector CO_2 emissions, suggesting an optimal delivery density to reduce emissions [19]. Consolidating distribution density reduces emissions and costs. Distribution density optimization employing strategic techniques reduces carbon emissions significantly and may minimize transportation-related carbon emissions. The second hypothesis of the study is as follows:

H2: An increase in delivery density is expected to correlate with higher carbon emissions due to the elevated energy consumption inherent in logistics activities.

Alternative energy affects carbon emissions considerably. Increasing renewable energy use may reduce carbon emissions per capita over time. [20] found that economic growth and nonrenewable energy aggravate environmental degradation, whereas renewable energy reduces it. These findings emphasize the need to lower carbon emissions and prevent climate change by promoting alternative energy sources. The third hypothesis of the study is as follows:

H3: The utilization of alternative energy sources within logistics activities is projected to improve efficiency and subsequently decrease carbon emissions.

GHG emissions are greatly affected by supply chain efficiency. Supply chain components may reduce their environmental impact and energy consumption by 50% by employing more energy-efficient products, more flexible production methods, and better product quality [21]. Sustainable supply chain development and shared facility investments reduce carbon emissions and boost income. Supply chain management that considers production and transportation carbon emissions may enhance solutions and decrease emissions. Improved supply chain efficiency reduces carbon emissions. Hence, efficient coordination throughout the supply chain system may help meet emissions objectives [22]. These findings demonstrate the importance of supply chain efficiency for sustainable operations and carbon reduction. The fourth hypothesis of this study is as follows:

H4: Enhancing supply chain efficiency is anticipated to lead to a reduction in carbon emissions.

Carbon emissions are strongly impacted by infrastructure spending. Building information infrastructure may reduce emissions directly and indirectly via technology innovation. Rail infrastructure has a negligible impact on carbon emissions, whereas air transport infrastructure significantly increases them [23]. [24] found increasing CO_2 emissions due to the relationship between rail transport infrastructure and GDP. Cities that efficiently invest in infrastructure have fewer carbon emissions and greater production. However, inefficiently spending cities emit more carbon and produce less. Additionally, rigorous environmental rules are essential to achieve emissions reduction objectives during significant public infrastructure investment. Strict environmental rules, public infrastructure coordination, and information infrastructure building may harness infrastructure investment to reduce carbon emissions [25]. Despite sizeable public infrastructure investments, rigorous environmental restrictions are needed to meet carbon reduction objectives. Investment in information infrastructure reduces the direct and indirect impacts of technological innovation on carbon emissions. [26] found that coordinating public infrastructure supply with environmental regulations may reduce emissions and pollutants. Investments in renewable energy, energy storage, clean mobility, carbon capture, and zero-emission power generation may help decarbonize and reduce carbon emissions. By using climate-smart infrastructure and sustainable practices, infrastructure developments may minimize carbon emissions and climate change. The study's final hypothesis is as follows:

H5: Investments in infrastructure are expected to have a mitigating effect on carbon emissions.

Table 1 shows the research gaps extracted from the past literature.

Tab. 1

Research Gaps and Study Contributions Based on Previous Literature Support

Authors	**Research gaps and study's contribution**
[27]	The referenced article leans towards technological advancements for traffic forecasting, while our study places a greater emphasis on the sustainability aspects of last-mile delivery operations. The study extends beyond technological advancements in traffic forecasting by emphasizing the sustainability aspects of last-mile delivery operations, particularly investigating the impact of vehicle types and route efficiency on carbon emissions reduction.
[28]	While the referenced study focuses on route optimization using a modified Ant Colony Optimization algorithm, our study takes a broader approach,

Authors	Research gaps and study's contribution
	exploring the interplay of multiple factors, including vehicle types and urban infrastructure, for sustainable last-mile delivery operations.
[29]	The referenced study concentrates on the operational challenges of incorporating new mobility-assist elements into e-grocery delivery, addressing vehicle routing complexities with a focus on mixed vehicles and load-dependent considerations. Our study analyzed the role of delivery route density and infrastructure investment to move forward towards the decarbonization agenda.
[30]	The referenced study focused on developing a methodology for prioritizing best practices in a Brazilian parcel delivery service as a case study. Our study differs in its specific objectives and approaches for analyzing sustainable last-mile delivery optimization, which are lacking in the cited study.
[31]	While the cited study focuses on route optimization in heterogeneous fleets, our study explores sustainability aspects and the interplay of various factors, broadening the scope beyond vehicle routing to include urban infrastructure and environmental considerations.
[32]	The reference study has a broader focus on reviewing trends in environmentally sustainable solutions for urban last-mile deliveries in the e-commerce market. Our study takes a more focused and investigative approach by exploring the interplay of factors related to green supply chain efficiency and route optimization in designing for a carbon neutrality agenda.
[33]	In contrast to the integration-focused approach of the referenced study, our research emphasizes sustainable last-mile delivery operations by examining the impact of vehicle types and route efficiency on carbon emissions reduction, contributing unique insights to the field.
[34]	Our study builds upon the challenges identified in the referenced literature by investigating last-mile delivery optimization strategies under stochastic travel times, offering novel solutions to address uncertainties in delivery operations.
[35]	Our study complements the vehicle routing-focused approach of the cited study by exploring green supply chain management processes for improving logistics activities, providing valuable insights into sustainable last-mile delivery operations.
[36]	The referenced study presents a literature review that focuses on sustainability practices in urban routing and identifies gaps in the related literature and suggests directions for future research, concluding that the economic dimension is the prominent driver among the three pillars of sustainability. Investigating the interaction of many aspects in last-mile delivery optimization, our research takes a deep and exploratory approach.
[37]	Our research promotes sustainable last-mile delivery operations by considering factors like carbon emissions reduction and urban infrastructure, unlike the referenced study's focus on strategy and solution selection.

2.1. Theoretical Framework

2.1.1. Pigouvian Taxation (or Pigouvian Subsidies)

Emission taxes, a kind of Pigovian taxation, may decrease pollution by considering external costs and encouraging emission reduction. Making pollution charges internally motivates polluters to cut emissions and utilize greener technologies [38]. Group size and communication dynamics affect Pigovian taxes like the "average Pigouvian tax" (APT). Battery electric vehicle (BEV) traffic restriction exemptions are Pigovian taxes that promote uptake and sustainability. Pigovian tariffs reduce fossil fuel usage by reflecting the social and environmental costs of waste. However, tax rates and subsidies must be adjusted, and customized taxes are impracticable [39]. Many Pigovian tax versions have been proposed to address carbon emissions and social issues. A carbon tax strategy maximizes social welfare and strives to improve society and individual conduct. Multi-agent reinforcement learning methods like the Learning Optimum Pigovian Tax (LOPT) may enhance societal welfare by approaching optimum taxes [40]. Pigovian taxes may cut carbon emissions and address social concerns.

2.1.2. Porter's Environmental Hypothesis

The Porter hypothesis states that well-designed environmental limitations may increase corporate performance and innovation, although its significance varies by location. Environmental policy bribery in underdeveloped nations may reduce regulatory costs and boost innovation, defying Porter's theory [41]. Tax rebates and incentives in China may boost green investment among enterprises affected by environmental restrictions. Despite an increase in local green patents, China's urban environmental policies did not increase green total factor production. Well-designed environmental policies may increase technological innovation and competitiveness. [42] suggest that environmental rules may enhance a company's environmental investment and profitability, particularly for socially backed activities. Environmental restrictions may impact industrial innovation. However, environmental policy bribes might damage regulatory measures without detection [43]. Environmental regulations may affect environmentally aware innovation as political institutions grow. Even if environmental regulations increase green patents, factor productivity may not increase. Legal restrictions may affect the total production of the green factor. Porter's hypothesis has pros and cons when applied to how environmental limits affect innovation and productivity.

Based on the mentioned theoretical framework, Figure 1 shows the conceptual framework of the study for ready reference.

Figure 1 illustrates that achieving sustainable last-mile delivery optimization entails reducing carbon emissions associated with delivery route optimization, delivery density, and alternative energy usage. Supply chain efficiency and infrastructure investment act as mediators in this relationship, facilitating progress toward the decarbonization agenda.

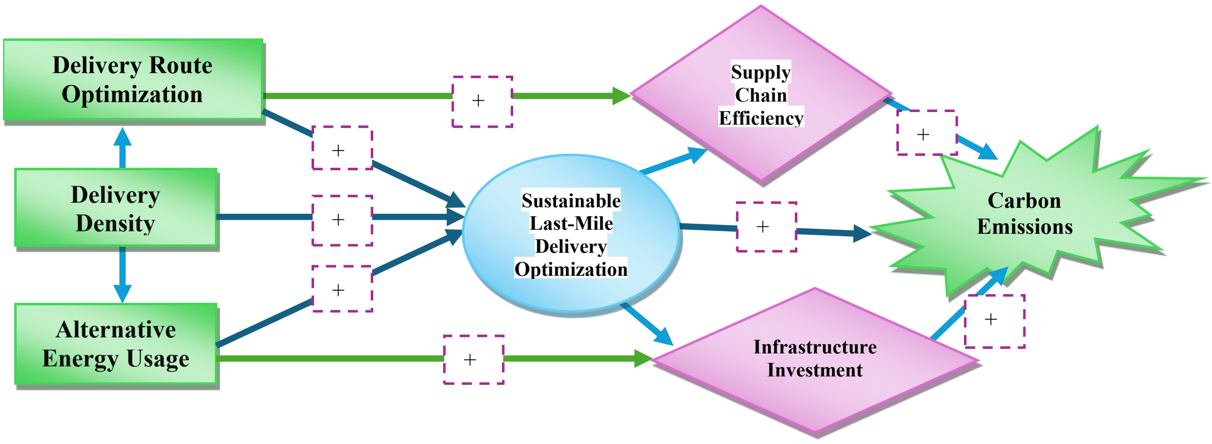

Fig.1. Conceptual Framework

3. DATA AND METHODOLOGY

The study includes the following variables for empirical analysis, i.e.,
Dependent Variable:
- Carbon Emissions from Transport (TCO2): This crucial variable measures last-mile delivery CO_2 emissions. The World Development Indicators database provides statistics on transportation CO_2 emissions as a % of total fuel use [44].

Independent Variables:

1) Delivery Route Optimization (DRO): It measures delivery route efficacy by average distance, number of stops, and delivery time. Transport Efficiency (% of commercial service exports) is an indirect delivery route optimization statistic that is used in this study.
2) Delivery Density (DD): Higher distribution density may enhance delivery efficiency and carbon emissions. The urban population density, measured in people per square kilometer, indicates a region's density. It shows a city's population density and delivery options. The requirement for last-mile delivery services is correlated with urban population density, which influences their efficacy and environmental impact.
3) Alternative Energy Usage (AEU): The proportion of a country's or region's energy consumption from renewable sources indicates how much electricity we utilize and how many green technologies are employed. Green energy usage has declined since transitioning to more efficient and renewable energy sources reduces transportation emissions. Thus, the study used renewable energy consumption (% of total energy use) as a proxy for the AEU variable.
4) Supply Chain Efficiency (SCE): It indicates a supply chain's ability to optimize resources and processes, which impacts environmental sustainability. SCE optimizes transport routes to reduce carbon emissions by reducing unnecessary mileage and fuel use. Sustainable practices, simpler customs processes, and cutting-edge technology contribute to SCE. The goal of high SCE is an efficient supply chain that maximizes economic efficiency and minimizes environmental impact. The logistics performance indicator is used as a proxy for SCE in this study.

5) Infrastructure Investment (INVEST): Quality urban infrastructure, including roads and traffic management, may affect mobility and carbon emissions. Gross Fixed Capital Formation (GFCF, constant 2015 US$) represents the total value of fixed assets, such as buildings, infrastructure, and equipment, that are used for production. The higher the GFCF, infrastructure, the more infrastructure improvements may increase or decrease carbon emissions.

Pakistan has several economic sectors, making it a booming economy. Researching emerging economies is essential due to their unique opportunities and risks. Pakistan's urbanization, infrastructural constraints, and population dispersion make last-mile delivery difficult. [45] found that last-mile distribution is vital in emerging countries like Pakistan. Due to its involvement in global supply chains, notably in textiles and manufacturing, the country's last-mile delivery impact on international trade must be examined. Pakistan's study may assist in understanding last-mile distribution's environmental implications and create sustainable approaches. [46] note that expanding markets like Pakistan's last-mile deliveries reveal how mobile applications and other transportation modes are being implemented. Additionally, selecting Pakistan's economy involves other crucial factors: a) Pakistan's economic diversity may help us understand how economic sectors and regions affect last-mile delivery [47], b) Pakistan, a South Asian country, may provide insight into how regional connectivity, trade agreements, and cross-border logistics affect last-mile delivery [48], c) Consumer behavior, preferences, and demands impact last-mile delivery strategies and efficiency; Pakistan's diverse and large population may provide insight into these aspects [49], and d) Pakistani last-mile delivery technology illuminates technological advances, challenges, and successful methods.

3.1. Econometric Framework

The Augmented Dickey-Fuller (ADF) unit root test, crucial for empirical demonstrations, was used to determine stationarity from time series data. The basic ADF test in time series analysis may determine whether a series is stationary. This evaluation is essential for accurate forecasting. After data differencing, we may test the stationarity hypothesis if the time series does not have a unit root. For regression analysis modeling tool selection, the ADF test determines data trendiness or stochasticity. Policymaking and strategic planning benefit from the ADF test's illumination of long-term economic determinants. Equations (1) to (7) show the ADF formulation of the given model, i.e.,

$$\Delta(TCO2)_t = \alpha + \beta(TIME) + \gamma(TCO2)_{t-1} + \delta_1\Delta(TCO2)_{t-1} + ... + \delta_{p-1}\Delta(TCO2)_{t-p-1} + \varepsilon_t \tag{1}$$

$$\Delta(DRO)_t = \alpha + \beta(TIME) + \gamma(DRO)_{t-1} + \delta_1\Delta(DRO)_{t-1} + ... + \delta_{p-1}\Delta(DRO)_{t-p-1} + \varepsilon_t \tag{2}$$

$$\Delta(DD)_t = \alpha + \beta(TIME) + \gamma(DD)_{t-1} + \delta_1\Delta(DD)_{t-1} + ... + \delta_{p-1}\Delta(DD)_{t-p-1} + \varepsilon_t \tag{3}$$

$$\Delta(AEU)_t = \alpha + \beta(TIME) + \gamma(AEU)_{t-1} + \delta_1\Delta(AEU)_{t-1} + ... + \delta_{p-1}\Delta(AEU)_{t-p-1} + \varepsilon_t \tag{4}$$

$$\Delta(SCE)_t = \alpha + \beta(TIME) + \gamma(SCE)_{t-1} + \delta_1\Delta(SCE)_{t-1} + ... + \delta_{p-1}\Delta(SCE)_{t-p-1} + \varepsilon_t \tag{5}$$

$$\Delta(INVEST)_t = \alpha + \beta(TIME) + \gamma(INVEST)_{t-1} + \delta_1\Delta(INVEST)_{t-1} + ... + \delta_{p-1}\Delta(INVEST)_{t-p-1} + \varepsilon_t \tag{6}$$

Where,
TCO2: Carbon emissions from transport
DRO: Delivery route optimization
DD: Delivery density

AEU: Alternative energy use
SCE: Supply chain efficiency
INVEST: Infrastructure investment, and
Δ, t, and ƹ show difference operator, time, and error term, respectively.

[50-51] introduced ARDL models, which have various advantages over other methods. Unlike other cointegration approaches, the ARDL does not need all variables to be integrated in the same sequence. Any order of integration – fractionally integrated, zero-order, and one-order – can be used with the ARDL approach. Second, unlike sensitive cointegration approaches, the ARDL test may be employed with small samples. Thirdly, the ARDL technique, known for its reliability, generally yields unbiased long-run model estimates and reliable t-statistics even with endogenous regressors. [51] made many assumptions while developing limits testing. The dependent variable must equal I(1), there must be no degenerate circumstances, and the independent variables must not be external to the model. A generalized F-test for all lagged level variables and a t-test for the dependent variable's lagged level were suggested by [51] as cointegration tests. These tests must assume an I(1) dependent variable to avoid degenerate scenarios. Degenerate occurrences arise when the error correction term's dependent or independent variable lagged levels are statistically irrelevant. In the degenerate lagged dependent variable and independent variable(s) cases, the delayed values of the dependent and independent variables are less essential. Cointegration is incorrect because this partial error correction factor leaves the residual gap unbridged. Overall, the F-test significance implies that the lag levels of the variables are jointly significant when executing the limits test. Lagged levels of the dependent variable or independent variable may explain the F-test's statistical significance. A t-test for the dependent variable's lagged level is needed to rule out a degenerate lagged dependent variable. Assuming the dependent variable is I(1), supplemental eliminates degenerate lagged independent variable(s). The lagged level dependent variable must be substantial for the ARDL equation to become a Dickey-Fuller equation. This delayed dependent variable term's relevance shows I(0) is the dependent variable. Finally, [51] introduced the ARDL limits cointegration evaluation approach. Traditional cointegration tests do not support regressors with unknown or mixed integration orders, I(0) or I(1), while this technique does. However, the ARDL limits test may show degenerative non-cointegration. Equation 7 shows the ARDL model specification, i.e.,

$$\begin{aligned}\ln(TCO2)_t &= \alpha_0 + \sum_{i=1}^{p}\phi_i \Delta \ln(TCO2)_{t-i} + \sum_{i=0}^{q}\theta_i \Delta \ln(DRO)_{t-i} + \sum_{i=0}^{r}\theta_i \Delta \ln(DD)_{t-i} + \sum_{i=0}^{t}\varphi_i \Delta \ln(AEU)_{t-i} \\ &+ \sum_{i=0}^{u}\varphi_i \Delta \ln(SCE)_{t-i} + \sum_{i=0}^{v}\varphi_i \Delta \ln(INVEST)_{t-i} + \delta_1 \ln(DRO)_t + \delta_2 \ln(DD)_t + \delta_3 \ln(AEU)_t + \delta_4 \ln(SCE)_t \\ &+ \delta_5 \ln(INVEST)_t + \varepsilon_t \end{aligned} \tag{7}$$

Where Δ shows difference operator.

The ARDL paradigm requires all variables' lagged coefficients to be significant for an unconstrained error correction equation to be cointegrated. The general F-statistic relevance does not establish cointegration since it does not exclude degenerate cases. A t-test on the dependent variable's lagged level may identify the degenerate lagged dependent variable scenario in Pesaran et al.'s ARDL limits test. If I(1) is the dependent variable, degenerate lagged independent variables are irrelevant. This may be used alongside [51]'s other two tests to examine the degenerate lagged independent variable(s) scenario. By loosening the assumption of an I(1) dependent variable, we may assess cointegration and delayed independent variable tests:

- H0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$
- H1: $\delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq 0$

Equation (8) shows the error correction term (ECT) within the ARDL formulation for robust inferences.

$$\begin{aligned}\ln(TCO2)_t &= \alpha_0 + \sum_{i=1}^{p}\phi_i \Delta\ln(TCO2)_{t-i} + \sum_{i=0}^{q}\theta_i \Delta\ln(DRO)_{t-i} + \sum_{i=0}^{r}\theta_i \Delta\ln(DD)_{t-i} + \sum_{i=0}^{t}\varphi_i \Delta\ln(AEU)_{t-i} \\ &+ \sum_{i=0}^{u}\varphi_i \Delta\ln(SCE)_{t-i} + \sum_{i=0}^{v}\varphi_i \Delta\ln(INVEST)_{t-i} + \delta_1\ln(DRO)_t + \delta_2\ln(DD)_t + \delta_3\ln(AEU)_t + \delta_4\ln(SCE)_t \\ &+ \delta_5\ln(INVEST)_t + \lambda(ECT) + \varepsilon_t\end{aligned} \tag{8}$$

Where λ shows the adjustment parameter.

Equation (9) shows the VAR specification of Granger causality specification to assess cause-and-effect relationships between the studied variables, i.e.,

$$\begin{bmatrix}\ln(TCO2)_t\\ \ln(DRO)_t\\ \ln(DD)_t\\ \ln(AEU)_t\\ \ln SCE)_t\\ \ln INVEST)_t\end{bmatrix} = \begin{bmatrix}\tau_0\\ \tau_1\\ \tau_2\\ \tau_3\\ \tau_4\\ \tau_{45}\end{bmatrix} + \sum_{i=1}^{p}\begin{bmatrix}\sigma_{11t}\sigma_{12t}\sigma_{13t}\sigma_{14t}\sigma_{15t}\\ \sigma_{21t}\sigma_{22t}\sigma_{23t}\sigma_{24t}\sigma_{25t}\\ \sigma_{31t}\sigma_{32t}\sigma_{33t}\sigma_{34t}\sigma_{35t}\\ \sigma_{41t}\sigma_{42t}\sigma_{43t}\sigma_{44t}\sigma_{45t}\\ \sigma_{51t}\sigma_{52t}\sigma_{53t}\sigma_{54t}\sigma_{55t}\\ \sigma_{61t}\sigma_{62t}\sigma_{63t}\sigma_{64t}\sigma_{65t}\end{bmatrix} \times \begin{bmatrix}\ln(TCO2)_{t-1}\\ \ln(DRO)_{t-1}\\ \ln(DD)_{t-1}\\ \ln(AEU)_{t-1}\\ \ln(SCE)_{t-1}\\ \ln(INVEST)_{t-1}\end{bmatrix} \tag{9}$$

$$+ \sum_{j=p+1}^{d\max}\begin{bmatrix}\theta_{11j}\theta_{12j}\theta_{13j}\theta_{14j}\theta_{15j}\\ \theta_{21j}\theta_{22j}\theta_{23j}\theta_{24j}\theta_{25j}\\ \theta_{31j}\theta_{32j}\theta_{33j}\theta_{34j}\theta_{35j}\\ \theta_{41j}\theta_{42j}\theta_{43j}\theta_{44j}\theta_{45j}\\ \theta_{51j}\theta_{52j}\theta_{53j}\theta_{54j}\theta_{55j}\\ \theta_{61j}\theta_{62j}\theta_{63j}\theta_{64j}\theta_{65j}\end{bmatrix} \times \begin{bmatrix}\ln(TCO2)_{t-j}\\ \ln(DRO)_{t-j}\\ \ln(DD)_{t-j}\\ \ln(AEU)_{t-j}\\ \ln(SCE)_{t-j}\\ \ln(INVEST)_{t-j}\end{bmatrix} + \begin{bmatrix}\varepsilon_1\\ \varepsilon_2\\ \varepsilon_3\\ \varepsilon_4\\ \varepsilon_5\\ \varepsilon_6\end{bmatrix}$$

Equations (10) to (15) show multivariate Granger causality system, i.e.,

$$TCO2_t = c_1 + \sum_{i=1}^{2}\delta_1 DRO_{t-i} + \sum_{i=1}^{2}\delta_2 DD_{t-i} + \sum_{i=1}^{2}\delta_3 AEU_{t-i} + \sum_{i=1}^{2}\delta_4 SCE_{t-i} + \sum_{i=1}^{2}\delta_5 INVEST_{t-i} + \varepsilon \tag{10}$$

$$DRO_t = c_1 + \sum_{i=1}^{2}\delta_1 TCO2_{t-i} + \sum_{i=1}^{2}\delta_2 DD_{t-i} + \sum_{i=1}^{2}\delta_3 AEU_{t-i} + \sum_{i=1}^{2}\delta_4 SCE_{t-i} + \sum_{i=1}^{2}\delta_5 INVEST_{t-i} + \varepsilon \tag{11}$$

$$DD_t = c_1 + \sum_{i=1}^{2}\delta_1 DRO_{t-i} + \sum_{i=1}^{2}\delta_2 TCO2_{t-i} + \sum_{i=1}^{2}\delta_3 AEU_{t-i} + \sum_{i=1}^{2}\delta_4 SCE_{t-i} + \sum_{i=1}^{2}\delta_5 INVEST_{t-i} + \varepsilon \tag{12}$$

$$AEU_t = c_1 + \sum_{i=1}^{2}\delta_1 DRO_{t-i} + \sum_{i=1}^{2}\delta_2 DD_{t-i} + \sum_{i=1}^{2}\delta_3 TCO2_{t-i} + \sum_{i=1}^{2}\delta_4 SCE_{t-i} + \sum_{i=1}^{2}\delta_5 INVEST_{t-i} + \varepsilon \tag{13}$$

$$SCE_t = c_1 + \sum_{i=1}^{2} \delta_1 DRO_{t-i} + \sum_{i=1}^{2} \delta_2 DD_{t-i} + \sum_{i=1}^{2} \delta_3 AEU_{t-i} + \sum_{i=1}^{2} \delta_4 TCO2_{t-i} + \sum_{i=1}^{2} \delta_5 INVEST_{t-i} + \varepsilon \tag{14}$$

$$INVEST_t = c_1 + \sum_{i=1}^{2} \delta_1 DRO_{t-i} + \sum_{i=1}^{2} \delta_2 DD_{t-i} + \sum_{i=1}^{2} \delta_3 AEU_{t-i} + \sum_{i=1}^{2} \delta_4 SCE_{t-i} + \sum_{i=1}^{2} \delta_5 TCO2_{t-i} + \varepsilon \tag{15}$$

The study applied impulse response function (IRF) and variance decomposition analysis (VDA) to assess the direction and magnitude between the variables for the next 10 years' time period. The variance shocks over the time period are accessed by the variables used in the study, which helps to suggest inter-temporal policy implications for the country.

4. RESULTS AND DISCUSSION

Table 2 provides the descriptive statistics of the study variables. For transport emissions (TCO2), the mean value is approximately 27.735 metric tons per kilometer, with a standard deviation of 1.599. The distribution exhibits negative skewness (-1.260) and positive kurtosis (3.699), indicating a left-skewed distribution with heavier tails and greater peakness than a normal distribution.

Tab. 2

Descriptive Statistics

Methods	TCO2	AEU	DD	DRO	INVEST	SCE
Mean	27.735	47.956	66068466	42.472	5.13E+08	2.393
Maximum	29.701	53.130	88979079	67.524	1.20E+09	2.697
Minimum	23.268	42.100	44041395	11.083	17000000	2.080
Std. Dev.	1.599	2.916	13387792	16.818	5.08E+08	0.183
Skewness	-1.260	0.040	0.001	-0.565	0.573	0.383
Kurtosis	3.699	2.214	1.836	2.098	1.463	2.477

Alternative energy use (AEU) has a mean of approximately 47.956 megawatt-hours and a standard deviation of 2.916. The skewness is close to zero (0.040), suggesting a relatively symmetrical distribution, while the kurtosis (2.214) indicates less peakness compared to carbon emissions. Delivery density (DD), measuring the number of deliveries per unit area, has a mean of approximately 66,068,466 with a standard deviation of 13,387,792. Both skewness and kurtosis values are close to zero, indicating an approximately symmetrical distribution with less peakness compared to variables like carbon emissions and alternative energy use. Delivery route optimization (DRO), representing the average distance traveled per delivery, has a mean of approximately 42.472 kilometers and a standard deviation of 16.818. The distribution shows slight left-skewness (-0.565) and less peakness (kurtosis = 2.098) compared to carbon emissions. Infrastructure investment (INVEST) has a mean of approximately 5.13E+08 (5.13 billion) and a standard deviation of 5.08E+08 (5.08 billion). The skewness (0.573) and kurtosis (1.463) values suggest a slightly right-skewed distribution with less peakness compared to carbon emissions. Regarding supply chain efficiency (SCE), the mean turnover rate is approximately 2.393 with a standard deviation of 0.183. The skewness (0.383) and kurtosis

(2.477) indicate a slightly right-skewed distribution with greater peakness compared to a normal distribution.

Table 3 shows the ADF unit root estimates and reveals that both the TCO2 and AEU variables display non-stationarity at the intercept level, indicating a trend component in their original series. However, after taking the first difference, both CO_2 and AEU series become stationary, suggesting they are integrated of order 1 (I(1)).

Tab. 3

Unit Root Estimates

Variables	Level		First difference		Decision
	Intercept	**Intercept and Trend**	**Intercept**	**Intercept and Trend**	
TCO2	-1.384 (0.574)	-1.604 (0.764)	-4.313 (0.002)	-4.288 (0.012)	I(1)
AEU	-1.832 (0.358)	-2.689 (0.249)	-3.873 (0.007)	-3.896 (0.028)	I(1)
DD	1.576 (0.999)	-5.343 (0.001)	-3.856 (0.008)	-3.451 (0.070)	I(0)
DRO	0.528 (0.984)	-3.321 (0.085)	-4.738 (0.001)	-4.807 (0.004)	I(0)
INVEST	-1.502 (0.517)	-1.227 (0.883)	-5.189 (0.000)	-5.248 (0.001)	I(1)
SCE	-2.370 (0.159)	-2.272 (0.433)	-4.804 (0.001)	-4.740 (0.005)	I(1)

A small bracket shows the probability value.

In contrast, the DD and DRO variables demonstrate stationarity at the intercept level, implying no trend component in their original series. Additionally, both the INVEST and SCE variables exhibit non-stationarity at the intercept level but achieve stationarity after differencing, indicating they are also integrated of order 1 (I(1)).

Table 4 displays the lag length selection criteria and reveals that the likelihood ratio (LR), FPE, AIC, SC, and HQ for lag 1 are all statistically significant, suggesting that incorporating a lag enhances the model's fit compared to a lag of 0. Therefore, based on the lag length selection criteria, the study employed lag 1 for ARDL estimation.

Tab. 4

Lag Length Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1168.145	NA	6.76e+31	90.31883	90.60916	90.40244
1	-978.4921	277.1848*	5.40e+26*	78.49939*	80.53170*	79.08462*

* indicates lag order selected by the criterion

ARDL estimates' short- and long-run coefficients are in Table 5. A negative and statistically significant coefficient for the error correction term (-0.438; p = 0.0012) suggests a 43.8% correction per year. ARDL calculations help us understand how explanatory variables impact transport emissions (TCO2) in the short and long run. When using alternative energy sources, the coefficient reduces transportation emissions statistically. Alternative energy sources may increase emissions due to carbon emissions during manufacturing or conversion. However, the alternative energy sources employed may affect this connection [52]. The delivery density coefficient shows a short-term positive and statistically significant influence on transport emissions. Per capita express delivery volumes initially boost emissions before decreasing, demonstrating that China's express delivery company has increased carbon emissions. Denser delivery operations need more trucks and fuel, which increases emissions. [53] emphasize the importance of transport efficiency in sustainable urban development. A negative association between carbon emissions and the delivery route optimization coefficient is seen in the short term despite not being statistically significant. Route optimization aims to reduce pollutants and fuel consumption; though the results are reasonable, the efforts may have needed to be revised or crucial factors disregarded. In the short run, infrastructure expenditures reduce transport emissions statistically. Energy-intensive construction and operation procedures may explain the link between infrastructure investment and emissions. Infrastructure projects' environmental implications may vary in scale [54].

Tab. 5

ARDL Estimates

Dependent Variable: D(CO_2)				
Selected Model: ARDL(1, 1, 1, 1, 1, 1)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(AEU)	0.318005	0.118542	2.682633	0.0179
D(DD)	1.96E-06	4.83E-07	4.057836	0.0012
D(DRO)	-0.031892	0.035537	-0.897431	0.3847
D(INVEST)	1.16E-09	5.23E-10	2.219727	0.0435
D(SCE)	0.297408	0.948027	0.313712	0.7584
CointEq(-1)*	-0.438933	0.108023	-4.063316	0.0012
Long Run Coefficients				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
AEU	0.823807	0.158802	5.187639	0.0013
DD	-1.29E-07	6.01E-08	-2.139052	0.0697
DRO	-0.105009	0.037010	-2.837352	0.0251
INVEST	4.49E-09	6.65E-10	6.744138	0.0003
SCE	3.505123	1.815174	1.931012	0.0948
C	-17.87753	12.52093	-1.427812	0.1964

The long-run estimates examine the variables' equilibrium linkages and effects over time. Alternative energy sources reduce transport emissions over time. This shows that switching to renewable energy sources decreases emissions, reflecting the decarbonizing power systems and balancing environmental concerns, energy independence, and economic development [55]. Carbon emissions and delivery density (DD) are strongly inversely related over time. Higher delivery densities increase transportation-related emissions in the short term, despite technological advances, consumer behavior changes, and new urban planning methods that may reduce these environmental impacts. For delivery route optimization, the coefficient shows a statistically significant long-term negative effect on carbon emissions. Because it increases distribution efficiency and reduces travel, it may reduce carbon emissions. Route planning may reduce chain supermarket distribution expenses, including travel and carbon emissions [56]. Joint delivery models may lower operational costs, carbon emissions, and customer satisfaction by improving horizontal cooperation and resource pooling across express businesses. Long-term route optimization improves transport and logistics, reducing emissions and energy use. Delivery route optimization reduces emissions and maintains the environment by reducing wasted time and vehicle utilization. Long-term infrastructure expenditures reduce transport emissions statistically. Long-term investment in energy-intensive infrastructure projects increases emissions [57]. However, infrastructure investment decisions must include environmental sustainability and economic growth tradeoffs. Green infrastructure solutions that reduce emissions and optimize resource utilization are also needed.

Comparing short-run and long-run coefficients may reveal a lot about evolving correlations and impacts on transportation emissions. AEU and INVEST reduce emissions, but their effects may vary, highlighting the complexities of energy transitions and infrastructure development. Comparing the short- and long-term relationships between DD, DRO, and emissions shows that environmental impacts must take temporal dynamics and socioeconomic context into consideration. These comparisons have improved our understanding of carbon emission drivers, and we need sustainable development plans and integrated policy frameworks to alleviate environmental concerns and improve people's economic and social situations. DRO's relevance and negative coefficient will reduce carbon emissions over time. Optimization of delivery routes reduces trip time and improves distribution efficiency. Chain supermarket route planning may reduce travel and carbon emission costs [58]. Resource pooling and horizontal cooperation in joint delivery models may minimize operational costs and carbon emissions for express enterprises. This boosts client satisfaction. Table 6 displays Granger causality estimates for convenience.

Tab. 6

Granger Causality Estimates

Null Hypothesis	F-Statistic	Prob.
DD →AEU	4.75328	0.0205
DRO →DD	9.41670	0.0013
DD →DRO	4.38472	0.0264
INVEST → DD	4.07474	0.0328
DD →SCE	9.92583	0.0010

→ shows one-way linkages between the variables

DD has a unidirectional causal association with AEU (F-statistic = 4.753 and p-value of 0.020). Changes in delivery density influence both delivery service demand and delivery company operations; hence, they affect alternative energy consumption. [59] suggest that collaborative distribution and speedy delivery utilizing new energy vehicles may reduce carbon emissions and increase vehicle load rates. There is a bidirectional relationship between DD and DRO, which implies that changes in DRO may precede and influence changes in DD; conversely, changes in DD may precede and have significant predictive power over changes in DRO. [60] found that customer demand and delivery patterns optimize routes. Changes in infrastructure investment may anticipate or impact changes in DD (a directional relationship between the two variables), as shown by the relationship between INVEST Granger and DD (F-statistic = 4.074, p = 0.032). Infrastructure development increases product and service dispersion, lowering transportation costs [61]. Finally, considering that DD Granger induces SCE, we show that DD changes may precede and strongly predict SCE changes (F-statistic 9.925, p-value 0.001). Changes in DD may impact or precede changes in SCE, suggesting a one-way directional relationship between them.

The IRF projections in Table 7 demonstrate that AEU will cut transport emissions from 2026 to 2031.

Tab. 7

IRF Estimates

Response of TCO2						
Years	**TCO2**	**AEU**	**DD**	**DRO**	**INVEST**	**SCE**
2024	0.748640	0	0	0	0	0
2025	0.619255	0.295877	-0.026535	-0.304699	0.368766	0.125223
2026	0.433358	-0.022265	0.061183	-0.289095	0.458233	0.148294
2027	0.257253	-0.156756	0.117107	-0.252786	0.492535	-0.093380
2028	0.093947	-0.065828	0.139197	-0.249090	0.544305	-0.185876
2029	-0.003293	-0.111272	0.138362	-0.176705	0.503714	-0.058373
2030	-0.076204	-0.179523	0.088816	-0.083803	0.371873	0.003912
2031	-0.150600	-0.100281	0.047693	-0.024197	0.265060	-0.041077
2032	-0.185757	0.014358	0.074376	0.037336	0.224058	-0.036566
2033	-0.174883	0.051483	0.139161	0.121794	0.192371	0.023943

Delivery density and infrastructure investment are expected to increase transport emissions over the next 10 years. DRO is initially projected to decrease transport emissions from 2025 to 2031, but it is expected to rise afterward. SCE is expected to decrease transport emissions from 2027 onward until 2032, after which it is expected to increase. As the analysis progresses, the responses of the variables to shocks evolve, indicating a complex interplay between carbon emissions and the factors influencing them. These insightful outcomes contribute to a deeper understanding of the dynamics within the system and can inform strategies for managing and mitigating carbon emissions effectively. Table 8 shows the VDA estimates.

Tab. 8

VDA Estimates

Variance Decomposition of TCO2							
Years	**S.E.**	**TCO2**	**AEU**	**DD**	**DRO**	**INVEST**	**SCE**
2024	0.748640	100	0	0	0	0	0
2025	1.129910	73.93601	6.857031	0.055149	7.272011	10.65157	1.228228
2026	1.335769	63.42828	4.934160	0.249258	9.887309	19.38968	2.111317
2027	1.484573	54.35303	5.109516	0.824039	10.90395	26.70454	2.104929
2028	1.621529	45.89502	4.447664	1.427618	11.49954	33.65178	3.078378
2029	1.717338	40.91730	4.385060	1.921883	11.31096	38.60479	2.860013
2030	1.772146	38.61041	5.144233	2.056021	10.84576	40.65725	2.686330
2031	1.802233	38.03032	5.283524	2.057977	10.50469	41.47415	2.649337
2032	1.827900	38.00250	5.142352	2.166149	10.25347	41.82006	2.615472
2033	1.856404	37.73195	5.062564	2.662086	10.37145	41.61954	2.552408

The results suggest that infrastructure investment is likely to exert the greatest variance shocks on transport emissions, with a magnitude of 41.619%, followed by DRO, AEU, DD, and SCE with variance shocks of 10.371%, 5.062%, 2.662%, and 2.552%, respectively, for the next 10 years. These variables demonstrate varying degrees of impact, with infrastructure investment and delivery route optimization showing particularly notable contributions. As we progress towards later periods, the contributions of alternative energy use, delivery density, and supply chain efficiency also become more apparent. However, transport emissions remain the primary driver of variance throughout the analyzed period, indicating their central role in the dynamics of the system.

5. CONCLUSIONS AND POLICY RECOMMENDATIONS

The escalating environmental issues and ecological concerns require strict control over transport emissions. Our study on sustainable last-mile delivery optimization represents a critical stride toward fostering environmentally responsible transportation practices. The results show a strong negative correlation between CO_2 and DD, underscoring the potential for emission reduction through increased delivery density, while the significant negative correlation between CO_2 and DRO highlights the importance of efficient route planning. However, the weak positive correlation between CO_2 and INVEST suggests the necessity for strategic environmental interventions alongside investment efforts. Furthermore, the Granger causality estimates unveil directional relationships among key variables, emphasizing the influence of delivery density on alternative energy use and the reciprocal nature of the relationship between delivery density and route optimization. The significant relationship between infrastructure investment and delivery density highlights the role of infrastructure development in optimizing last-mile delivery operations. Additionally, fluctuations in delivery density significantly influence supply chain efficiency, underlining the importance of targeted interventions to enhance operational efficiencies and minimize environmental impacts. Through proactive measures and technological innovations, stakeholders can navigate towards a greener, more efficient last-mile delivery system, aligning with broader sustainability goals while fostering economic prosperity and societal well-being.

To increase urban delivery efficiency and sustainability, a comprehensive collection of short-, medium--, and long-term policy statements may be created. Offering incentives for delivery route merging is needed to encourage logistics companies to cooperate immediately. Price schemes that incentivize off-peak delivery may achieve this aim while lowering peak-hour emissions and congestion. Advanced routing algorithms and real-time tracking technologies will improve route planning and resource use, while urban loading and unloading zones will ease last-mile delivery. Delivery drivers may reduce fuel use and emissions by taking eco-driving courses and obtaining incentives. Land-use laws and zoning constraints should soon favor mixed-use buildings and higher-density cities, making neighborhoods more walkable and reducing long-distance commuting. Public-private partnerships that invest in shared mobility solutions may diversify transport options and reduce last-mile delivery dependency on individual car ownership. Congestion pricing and low-emission zones encourage cleaner mobility by charging vehicles for their emissions. Real-time traffic data in delivery management systems may improve route choices, delivery delays, and emissions. Regulations should support transit-oriented development and pedestrian-friendly infrastructure to keep cities small and sustainable. Public transit improvements may reduce delivery reliance on private cars and improve mobility. Telecommuting and flexible scheduling may alleviate travel congestion and promote sustainable delivery. Encouraging innovative ecosystems to develop autonomous vehicles and drones will transform last-mile logistics and reduce emissions.

Digital infrastructure investments and smart city infrastructure interoperability standards may optimize delivery routes and demand pattern prediction. To reinforce transport networks against climate-related hazards, a circular economy model and infrastructure investment objectives must be linked to adaptation goals. Circular economy principles across the supply chain may optimize resource use and minimize environmental impact. This will improve urban delivery sustainability.

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