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Population Density: An Underlying Mechanism Between Road Transportation and Environmental Quality

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Mounting degradation in the environmental quality (EQL), specifically from the transport industry, is a big threat and challenge for sustainable development. The transport sector's emission has gained researchers' attention on climate change and transportation because of its increasing share in global emission. This study, thus, aims to analyze the links among road infrastructure (RIN), road transport energy consumption (RTEC), and environmental quality with the moderating role of population density (PDN). The study has used a dataset of five South Asian countries from 1971 to 2014. The study applies the Breusch–Pagan LM test to identify the issue of cross-sectional dependence. CIPS (second-generation unit root test) is applied to check the stationarity properties of the data, whereas the Westerlund (Oxf. Bul. Econ. Stat., 2007, 69 (6), 709–748) co-integration test is used to confirm the long-run association among the variables. Moreover, a fully modified ordinary least square (FMOLS) model is applied to analyze the effect that road transportation has on environmental quality. The study finds a positive effect of road infrastructure, road density (RDN), energy intensity (EIN), and road transport energy consumption on transport-generated emissions, which indicates that road transportation is harmful to environmental quality. Our results confirm the significant moderating role of population density in strengthening the relations of road infrastructure, road transport energy consumption, and environmental quality. It is concluded that population density works as a bridge between road infrastructure, road transport energy consumption, and environmental quality, which helps capture a strong impact of road transportation. We offer the planners of road transportation with a novel and practical approach to examine population density changes policy in the growing countries to analyze the environmental quality.

Keywords: road infrastructure, road transport energy consumption, energy intensity, population density, environmental quality, road transportation and environment quality

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1 INTRODUCTION

The road transport infrastructure (RTIN) is considered a primary tool to promote economic growth (EGR) in countries. Worldwide transport is altering all human life aspects, from trade to culture, manufacturing, research, education, defense, and entertainment, among others. Parallel to industrial and agricultural sectors (Elahi et al., 2021b; Elahi et al., 2022a; Elahi et al., 2022b), the South Asian countries are typically conscious of the transport sector's strength which is effectual in transmuting the resources into communication and knowledge. The effects (both direct and indirect) of transportation favorably contribute to development and EGR of a region (Maparu and Mazumder, 2017; Mohmand et al., 2017). Liddle (2012) shows that transportation has long-term links with income. Liddle and Lung (2013), in another research, recognized that a unidirectional causality transforms from EGR to transportation energy.

Besides the significance of RTIN in EGR, it also contributes toward a lower environmental quality (EQL). The mounting degradation in EQL, specifically from the transport industry, is a big threat and challenge for sustainable development in the South Asian nations. The transport sector's emission has gained researchers' attention on climate change and transportation because of its increasing share in global emission and tenacious development (Timilsina and Shrestha, 2009). Climate change has a negative impact on the ecosystem (Tran et al., 2018; Abid et al., 2019; Elahi et al., 2019b; Elahi et al., 2021a). World travel will grasp "about 115-trillion travelers and freight taken by 2050 or double that of 2010 passenger levels." This travel of passengers accounts for nearly 70% of this increase, with an inclination in travelers and truck movements accounting for about one-half of the total estimated growth of passenger travel. About 90% of estimated inclinations in global travel are probable in the regions. Likely to the industrial sector (Tu et al., 2019; Zhao et al., 2020; Peng et al., 2021), the transportation sector remains a prime cause of CO_2 emission (CO_2E) in many nations regardless of the datum that its share of overall regional CO_2E has stayed constant at nearly 10% over last 25 periods (Cai et al., 2012; Shahbaz et al., 2015; Aggarwal and Jain, 2016). Many studies have reported that environmental emissions damage human health (Gu et al., 2019; Gu et al., 2020a; Gu et al., 2020b). **Figure 1** shows the trends in CO_2E from the transport of selected South Asian economies.

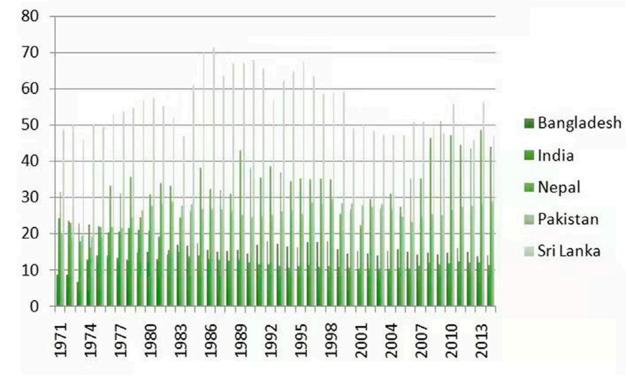

FIGURE 1 | CO_2 emission from transport.

Preceding studies described the transportation industry's contribution to increasing environmental degradation globally. Chandran and Tang (2013) explained that transport energy consumption (TEC) produces CO_2, which changes due to variations in weather. Moreover, online shopping caused a decline in GHG (greenhouse gas) emissions from transportation (Liu et al., 2016), and road transportation also enhances CO_2E. The automobiles driven by gasoline produce 32.6% CO_2E, whereas freight automobile motorized by gasoline light and the vehicles powered by diesel generates 25% and 12% CO_2E, respectively (Solís and Sheinbaum, 2013). Shahbaz et al. (2015) concluded that TEC inclines CO_2E in Tunisia. Andreoni and Galmarini (2012) also claimed that TEC enhances CO_2E in Eurostat. Liddle and Messinis (2015) examined GDP growth and transport-related emissions in 84 cities. Their findings indicated that at the first stage, per capita emission inclines, and after a specific period of time, it starts declining at an observed level of income. It is evidenced that with other things remaining equal, the population growth leads to a rise in emissions in the transportation industry, and the speed of this inclination can further be enhanced by promoting road transportation (Kharbach and Chfadi, 2017).

Only a few studies have been conducted on emissions from road transport. Road transport is a major factor that contributes to carbon footprints of the road traffic industry, and the reduction in carbon footprints has become a primary purpose of the sustained policy of transportation (Zhang et al., 2014). The road infrastructure (RIN) impacts CO_2E as the road-added value, and RIN enhances CO_2E. The increasing road transport energy consumption (RTEC) continuously threatens national and international energy security (Shahbaz et al., 2015). Energy efficiency and fuel rates play a crucial role in decreasing CO_2E produced from road traffic (Talbi, 2017; Sheng et al., 2019; Zhong et al., 2020; Zhong et al., 2021).

RIN and RTEC are crucial factors in EGR. They are the prime contributors to road traffic CO_2E, specifically in the South Asian countries. However, population density (PDN) is also a crucial factor that enhances CO_2E (Wu et al., 2021; Zhao et al., 2021). As the population grows, it causes a surge in the number of vehicles and fuel demands, which accelerates CO_2E. The PDN not only enhances human activities but also causes an increase in the growth of household income (Peterson, 2017). A larger populace needs a large amount of energy in the form of coal, natural gas, and electricity for continual living and work (Peng et al., 2020; Zhang et al., 2020; Tahir et al., 2021; Peng et al., 2022). Because of South Asia's rising populace in the last decades, the region has become a high CO_2 emitting region. The regions' diverse modes of transportation and escalating RIN call for examining region CO_2E from its road transport through PDN. Thus, we expect a significant moderating effect of PDN in the nexus of RTEC, RIN, and EQL.

The growing number of traffic vehicles in the South Asia region boosts the RTEC, which has opposing effects on the EQL. However, the phenomenon of CO_2E from road traffic is overlooked in the existing debate in the context of South Asian countries. Thus, we aim to seek the impact of road transportation on EQL in the South Asian context. Why this study chooses the context of South Asian countries is interesting. A rapid increase in the modes of transport lacking with the quality fuel successively enhances the issue of environmental pollution, which tries to resolve the problems cited above. Environmental sustainability is imperative in each economic sector (Huo et al., 2022). A rise in energy demand leads toward a surge in coal usage (Peng et al., 2018; Shen et al., 2019). The growing usage of oil, electricity, natural gas, and crude oil in the road traffic sector is the prime reason for adverse climate effects (Dingil et al., 2019). The rise in energy consumption highlights the links between RTEC and EQL. Since 2000, the mean growth rate of coal has been 13%, showing that coal energy consumption has inclined over time. Natural gas is increasing at a mean annual rate of about 10%. Thus, to eliminate tragic climate changes, we essentially need to eliminate (or at least play down) the usage of road energy (Peng et al., 2021; Wang et al., 2021). Thus, this study aims to analyze the links among RTEC, energy intensity (EIN), RIN, road density (RDN), and EQL with the moderating role of PDN.

We contribute to the debate in the following ways. First, the RTEC and RIN are the chief antecedents of EGR. Regardless of the contribution to economy, on the other hand, these determinants also pollute the environment. Due to production shifting, emissions have been reduced in some nations. RTEC and RIN are still extreme contributors of transport-generated emissions (TGE), more specifically in South Asia. Most of the available empirical research studies emphasize on the total energy consumption from the road traffic sector. We, thus, mainly emphasize on RTEC and RIN. Second, as established earlier, a larger populace needs a large amount of energy in the form of coal, natural gas, and electricity for continual living and work (Peng et al., 2019). Because of South Asia's rising populace in the last decades, the region has become a high CO_2 emitting region. The regions' diverse modes of transportation and escalating RIN call for examining the regions' CO_2E from its road transport. Thus, we contribute to the debate by analyzing the PDN as a moderating variable in the relations of RTEC, EIN, RIN, RDN, and EQL. Third, to the best of our knowledge, this is the first attempt to examine transport-generated emissions in South Asian nations' scenario.

The remainder part of this article is divided as follows: **Section 2** presents the literature review and establishes hypotheses; **Section 3** details the data, methods, and research techniques; and **Sections 4**, **5** present results and analysis and conclusion with implication and future avenues, respectively.

2 LITERATURE REVIEW

2.1 Road Infrastructure, Road Density, and Environmental Quality

Several scholars have conducted their studies to identify the antecedents of CO_2E, which is the greatest contributor to the deterioration in EQL. Several factors have been explored by researchers as either positively or negatively contributing to the level of CO_2E. However, TGE received limited attention from researchers. TGE have the biggest share in deteriorating the EQL. Transport infrastructure is a key element that promotes the EGR of a nation. Global transport changes the different aspects of human lives. However, an increase in transportation is also aligned with many negative externalities in the form of increasing ecological footprints, transport-generated GHG emissions, and so on (Demir et al., 2015).

Undoubtedly, an increase in RIN leads to an increase in RDN. For instance, one road will be used for more vehicles, eventually increasing TGE, which is detrimental for the EQL (Poudenx, 2008). Surprisingly, researchers gave limited attention to this area. Only a few studies have reported some linkages between RIN, RDN, and EQL. For instance, Sharifi et al. (2021) tested the empirical connection between RIN and EQL and stated that RIN is significantly related to the level of CO_2E. They mentioned in their study that efficient RIN guarantees improved EQL. At the same time, they emphasized on the fact that efficient fuels or green CNGs must be used in vehicles. Ahmed et al. (2020) conducted a study in the context of India to explore the drivers of TGE. They identified that RIN is one of the most critical driving factors of TGE because the greater the lengths of the road, the more vehicles have to be driven there, which will consume more energy and resultantly lead to an increase in CO_2E.

Rasool et al. (2019) also confirmed that transport energy deteriorates the environment. The study concluded that the more the length of the road, the more energy will be used, which will impose adverse effects on the EQL. Dingil et al. (2019) stated that an increase in transportation demands imposes intimidating effects on energy usage and accessibility. If there are more vehicles on the road, there will be an increase in TGE. Hence, an increase in RDN is positively aligned with an increase in TGE. Zhang et al. (2019) reported that the more there is traffic on the road, the more will be the CO_2E. Henceforward, the results suggested a positive affiliation among RDN, RIN, and CO_2E. After reviewing the abovementioned literature, we propose the following:

H_1: "There exists a positive relationship between RIN and TGE."
H_2: "There exists a positive relationship between RDN and TGE."

2.2 Road Transport Energy Consumption, Energy Intensity, and Environmental Quality

A vast amount of research has been found in the available body of knowledge that has scrutinized the role of RTEC and EIN in the level of CO_2E. Researchers believe that a higher level of RTEC and EIN leads toward a high level of CO_2E. They proved it empirically by conducting research on different nations using diverse econometric techniques. There is never-ending literature on the nexus among these variables. Therefore, we reported some recent studies only. Emir and Bekun (2019) conducted a study on Romania and investigated the role of EIN on the level of CO_2E. The results showed a positive affiliation between EIN and CO_2E. Yaw Naminse and Zhuang (2018) revealed similar findings in the case of China. The transport sector is highly responsible for high EIN because the fuel used in the voiceless constitutes a large amount of energy produced from conventional or unclean sources. Chandran and Tang (2013) researched that RTEC constitutes a substantial share of the level of CO_2E. Shahbaz et al. (2015) also found that RTEC positively contributes to the level of GHG emissions, and hence, the authors declared RTEC as a significant determinant of CO_2E. Andreoni and Galmarini (2012) studied the determinants of Eurostat's CO_2E and found that intense energy consumption is one of the major determinants of adverse EQL, specifically, if it is produced from unconventional sources (e.g., fossil fuels).

Aggarwal and Jain (2016) found that the transport sector remains a major determinant of GHG emissions in most of the countries, and traffic generated constitutes around 4.2% of the global CO_2E. Zhang et al. (2017) provided empirical evidence from Pakistan that EIN plays a substantial role in increasing the level of CO_2E and temperature in the environment. Solís and Sheinbaum (2013) found that a vehicle powered by "gasoline" accounts for almost a 33% share of the CO_2E. Hence, the study declared that RTEC is a detrimental factor for the global EQL. Rasool et al. (2019) explained that intense energy consumption produced from unclean sources is the biggest contributor to the level of GHG emissions. They reported that the transportation sector of Pakistan is the second major sector that relies on unclean and conventional sources of energy. According to their findings, the transport sector accounts for a 28% share of conventional energy sources with adverse consequences on the EQL. Summarizing the abovementioned literature, we proposed that a vast number of studies on the nexus of RTEC-EIN-CO_2 are reported. However, to the best of the authors' knowledge, researchers have overlooked the role of RTEC and EIN on TGE. As mentioned earlier, TGE is the biggest contributor to the global CO_2E. Therefore, there is an increasing scope to conduct studies in the context of TGE. However, reviewing the abovementioned literature, the following is hypothesized:

H_3: "There exists a positive relationship between RTEC and TGE."
H_4: "There exists a positive relationship between EIN and TGE."

2.3 Moderating Role of Population Density

Rahman (2017) investigated the nexus between CO_2E, EGR, PDN, energy use, and exports for the panel data of eleven Asian countries from 1960 to 2014. He found that PDN, exports, and energy use adversely influence the EQL in the long run. Rahman (2020) analyzed the impact of EGR, PDN, trade, and energy usage on EQL in India using a dataset of 1971 to 2011. He highlighted the negative effect of energy usage and PDN on EQL. Tiwari et al. (2020) examined the trade-off between the transportation sector and CO_2E in the US and found that the transportation sector enhances CO_2E. Indriana et al. (2022) checked the impact of transportation on EQL in Indonesia and found a significantly negative effect on transportation on EQL.

This study believes that PDN is a factor that can accelerate the effect of predictors on the TGE. The possible justification behind this is that as there is an increase in population, the demand of energy, fuels, and transportation will also increase (Peterson, 2017). More road infrastructures will be required to meet the overwhelming demand for traffic routes. An increase in PDN also leads to an increase in road density because due to increase in population, there will be more traffic congestion. All these circumstances tend to increase the TGE (Peterson, 2017). When there is more population, more energy will be required to meet the increasing energy demands. The demand for coal, natural gas, and electricity will also increase with an increase in PDN, which tends to increase the level of CO2E (Aljoufie, 2021). Hence, we proposed that PDN can play a moderating role in the nexus between RIN, RDN, RTEC, EIN, and EQL. However, so far, no study has been conducted considering PDN as a moderator. Thus, the following is hypothesized:

H_{5a}: "Population density accelerates the effect of RIN on TGE."
H_{5b}: "Population density accelerates the effect of RDN on TGE."
H_{5c}: "Population density accelerates the effect of RTEC on TGE."
H_{5d}: "Population density accelerates the effect of EIN on TGE."

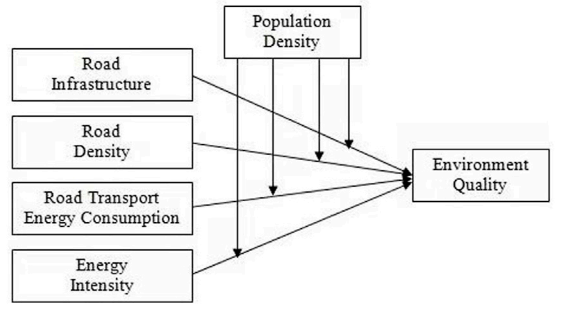

FIGURE 2 | Conceptual framework.

2.4 Conceptual Framework

The conceptual framework of the research is shown in **Figure 2**.

3 DATA AND METHODOLOGY

3.1 Data and Variables

In order to achieve the desired objectives, this study used a "balanced panel dataset" of five countries of South Asia (Pakistan, Bangladesh, Nepal, Sri Lanka, and India) for 1971 to 2014. The time span is selected based on data availability, as the data on most of the variables were limited to 2014. Other South Asian countries were not included in the sample due to data unavailability. The data were obtained from World Development Indicators (WDI) and the National Bureau of Statistics (NBS). The study takes RTEC, EIN, RIN, and RDN as predictors. EQL is used as an outcome, whereas PDN is assumed a moderating variable. The study has also used EGR and PP as control variables. **Table 1** presents the proxy measures of variables with data sources.

TABLE 1 | Variables.

Variable	Definition/measurement	References	Source
Dependent variable			
Environmental quality (EQL)	"Transport-generated CO_2 emissions (TGE) (% of total fuel combustion)"	Danish and Baloch (2018), Rasool et al. (2019)	WDI
Independent variables			
Road infrastructure (RIN)	"Total length of roads (kilometers per capita)"	Danish and Baloch (2018), Rasool et al. (2019)	NBS
Road density (RDN)	"Total length of roads/population"	Aljoufie (2021)	NBS
Road transport energy consumption (RTEC)	"Road energy consumption (kg of oil equivalent per capita)"	Danish and Baloch (2018), Rasool et al. (2019)	WDI
Energy intensity (EIN)	"Road energy consumption/GDP"	Danish and Baloch (2018)	WDI
Moderating variable			
Population density (PDN)	"Population density (people per sq. km of land area)"	Danish and Baloch (2018), Aljoufie (2021)	WDI
Control variables			
Economic growth (EGR)	"Per capita GDP (current US$)"	Chen et al. (2020)	WDI
Population (PP)	"Population (total)"	Aljoufie (2021)	WDI

Note: WDI: World Development Indicators; NBS: National Bureau of Statistics.

3.2 Empirical Model

In line with the preceding studies, the below mentioned functional equation is used to analyze the effect of RTEC, EIN, RIN, and RDN on EQL:

$$TGE_{it} = \mathbf{f}\left(RTEC_{it,}EIN_{it}, RIN_{it}, RDN_{it}\right)$$

where *RTEC* is road transport energy consumption, *EIN* is energy intensity, *RIN* is road infrastructure, *RDN* is road density, and *TGE* is transport-generated emissions for country *i* at time *t*.

A commonly used practice in the available literature is to capture the moderating effect to create the interaction term of particular variables (Agbloyor et al., 2014; Aibai et al., 2019). We, therefore, follow similar patterns to establish various interaction terms to capture the moderating influence of PDN on RTEC, EIN, RIN, RDN, and EQL relations. However, the study's empirical models have the basic forms as follows:

$$TGE_{it} = f\left(RIN_{it,}RDN_{it}, RTEC_{it}, EIN_{it}, EGR_{it}, PP_{it}\right) \quad (1)$$

$$TGE_{it} = f\left(RIN_{it,}RDN_{it}, RTEC_{it}, EIN_{it}, RIN_{it}{*}PDN_{it}, EGR_{it}, PP_{it}\right) \quad (2)$$

$$TGE_{it} = f\left(RIN_{it,}RDN_{it}, RTEC_{it}, EIN_{it}, RDN_{it}{*}PDN_{it}, EGR_{it}, PP_{it}\right) \quad (3)$$

$$TGE_{it} = f\left(RIN_{it,}RDN_{it}, RTEC_{it}, EIN_{it}, RTEC_{it}{*}PDN_{it}, EGR_{it}, PP_{it}\right) \quad (4)$$

$$TGE_{it} = f\left(RIN_{it,}RDN_{it}, RTEC_{it}, EIN_{it}, EIN_{it}{*}PDN_{it}, EGR_{it}, PP_{it}\right) \quad (5)$$

We formulate a separate model for the interaction term to take a higher degree of freedom (*n*-*k*), where "*n*" is the total number of observations and "*k*" is the total number of predictors.

3.3 Econometric Techniques

3.3.1 The Detection of Cross-Sectional Dependency

Because of the increasing trends of interdependency, the panels of diverse nations evidence the cross-sectional dependency (CSD), which makes it compulsory to perform a panel CSD test. This study proceeds with the analysis of the CSD test to recognize the panel estimation problems and guarantee that the panel estimators are unbiased, effective, consistent, and efficient. To detect this CSD issue, the existing debate provides diverse tests to check the probability of CSD, and Breusch and Pagan (1980) CSD test is one of those which the current study applies.

3.3.2 Panel Unit Root Tests

The panel stationarity tests of the first generation, such as "Phillip Perron, Im, Pesaran and Shin, Levin, Lin, and Chu and Augmented Dickey Fuller," have failed to defend the CSD test in the sets of panel data. Thus, this study uses a second-generation unit root test to reduce the concern of stationarity. This second-generation unit root test is named lm, Pesaran and Shin (CIPS), which provides accurate and efficient information regarding the series' order of integration. Because of their asymptotic supposition, these panel unit root tests are robust and better in performance, and they do not require "(N $\rightarrow\infty$)."

3.3.3 Panel Co-Integration Test

Prior to examining the order of integration of study variables, it is essential to investigate the long-run relations among the series. Therefore, a co-integration test, namely, the error correction model (ECM), is developed by Westerlund (2007). This ECM test considers slope heterogeneity and CSD concerns. It is deeply based on the prior information on a subject of series' order of integration, which tolerates the solidity ranks of predictors to be diverse. Thus, the ECM is generally applied in common situations. In addition to this, this technique is a "discretionary bootstrap process," which permits repeating the long-run test of co-integration several times. Generally, it has four kinds of test statistics: "Gt and Ga (mean group statistics) and Pt and Pa (panel statistics)." Gt and Ga assume H_1 (alternate hypothesis) with at least one long-run relation, whereas Pt and Pa assume H_1 as the panels are long-run co-integrated (Usman et al., 2021). The specification of the ECM test is shown as follow:

$$\Delta TGE_{it} = \beta_{0i} + \sum\nolimits_{i=1}^{q}\beta_i \Delta TGE_{i,t-i} + \sum\nolimits_{i=1}^{q}\varphi_i \Delta X_{i,t-i} + \gamma_i ECM_{i,t-i} + e_{it} \quad (6)$$

where TGE is transport-generated emissions, X is the vector of predictors, and γ_i is the error term's speed of adjustment. If $\gamma_i = 0$, it means there is no error correction (meaning that no co-integration exists among the variables); $\gamma_i < 0$ indicates the existence of co-integration among the variables; e is the error term assumed to be normally distributed at zero mean value and constant variance (Elahi et al., 2019a; Elahi et al., 2019c; Elahi et al., 2020).

3.3.4 The Estimations of Long Run

Before confirming long-run relations among the series, the estimates of long-run factors are predicted. We employ the fully modified ordinary least square (FMOLS) test to anticipate the impact of predictors on EQL and detain the moderating impact of PDN. This method can seize the serial correlation by permitting asymptotic consistency. However, the FMOLS method is only applied when co-integration among the series is observed. The FMOLS estimates are extracted from the following equation:

$$Y_{it} = \alpha_i + \acute{X}_{it}\,\delta + \sum_{j=-q_1}^{j=q_2} L_{ij}\Delta X_{it+j} + \mu_{it} \tag{7}$$

where Y is the outcome variable, X is the vector of explanatory variables, and L_{ij} are the lag/lead coefficients of regressors at the first difference.

4 EMPIRICAL RESULTS

4.1 Descriptive Statistics, Data Normality, and Multicollinearity

The summary statistics of the variables of interest is given in **Table 2** which shows the mean, median, highest and lowest values and standard deviation along with the values of Jarque–Bera of all the variables. Examination of data's normality is crucial to get superior results. In this regard, the Jarque–Bera (JB) test has been used. Findings depict that the data of RTEC are normality distributed (as shown by insignificant prob. value), whereas the problem of non-normality exists in the series of the remaining variables (as shown by significant probability values). Our five variables (EGR, EIN, TGE, PDN, RIN, RDN, and PP) suffer from non-normality, indicating the data normality issue. Thus, these outputs report that the issue of non-normality exists, which indicates the existence of CSD. The test of CSD is hence necessary. The correlation among variables is offered in **Table 3**. The output indicates that there is no "problem of multicollinearity" as a reasonable correlation exists among the predictors. The correlation coefficient (r) between two predictors is less than the threshold (i.e., $r < 0.70$).

4.2 Cross-Sectional Dependency

The issue of CSD is very common in the panel data, and the results of normality test also signboard this concern. The identification of this issue using the CSD test is crucial. First, this study conducts the Breusch–Pagan LM test to identify this issue of CSD. The outputs of the Breusch–Pagan LM test are displayed in **Table 4**, suggesting a CSD problem in the dataset. However, all the series (EGR, EIN, TGE, PDN, PP, RIN, and RDN) are statistically significant. It shows that the shock in an economy interrupts the outcomes of other economies in the sample. This output suggests using second-generation techniques to obtain efficient, robust, and consistent findings.

4.3 Stationary Properties of Data

After assuring that the issue of CSD exists in the data, we examine the stationary properties of study variables under consideration of CIPS (a second-generation unit root test). This test is conducted at a level (first difference) with and without trend conditions. **Table 5** lists the outputs, indicating that all the series suffer from the unit root problem at the level with and without trend conditions. In addition, all the variables of interest achieve significance at 1% and 5% levels when the test is conducted at the first difference. The results show that all the series are integrated of order 1 or I (1).

4.4 Test of Co-Integration

After identifying the order of integration, the next step is to apply a suitable test to confirm the long-run association among the chosen variables. We used Westerlund's (2007) co-integration test to check "whether variables move together in the long run or not." The test is repeated five times (one time for each model). Outputs of this test are given in **Table 6**, indicating that the entire panel (Pa and Pt) and group (Ga and Gt) statistics significantly reject the null hypotheses of "no co-integration." This confirms the existence of co-integration relation among the selected series during the time span of 1971–2014 for the case of South Asian economies.

4.5 Fully Modified Ordinary Least Square Model

Estimating the long-run dynamic parameters is the foremost and final step of estimations. This study uses FMOLS to estimate the dynamic long-run estimates among the selected variables. The FMOLS results derived from **Eqs. 1–5** are presented in models 1–5. Model 1 depicts the estimation of basic model 1, whereas models 2–5 detain the moderating effect of PDN.

The results of FMOLS (shown in **Table 7**) capture the positive effect of RIN on TGE as the coefficient of RIN is positive and statistically significant in all the stated models. The coefficient of RIN in model 1 implies that a 1-unit rise in RIN tends to increase TGE by 0.4346 units at a 5% level. It signifies that RIN is disadvantageous in promoting the EQL, which means the higher the RIN, the lower will be the EQL. These findings are similar to the findings of many other researchers (such as Poudenx, 2008; Rasool et al., 2019; Ahmed et al., 2020; Sharifi et al., 2021). Thus, the results acknowledge H_1. PDN also shows a significant and positive effect on TGE in models 2–5, which can be explained in such a way that PDN enhances TGE by 0.3467 (model 2), 0.3147 (model 3), 0.3947 (model 4), and 0.4412 (model 5) units, which is in line with prior studies (Rahman, 2017; Rahman, 2020). Thus, the PDN adversely influences EQL. Moreover, we can see that the effect of RIN on TGE becomes

TABLE 2 | Descriptive statistics.

Particulars	EGR	EIN	TGE	PDN	PP	RTEC	RIN	RDN
Mean	7.5269	0.9839	2.7892	1.5224	2.6354	3.4798	2.9564	1.3469
Median	6.6202	0.8921	2.3137	1.6480	2.9642	2.6845	2.7621	1.1354
Maximum	8.25400	4.1434	7.4285	3.0431	7.3468	6.5718	4.6145	2.3141
Minimum	6.6298	0.1349	0.7448	1.4886	3.6426	1.7652	1.0647	0.3011
Std. Dev.	0.6136	0.6953	1.1885	0.5408	1.0246	1.4821	0.3458	0.1570
JB	3.9250	2.8421	4.7285	3.0542	2.0116	1.8142	3.6412	4.3254
Probability	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.4036	0.0000[a]	0.0000[a]

Note: (a) denotes the significance level at 1%; JB is Jarque–Bera.

TABLE 3 | Test of multicollinearity.

Variables	RIN	RDN	RTEC	EIN	PDN	EGR	PP	TGE
RIN	1							
RDN	0.2346	1						
RTEC	0.3154	0.1455	1					
EIN	0.4138	0.2110	0.1942	1				
PDN	0.5014	0.3411	0.2444	0.2587	1			
EGR	0.4021	0.3002	0.1863	0.1697	0.2781	1		
PP	0.3266	0.4961	0.3471	0.3571	0.1767	0.2850	1	
TGE	0.1982	0.2471	0.2484	0.2964	0.3021	0.1991	0.4315	1

TABLE 4 | Cross-sectional dependency (CSD).

Variables	Bruesch–Pagan LM	*p*-value	Decision
RIN	12.3844	0.0000[a]	"CSD exists"
RDN	14.8371	0.0000[a]	"CSD exists"
RTEC	21.4299	0.0000[a]	"CSD exists"
EIN	16.4099	0.0000[a]	"CSD exists"
PDN	19.8505	0.0000[a]	"CSD exists"
EGR	11.5179	0.0000[a]	"CSD exists"
PP	14.8510	0.0000[a]	"CSD exists"
TGE	13.2373	0.0000[a]	"CSD exists"

Note: a denotes the significance level at 1%; CSD is cross-sectional dependence.

stronger in model 2 when PDN is incorporated as a moderating factor in the model (i.e., the coefficient of RIN*PDN is higher in magnitude and significance than the coefficient of RIN in model 1). The results imply that a collective increase in RIN and PDN tends to increase TGE by 1.9374 units at a 1% significance level. The results signify that a 1-unit increase in PDN tends to increase the impact of RIN on TGE by 1.501 units (i.e., 0.4364–1.9374). This verifies that PDN plays an enhancing role in the relation of RIN and TGE. Thus, H_{5a} is supported.

The coefficient of RDN is positive and significant, which fulfills our expectations. The results state that 1-unit inclination in RDN causes an upsurge of TGE by 0.7344 units at a 5% level. Herein, H_2 is accepted. Furthermore, the effect of RDN on TGE becomes more noticeable when PDN is taken as a moderator. The coefficient of RDN*PDN is higher in magnitude and significance than the coefficient of RDN in model 1. This implies that a 1-unit rise in RDN and PDN collectively brings about a 1.6341-unit rise in TGE at a 1% level. Thus, the 1-unit increase in PDN tends to enhance the effect of RDN on TGE by 0.8997 (0.7344–1.6341) units. As predicted, the results confirm the significant moderating role of PDN in the relation of RDN

TABLE 5 | Second-generation unit root test.

Variables	Level		First-difference		OI
	Without trend	With trend	Without trend	With trend	
RIN	−10.387	−10.883	−27.3745[a]	−28.3845[a]	I (1)
RDN	−12.387	−9.2675	−30.3874[b]	−32.3874[a]	I (1)
RTEC	−14.994	−11.285	−26.9876[a]	−29.3840[b]	I (1)
EIN	−11.737	−8.2764	−28.8374[a]	−32.2003[a]	I (1)
PDN	−9.9354	−15.269	−35.8374[a]	−40.3745[a]	I (1)
EGR	−15.863	−11.387	−28.3874[a]	−43.8274[a]	I (1)
PP	−10.966	−9.9264	−24.7333[a]	−30.8274[a]	I (1)
TGE	−9.2764	−10.837	−20.8364[a]	−26.7364[a]	I (1)

Note: a and b indicate the significance level at 1% and 5%, respectively; OI is the order of integration.

TABLE 6 | Westerlund co-integration (CI) test.

Particulars		Gt	Ga	Pt	Pa	Decision
Model 1	*Statistic*	−24.2734[a]	−16.3263[a]	−17.9927[a]	−11.3764[c]	“CI exists”
	R.P.V	0.0000	0.0000	0.0031	0.0740	
Model 2	*Statistic*	−16.3387[b]	−20.3764[a]	−25.8738[a]	−32.8374[a]	“CI exists”
	R.P.V	0.0456	0.0000	0.0000	0.0000	
Model 3	*Statistic*	−11.3664[b]	−28.8734[a]	−22.0304[a]	−18.3745[b]	“CI exists”
	R.P.V	0.0433	0.0000	0.0000	0.0374	
Model 4	*Statistic*	−20.3764[a]	−32.6773[a]	−31.374[a]	−36.872[a]	“CI exists”
	R.P.V	0.0034	0.0000	0.0000	0.0000	
Model 5	*Statistic*	−11.3746[c]	−27.8114[a]	−24.8303[a]	−22.8737[b]	“CI exists”
	R.P.V	0.0883	0.0065	0.0032	0.0284	

Note: a, b, and c indicate the significance level at 1%, 5%, and 10%, respectively; CI is co-integration.

TABLE 7 | Fully modified ordinary least square model.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	1.8344[c]	1.8273[b]	1.2773[c]	1.9273	1.3774[c]
RIN	0.4364[b]	0.3984[b]	0.3873[b]	0.3864[b]	0.7454[b]
RDN	0.7344[c]	0.8742[a]	1.2723[b]	0.9381[b]	0.8534[a]
RTEC	0.1702[a]	0.3874[b]	0.2873[a]	0.9630[a]	0.8353[b]
EIN	0.8187[b]	0.3981[a]	0.8334[a]	0.8274[b]	0.3864[c]
EGR	0.3781[b]	0.1003[b]	0.9367[b]	0.9887[b]	0.9375[c]
PP	1.8374[b]	1.8264[b]	1.7638[b]	1.9934[c]	1.8356[a]
PDN	—	0.3467[b]	0.3147[b]	0.3947[b]	0.4412[b]
RIN*PDN	—	1.9374[a]	—	—	—
RDN*PDN	—	—	1.6341[a]	—	—
RTEC*PDN	—	—	—	1.8746[a]	—
EIN*PDN	—	—	—	—	1.8374[a]
R^2	70.8384	78.3474	75.8633	79.7664	73.8374
Adj. R^2	68.2294	76.8003	72.9374	77.3764	70.8229

Note: a, b, and c indicate the significance level at 1%, 5%, and 10%, respectively; dependent variable, TGE.

and TGE. It is argued that PDN works as a bridge between RDN and TGE, which helps capture the strong impact of RDN on TGE. Hence, H_{5b} is sustained.

RTEC positively affects TGE as the coefficient of RTEC is positive and significant in all the stated models. The coefficient of RTEC in model 1 implies that the 1-unit rise in RTEC tends to increase TGE by 0.1702 units at the 1% level. It signifies that RTEC is not advantageous in promoting the EQL, which means the higher the RTEC, the lower will be the EQL. The findings are in accordance with those of prior studies (Andreoni and Galmarini, 2012; Chandran and Tang, 2013; Shahbaz et al., 2015; Aggarwal and Jain, 2016). Hence, the results acknowledge H_3. Moreover, we can see that the effect of RTEC on TGE becomes stronger in model 2 when PDN is incorporated as a moderator in the model (the coefficient of RTEC*PDN is higher in magnitude and significance than the coefficient of RTEC in model 1). The results imply that a collective increase in RTEC and PDN tends to increase TGE by 1.8746 units at the 1% level. The results signify that the 1-unit increase in PDN tends to increase the impact of RTEC on TGE by 1.7044 units (i.e., 0.1702–1.8746). It indicates that PDN plays an enhancing role in the relation of RTEC and TGE. Thus, H_{5c} is acknowledged.

The coefficient of EIN states the positive affiliation between EIN and TGE. Its coefficient in model 1 implies that the 1-unit rise in EIN enhances TGE by 0.8187 units at 5%. These results are also in agreement with our expectations and align with the findings of previous researchers (Yaw Naminse and Zhuang, 2018; Emir and Bekun, 2019). EIN is the basic ingredient of TGE; it is empirically proven that the higher the EIN, the higher will be the TGE. Hence, H_4 is also accepted. Moreover, the effect of EIN on TGE becomes more noticeable when PDN is taken as a moderator. The coefficient of EIN*PDN is higher in magnitude and significance as in model 1. This implies that the 1-unit rise in EIN and PDN collectively brings about a 1.8374-unit rise in TGE at the 1% level. Thus, the 1-unit increase in PDN tends to enhance the effect of EIN on TGE by 1.0187 (0.8187–1.8374) units. As predicted, the results confirm the significant moderating role of PDN in the relation of EIN and TGE. It is argued that PDN works as a bridge between EIN and TGE, which helps capture a strong impact of EIN on TGE. Hence, H_{5d} is sustained.

In addition, the control variables EGR and PP also show a significant positive influence on TGE. Moreover, the value of adjusted R^2, shown in model 1, states that 68.23% of variations in TGE are collectively explained by all the predictors. However, the magnitude of R^2 in models 2–4 is higher than that of model 1, which verifies the significant moderating role of PDN in the relation of RIN, RDN, RTEC, EIN, and TGE (EQL).

4.6 Discussion

The findings indicate a crucial change in the PDN in the South Asian region from 1971 to 2014. These variations seem to intensify the demand for transport infrastructure. As the PDN increases, the parking and road demands in the region also seem to enhance. Our statistical results show an interaction effect of PDN and transport infrastructure on the EQL. We find a strong moderating effect of PDN on the relations of RIN, RDN, RTEC, EIN, and EQL. We found a notable effect change of predictors with change in PDN in the sample period. We observe that an increased population seems to emphasize a crucial effect of PDN regulation changes in South Asia. Thus, the effect of PDN changes influences the relationships of RIN, RDN, RTEC, EIN, and EQL.

The findings reveal that PDN also significantly influences RTEC. Thus, transportation planning must not be ignored while formulating policies on the change in PDN. In reality, the effect of PDN on transportation and EQL must be studied and examined (Heres-Del-Valle and Niemeier, 2011; Palm et al., 2014), specifically in the case of South Asia, where there is an absence of effective public transportation. Our findings show that any such improvements aimed at enhancing the PDN must be supported by the reliable and efficient RTIN, including the suitable volume of roads, road quality, mass fast communal transport system, and parking lots (Fouracre et al., 2003), which will create chaotic problems neither for the country sustainability nor for livability.

The preceding studies suggested that the countries with high PDN will lower the EQL as they enhance the per-person infrastructure of public transport (Dingil et al., 2018). Accordingly, it is significant to establish a comfortable, affordable, and efficient public transport system in South Asia by adopting an integrated planning approach in which the transportation and RTEC are well-harmonized. It will eradicate the negative effect of road transportation and PDN on EQL and the application of South Asia domestic plans and ensure a livable and sustainable environment.

We offer the planners of road transportation a novel and practical approach to examine complex secular PDN change policy in the growing countries to analyze the EQL. In spirit, policymakers and urban planners need an understanding of RTEC and transport infrastructure policy implications (Aljoufie, 2014). The ability to measure the influence of the application of local plans which encourage changes in PDN facilitates the evaluation and understanding of road infrastructure, energy use, and EQL. Such planning will eradicate the gap between road infrastructure and energy use facilities and policies by integrating policies and plans that resultantly offer a livable and sustainable environment (Waddell, 2011).

5 CONCLUSION AND IMPLICATIONS

The RTIN is considered a primary tool to promote EGR. The worldwide transport is altering all the human life aspects. The South Asian countries are typically conscious of the transport sector's strength, which is effectual in transmuting the resources into communication and knowledge. The effects of transportation not only favorably contribute to the EGR of a region, but it also contributes to a lower EQL. The mounting degradation in EQL, specifically from the transport industry, is a big threat and challenge for sustainable development in the South Asian nations. The transport sector's emission has gained researchers' attention on climate change and transportation because of its increasing share in global emission and tenacious development. Thus, this study aims to analyze the links among RTEC, EIN, RIN, RDN, and EQL with the moderating role of PDN. To achieve the desired objectives, the study has used a "balanced panel dataset" of five South Asian countries (Pakistan, Bangladesh, Nepal, Sri Lanka, and India) for 1971 to 2014.

The FMOLS result captures the positive effect of RIN on TGE and states that the 1-unit rise in RIN tends to increase TGE by 0.4346 units. It signifies that RIN is disadvantageous in promoting the EQL, which means the higher the RIN, the lower will be the EQL. Thus, the results acknowledge H_1. The RDN also has a positive effect on TGE, which state that the 1-unit inclination in RDN causes an upsurge in TGE by 0.7344 units, accepting H_2. There is a positive effect of RTEC on TGE, which implies that the 1-unit rise in RTEC tends to increase TGE by 0.1702 units, which acknowledges H_3. The EIN also has a positive impact on TGE, which implies that the 1-unit rise in EIN enhances TGE by 0.8187 units. These results also agree with our expectations, and hence, H_4 is also accepted. As predicted, the results confirm the significant moderating role of PDN in strengthening the relation of RTEC, EIN, RIN, RDN, and EQL. It is argued that PDN works as a bridge between the predictors and EQL, which helps capture the strong impact of predictors on the outcome variable. Hence, H_5 is sustained.

Our findings reveal that RTIN positively contributes to TGE, which is harmful to the EQL. It indicates that the transport infrastructure is worst in South Asian countries. This study argues that policymakers should revise the existing policies and regulations and the South Asian government requires expanding RTIN, which in turn enhances economic activities. Certainly, an increased infrastructure causes an enhancement in the traffic rate and household activities. Thus, the rise in economic activities and traffic rate lead to enhancement of TGE in the region. The positive effect of RTEC and EIN on TGE means that RTIN is harmful to the EQL. Indeed, the rise in RTIN aggravates the populace to the trail and encourages them to utilize private cars, more congestion, long travel, and accordingly more consumption of energy and more TGE. Significant attention must be paid to taking precautionary measures for the worse impacts of RTIN on EQL (Achour and Belloumi, 2016). Askarzadeh (2017) stated that the domestic sector holds a major part of overall traffic on roads. The means of transportation, shifting from private to public means of transportation, can decrease the transportation demand by changing the travelers' demand (Karndacharuk et al., 2014). Moreover, we suggest that the region works with domestic entities such as educational institutions and non-government entities to resolve the issue. The development of electric and hybrid energy transport can minimize the TGE in South Asia (Xu and Lin, 2015). The emission declines are linked to replacing low-carbon substitutes for high-carbon equivalent. Thus, to avoid unpleasant effects of road transport, the governments need to emphasize on reducing traffic vehicles on roads in line with our econometric estimation rather than cutting the networks of roads.

The governments of South Asia should take initiatives to overcome the issue of energy consumption and EQL which is caused by road transport. The fluctuations are seen in the fuel rates that are not set in accordance with the future needs or demand and supply, which enhances the external threats of energy availability. Policymakers should design a "Clean Transport Policy" for South Asia, which will lessen the TGE, and hence the EQL will be improved. Governments should address the electric energy crises of the region so that the populace can make use of hybrid and electric vehicles. Moreover, subsidies should be given to the individuals using environment-friendly vehicles. The government should also ensure the availability of energy-efficient public vehicles, which use a separate track to save time and must be accessible at lower rates. The cost- and time-saving transportation system will motivate the populace to prefer public transportation over private ones.

We also highlighted some probable areas to be examined in the future. The transport sector is categorized into organizations: public transport and road transport. Future investigations can compare both to highlight which organization is more energy-efficient and economically advantageous. Moreover, our data were limited to 1971–2014 (the data were available for this period only); changes that occurred in 7 years from 2015 to 2021 are not included in our study. However, policies suggest that the study has not been much affected by this as the road is a highly popular mode of transport in South Asia. Further studies can incorporate disaggregated data in road transportation to analyze TGE.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors without undue reservation.

AUTHOR CONTRIBUTIONS

Conceptualization: AD and JM. Methodology: AD. Software and validation: JM. Formal analysis is done by GSS and NC-B, and Writing original draft is done by AD. Investigation, resources, and data curation: AV-M. Writing—original draft preparation: GSS and NC-B. Writing—review and editing: GSS and NC-B. Visualization and supervision: AD and AV-M.

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