Public Transport Resilience and Robustness: A Systematic Review of Metrics, Modeling Paradigms, and Operational Decision-Support Architectures

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Abstract: - Urban metro systems are increasingly exposed to operational failures, demand shocks, and climate-related disruptions. Despite rapid growth in resilience research, conceptual ambiguity and methodological fragmentation persist. Robustness, reliability, and resilience are frequently conflated, recovery dynamics are inconsistently modeled, and passenger-centered performance metrics remain underdeveloped. This compliant systematic scoping review synthesizes 194 studies (2005–2025), of which 72 met strict inclusion criteria requiring explicit public transport focus and quantifiable resilience or robustness indicators. Studies were classified by disruption type, methodological paradigm (optimization/control, simulation, network science, data-driven models), recovery strategy (bus bridging, short-turning, passenger flow control), and data source (AFC, AVL, APC, GTFS).

Results reveal six dominant research clusters, with strong growth after 2019. However, most contributions operationalize resilience through static connectivity or efficiency loss metrics, while comparatively few model recovery trajectories, passenger delay distributions, accessibility degradation, or multimodal capacity interactions under uncertainty. Optimization-based disruption management and uncertainty-aware substitute bus models demonstrate the highest operational relevance, yet empirical validation and equity-sensitive indicators remain limited. We propose a unified three-layer resilience architecture linking topology, operations, and passenger behavioral response under stochastic recovery. Advancing metro resilience requires shifting from static robustness indices toward calibrated passenger-impact recovery curves integrated into real-time decision-support systems.

Key-Words: - Metro Disruptions; Public Transport Resilience; Bus Bridging; Passenger Flow Control; Robust Timetabling; Multimodal Networks

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1 Introduction

Disruptions in high-capacity urban rail systems are not merely "delays"; they often trigger a coupled failure mechanism: reduced train capacity produces platform crowding, crowding increases dwell times, and longer dwell times further reduce capacity. In dense metro networks, this feedback can spread through transfer hubs and create cascading impacts that are disproportionate to the initial incident. As a result, resilience in metro and multimodal public transport has shifted from a peripheral concern to a core operational and planning objective.

Within the reviewed literature, resilience is typically distinguished from reliability and robustness by its explicit focus on performance degradation, recovery, and adaptation over time. Comprehensive transport resilience reviews emphasize that resilience metrics must align with the shock–response–recovery narrative and must be interpreted alongside related concepts such as vulnerability, robustness, and redundancy [1], [2], [3].

A critical reason metro resilience is challenging is that the system is intrinsically multimodal during disruptions: operators rely on substitute bus services (bus bridging) and travellers change routes, modes, departure times, and even activity patterns. Recent disruption-focused models address these operational levers explicitly, for example by optimizing the initiation time and contracting of substitute bus services under uncertain recovery time [4], [5], by coordinating bus bridging with metro short-turning and passenger assignment [6], or by designing evacuation schemes that leverage the existing urban bus network under heterogeneous risk-taking behaviour [7].

Despite this progress, important uncertainties remain. First, many resilience indices are computed from network topology or infrastructure attributes without modelling passenger demand, crowding, and operational constraints; network-based metro resilience work has highlighted both the value and the limitations of such approaches [8], [9], [10]. Second, data-driven passenger flow prediction has expanded rapidly, but the pathway from prediction to robust, implementable control policies is less developed [11], [12], [13]. Third, passenger experience, risk perception, and equity considerations are often treated as secondary, even though disruption impacts are experienced primarily by passengers [14], [15], [16].

2 Methodology

This paper is a systematic scoping review designed to map methods and evidence across a broad, interdisciplinary literature. Because the evidence includes heterogeneous modelling, simulation, and empirical studies, formal meta-analysis is not generally feasible; instead we apply structured evidence mapping and narrative synthesis.

The starting point was a library of 194 articles spanning 2005–2025. The corpus includes journal articles, conference papers and a small amount of grey literature relevant to metro systems, urban rail, buses and multimodal public transport (including passenger-flow modelling, network resilience metrics, timetable/route design, simulation, and passenger experience). Each record was screened using its title and (where available) abstract. Records were classified into one of seven topical clusters based on folder structure and content: Disruption-based management, Passenger flow, Route and timetable, Multimodal networks, Simulation, Passenger experience, and Resilience frameworks. For cross-cutting analysis, each paper was also assigned a primary method family (optimisation/control, simulation, data-driven/ML, network science/metrics, passenger behaviour/experience, policy/accessibility, or mixed). This second label was derived from keywords in the title/abstract and verified by spot-checking full texts for representative studies in each family.

For each paper we extracted (where available): publication year; title; DOI; disruption context (planned vs unplanned; partial vs full line closure; uncertain recovery); data sources (e.g., AFC smart-card data, AVL, surveys, GTFS, synthetic scenarios); core outcomes (delay, headway regularity, throughput, crowding, accessibility, emissions, satisfaction); validation approach (calibration to observed data, sensitivity analysis, scenario stress testing); and stated implementability (inputs required, computation time, and operator relevance). The review integrates studies by thematic mechanisms rather than listing one-study-per-paragraph. For each theme we compare modelling choices, identify consistent findings and contradictions, and highlight practical constraints. We also propose an integrated framework linking network structure, operations, passenger behaviour, information provision, and recovery dynamics.

3 Results

The corpus contains 194 records published between 2005 and 2025, with a strong concentration after 2019 (peak output in 2022, n=50). Table 1 summarizes the topical clusters and primary method families used in the corpus. A practical interpretation is that the field is simultaneously expanding in data-driven prediction and simulation capability, while operational decision support remains dominated by optimisation/control and disruption-focused modelling. The literature draws on ecological and engineering traditions, but PT research often conflates robustness and resilience. Robustness typically refers to absorptive capacity (minimal degradation under disturbances), while resilience extends to recovery and adaptation. A persistent issue is that topology-only connectivity metrics are frequently labeled as “resilience,” despite not representing recovery trajectories or passenger-impact outcomes.

3.1 Disruption Types And Outcomes Assessed

Across the disruption-focused and resilience-oriented studies, disruptions are most often operational (incidents, signal failures, rolling-stock issues, station closures) or institutional (strikes), with uncertain recovery time frequently treated as a key driver of decision making for substitute services [4, 17]. A second recurring stressor is demand surge or crowding amplification during partial capacity loss, which motivates passenger flow control and coordinated train/bus operations [6, 13, 18]. The most common quantitative outcomes are passenger delay (often total generalized delay), system throughput, and service regularity; fewer papers measure passenger exposure to crowding, distributional equity, or health/access outcomes [14, 16, 19].

Table 1. Evidence map of the reviewed corpus

Cluster	Number of studies	Typical emphasis (from titles/abstracts)
Resilient Based	38	Definitions, indices/metrics,

		vulnerability, infrastructure and network resilience
Multimodal Network Based	36	Multimodal assignment/route choice, metro-bus integration, alternative services
Passenger Flow Based	33	Demand estimation/prediction, crowding and passenger flow control, AFC/AVL analytics
Route & Timetable Based	32	Transit network design, timetabling, operational planning, walking access
Passenger Experience Based	21	Service quality, satisfaction, perceived safety/risk, vulnerable groups
Disruption Based	17	Substitute bus services (bus bridging), rescheduling, emergency response
Simulation Based	17	Agent-based and microscopic simulation, calibrated what-if evaluation

The temporal trajectory of the included studies is depicted in Figure 1. The distribution reveals a progressive increase in research activity, particularly after the mid-2010s, indicating growing academic engagement with the topic over the last decade.

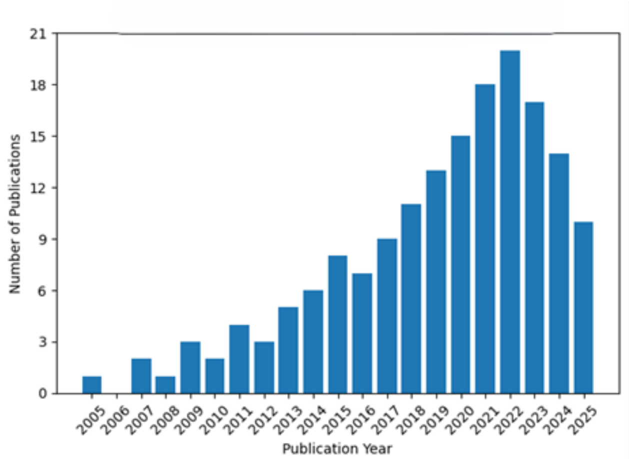

Fig. 1: Publication year distribution

To better understand the epistemological orientation of the field, the included studies were classified according to their primary methodological paradigm. Each paper was assigned to a single dominant category based on the principal analytical approach driving its core contribution. This classification enables identification of methodological dominance patterns and highlights the relative prevalence of analytical, empirical, and simulation-based approaches within the final corpus. Figure 2 presents the distribution of studies across the identified methodological paradigms.

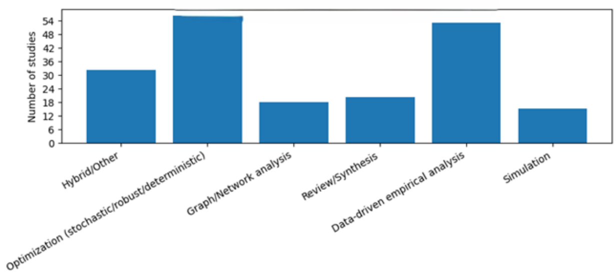

Fig. 2: Primary methodological paradigm

As illustrated in Figure 2, optimization-based approaches constitute the most prevalent methodological paradigm within the corpus, closely followed by data-driven empirical analysis. Together, these two categories account for the majority of contributions, indicating a strong emphasis on quantitative modeling and algorithmic solution frameworks. Hybrid approaches also represent a substantial share, suggesting increasing methodological integration across paradigms.

In contrast, simulation-based studies and purely network-analytic approaches appear less frequently, while review and synthesis contributions remain comparatively limited. This distribution reflects a field predominantly oriented toward operational and computational problem-solving, with comparatively fewer contributions dedicated to conceptual consolidation or methodological synthesis. the results reveal a quantitatively dominated research landscape, characterized by a strong reliance on optimization and empirical modeling techniques.

3.2 Operational And Performance-Based Resilience Metrics

Operational resilience shifts the outcome from connectivity loss to passenger impact. Metrics include passenger delay, recovery time, headway reliability, service availability, crowding/denied boarding, and accessibility degradation. Disruption management studies operationalize resilience through dispatching, re-timetabling, short-turning, and substitute bus services (bus bridging). A central methodological challenge is selecting a “function” measure Q(t) that is meaningful for agencies (e.g., accessibility rather than ridership).

Uncertainty-aware PT resilience models use stochastic programming, robust optimization, and scenario-based planning to hedge against uncertain disruption duration, location, and demand response.

While theoretically strong, many studies rely on assumed scenario sets due to limited incident distribution data, and few report decision-value metrics such as VSS or EVPI that quantify the benefit of stochastic modeling over deterministic approximations.

Empirical resilience measurement is enabled by AVL (realized trajectories, delays), APC (boarding/alighting and crowding proxies), AFC/smart cards (OD and transfer inference), and GTFS/GTFS-RT (schedule vs realized service comparison). Machine learning is commonly applied for demand prediction and anomaly detection, but its resilience contribution depends on integration into operational decision loops. Digital twin concepts are increasingly discussed but remain under-evaluated for real-time disruption response in most published studies.

3.2.1 A Unified Passenger-Centered System Performance Function

A central limitation identified in the reviewed literature is the absence of a standardized system performance function capable of representing resilience beyond topology-based or efficiency-loss metrics. In many studies, resilience is inferred from static structural indicators or aggregate service measures that do not explicitly capture passenger-experienced impacts or recovery dynamics. To address this gap, resilience must be formulated as a time-dependent system performance trajectory grounded in measurable operational and passenger-centered variables.

In this study, system performance at time t, denoted as $Q(t)$, is defined as a normalized composite function integrating service efficiency, passenger delay, crowding conditions, and accessibility [18], [20]:

$$Q(t) = \omega_1 \cdot \left(1 - \frac{D(t)}{D_0}\right) + \omega_2 \cdot \frac{S(t)}{S_0} + \omega_3 \cdot \left(1 - \frac{C(t)}{C_{max}}\right) + \omega_4 \cdot \frac{A(t)}{A_0} \quad (1)$$

Where $Q(t)$represents the normalized system performance level, bounded between 0 and 1. The term $D(t)$denotes total passenger delay at time t, while D_0represents the baseline delay under normal operating conditions. The ratio $S(t)/S_0$captures the relative service throughput compared to nominal capacity. Crowding effects are represented through $C(t)$, defined as passenger load factor or density, normalized by a critical threshold C_{max}. Accessibility is represented by $A(t)$, reflecting the reachable opportunities or effective connectivity of the network under disruption, normalized by its baseline level A_0. The weighting coefficients $\omega_i$are convex weights satisfying $\sum \omega_i = 1$, allowing policy-dependent prioritization of performance dimensions.

This formulation ensures that system performance is not evaluated solely from an operator perspective (e.g., throughput), but instead reflects a joint operational–passenger outcome space, where efficiency, service continuity, and user experience are simultaneously considered.

Within this framework, resilience is not interpreted as a static property but as a temporal recovery process. Accordingly, resilience is defined as the normalized area under the system performance curve over a disruption and recovery horizon:

$$R = \frac{1}{T} \int_{t_0}^{t_1} Q(t)\, dt \quad (2)$$

where Rrepresents the overall resilience level, $T = t_1 - t_0$is the evaluation horizon, and $Q(t)$describes the system performance trajectory. This definition aligns with the shock–response–recovery paradigm and ensures that both magnitude of degradation and speed of recovery are explicitly captured.

A key challenge in resilience assessment is the incorporation of qualitative dimensions such as equity and accessibility into quantitative operational metrics. To address this, passenger impacts are disaggregated across user groups and aggregated through weighted formulations.

Passenger delay is defined as:

$$D(t) = \sum_{i \in P} w_i \cdot d_i(t) \quad (3)$$

where $d_i(t)$represents the experienced delay for passenger group i, and $w_i$denotes an equity weight reflecting the relative importance of that group. These weights can be defined based on socio-economic characteristics, mobility constraints, or policy priorities, enabling the explicit incorporation of distributional effects into system evaluation.

Accessibility under disruption is expressed as:

$$A(t) = \sum_{i \in N} O_i \cdot f(c_{ij}(t)) \quad (4)$$

where $O_i$denotes the number of opportunities associated with node i, $c_{ij}(t)$represents the generalized travel cost between nodes $i$and j, and $f(\cdot)$is an impedance function capturing travel resistance. This formulation reflects the degradation of effective connectivity and access under disrupted conditions.

Through these formulations, qualitative constructs such as equity, accessibility, and passenger experience are transformed into operationally measurable variables, enabling their integration into real-time or scenario-based resilience evaluation without oversimplifying their underlying dynamics.

3.3 Modelling families: capabilities and limitations

Network science approaches typically treat a metro or multimodal system as a graph and evaluate robustness/resilience through connectivity, efficiency, or criticality measures. This family is valuable for identifying structurally important stations/links and for stress testing removal or capacity degradation scenarios [8], [9], [10]. However, topology-only indices can misrepresent operational impact when the main disruption mechanism is passenger overload, transfer penalties, or train dispatch constraints. In the reviewed corpus, network-based work increasingly recognizes this limitation and calls for flow-weighted, demand-aware metrics and integration with operational models.

Optimisation and control models provide the most direct bridge from analysis to operational decision support. Within metro disruption management, a core set of studies formalizes the substitute bus decision as an optimisation under uncertain recovery time, including the optimal initiation timing and contracting strategy for substitute bus services [4]. Complementary work expands the decision space to include coordination between metro short-turning and bus bridging, and assigns passengers to services to minimize total delay [6]. Route design for bus bridging is also treated as a structured problem, with disruption patterns between O–D pairs mapped to candidate bridging routes [21]. Two technical issues recur across these models. First, uncertainty about disruption recovery time is not a minor detail: it changes whether the fixed initiation cost of substitute service can be justified and how aggressively passengers should be re-routed. Models that explicitly embed uncertain recovery time demonstrate different optimal policies compared with deterministic formulations [4]. Second, feasibility and implementability depend on fleet availability, road congestion effects, and operator contracting constraints, elements that are often simplified or treated parametrically.

Beyond substitute buses, robust train scheduling and service design under disruption is studied through rescheduling and control strategies. Skip-stop and short-turning strategies appear in both disruption-specific and resilience-oriented simulation/optimisation work, often motivated by the need to preserve throughput and manage crowding [22], [23], [24]. Last-train timetabling and coupled bus bridging for stranded passengers illustrates how disruption management can extend beyond immediate incident response into end-of-service recovery planning [25].

Simulation is the main tool for evaluating complex ‘what-if’ scenarios where analytical optimisation becomes intractable or where behavioural response matters. Recent simulation reviews catalogue a wide range of approaches, from agent-based models (ABM) to microscopic multimodal simulation and hybrid frameworks [26], [27]. Simulation studies are especially useful for (i) propagating crowding and dwell-time effects, (ii) capturing capacity interactions between metro and road-based substitute services, and (iii) testing strategies such as skip-stop, frequency adjustment, and multimodal re-routing under realistic constraints [28], [29].

Nevertheless, simulation-based evidence is only as credible as its calibration and validation. A persistent weakness in the corpus is limited reporting of calibration quality, uncertainty ranges, and transferability. Where calibration is performed, it typically relies on AFC/AVL data or passenger counts; where it is absent, findings should be interpreted as scenario-specific insights rather than generalizable evidence. Passenger flow prediction is the fastest-growing thread in the corpus. Deep learning and spatio-temporal models are used to forecast station inflows/outflows and origin–destination matrices, often using smart-card data and external covariates [30]. These models are valuable for early warning and demand-aware planning, but prediction alone does not guarantee resilience gains.

The core translational gap is moving from prediction to decision. A smaller set of papers formulates online or robust passenger flow control and train scheduling, explicitly linking demand states to control actions [13], [18], [23]. Even here, implementability depends on how control actions are operationalized (e.g., gating, headway control, platform management, transfer restrictions), and on whether passenger behavioural adaptation (route switching, balking, compliance) is modelled or assumed.

3.3.1 Quantifying the Value of Stochastic Modelling

Despite the growing use of stochastic and robust optimization approaches, the reviewed literature rarely quantifies their decision value relative to deterministic approximations. This represents a critical gap, as the practical relevance of stochastic modelling depends not on theoretical sophistication, but on measurable improvements in decision quality.

Two standard metrics from stochastic optimization theory are particularly relevant:

- Value of the Stochastic Solution (VSS)
- Expected Value of Perfect Information (EVPI)

These are defined as:

$VSS = Z_{\text{det}} - Z_{\text{sto}}(5)$

$EVPI = Z_{\text{perfect}} - Z_{\text{sto}}(6)$

where Z_{det} represents the objective value obtained under deterministic assumptions, Z_{sto} corresponds to the stochastic solution, and Z_{perfect} denotes the solution under perfect foresight.

The VSS quantifies the benefit of explicitly modelling uncertainty, while EVPI represents the upper bound on the value of additional information. Incorporating these metrics into resilience studies enables a rigorous assessment of whether stochastic formulations materially improve disruption-response decisions.

3.4 Multimodal Networks And Alternative Services

Multimodal modelling is essential because disruption response typically shifts demand across modes. Several papers develop or calibrate multimodal route choice and assignment frameworks, including formulations of dynamic user equilibrium and temporal validation of multimodal assignment [31], [32], [33]. These studies clarify that realistic multimodal resilience assessment requires representing transfer penalties, capacity constraints, and travellers' heterogeneous preferences.

A distinct multimodal disruption-management line focuses on scheduling and deploying alternative services when rail is disrupted. Scheduling multimodal alternative services explicitly frames substitute options as a coordinated service design problem under constraints [34]. Other multimodal planning studies investigate integration policies (e.g., metro-bus integration and priority measures such as exclusive bus lanes) that indirectly shape system resilience by providing latent flexibility [35], [36].

Active integration with micromobility is also present, particularly via bike sharing. Work on bike sharing in conjunction with public transport highlights both potential resilience benefits (additional first/last-mile flexibility) and equity risks (unequal station siting and access) [37], [38], [39].

3.5 Passenger Experience, Equity, And Externalities

Passenger-focused studies emphasize that perceived quality, safety, information, and convenience strongly influence compliance with disruption management measures. Survey-based satisfaction and perception models are common, including work linking corporate image and service attributes to behavioural intentions and broader passenger satisfaction evaluations in urban contexts [40], [41], [42]. However, many studies are context-specific, rely on cross-sectional designs, and use different constructs and scales, making synthesis difficult. Equity and vulnerable groups appear more explicitly in recent work. Studies assessing impacts on vulnerable populations highlight that disruptions and low service reliability can deepen accessibility disadvantages . Walking access and station catchment studies show that "last-mile" constraints can dominate mode choice and realized accessibility, especially where service frequency drops during disruptions.

Finally, some papers quantify broader externalities of disruption. For example, strike-focused analyses relate public transport withdrawals to traffic and pollution impacts, and COVID-era studies link public transport disruptions to access to healthcare and wellbeing, illustrating how resilience extends beyond engineering performance into social outcomes [19], [43].

4 Discussion

Taken together, the corpus suggests that metro resilience is best understood as a coupled system of (i) network structure, (ii) operational control, (iii) passenger behavioural response, (iv) information and governance, and (v) recovery dynamics. Conceptual resilience work emphasizes the need to operationalize resilience in ways that are measurable, decision-relevant, and linked to recovery trajectories [2], [3]. Disruption-management models demonstrate that operational levers (substitute buses, short-turning, passenger allocation) can change both the depth of performance loss and the speed of recovery [4], [6]. Meanwhile, passenger flow prediction/control literature provides the demand-state observability needed for adaptive management [11], [13], [18].

Based on this synthesis, a deployment-grade resilience 'digital twin' for metro and multimodal systems would minimally require: (1) a demand module calibrated to AFC/AVL data; (2) an operations module representing train dynamics, capacity, and control actions (including short-turning/skip-stop and station management); (3) a multimodal substitution module for buses and other modes under road congestion constraints; (4) behavioural response models for route/mode switching, compliance with control measures, and risk perception; and (5) an uncertainty layer capturing disruption duration and demand volatility. The literature contains strong building blocks for each module, but limited evidence of fully integrated and validated end-to-end implementations.

Several practical implications emerge consistently. First, substitute bus decisions should be treated as uncertainty-sensitive: initiation and contracting policies depend critically on the distribution of recovery time and the fixed costs of activation [4], [43]. Second, bus bridging is most effective when coordinated with metro operating plans (short-turning, transfer management) rather than applied as a standalone add-on [6], [21]. Third, passenger flow control is not only about prediction accuracy but about actionable control policies and communication that shape compliance and prevent crowding amplification [13], [18]. Fourth, equity and accessibility outcomes should be monitored explicitly, particularly for vulnerable groups and essential services, because disruption impacts are not evenly distributed [14], [19].

This review has three main limitations. First, the evidence base is a curated corpus rather than a full database search; therefore, the review characterizes the provided library and synthesizes it, but does not claim exhaustive global coverage. Second, many modelling papers provide limited details on calibration, uncertainty, and real-world implementability; this constrains the strength of any generalizable 'what works' claims. Third, heterogeneous definitions of resilience and inconsistent outcome reporting hinder comparison across studies, a challenge also emphasized in transport resilience concept reviews [2].

4.1 From Prediction to Operational Decision Support

A key limitation identified in the literature is the persistent translational gap between high-accuracy prediction models and implementable control policies. While advances in demand forecasting and disruption detection improve system observability, their contribution to resilience remains limited unless integrated into closed-loop decision-support systems.

To address this, the proposed digital twin framework must operate as an **integrated control architecture**, linking real-time state estimation, short-term prediction, decision optimization, and feedback. In this structure, predicted demand and disruption states inform adaptive control actions (e.g., dispatching, rerouting, flow regulation), which are continuously updated based on observed system response.

Critically, disruption-response strategies such as bus bridging, metro short-turning, and passenger flow control should not be treated as standalone interventions. Instead, they must be **jointly coordinated** within a unified optimization framework that minimizes passenger delay and crowding subject to operational constraints, including fleet availability, road congestion, and station capacity limits.

Beyond technical integration, deployment of such systems raises governance challenges. Decision-support tools must ensure transparency, auditability, and equity, particularly when disruption-management measures disproportionately affect vulnerable users. This requires embedding accessibility and distributional considerations directly into performance metrics and decision objectives.

Future research should therefore move beyond static resilience indices toward uncertainty-aware, multimodal, and behaviorally consistent decision-support systems, capable of guiding real-time disruption management in high-capacity urban rail networks.

5 Conclusions

This systematic scoping review synthesized 194 studies (2005–2025), of which 72 satisfied strict inclusion criteria requiring explicit public transport focus and quantifiable resilience or robustness constructs. The literature has expanded rapidly, yet conceptual precision has not advanced proportionately. A substantial share of studies labeled as "resilience" rely on static connectivity or efficiency-loss metrics that measure structural robustness rather than recovery dynamics, passenger delay propagation, or accessibility degradation. At the same time, disruption-management models demonstrate that operational policies, substitute bus services, short-turning, coordinated passenger allocation are highly sensitive to uncertainty in disruption duration and demand response, but probabilistic evaluation and empirical validation remain inconsistent. Optimization sophistication frequently exceeds calibration transparency, limiting confidence in real-world transferability.

Collectively, the evidence indicates that metro resilience is not a purely structural attribute but an emergent property of interacting network, operational, demand, behavioral, and uncertainty layers. Passenger-centered recovery trajectories, not topology-only indicators must become the primary performance reference. Governance implications are clear: resilience assessment should be grounded in calibrated operational data, evaluated under probabilistic disturbance scenarios, and explicitly integrate accessibility and equity impacts. Without tighter definitions, stronger validation, and end-to-end multimodal decision-support integration, resilience risks remaining rhetorically persuasive but operationally ambiguous. The next stage of research must shift from producing additional indices toward delivering implementable, uncertainty-aware, passenger-focused systems capable of guiding real-time disruption management

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Conflict of Interest

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