

Article

The Effectiveness of Improvement Measures in Road Transport Network Resilience: A Systematic Review and Meta-Analysis

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Abstract: Achieving improvement in the resilience of road transport networks by ensuring their smooth functioning and prompt recovery in the event of damage is crucial. This study focused on optimal measures and compared the effect of improvement measures on the resilience of road transport networks. A meta-analysis was performed to assess whether and to what degree the resilience of road transport networks was improved with different categories of measures. The articles were divided based on improvement measures, such as infrastructure investment, structure and planning, traffic signal management, and recovery schedule. The methodology of how to define and measure the resilience of road transport networks is considerably diverse, and most definitions are based on basic infrastructure structures. The efficiency of four types of improvement methods was grouped: structure and planning, infrastructure investment, recovery schedule, and traffic signal management. This study supports the use of structure and planning as a promising way for improving the resilience of road transport networks. Increasing comparability in studies and finally developing effective improvement measures in transport planning and decision making require more precise conceptual and methodological standardization in road transport network resilience.

Keywords: infrastructure investment; structure and planning; traffic signal management; recovery schedule



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1. Introduction

As the link between various districts, a resilient road transport network (RTN) is a crucial piece of infrastructure that supports the daily operation of a city in an orderly manner. The structure of RTNs has recently become more complex because of the expansion of cities. In addition, the adverse impact of unexpected events, e.g., natural disasters [1–3], terrorist attacks [4], severe climates [5], the COVID-19 pandemic, and major accidents [6], on RTNs is also becoming increasingly serious. Damaged RTNs decrease travel efficiency and result in significant societal economic losses during grid disturbances [7]. The capacity of RTNs to actively adapt in response to these unexpected events is called resilience [8]. Research (e.g., [9,10]) has shown that if an RTN is more resilient, it will recover faster and cause less economic damage after a major incident, such as a bank robbery or a car skidding on wet roads. Therefore, how to improve the resilience of RTNs is of utmost relevance.

The resilience of RTNs must be accurately defined and assessed to develop effective measures for improving the resilience of RTNs. Historically, the resilience of an RTN has been defined as its ability to mitigate the effects of a disaster and maintain its own function [11,12]. However, concerns have been raised about the validity of the current approach due to the overlooked temporal aspects of resilient coping and the failure to

consider the flexibility of an RTN's functioning, as well as its potential to improve resilience [13,14]. According to current theoretical frameworks, the resilience of Current theoretical frameworks posits that the resilience of RTNs is characterized by their ability to withstand and adapt to challenging circumstances over time. "Resistance" means that the RTN can remain resilient even in the face of disturbances, as it has the capacity to counteract the negative effects of these disturbances. This capacity to mitigate disruptions ensures that the RTN can continue to operate normally despite external challenges, safeguarding its core functionality [15]. "Recovery" means that, after a disturbance, such as a disaster, the RTN can quickly recover and return its damaged parts to the desired initial state or a new state [16]. "Adaptation" is the ability of an RTN to dynamically modify its structure via active or passive learning mechanisms, enabling it to effectively navigate forthcoming uncertainties by making adjustments [17].

Numerous studies (e.g., [18,19]) have examined the concept of resilience in RTNs from various perspectives, including trait-based assessments of network topology, process-oriented evaluations of dynamic evolution, and outcome-focused investigations of traveler characteristics. This range of conceptualizations has played a crucial role in developing a multi-dimensional comprehension of the resilience of the RTN.

Recent studies (e.g., [20–22]) have identified the resilience of RTNs as a moldable element that could be improved by tailored measures or strategies. This issue illuminates an RTN's capacity to deal with unforeseen events and explains how an RTN recovers or bounces back from these unexpected events. Previous research has suggested improvement measures that focus on improving some specific dimensions of RTN resilience [23]. Given the predominant focus of the current literature (e.g., [24,25]) on network topology, it is unsurprising that this phenomenon has emerged. Furthermore, despite the existing research, such as Huang et al. [25], McPhearson et al. [26], and Vercruysse et al. [27], which all acknowledge the multifaceted nature of the resilience of RTNs, a definitive consensus on its definition and a universally accepted "gold standard" for improving the resilience of RTNs remain elusive.

As a multisystem, the resilience of an RTN is influenced by numerous domains according to the current theory [16,28]. Most of the available RTN-based resilience measures involve different approaches: infrastructure investment (II), structure and planning (SP), traffic signal management (TSM), and recovery scheduling (RS).

II aims to improve the resilience of RTNs through greater investment or a rational allocation of funds. Hu et al. [29] proposed that roadside tree retrofit investments increase the resilience and anticipated recovery effectiveness of a road network while also dramatically reducing the estimated economic losses of roadside tree blowdowns. The research by Guo et al. [30] provided theoretical justification for location choices and facilities. In order to accommodate the needs of many parties, this arrangement of emergency rescue facilities in a multimodal transport network struck a compromise between cost, complete coverage, and rescue time. There are also studies that address both; Colon et al. [31] held two viewpoints in their research: one is that disaster losses can be reduced by strengthening infrastructure assets; additionally, enhancing infrastructure asset maintenance and speeding up repairs can potentially deliver resilience at significantly lower costs.

SP aims to improve the resilience of RTNs through improved redundancy, thus protecting critical nodes and links or optimizing network structures. Assigning options to users to reduce the effects of disruptions and strengthen RTN resilience against the disruptive events of a disaster helps increase network resilience. Developing an emergency reaction and recovery strategy has been supported by several scholars (e.g., [6,32,33]). Protecting critical nodes and links also has a positive effect on improving the resilience of RTNs, but various researchers have different definitions of "critical", including vulnerability [34], robustness [1], reliability [35], road intersections [29], and so on. Therefore, power-law-based structural relationships in a road network [36] or topology [37] can also contribute to the improvement of the resilience of an RTN. Hong et al. [38] defined resilience as variations in resident mobility patterns. The prioritization of equitable resource distribution at the

local government level has also been proposed, including measures such as optimizing the locations of shelters and evacuation routes, directing outreach efforts toward vulnerable populations, and providing support to disadvantaged neighborhoods.

TSM aims to improve the resilience of RTNs by establishing equitable and sustainable traffic signal settings. A flexible signal control was proposed by Chiou [39], who also confirmed that it might be more resilient than the existing ones in the face of the significant consequences of exposure risk when hazardous transportation is present. The findings of Shang et al. [40] demonstrated that, in most circumstances, especially in cases of moderate and severe disruptions, the adaptive signal control they proposed in the study, based on deep reinforcement learning, can achieve superior resilience.

RS aims to improve the resilience of RTNs by optimizing recovery activities and forming their priorities. In order to examine the optimization of a road network recovery method under uncertainty, with the goal of maximizing network resilience, Li et al. [41] developed a resilience-based bilevel programming model. Li et al. [42] also modeled the dynamic resilience and sequential repair actions of road networks under extreme environments and proposed a time-dependent resilience analysis framework. Three optimization strategies were created based on the study findings to increase the network's resilience to failures. According to the optimal restoration strategy reference, Mao et al. [43] determined the ideal time sequence for priority recovery segments and recovery tasks to enable transportation authorities to plan operations for disaster rehabilitation.

Bešinović [44] prepared a special field definition of resilience in rail transport and a comprehensive and up-to-date review of railway resilience articles. The study, which classified resilience measures and approaches, showed that system-based measures had better effects on transport services. Furthermore, Li et al. [45] conducted a systematic review focusing on novel governance, engineering, and existing technologies aimed at enhancing urban ecological infrastructure. The findings of their review were utilized to support the implementation of newly developed and improved urban ecological theories. Their study provided a solid and inspiring new foundation for accelerating more environmentally sustainable urbanization. Other studies (e.g., [34,44,45]) found evidence that these resilience-based improvement measures had positive effects on the resilience of RTNs. Additionally, these conceptualizations may target distinct aspects of RTN resilience, be executed in isolation, adopt varying theoretical frameworks, and yield differing levels of efficacy. Given this diversity of characteristics, it is very timely to analyze the impact of improvement measures on RTN resilience, which can provide more convincing evidence and connections. There is a research vacuum in the absence of a comprehensive study or meta-analysis of the impact of improvement approaches on RTN resilience. Thus, the quantitative effect of various improvement measures on the resilience of RTNs has not been evaluated on the global level. As a result, this study's innovation is to analyze, compare, and integrate current data on effective measures of RTN resilience based on a systematic review and meta-analysis. Therefore, this study has the potential to make valuable contributions to the sustainable development of RTNs by employing integrated socio-economic approaches. These approaches encompass various aspects such as investments, planning, management, and scheduling, which can collectively influence the resilience of RTNs. The aims of this study are as follows:

- (1) Systematically reviewing the literature related to RTN resilience improvement measures and providing an overview of different types of improvement measures, methodological features, analytical approaches, and their effectiveness;
- (2) Investigating the improvement of RTN resilience through different types of improvement measures.

Finally, this study could be used to address the following question: Which types of measures are most effective in improving RTN resilience?

This paper is organized into four main sections. The "Materials and Methods" section describes seven subsections regarding the search strategy, the study selection, eligibility criteria, inclusion studies, quality assessment, the coding procedure, and data analysis.

The “Results and Discussion” section analyzes the interpreted results, comprising study characteristics, risk of bias assessment, and a meta-analysis. Finally, “Conclusions” are discussed in the last section.

2. Materials and Methods

This study is a systematic review and meta-analysis that used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards [46].

2.1. Search Strategy

This study conducted a comprehensive keyword search to gather all relevant studies in Science Direct, Springer, Worldlib, Web of Science, Wiley, Scopus, CKNi, Incopat, and IResearchbook for English and Chinese language publications up to 31 December 2022. Critical search terms included “RTN”, “urban”, “transportation”, “traffic” and “resilience”, “road performance”, “improve”, “enhancement”, “adapt”, “measure”, “assess”, and “model”. The searches encompassed a wide range of parameters, with no limitations imposed on date, publication status, or publication format. Subsequently, the records retrieved were systematically imported into a Reference Manager tool and rigorously screened against predetermined inclusion and exclusion criteria. If there are any future publications, it is important to note that this study conducted a thorough examination of the reference lists of pertinent articles that were identified during the search process, along with articles that satisfied the predetermined inclusion criteria. This meticulous approach ensured a comprehensive and thorough examination of all the relevant literature.

2.2. Study Selection

In accordance with PRISMA guidelines, a meticulous study selection process was carried out by two independent reviewers. The initial search was conducted by the first author using the predefined search terms and criteria mentioned above. The obtained results were then imported into the Endnote Desktop Software, where duplicates were systematically removed. Subsequently, to ensure that all studies met the eligibility criteria, two independent reviewers meticulously reviewed the titles and abstracts of potentially relevant studies. Full texts of the criteria-compliant studies were downloaded and imported into Covalence, along with the full texts of studies for which a definitive decision could not be made solely based on the title and abstract. Title, abstract, and full-text screening were carried out independently by two reviewers utilizing a structured preform. In cases of any discrepancies, a third researcher was consulted for resolution. This approach was adopted to maintain rigor and accuracy in the study selection process. The PRISMA flow diagram below (Figure 1) shows the outcomes of the search process and provides an overview of the total number of studies that were included or excluded.

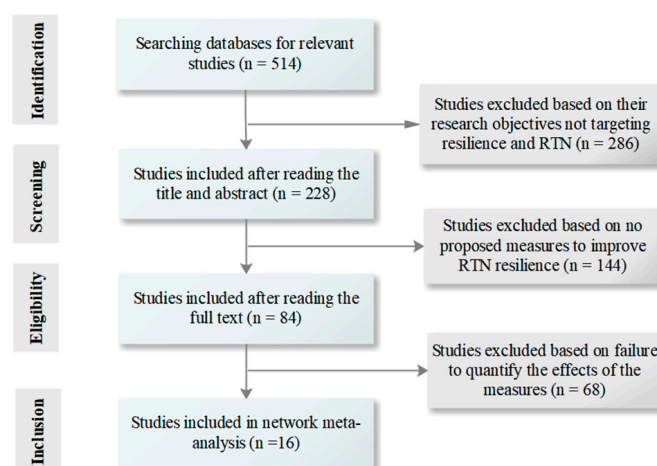


Figure 1. Flowchart of the literature search.

2.3. Eligibility Criteria

In order to be considered for inclusion, studies had to meet the following criteria: (1) focusing on improving the resilience of RTNs through one or more improvement measures; (2) providing a clear definition and measurement of the resilience of RTNs; (3) reporting quantitative results that assess the effectiveness of the improvement measures; and (4) having been published in peer-reviewed journals in English or Chinese prior to 31 December 2022.

The selected studies were deemed ineligible for inclusion if they met any of the following criteria: (1) containing conspicuous errors such as statistical inaccuracies or data plagiarism; (2) utilizing qualitative methods without measuring the resilience of RTNs; (3) using qualitative analysis without measuring the effect of improvement measures on the resilience of RTNs; (4) being based on the same dataset, in which case, only the earliest study was retained, and all subsequent studies were excluded; and (5) having been published both as a journal article and as a dissertation, in which case, the earlier study was included, while the later study was omitted to ensure no data duplication.

2.4. Inclusion Studies

A preliminary screening was carried out to eliminate duplicate or irrelevant studies, resulting in a total of 514 studies. Next, the abstracts of these studies were carefully reviewed, and 286 were excluded, as they primarily focused on robustness, rapidity, railways, or logistics, which were not related to the resilience of RTNs. After thoroughly reviewing the full texts of the 228 remaining studies, this study determined that an additional 144 studies needed to be excluded; these only contained a framework for assessing the resilience of RTNs and did not propose improvement measures. After the above screening, only 84 papers entered the next round of selection. However, 68 studies were excluded that only proposed improvement measures and did not quantify their effect on the resilience of RTNs. Finally, the remaining 16 studies met the eligibility criteria and were included in the meta-analysis.

In this set of meta-analyses, this study distinguished four categories of improvement measures for RTN resilience: (a) II; (b) SP; (c) TSM; and (d) RS. Figure 1 shows the flowchart of the study.

2.5. Quality Assessment

Using the Review Manager Software, two reviewers independently assessed the quality of the literature using the Cochrane Collaboration's risk of bias method [47]. Discrepancies were addressed through discussion with a third reviewer. The following six factors were examined for bias risk: (1) creation of random sequences (bias in selection); (2) allocation concealment (selection bias); (3) blinding of participants and personnel (performance bias); (4) blinding of outcome assessment (detection bias); (5) incomplete outcome data (attrition bias); and (6) selective reporting (reporting bias). The risk of bias in all studies was classified as high (+), low (−), or unclear (?).

2.6. Coding Procedure

This study retrieved the improvement measures in the studies and the particular values of RTN resilience before and after the application of an improvement measure from each study to perform the meta-analysis. Table 1 shows the elements that were extracted from each included study. These elements include (1) authors and year of publication; (2) study area; (3) type of improvement measure; (4) RTN measuring instrument flexibility type; (5) specific measures to improve the resilience of RTNs; and (6) RTN resilience improvement values after implementation of improvement measures.

2.7. Data Analysis

The Review Manager software (version 5.3) was used to conduct the meta-analysis. This study determined the impact value, the mean difference before and after the installation

of an improvement method, and 95% confidence intervals (CI) for RTN resilience. It is considered to be statistically significant when $p < 0.05$. To assess statistical heterogeneity, both p -value and I^2 tests were used. Heterogeneity was considered heterogeneous if $p \leq 0.05$ or $I^2 \geq 50\%$, and in such cases, random effects models were employed. Conversely, if $p \geq 0.05$ and $I^2 \leq 50\%$, the data were considered not heterogeneous, and fixed effects models were used. Additionally, a sensitivity analysis was performed to assess the reliability and stability of the results. To ensure a comprehensive analysis of the results in accordance with established research practices, each study was excluded individually, and the cumulative effects were recalibrated based on the remaining studies. This rigorous approach helped to maintain the integrity of the analysis.

3. Results and Discussion

The RTN resilience results are discussed in detail in three subsections, including study characteristics, risk of bias assessment, and meta-analysis, as follows.

3.1. Study Characteristics

Table 1 shows the characteristics of the 16 studies in this meta-analysis. Two studies were published in 2020 [6,29,40,48,49] and 2021 [35,50,51], and three studies were published in 2018 [39,52,53]. Three other studies were published in 2022 [54], 2019 [55], and 2016 [53].

Nine studies were carried out in China; two in the USA; and one each in The Netherlands, Nepal, Japan, and the UK. There was also a study that was conducted on a global scale.

Table 1. Characteristics of the studies included in the meta-analysis.

| Reference | Country | Category | Evaluation Indicator | Measure | Data | Result |
|-------------------|-----------------|----------|-----------------------------------|---|-------|--|
| Koks et al. [56] | Global | II | Risk of road exposure to flooding | Increasing flood protection | 60% | Improving road designs by investing a mere 2% of their total value into upgrading drainage and flood defenses could yield favorable returns for a substantial 60% of roads that face the risk of flooding. |
| Gao et al. [35] | China | II | Critical link reliability | Repair of 73% of total links by using 105 units of cost | 91.7% | Network resilience increased by 91.7%. |
| Hu and Yang [29] | China | II | Expected recovery efficiency | Increase in budget | 8.87% | The budget has been increased from USD 25 million to USD 75 million, anticipating an 8.87% improvement in recovery efficiency. |
| Zheng et al. [49] | China | II | Network capacity flexibility | Multimodal subsidy design | 18.5% | Compared to the no-subsidy scheme, the comprehensive subsidy scheme increases network capacity flexibility from 427 to 506 under the total flexibility model, an increase of 18.5%. |
| Yap et al. [55] | The Netherlands | SP | The social cost of disruption | Additional temporary stations | 8% | An 8% reduction in social costs. |
| Liu et al. [51] | China | SP | Failure rate of station networks | Improving the tolerance coefficient of the station | 67.2% | A 67.2% reduction in the peak failure rate (0.198–0.065) when increasing the station tolerance coefficient ($\varepsilon \geq 0.45$). |

Table 1. Cont.

| Reference | Country | Category | Evaluation Indicator | Measure | Data | Result |
|-----------------------|---------|----------|---|---|--------|---|
| Zhang and Wang [53] | USA | SP | Novel metric based on system reliability and network connectivity (WIPW) | Changing the network topology through new construction | 72.3% | Improved network resilience by replacing network topology with new construction: WIPW increased from 0.61 to 1.05, a 72.3% increase. |
| Yadav et al. [6] | USA | RS | Prioritizing a recovery sequence based on predefined metrics | Network-centricity-based recovery methods | 7% | Recovery based on node betweenness, outperforming the GA approach by nearly 7% in one scenario. |
| Zhang and Wang [53] | China | RS | Global efficiency of the network (E) after removing some nodes | EWM-TOPSIS | 8% | With regards to pre-flooding targeted attacks, the total loss of E is found to be reduced by 8% compared with when flooding occurs first. |
| Aydin et al. [54] | Nepal | RS | Recovery times | Dynamically simulating a sequence based on the time variable | 84.11% | Average road recovery time 25%. Segments recovered dropped from 251.73 to 40.04. |
| Ishibashi et al. [48] | Japan | RS | Post-disaster functionality of road networks | Retrofitting prioritization for structures | 3.58% | In Owase, R_{\max} improved from 81.0 to 83.9 after prioritizing different retrofitting structures. |
| Yanni et al. [52] | China | RS | The level of node connectivity after a system outage and the ability to restore node connectivity to an acceptable level through appropriate remediation measures | Optimal recovery strategy based on system resilience | 5.2% | In cases of multiple interchange failures, the optimal recovery strategy had 5.2% greater system resilience than the worst recovery strategy. |
| Shang et al. [40] | China | TSM | Relative area index | Adaptive signal control based on deep reinforcement | 4.65% | Relative area index increases from 0.25 to 4.65 at a 75% capacity reduction. |
| Chiou et al. [39] | China | TSM | The model benefit of resilient linked signals (MB) | Flexible signal control | 4.5% | Flexible signal control achieves the highest resilience in an MB of nearly 4.5%. |
| Abudayyeh et al. [50] | UK | TSM | Travel time | Adopting a bilevel optimization framework using the CE algorithm | 6% | Applying signal optimization reduces travel time by almost 6%. |
| Tao et al. [57] | China | TSM | Resilience loss (RL) | Designed a two-level algorithm based on a greedy strategy and gradient descent to solve the proposed network-wide traffic signal optimization model | 1.4% | The proposed resilience-based traffic signal optimization model improved the system resilience under different conditions. The resilience loss is reduced by a maximum of 1.4%. |

3.2. Risk of Bias Assessment

Figure 2 presents the risk of bias assessment for 16 studies. Most of the studies were found to have a high risk of bias in at least one aspect, resulting in an overall bias assessment of unclear or high risk. As each study included a single sample, all studies were rated as having a high risk of random sequence generation. As the aims of the studies were to evaluate the effect of improvement measures on the resilience of RTNs, ensuring the blinding of participants and personnel was challenging. Therefore, this domain was always rated as having an unclear or high risk. Fourteen studies overcame the detection bias (87.5%). The outcomes of these studies were assessed via quantitative measures; therefore, they were blinded. Most of the studies were rated as having a low risk of attrition bias, as they effectively addressed incomplete outcome data issues. Additionally, since all studies compared the resilience of an RTN before and after implementing an improvement measure, the risk of selective reporting bias was found to be low.

| | Random sequence generation (selection bias) | Allocation concealment (selection bias) | Blinding of participants and personnel (performance bias) | Blinding of outcome assessment (detection bias) | Incomplete outcome data (attrition bias) | Selective reporting (reporting bias) | Overall bias |
|--------------------------|---|---|---|---|--|--------------------------------------|--------------|
| (Koks et al., 2019) | + | + | + | + | ? | + | + |
| (Gao et al., 2021) | + | + | ? | ? | + | + | ? |
| (Hu et al., 2020) | + | + | + | + | + | + | ? |
| (Yap et al., 2018) | + | + | + | + | + | + | ? |
| (B. Liu et al., 2021) | + | + | + | + | + | + | ? |
| (W. Zhang & Wang, 2016) | + | + | ? | + | + | + | + |
| (Yadav et al., 2020) | + | + | ? | ? | + | + | + |
| (Y. Zhang & Ng, 2021) | + | + | + | + | + | + | ? |
| (Aydin et al., 2018) | + | + | + | + | + | + | ? |
| (Ishibashi et al., 2020) | + | + | ? | + | + | + | + |
| (Yanni et al., 2021) | + | + | ? | + | + | + | + |
| (Shang et al., 2020) | + | + | + | + | ? | + | + |
| (Chiou, 2018) | + | + | ? | + | + | + | + |
| (Abudayyeh et al., 2021) | + | + | ? | + | + | + | + |
| (Zheng et al., 2020) | + | + | + | + | + | + | ? |
| (Tao et al., 2022) | + | + | ? | + | + | + | + |

Figure 2. Risk of bias assessment [6,29,35,39,40,48–57].

3.3. Meta-Analysis

The meta-analysis presented a resilience perspective that, although preliminary and conceptual, has the potential for broad application in establishing connections between RTN stability and sustainability. A range of relevant contexts may be studied, such as RTNs focusing on a certain mode of transportation [58], improving the resilience of a specific route [59], quantifying the impact of a particular disaster [60], the ratio of RTN resilience improvement degrees and the cost of various measures [61], and changes in harmful gas emissions before and after the implementation of various measures [50]. This highlights the broad application potential of meta-analysis in RTN resilience studies, including not only transport aspects but also, for instance, economic, environmental, and city planning issues, as well as meta-analysis research more generally. Several measures for improving RTN resilience were discussed, and tools for quantitative analyses were presented.

II: Four studies reported II measures that could be used for meta-analysis [29,35,49,56]. Koks et al. [56] defined the resilience of RTNs as the risk of road exposure to flooding, and they suggested that resilience could be improved by increasing flood protection. They concluded that improving road designs by investing a mere 2% of their total value into upgrading drainage and flood defenses could yield favorable returns for a substantial 60% of roads that face a risk of flooding. Gao et al. [35] considered resilience the reliability of critical links in RTNs, and they increased 91.7% of the network's resilience by repairing 73% of the total links using 105 units of cost. Hu et al. [29] defined resilience in terms of the expected recovery efficiency of an RTN, and their study found that, when the budget increases from USD 25 million to USD 75 million, the expected recovery efficiency increases by a total of 8.87%. Zheng et al. [49] focused on network capacity elasticity by using a multi-modal subsidy design approach to improve the resilience of an RTN, and their results showed that, compared with a no-subsidy scheme, a comprehensive subsidy scheme increases network capacity flexibility from 427 to 506 under a total flexibility model, an increase of 18.5%.

Figure 3 shows the effect of the II measures on promoting the resilience of RTNs. The result of the meta-analysis showed a statistically significant difference in the improvement of RTN resilience through the use of II. However, there was a high degree of heterogeneity in the studies ($I^2 = 99.4\%$, $p = 0.000$). The overall effect of II on the RTN resilience improvement was 0.45 (95% CI: 0.01–0.88) after combining based on the random effects model. A sensitivity analysis revealed that no study was able to influence the outcomes.

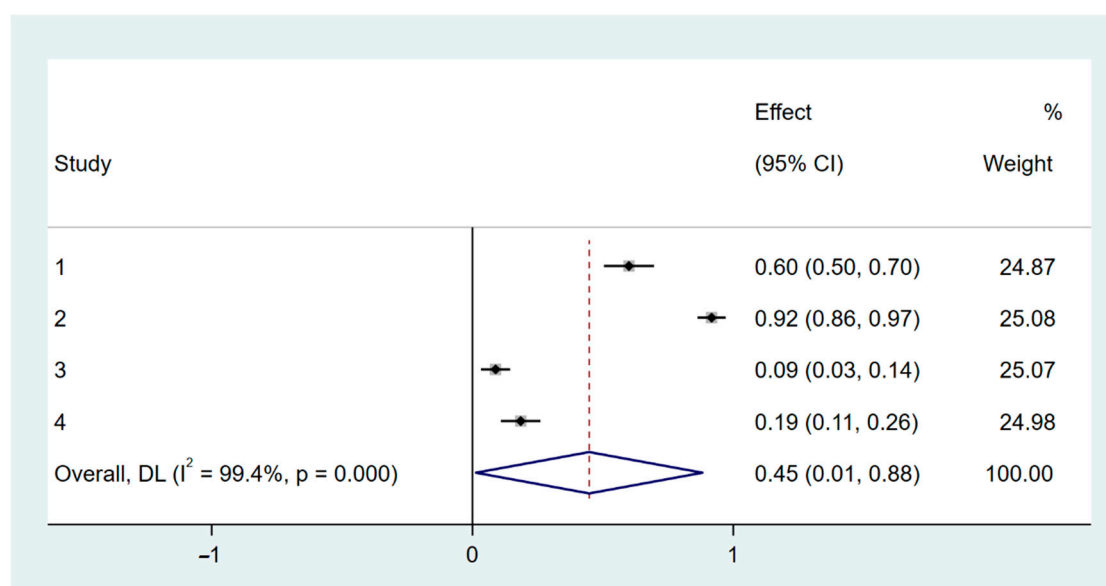


Figure 3. Forest plot of the effect of II measures on RTN resilience improvement.

SP: Figure 4 analyzes measurements of the effects of SP on RTN resilience improvement reported in three studies [50,53,55]. Yap et al. [55] used the social cost of disruption to evaluate the resilience of RTNs, and their approach was applied to a case study in The Netherlands, which resulted in an 8% social cost reduction for the two additional temporary stations. This may demonstrate a different result in other regions. The research perspective of Liu et al. [50] was the station network; they considered resilience the failure rate of the station network, and they improved resilience by increasing the fault tolerance coefficient of the station. The results calculated, with a real case, showed that the peak failure rate can be reduced by 67.2% (0.198–0.065) when the station fault tolerance factor is increased ($\epsilon \geq 0.45$). The authors of [54] used a metric based on system reliability and network connectivity (WIPW) to calculate the resilience of RTNs, and they found that new constructions that change the network topology can improve the resilience of RTNs. Their results showed that the WIPW increased from 0.61 to 1.05, an increase of 72.3%.

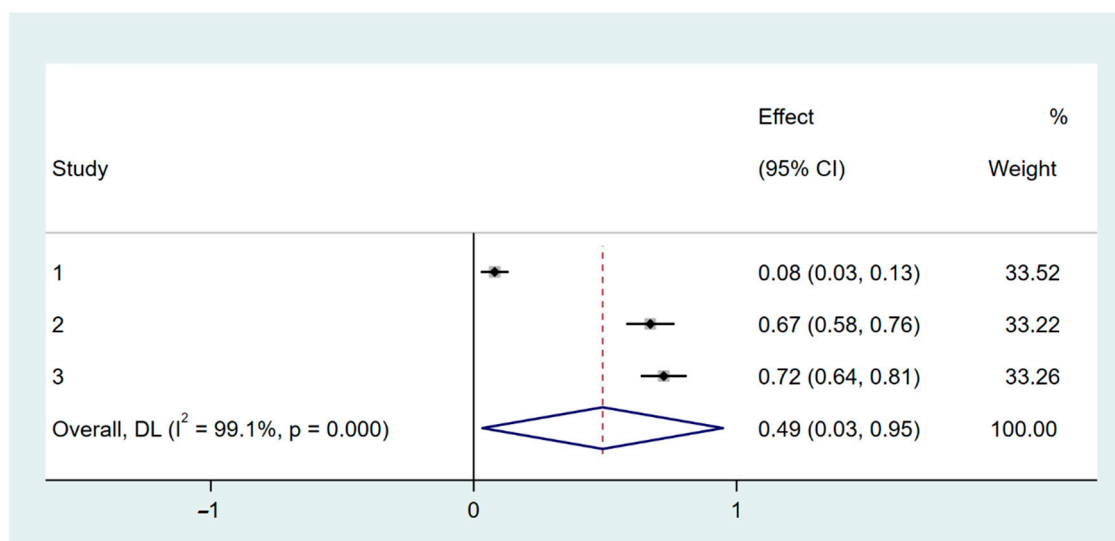


Figure 4. Forest plot of the effect of SP measures on RTN resilience improvement.

For SP measures, there was a statistically significant difference with high heterogeneity ($I^2 = 99.1\%$, $p = 0.000$). Based on the combined random effects model, the total effect value is 0.49, i.e., 95% CI (0.03–0.95). Since only three papers were available, this study used a switching effects model (random effects model/fixed effects model) approach to perform sensitivity analysis. The results were demonstrated to be stable.

RS: Five of the studies demonstrated the effects of RS on improving the resilience of RTN [6,48,52–54]. Yadav et al. [6] prioritized recovery sequences based on predefined metrics; they used network centrality-based recovery methods and found that recovery approaches based on network centrality demonstrated similar effectiveness when compared with the optimization-based GA approach in terms of performance. However, there was one scenario where the recovery approach based on node connectedness outshone the GA approach by nearly 7%. Zhang and Ng [54] expressed the resilience of an RTN in terms of the global efficiency of the network (E) after removing some nodes, and they found that, with regard to pre-flooding targeted attacks, the total loss of E (83%) was reduced by 8% compared with when flooding occurs first after using the entropy weight method (EWM)–technique for order preference by the similarity to ideal solution (TOPSIS) method. Aydin et al. [54] defined the resilience of RTNs as the recovery time of a road network. By dynamically modeling a sequence based on the time variable to improve resilience, they found that the mean recovery time of 25% of recovered road segments dropped from 251.73 to 40.04. Ishibashi et al. [48] used the post-disaster function of RTNs as their resilience definition and expressed it in terms of R_{\max} . They prioritized the retrofitting of structures and increased the R_{\max} of Owase from 81.0 to 83.9. Yanni et al. [52] considered resilience

to be the level of node connectivity after a system outage and the ability to restore node connectivity to an acceptable level through appropriate restoration measures. They used an optimal recovery strategy based on system resilience to improve the resilience of an RTN. In cases of multiple interchange failures, the system resilience of the optimal recovery strategy was 5.2% greater than that of the worst recovery strategy.

The combined effects reflected that the effect value was 0.21, i.e., 95% CI (−0.01, 0.44), which implied that RS could increase the resilience of RTNs to a certain extent (Figure 5). However, the collected research showed statistically significant heterogeneity ($I^2 = 99.1\%$). The sensitivity analysis identified Aydin et al.'s [54] study as an outlier that could have potentially influenced the size of the effect and the heterogeneity of the findings. As a result, additional analysis was conducted after excluding this outlier, and the results showed minimal heterogeneity (effect size: 0.06, i.e., 95% CI (0.03–0.08), $I^2 = 11.6\%$, and $p = 0.323$).

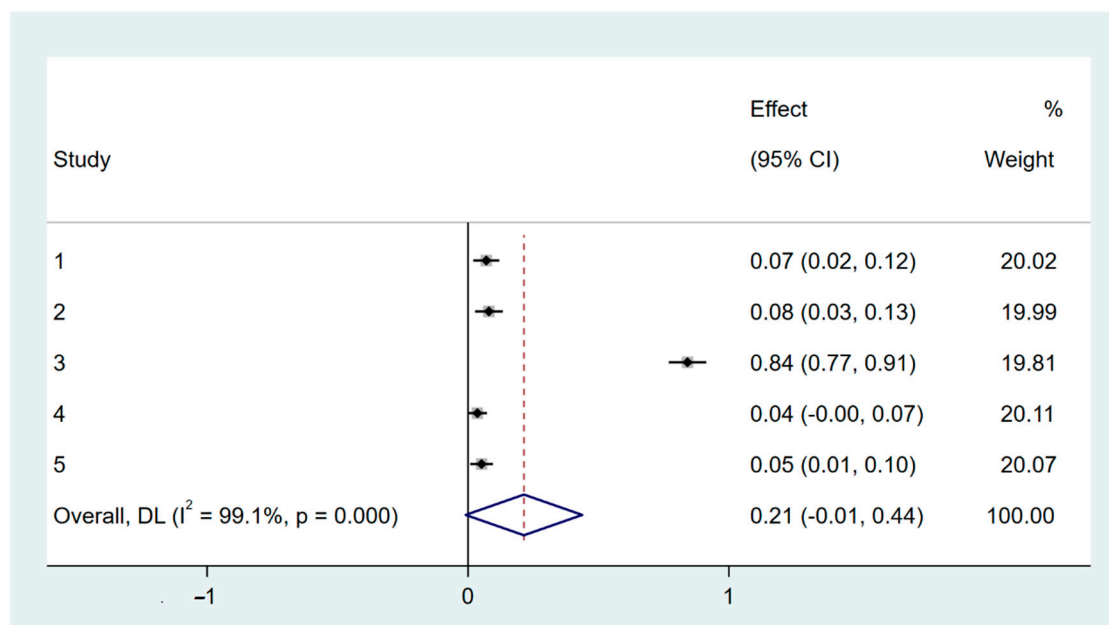


Figure 5. Forest plot of the effect of RS measures on RTN resilience improvement.

TSM: Four studies reported TSM measures that could be used for integrated analysis [39,40,50,57]. Shang et al. [40] used the relative area index to represent resilience in their paper, and they applied a method based on adaptive signal control with depth reinforcement to improve the resilience of RTNs, and this can increase the relative area index from 0.25 to 4.65 at a 75% capacity reduction in the affected section. Chiou [39] found the model benefit of a resilient linked signal (MB) and used flexible signaling control to improve the resilience of an RTN. This approach could achieve the highest level of resilience (nearly 4.5%) compared with others using MB. Dana Abudayyeh et al. [50] defined travel time as resilience in their study, and they adopted a bilevel optimization framework using the CE algorithm to draw the conclusion that applying signal optimization can reduce travel time by almost 6%. To solve the suggested network-wide traffic signal optimization model, Tao et al. [57] devised a two-level method based on the greedy approach and gradient descent, and the resilience of RTNs was characterized as resilience loss (RL). The findings showed that the suggested model might increase system resilience under various scenarios. The maximum resilience loss was lowered by 1.4%.

The meta-analysis revealed that there was no statistically significant difference between TSM measures in terms of improving the resilience of RTNs, and there was less heterogeneity in several studies ($I^2 = 34.5\%$, $p = 0.205$). Using the random effects model and combining the four studies, the total effect size was 0.04, i.e., 95% CI (0.01–0.06) (Figure 6). This study, after performing sensitivity analysis, found that the study by Tao et al. [57] is an anomaly whose

presence may bias the effect size and heterogeneity. When this study excluded it, the results showed no heterogeneity in several of the other studies ($I^2 = 0$, $p = 0.877$).

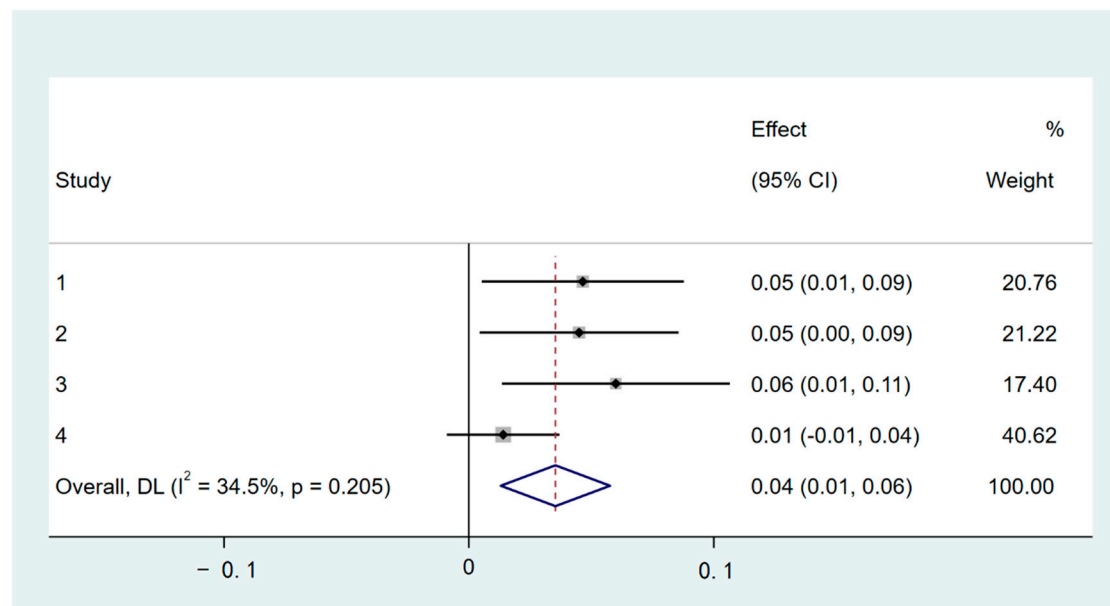


Figure 6. Forest plot of the effect of TSM measures on RTN resilience improvement.

As the systematic review shows, resilience-focused improvement measures can be divided into four categories: (a) II; (b) SP; (c) TSM; and (d) RS. All the included studies were independent, with considerable inter-study heterogeneity. Some of the studies (e.g., [52,53,57]) showed an unclear-to-high risk of bias. Considering the broad range of improvement measures that have been demonstrated to be related to the resilience of RTNs, it is worth noting that these measures all improved the resilience of RTNs in all the studies. There is considerable variability in how the resilience of RTNs is measured and which categories of improvement measures are implemented. Where meta-analysis was possible, SP measures showed the highest effect on the improvement of the resilience of RTNs (0.49 improved; 95% CI: 0.03–0.95). In addition, II also has a significant effect on improving the resilience of RTNs (0.45 improved; 95% CI: 0.01–0.88). RS has a moderate effect on improving the resilience of RTNs (0.21 improved; 95% CI: 0.01–0.44), while TSM showed the lowest effect, which did not significantly improve the resilience of RTNs (0.04 improved; 95% CI: 0.01–0.06). Considering the significant heterogeneity between studies, these results hold valuable information as they compare and rank the effects of various categories of improvement measures on the resilience of RTNs. Despite the notable variations among the studies, the findings provide meaningful insights into how different types of improvement measures impact the resilience of RTNs. In addition, SP is a promising approach to improving the resilience of RTNs.

With this systematic review, our study recognizes that the effect of improvement measures on the resilience of RTNs may be subject to different definitions and measurement indicators. This supports the notion that the definition of the resilience of RTNs results from complex associations in many aspects, such as resistance, recovery, and adaptation [62,63]. The measurement of the resilience of RTNs may also be carried out from a multilevel perspective, such as trait (network topology) [64,65], process (dynamic evolution), and outcome perspectives (traveler characteristics) [66].

The importance of various measures relative to improving the resilience of RTNs was identified in this meta-analysis. This review identified all categories of improvement measures, such as SP, II, RS, and TSM. The findings indicate that all four types of improvement strategies have the potential to increase RTN resilience.

II is a key factor in RTN resilience improvement. It aims to increase investment in the construction, maintenance, and upgrading of infrastructure to improve the resilience of

RTNs. Such measures focus on the resistance aspect, fundamentally improving the strength of RTNs to increase their resilience in the face of disasters or accidents. In this study, measures to subsidize and charge for road access were categorized as II as well because such measures also fall under the area of enhancing resilience through the distribution of program funds or costs. SP is a class of measures that has received the most attention from scholars. It is the same as II, which improves the resilience of RTNs from the perspective of pre-disaster resistance. In addition, there is much evidence that it is relatively effective. Improving redundancy, protecting critical nodes and links, and optimizing network structures are the main means of implementing this type of measure. RS includes methods for optimizing recovery strategies and determining recovery sequences, which emphasize the recovery and adaptation processes after a disruption. As for TSM, most of the related studies were conducted by establishing equitable and sustainable traffic signal settings that improve the resilience of RTNs by directly or indirectly influencing travelers' travel choices and behavioral patterns.

None of these can serve as a "gold standard" [67,68] for measuring the resilience of RTNs. Inaccurate assessments have the potential to yield misleading information, thereby compromising the effectiveness of improvement measures [69,70]. These findings underscore the lack of consistency in the approaches employed in the field, underscoring the need for standardized definitions, conceptual frameworks, and measurement tools. There are other potentially important improvement measures that were not included in this paper, such as information provision. Providing clearer, more timely information to passengers and management can help improve the resilience of RTNs during disasters and the speed of recovery afterward. Yap et al. [55] and Wang et al. [57] also agreed with this view. The resilience of RTNs can also be improved by enhancing communication between operators and users [71].

This systematic review and meta-analysis provides an overview of existing resilience-focused improvement measures for the resilience of RTNs and provides quantitative data on their effectiveness. The findings may offer guidance for future measures and strategies aimed at improving the resilience of RTN. It has been well proven that SP has the highest effect on the improvement of RTN resilience. In addition, the results showed that II also has a significant effect, and RS has a moderate effect, while TSM did not significantly improve the resilience of RTN. By implementing such improvement measures with significant effectiveness as early as possible, the resilience of RTNs is not only improved in its ability to cope with and recover from damage events or natural disasters but also indicates directions for future practice and research on the development of targeted measures to improve the resilience of RTN.

Similar to other studies, this systematic review and meta-analysis has some limitations. Firstly, aiming to provide a contemporary understanding of the topic, this study limited the search to articles published within the past two decades. This study conducted an extensive search only across nine databases, restrictively focusing on articles written in English or Chinese. It should be acknowledged that some relevant studies may be missing. Literature research may be able to minimize the impact of this constraint by encompassing diverse countries and geographical regions. Secondly, the limitations identified in this study shed light on the inconsistencies associated with defining, conceptualizing, and measuring the resilience of RTNs; that is, this study examined the effect of different categories of improvement measures on the resilience of RTNs, which may vary depending on how the resilience of an RTN is measured. Thirdly, the lack of sufficient quantitative data undermines the support for the practice of meta-analysis, indicating that the improvement measures examined in previous quantitative studies, including those analyzed in this meta-analysis, might not cover all possible categories. Finally, the majority of the included studies were rated as having an unclear or high overall risk of bias. However, this heightened risk of bias appears to be a consistent finding in systematic reviews evaluating the effectiveness of resilience-focused improvement measures.

4. Conclusions

The present study contributes to establishing a body of evidence for improving the RTN resilience measures and reveals their effectiveness in improving the resilience of RTNs based on meta-analyses. Therefore, the novelty of this study is to evaluate, compare, and integrate the current evidence on the effective measures of the resilience of RTNs based on a systematic review. This study highlighted limitations in prevailing ways of conceptualizing and evaluating the resilience of RTNs, which may prevent policymakers from judging how and which measures to select and improve. This means that, on the one hand, the present study has the advantage of identifying and evaluating a set of approaches (i.e., II, SP, TSM, and RS) affecting the resilience of RTN, but, on the other hand, it has the limitation of prioritizing these approaches. An RTN is the result of a dynamic evolutionary process, characterized by a continuous cycle of resistance, recovery, and adaptation. To capture the complexity of such a network, it is essential to conceptualize and measure its resilience. This involves considering trait perspectives related to network topology, process perspectives that encompass the dynamic evolution of the network, and outcome perspectives that take into account the characteristics of travelers. By incorporating a broader range of system and contextual determinants, a more comprehensive understanding of RTN resilience can be achieved. Additionally, improvement measures were divided into four categories, that is, SP, II, RS, and TSM, and their positive effects on the resilience of RTNs are shown in the meta-analysis. To address the research question, it should be noted that the efficacies of the four kinds of improvement measures, SP, II, RS, and TSM, were organized in that order. This study recommends in-depth research to observe the changing process of the resilience of RTNs after improvement measures are implemented. It is also important to analyze the combined effects of multiple systems and contextual determinants on the improvement of RTN resilience in order to further bolster the growing body of evidence in this field and facilitate the development of increasingly efficacious approaches. The implications of RTN resilience can be considered integral in the disruption of transport networks. If transport networks are not resilient, or, in other words, the transport network cannot recover quickly from disruptions, unpredictable events can lead to significant transport delays that may result in higher lost time costs than the number of disruption costs in the transport network.

Based on this study, further studies on improvement measures for the resilience of RTNs can take the following recommendations into account: First, by considering the resilience of RTNs as a dynamic process, it is desirable to measure it separately at different time points. Further longitudinal research is required to fully capture the changing process of the resilience of RTNs after improvement measures are implemented. Second, as the data presented in this paper are insufficient to demonstrate the long-term effect of the implemented improvement measures on ATTN AE, it is advisable to extend the duration of future investigations to comprehensively evaluate their long-term effects. Third, recent theories on improving the resilience of RTNs indicate that it is a complex interaction between multiple systems and contextual determinants. Further studies could investigate the combined effect of these multiple systems and contextual determinants such as SP, II, RS, and TSM.

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