Urban and Building Science
https://www.sciltp.com/journals/ubs

Article

Delay-Induced Passenger Electricity Use in Public Transport: A Critical Review and Analytical Framework

Ali Safaeianpour

Interuniversity Department of Regional and Urban Studies and Planning, Politecnico di Torino, 10125 Torino, Italy; a.safaeianpour@studenti.polito.it

How To Cite: Safaeianpour, A. Delay-Induced Passenger Electricity Use in Public Transport: A Critical Review and Analytical Framework. *Urban and Building Science* **2026**. https://doi.org/10.53941/ubs.2026.100026

Received: 22 May 2026
Revised: 25 August 2026
Accepted: 26 August 2026
Published: 10 September 2026

Abstract: Public transport unreliability is usually evaluated through travel time, service quality and operational energy use, while the electricity associated with passengers' digital behaviour during disruptions remains largely outside transport-energy assessments. This study introduces Delay-Induced Passenger Electricity Use (DPEU) as a counterfactual framework for examining whether unreliable service changes passenger-related digital electricity consumption relative to equivalent normal-service conditions. A critical review integrates evidence on transport reliability, passenger accumulation, digital behaviour, smartphone electricity demand and supporting ICT infrastructure. The framework represents passenger exposure dynamically and distinguishes additional digital activity from activity that is temporally displaced or suppressed. An order-of-magnitude real-system application is developed for GTT Line 4 in Turin using a documented frequency-based service baseline and analytical headway perturbations rather than reconstructed historical disruption events. Parameter uncertainty is propagated through 300,000 Monte Carlo combinations. Device-side DPEU has theoretical bounds of approximately −4.05 to +4.05 Wh per disruption event, while the central 95% of simulated outcomes lies between approximately −1.37 and +1.36 Wh. Sensitivity analysis identifies the counterfactual behavioural difference as the principal determinant of DPEU, particularly its direction, while behavioural intensity, device power, and passenger exposure jointly determine its absolute magnitude. The results indicate that event-level DPEU is small relative to public-transport operational energy use. More importantly, the analysis provides a transparent approach for examining whether a delay-induced electricity effect exists, estimating its possible magnitude and uncertainty, and identifying the empirical observations required for future validation and practical assessment.

Keywords: public transport reliability; urban energy systems; sustainable mobility; passenger behaviour; indirect electricity consumption; delay-induced passenger electricity use (DPEU)

1. Introduction

Urban energy research has developed increasingly detailed approaches for identifying how energy demand, efficiency opportunities, and renewable-energy potential vary across cities. GIS-based methods have been applied to urban solar-energy assessment [1,2], while building-energy modelling and data-driven approaches have been used to investigate passive-design strategies and building performance [3]. In parallel, transport studies have examined the energy implications of travel demand [4,5], fleet operation and technologies [6,7], and public-transport electrification [8]. Together, these studies illustrate how urban energy use can be traced to identifiable systems, activities, technologies, and operating conditions.

Some electricity effects, however, may arise through interactions between systems rather than within the conventional boundaries used to assess them. Public transport provides a relevant setting for examining such interactions. Research has extensively investigated service frequency, reliability, accessibility, passenger experience, and modal integration [9,10], while transport-energy assessments have traditionally concentrated on vehicles, propulsion technologies, operational efficiency, and emissions [11,12]. Less attention has been given to whether the operating conditions of public transport can indirectly influence electricity-consuming activities undertaken by passengers.

Digital activity creates one possible pathway for such an effect. Smartphones are routinely used during travel and waiting for communication, information, navigation, entertainment, and other activities. These interactions consume electricity at the device level and can also involve communication networks and data-processing infrastructure. At a broader scale, assessments of information and communication technologies (ICT) demonstrate that user devices and supporting digital infrastructure contribute to sectoral electricity demand [13,14]. This establishes an energy dimension to digital activity, but does not by itself demonstrate that public transport delays generate additional electricity consumption. The central issue is therefore counterfactual. A passenger using a smartphone while waiting for a delayed service may have performed the same activity later onboard, at the destination, or during another part of the journey if the service had operated normally. Conversely, disruption may stimulate additional activity, for example through repeated information checking or route replanning, while crowded or uncomfortable waiting conditions may suppress digital engagement. Observing smartphone use during a delay is therefore insufficient to classify the associated electricity consumption as delay-induced. This study examines whether public transport unreliability changes passenger-related digital electricity consumption relative to an equivalent journey under normal service conditions. Delay-Induced Passenger Electricity Use (DPEU) is defined as the net change in digital electricity use attributable to this difference. DPEU may be positive when disruption induces genuinely additional digital activity, close to zero when activity is predominantly displaced between journey stages, or negative when disruption reduces digital engagement. The framework consequently treats both the direction and magnitude of DPEU as empirical questions rather than assuming that additional waiting necessarily creates additional electricity demand.

The practical significance of DPEU extends beyond the aggregate amount of electricity involved. At the passenger level, a disruption-related increase in smartphone activity may accelerate battery depletion during a journey, particularly when passengers repeatedly check service information, navigate alternative routes, communicate changes in arrival time, or engage in other energy-intensive digital activities [15–18]. In prolonged or repeated disruptions, reduced remaining battery capacity may affect access to functions that passengers increasingly depend on during travel, including navigation, ticketing, communication, real-time information, and emergency contact. These represent direct user-level implications of altered digital activity. Indirect effects may arise where the same behavioural changes alter demand on communication networks and data-processing infrastructure, or where they alter when and where devices subsequently require recharging [19–21]. At the transport-system level, DPEU can therefore be interpreted not only as an electricity-accounting issue but also as an indicator of how service unreliability interacts with passenger digital resilience and dependence on mobile services. The magnitude of these effects remains context-dependent, but identifying the pathway is practically relevant because mobile devices increasingly support passenger access to travel information, navigation, communication, and other digital services during public transport journeys.

To investigate this relationship, the study combines a critical review of public transport reliability, passenger accumulation and digital behaviour, and ICT electricity demand with an analytical framework that explicitly defines the counterfactual baseline and system boundary. The framework represents passenger exposure dynamically and distinguishes device-side electricity from supporting communication-network and data-centre components. An order-of-magnitude application to GTT Line 4 in Turin uses scheduled GTFS information and published service-frequency data to establish the normal-service reference, while uncertainty in passenger demand, behavioural response, disruption magnitude, and device power is examined through Monte Carlo simulation and sensitivity analysis. The objective is not to establish DPEU as a significant new component of urban electricity demand in advance, but to provide a transparent method for determining whether the effect exists, its possible direction and magnitude, and the observations required for its empirical estimation. The proposed relationship is summarised conceptually in Figure 1.

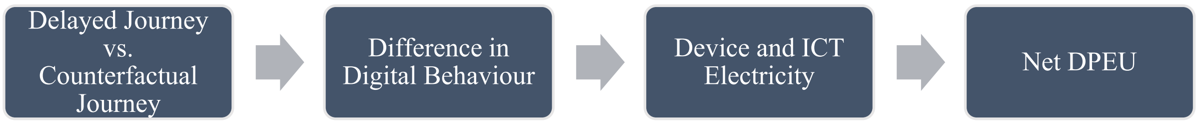

Figure 1. Conceptual overview of the DPEU framework.

2. Critical Review of the Evidence

2.1. Public Transport Reliability and Waiting

The quality of public transport depends not only on travel speed and service frequency, but also on the consistency with which the service operates. Reliability is particularly important because variations in service can directly affect waiting conditions and the distribution of passengers across vehicles. Soza-Parra et al. [22] showed that headway variability is an important source of unreliability and is associated with longer waiting and uneven passenger distribution. Their findings further show that the effects of reliability on passenger satisfaction are closely related to changes in waiting time and crowding conditions. These relationships suggest that reliability should be considered as part of the actual passenger experience rather than only as an operational performance measure. The way reliability is measured, however, depends on how the service is operated. For timetable-based services, reliability can be assessed by comparing scheduled and actual arrival or departure times. In high-frequency services, this approach becomes less representative because passengers may rely more on service frequency than on a specific timetable. In another study, Soza-Parra et al. [23] explain that passengers in frequency-based systems face uncertainty regarding the arrival of the next vehicle even when services operate regularly. Their study further shows that irregular headways affect passenger choices through changes in both waiting time and passenger density. Therefore, the meaning of a delay should not be limited to lateness relative to a published schedule. In frequent urban services, deviations from regular headways and the resulting excess waiting time provide a more suitable representation of unreliability.

Waiting time is also experienced differently from other parts of a public transport journey. Fan et al. [24], based on passenger surveys and direct observations at transit stops and stations, found that reported waiting time was generally longer than the objectively observed duration. They also showed that characteristics of the waiting environment, including basic stop amenities and perceived security, influence this difference. This indicates that the consequences of unreliable service are not determined only by the number of additional minutes. The conditions under which these minutes are experienced can also influence how passengers respond to waiting. Real-time passenger information adds another dimension to this relationship. Watkins et al. [15] found that passengers using mobile real-time information experienced shorter actual waits and smaller differences between perceived and measured waiting time than passengers relying on traditional information. However, later evidence suggests that this benefit is not universal. Liu and Miller [25] compared different real-time-information strategies using empirical bus data and found that the best strategy performed approximately as well as simply following the timetable, while its effectiveness varied across locations and times. Real-time information should therefore not be treated as a factor that automatically reduces waiting. Instead, its effects depend on how passengers use the available information and on the spatial and temporal characteristics of the service. These distinctions become particularly important when service unreliability is used to define the additional waiting period potentially associated with passenger digital activity. A single schedule-based definition cannot represent unreliability equally well across different forms of public transport. For timetable-oriented services, the difference between scheduled and actual operation can provide an appropriate reference. For high-frequency services, headway irregularity and excess waiting are more meaningful. The operational definition of unreliability therefore determines both the additional waiting period attributed to a disruption and the passenger population exposed to it. This distinction provides the basis for examining passenger accumulation and waiting dynamics in the following subsection.

2.2. Passenger Accumulation and Waiting Dynamics

The number of passengers affected by service unreliability is not necessarily constant throughout the waiting period. Passengers continue to arrive while a delayed vehicle is approaching, meaning that the population exposed to additional waiting can change over time. This relationship becomes particularly important when service intervals are irregular, as uneven headways can also produce uneven passenger distribution across consecutive vehicles [22]. A longer-than-expected headway may therefore expose a growing group of passengers to additional waiting, while consecutive vehicles can face different passenger loads. Passenger exposure to unreliability should consequently be understood as a dynamic process rather than represented only by a fixed number of people at a stop.

Passenger arrival patterns add another level of variation to this process. Mishalani et al. [26] model passenger arrivals and bus operations as a stochastic system when evaluating real-time bus arrival information. This approach is important because the number of passengers waiting at a given moment depends on the interaction between passenger arrivals and service operations rather than on delay duration alone. The appropriate representation of arrivals may also vary between services. Passengers using frequent services may arrive with less dependence on a specific scheduled departure, whereas timetable-oriented services can produce more schedule-dependent arrival behaviour. The passenger population affected by unreliability should therefore be considered as a time-dependent quantity. At a general level, this changing waiting population can be represented through a passenger-balance formulation:

$$N(t) = N_0 + \int_0^t \lambda(\tau) d_\tau - B(t) - R(t)$$

where $N(t)$ represents the number of passengers waiting at time t, N_0 is the number already present when the disruption period begins, and $\lambda(\tau)$ represents the passenger arrival rate over time. $B(t)$ represents passengers leaving the waiting population through boarding, while $R(t)$ represents those leaving through rerouting, abandoning the wait, or choosing another available travel option. This expression is introduced here as a general passenger-balance representation rather than a calibrated queueing model. Its purpose is to make explicit that passenger exposure changes throughout a disruption and cannot always be represented by multiplying a fixed passenger count by the total delay duration.

Information availability can further influence these waiting dynamics. Mishalani et al. [26] evaluate real-time bus arrival information within a framework in which passenger arrivals and bus operations are represented as stochastic processes. In another study, Mishalani et al. [27] further examine the relationship between actual and perceived waiting time in the context of evaluating real-time bus arrival information. Together, these studies show why information conditions should be considered when interpreting passenger waiting and exposure, although they do not provide a universal rerouting or abandonment rate. In the revised DPEU framework, such responses should therefore be represented transparently as behavioural possibilities rather than assumed numerical effects.

Passenger accumulation is also closely related to crowding. Soza-Parra et al. [22] show that headway irregularity is associated with uneven passenger distribution and examine the relationship between crowding and passenger satisfaction. However, this evidence does not establish that crowding necessarily increases or decreases smartphone use. This distinction is important for the present research. As waiting passengers accumulate, crowding may change the physical and social conditions in which digital activity occurs, but its influence on smartphone engagement should not be predetermined without direct behavioural evidence. Within a DPEU framework, crowding is therefore more appropriately treated as a potential behavioural moderator whose direction and magnitude should be established empirically or explored through sensitivity analysis.

Collectively, existing evidence indicates that passenger exposure to unreliable service develops dynamically through the interaction of service irregularity, passenger arrivals, boarding, information availability, and individual travel decisions. Treating passenger count as a fixed coefficient may therefore overlook an important temporal dimension of delay. Representing the waiting population as $N(t)$ provides a more appropriate basis for the revised DPEU framework and responds to the need to distinguish between the duration of a disruption and the number of passengers actually exposed to it. The next subsection extends this discussion from passenger accumulation to digital behaviour, examining whether additional waiting changes smartphone activity or simply shifts activity that would otherwise occur during another part of the journey.

2.3. Passenger Digital Behaviour During Waiting and Travel

Digital activities have become a common part of the time spent in public transport environments. Smartphones allow passengers to communicate, access information, browse online content, use social media, listen to media, or perform other activities while waiting and travelling. Wang et al. [28] examined smartphone use specifically among passengers waiting for buses and found that mobile activity was closely associated with the waiting experience. Their results indicate that smartphone use can influence how waiting time is perceived and that passengers respond differently depending on individual characteristics and waiting conditions. This evidence supports the presence of digital activity during waiting, but it does not by itself demonstrate that such activity is caused by a transport delay.

Digital activity is also common after passengers have boarded. Julsrud and Denstadli [29], based on passengers in two Norwegian cities, showed that smartphones and other mobile technologies have changed the way travellers use time on public transport. This means that waiting and travelling should not be treated as completely separate digital environments. A passenger using a smartphone during an unexpected wait may have used the same device later during the vehicle journey if the service had operated normally. This creates an important attribution problem for DPEU. Observing smartphone activity during a delay is not sufficient to classify the associated electricity consumption as delay-induced. Some digital activity may genuinely be additional, for example when unexpected waiting creates an opportunity for an activity that would otherwise not have occurred. Other activity may simply be displaced in time, with smartphone use taking place at the stop instead of during the subsequent journey. A third possibility is that the conditions created by the disruption reduce or interrupt digital activity. Existing travel-time-use research shows that activities undertaken during travel depend on the characteristics of the journey, the travel environment, and passenger characteristics. Ohmori and Harata [30], for example, found that participation in different onboard activities varied with factors including whether passengers were standing or seated and the duration of in-vehicle travel.

The possibility of temporal displacement is particularly important for defining a counterfactual condition. The relevant comparison is not between smartphone use during a delay and no smartphone use at all. Instead, the delayed journey should be compared with the digital activity that would reasonably have occurred during the same journey under normal service conditions. Research on the worthwhile use of travel time supports this approach by showing that travellers already allocate portions of their journey to different activities and that mobile devices affect the activities that can be performed while travelling. Wardman et al. [31], for example, examined what rail passengers did during their journeys, the time spent on these activities, and what they reported they would do in the absence of mobile devices. This demonstrates the importance of considering alternative activity patterns when evaluating the effect of digital technologies on travel-time use.

From the perspective of DPEU, three behavioural outcomes should therefore remain possible. First, a disruption may generate additional digital activity that would not have occurred during the equivalent normal journey. Second, it may produce temporal displacement, in which digital activity occurs during waiting rather than later in the journey, with little change in total activity. Third, digital activity may be suppressed or reduced under some conditions. The available literature does not provide sufficient evidence to assign a universal probability to these outcomes. Consequently, the revised framework should not assume that additional waiting automatically produces additional smartphone electricity consumption. These three possible behavioural outcomes and their relationship with the normal-service counterfactual are summarized in Figure 2.

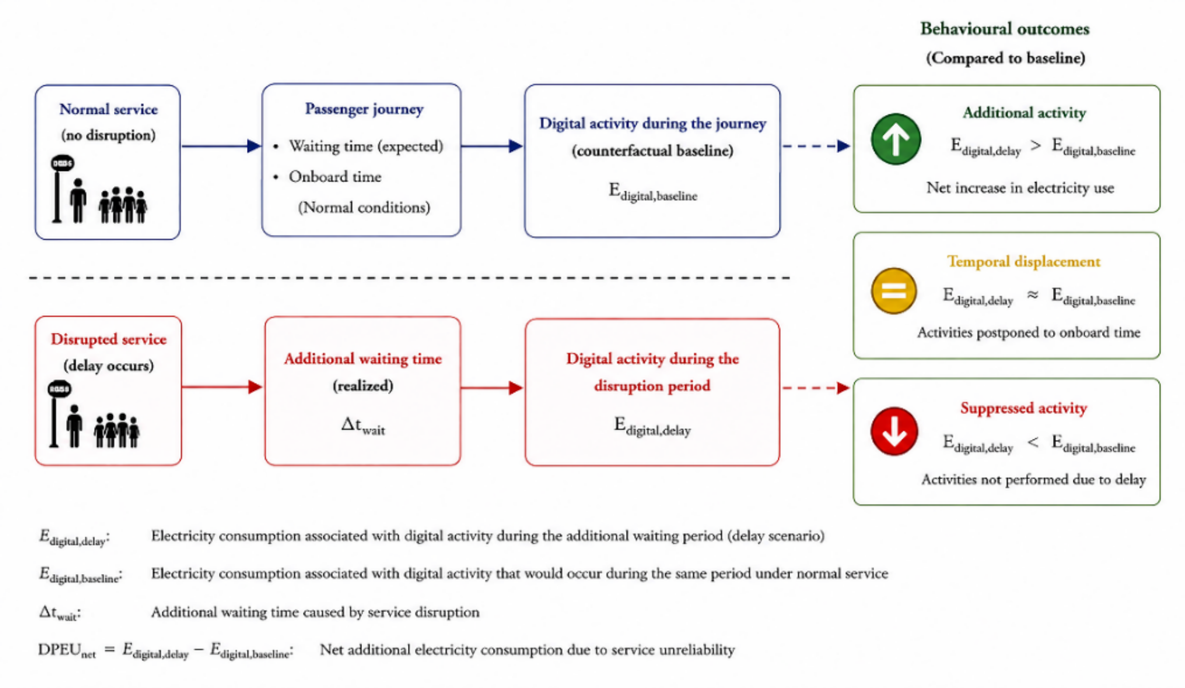

Figure 2. Counterfactual framework for passenger digital activity under public transport service disruption.

Passenger characteristics and travel conditions may further influence these outcomes. Evidence from travel-time-use studies shows considerable variation in activities across individuals and journey environments. Timmermans and van der Waerden [32] found that activities performed while travelling on public transport varied with passenger characteristics, while Ohmori and Harata [30] identified differences associated with onboard conditions and journey duration. Wang et al. [28] also reported heterogeneous responses to smartphone use during bus waiting. These findings suggest that a single fixed rate of smartphone engagement cannot represent all passengers or waiting situations. Behavioural variation should instead be recognised explicitly in the DPEU framework and later examined through parameter ranges and sensitivity analysis.

Taken together, the literature establishes that digital activity occurs both while passengers wait and while they travel, but it does not establish that service unreliability necessarily increases total digital activity over the complete journey. This distinction changes the interpretation of DPEU. The relevant quantity is not all smartphone activity observed during additional waiting, but only the change in digital activity relative to an equivalent journey without the disruption. Establishing this counterfactual provides the behavioural basis for distinguishing genuinely delay-induced electricity consumption from activity that has only shifted in time or location.

2.4. Smartphone Electricity Demand

Translating passenger digital activity into electricity consumption requires consideration of how smartphones use power under different operating conditions. A smartphone does not consume electricity at a constant rate during use because its power demand reflects the combined operation of components such as the display, processor and wireless interfaces. Zhang et al. [33] demonstrated this variability through component-level smartphone power modelling, in which consumption changes with factors including processor utilisation and frequency, display characteristics, and Wi-Fi or cellular operating states. Application-level electricity demand therefore depends on the combination and intensity of components activated during a particular activity, rather than on smartphone use alone. Consequently, smartphone electricity consumption during waiting should not be represented by a single fixed power value without considering the type and intensity of digital activity. Subsequent work has similarly treated applications as combinations of component-level demands rather than assuming that all smartphone activities have the same electricity intensity [34].

This variation is particularly relevant to passenger behaviour because common waiting-time activities can impose different demands on the device. Reading previously loaded content, messaging, web browsing, navigation and video streaming do not necessarily activate the same components or generate the same level of network traffic. Experimental research on mobile video, for example, has shown that power consumption depends on display characteristics, video settings and communication technology [35]. Therefore, two passengers using their smartphones for the same amount of time may consume different amounts of electricity depending on what they do, how the device is configured and how data are transmitted.

Device characteristics introduce further uncertainty. Power models developed for one smartphone generation cannot automatically be transferred to another because processor architecture, display technology, radio hardware and power-management strategies change over time. Kim et al. [36], for example, noted limitations in applying earlier smartphone power models to newer devices with multicore processors, advanced displays and graphics processors. This limits the reliability of assigning a universal device-level electricity coefficient to all passengers. For DPEU, literature-derived power values should therefore be treated as ranges or scenario parameters and, where possible, updated using measurements representative of contemporary devices.

Device-side measurements do not, however, represent the electricity consumed by the wider ICT infrastructure supporting online activities. This external component, including communication networks and data centres, is examined separately in the following subsection.

For the revised DPEU framework, device-side electricity associated with a period of digital activity can be represented generally as:

$$E_{dev} = \int_0^T P_{dev}(t)\, dt$$

where E_{dev} is the electricity consumed by the smartphone during the observation period T, and P_{dev} (t) is the device power demand at time t. The time-dependent form is preferable to a universal constant because power demand may change as passengers move between applications, communication states and device configurations. When detailed measurements are unavailable, an activity-specific average power value may instead be applied over a defined duration, provided that its source, device assumptions and uncertainty range are reported explicitly.

In summary, the available evidence shows that smartphone electricity consumption is activity-dependent, device-dependent and time-varying. This prevents digital engagement during additional waiting from being translated directly into electricity consumption through a single universal coefficient. Within DPEU, device electricity should instead be estimated using transparent activity-specific parameters and uncertainty ranges and subsequently compared with the device electricity expected under the normal-service counterfactual.

2.5. Communication Networks and Data-Centre Electricity

Digital activities performed by passengers can require electricity beyond that consumed directly by their smartphones. Online communication, browsing, social media, navigation, and streaming rely on supporting ICT infrastructure, including access and core networks and, depending on the service, data centres. Recent assessments of digital content consumption therefore consider end-user devices, transmission networks, and data centres as distinct parts of the digital system [19]. For DPEU, this means that changes in passenger digital behaviour may have electricity implications beyond the device itself.

Network electricity consumption, however, should not be assumed to increase directly in proportion to passenger data traffic. Researchers [21] show that a considerable share of network power is related to installed capacity and continuous operation rather than to the amount of data transferred at a particular moment. Consequently, simple electricity-intensity indicators such as kWh/GB can be misleading when used to estimate the incremental electricity caused by additional traffic. The relationship also depends on network technology, load, configuration, and power-management strategies. [20,21].

Data centres add another component because many digital services depend on remote computation, storage, and content delivery. Istrate et al. [19] assess digital consumption across activities including web browsing, social media, video and music streaming, and video conferencing within a system that includes devices and supporting digital infrastructure. Their analysis illustrates that the impacts of digital consumption depend on the type of activity and the infrastructure involved. For DPEU, different passenger activities should therefore not automatically be assigned the same infrastructure electricity intensity.

A key distinction is required between total ICT electricity consumption and the incremental electricity attributable to changed passenger activity. A network or data centre may consume substantial electricity in total, but only part of this demand may change when passenger-generated traffic changes. DPEU should therefore not allocate a proportional share of existing infrastructure electricity to delayed passengers. Instead, the relevant quantity is the change associated with digital behaviour under disrupted conditions relative to normal service. Where this marginal response cannot be measured reliably, it should be represented through uncertainty ranges or reported separately [21].

The digital electricity boundary ($E_{digital}$) of the revised framework can therefore be expressed as:

$$E_{digital} = E_{dev} + E_{network} + E_{DC}$$

where E_{dev} represents electricity consumed by the passenger device, $E_{network}$ represents electricity associated with the relevant communication networks, and E_{DC} represents electricity associated with remote processing, storage, and service delivery in data centres. This expression defines the operational digital-electricity components included within the framework; it does not imply that each component changes proportionally with passenger data traffic or that the total electricity consumption of shared ICT infrastructure can be attributed to an individual passenger. For DPEU, the relevant quantity is the change in these components between disrupted and corresponding normal-service conditions.

Taken together, the evidence supports extending the DPEU boundary beyond the smartphone while treating device, network, and data-centre electricity separately. This distinction avoids attributing the total electricity demand of shared ICT infrastructure to individual passengers and provides a clearer basis for defining the system boundary and uncertainty sources in the following subsection.

2.6. Indirect Electricity Effects and System Boundaries

Estimating DPEU requires a clear decision about which electricity effects can reasonably be attributed to a transport disruption. This is particularly important for digital systems because their environmental assessment can change considerably according to the processes and infrastructure included within the system boundary. Pasek et al. [37] identify system-boundary selection as one of the major methodological challenges in assessing ICT impacts, particularly because digital services depend on interconnected devices and infrastructures that are difficult to assign to individual activities. Recent methodological guidance from ITU-T L.1410 [38] similarly requires the system boundary of an ICT assessment to be consistent with the purpose and functional unit of the study. For DPEU, the boundary should therefore be defined around the specific change being investigated rather than around the total electricity consumption of the digital system.

This distinction is especially important when separating operational electricity from broader environmental effects. Bieser et al. [39], in their review of ICT environmental assessments, distinguish the footprint of ICT equipment and infrastructure from indirect effects arising when digital technologies influence activities in other sectors. Their analysis also shows that estimates of indirect impacts contain substantial methodological uncertainty. In the present framework, the transport disruption acts as the external condition, while changes in passenger digital behaviour represent the pathway through which an electricity effect may occur. The complete life-cycle footprint of smartphones or ICT infrastructure is therefore not assigned to DPEU simply because these technologies are used during waiting.

The same attribution principle applies to the counterfactual established in Section 2.3. Electricity consumption should be considered delay-induced only when it differs from the consumption expected during an equivalent journey under normal service conditions. Digital activity that is merely shifted from onboard travel to waiting should therefore not be counted as additional DPEU. Similarly, electricity that would have been consumed by shared infrastructure regardless of the disruption should not automatically be attributed to it. The boundary is consequently centred on the incremental change associated with service unreliability, rather than all electricity consumption occurring during the waiting period. This attribution can be represented generally as:

$$DPEU_{\text{net}} = E_{\text{digital}}^{\text{disrupted}} - E_{\text{digital}}^{\text{counterfactual}}$$

where $E_{\text{digital}}^{\text{disrupted}}$ represents electricity associated with passenger digital activity under disrupted service conditions, and $E_{\text{digital}}^{\text{counterfactual}}$ represents the corresponding electricity expected under normal service. The same system boundary must be applied to both terms. Depending on data availability, these terms can include the device, network, and data-centre components defined in Section 2.5. The resulting operational system boundary and the distinction between included and excluded components are illustrated in Figure 3.

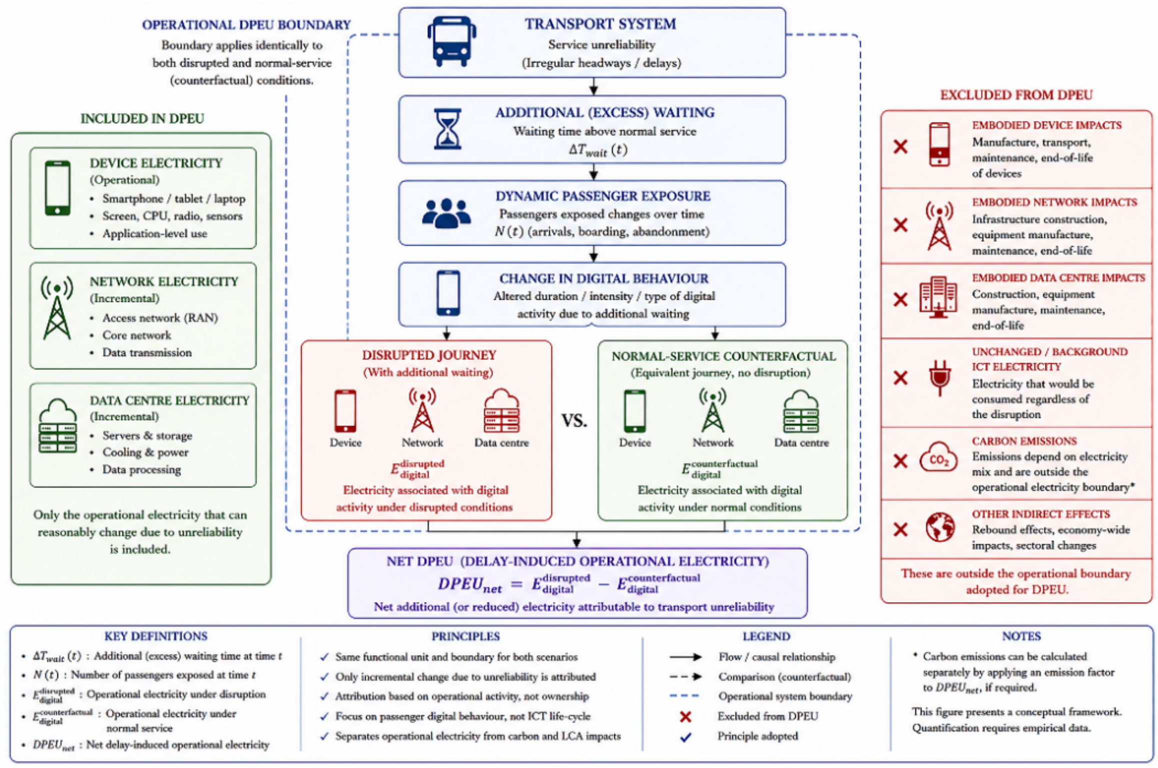

Figure 3. Operational system boundary and counterfactual structure of the revised DPEU framework.

The operational boundary further distinguishes DPEU from carbon emissions and the wider environmental footprint of digital technologies. Converting electricity consumption into greenhouse-gas emissions requires additional assumptions concerning the electricity mix, while a life-cycle assessment would additionally consider equipment production, maintenance, and end-of-life processes. These impacts may be relevant to broader assessments of digitalisation, but they are outside the operational electricity boundary adopted here. This narrower definition reduces the risk of combining fundamentally different environmental indicators and keeps DPEU focused on the electricity change associated with transport unreliability.

The revised boundary therefore includes operational electricity that can reasonably be associated with changes in passenger digital behaviour relative to normal service, while excluding unchanged background consumption and embodied impacts. This definition provides a consistent basis for the numerical application and uncertainty analysis developed later in the study.

2.7. Critical Synthesis and Research Gap

The reviewed evidence shows that the individual processes underlying DPEU are already recognised across several research fields, although they have largely been examined separately. Public transport research provides established approaches for analysing reliability, excess waiting, passenger accumulation and behavioural responses to service conditions. Recent reviews continue to identify reliability and waiting as important dimensions of passenger-oriented public transport performance, while the growing digitalisation of passenger information further changes how travellers interact with transport systems before and during their journeys [40,41]. However, these studies primarily examine service quality, passenger experience, information provision or travel decisions rather than the electricity implications of digitally mediated responses to unreliability.

Evidence on passenger behaviour also shows that waiting is not a uniform condition. Digital information and smartphone use can influence how passengers perceive and respond to waiting, while crowding information can affect decisions to board or continue waiting. Recent evidence further indicates that willingness to wait under real-time crowding information varies with crowding conditions, expected seating availability and trip characteristics [42]. These findings reinforce the need to represent passenger exposure and behaviour dynamically. At the same time, they do not establish that additional waiting necessarily produces additional digital activity. The counterfactual problem therefore remains central: activity observed during a disruption may be additional, displaced from another stage of the journey, or reduced by the conditions experienced during waiting.

The electricity literature introduces a different set of uncertainties. Device electricity varies with activity and hardware conditions, while the electricity associated with communication networks and data centres depends on infrastructure characteristics and allocation assumptions. Consequently, neither smartphone-use duration nor data traffic alone provides a sufficient basis for estimating the electricity attributable to a disruption. The critical issue is not the total electricity consumed while passengers are delayed, but the incremental difference between disrupted and normal-service conditions within a consistent system boundary. This distinction separates the proposed DPEU framework from a simple calculation in which passenger numbers, waiting minutes and a fixed electricity coefficient are multiplied together.

Taken together, the literature therefore reveals an integration gap rather than an absence of knowledge in the individual domains. Transport studies can describe when unreliability occurs and how passenger exposure develops; behavioural studies can inform how passengers respond to waiting and information; and ICT-energy research can support estimation of the electricity associated with digital activity. What remains insufficiently examined is the connection among these processes under a common counterfactual framework. In particular, existing evidence does not yet establish the magnitude of the net electricity difference caused specifically by public transport unreliability, nor whether this difference remains meaningful after temporal displacement of smartphone activity and the marginal behaviour of shared ICT infrastructure are considered. The main findings, remaining uncertainties, and their implications for the DPEU framework are synthesised in Table 1.

Table 1. Critical synthesis of evidence, uncertainties, and implications for the revised DPEU framework.

Evidence Domain	What Existing Evidence Establishes	Remaining Uncertainty or Limitation	Implication for DPEU	Key Sources
Transport reliability	Service unreliability affects waiting conditions and passenger distribution. Schedule deviation and headway irregularity are relevant under different operating conditions.	A single schedule-based definition cannot represent unreliability across all service types.	Define disruption according to service characteristics, including headway irregularity for high-frequency services.	[22–24]
Passenger exposure	Passenger exposure changes over time through arrivals, boarding and departures from the waiting population.	Arrival patterns and passenger responses vary across stops, periods and information conditions.	Represent exposure dynamically through $N(t)$, rather than using a fixed passenger count.	[22,26,27]
Passenger digital behaviour	Digital activity occurs during different stages of public-transport journeys and can be influenced by waiting and information conditions.	It remains uncertain whether activity during additional waiting is genuinely additional, temporally displaced or suppressed.	Compare disrupted behaviour with a normal-service behavioural counterfactual.	[28–30]
Crowding and information	Real-time information and crowding conditions can influence waiting and boarding behaviour.	Their direction and magnitude of influence on smartphone engagement remain uncertain.	Treat information and crowding as behavioural moderators rather than fixed effects.	[15,25,42]
Device electricity	Smartphone electricity consumption varies with activity, hardware and operating state.	No universal electricity-per-minute value represents all devices and activities.	Use activity-specific parameters or transparent uncertainty ranges.	[33,34,36]

Table 1. *Cont.*

Evidence Domain	What Existing Evidence Establishes	Remaining Uncertainty or Limitation	Implication for DPEU	Key Sources
ICT infrastructure	Online digital activity can involve electricity consumption in communication networks and data centres.	Incremental infrastructure electricity cannot necessarily be inferred directly from data volume.	Separate device, network and data-centre components and report attribution uncertainty.	[19,21]
System boundary	ICT assessments are sensitive to system-boundary and attribution choices.	Total ICT electricity consumption is not equivalent to electricity caused by a transport disruption.	Apply the same operational boundary to disrupted and counterfactual conditions.	[37–39]
Integrated evidence	Relevant evidence exists across transport, passenger behaviour and ICT-electricity research.	Their combined net electricity effect specifically attributable to transport unreliability remains insufficiently quantified.	Treat the existence, direction and magnitude of DPEU as empirical outcomes rather than assumptions.	This review

The unresolved issue is therefore not whether transport unreliability, passenger digital behaviour, and ICT electricity demand exist as separate phenomena, but whether their interaction produces a measurable net electricity change attributable to unreliable service. Addressing this question requires four elements that are not jointly established in the existing literature: a service-specific representation of passenger exposure, an explicit normal-service counterfactual, a consistent operational electricity boundary, and transparent treatment of behavioural and electricity-related uncertainty. These requirements define the analytical problem addressed in the following section.

3. Methodology

3.1. Study Design and Analytical Approach

This study uses a structured analytical approach to examine whether public transport unreliability can produce a measurable change in passenger-related electricity consumption. The analysis does not assume that electricity use observed during additional waiting is caused by the disruption. Instead, DPEU is evaluated as the difference between digital electricity consumption under disrupted service and the electricity that would be expected under comparable normal-service conditions. This counterfactual comparison is necessary because smartphone activity during waiting may represent genuinely additional use, activity shifted from another stage of the journey, or reduced activity under disrupted conditions. The study is organised in four stages. First, the critical review brings together evidence on public transport reliability, passenger accumulation, digital behaviour, and the electricity consumption of smartphones and supporting ICT infrastructure. The literature review was conducted as a focused critical review rather than a systematic review, with the purpose of integrating evidence from research domains that are usually examined separately [43]. Literature was identified primarily through Google Scholar and searches within the electronic platforms of major academic publishers, supplemented by backward and forward citation searching from relevant studies. Search terms were organised around the principal components of the proposed causal pathway and included combinations of public transport reliability, service delay, waiting time, headway irregularity, passenger accumulation, smartphone use, digital activity, mobile-device energy consumption, communication-network electricity, data-centre electricity, and ICT system boundary. No fixed publication-date restriction was imposed. Earlier studies were retained where they provided foundational evidence on passenger waiting, travel behaviour, or device-energy modelling, while recent studies were prioritised for rapidly evolving topics such as smartphone applications, communication-network electricity, data-centre energy use, and ICT environmental assessment. Studies were retained when they provided empirical evidence, methodological insight, or quantitative information directly relevant to at least one component of the DPEU framework. Broader studies of transport energy or digitalisation were used only where they contributed to the interpretation or system context and were not used to parameterise DPEU unless their measurements were compatible with the relevant model variable and system boundary. The review is used to identify both the variables that can be supported by existing evidence and those for which substantial uncertainty remains. Second, these relationships are translated into an analytical framework in which passenger exposure changes over time rather than being represented by a fixed passenger count. The framework also separates device-side electricity from electricity associated with communication networks and data centres. This structure allows operational, behavioural, and technological components to be represented separately while maintaining a common counterfactual basis for attribution. Third, the framework is applied to a real public transport context using available operational data. Operational data are used to establish the normal-service reference and, where suitable observations are available, to identify service irregularity. Where matched historical observations are unavailable, disruption conditions are represented through explicitly defined analytical perturbations rather than inferred from scheduled data. The purpose of this application is not to demonstrate in advance that DPEU is large, but to examine its plausible magnitude relative to the normal-service counterfactual. Parameters that cannot be observed directly from the available transport data, particularly those describing changes in passenger digital behaviour and electricity intensity, are therefore treated explicitly as uncertain rather than assigned a single assumed value. Finally, sensitivity and uncertainty analyses are used to examine how estimated DPEU changes as uncertain parameters and behavioural assumptions vary. This makes it possible to distinguish conclusions that are relatively stable from those that depend strongly on assumptions for which empirical evidence remains limited. The resulting approach therefore combines transport operations, passenger behaviour, and digital electricity accounting while keeping the counterfactual and uncertainty explicit throughout the analysis.

3.2. Definition and Counterfactual Formulation of DPEU

DPEU is defined in this study as the net change in passenger-related operational electricity consumption associated with public transport unreliability, relative to an equivalent normal-service condition. This definition differs from counting all electricity consumed by passengers while they are delayed. Electricity use that would also have occurred during a normal journey is not considered delay-induced simply because it takes place at a stop or station during a disruption.

The definition of the disruption depends on the operating characteristics of the service. For timetable-based services, the disrupted condition can be identified through deviations between scheduled and observed arrival or departure times. For high-frequency services, where passengers may not rely on individual scheduled departures, headway irregularity and the resulting excess waiting provide a more appropriate reference. This distinction follows the reliability evidence reviewed in Section 2.1 and prevents DPEU from depending on a single definition of delay that may not be suitable across different public transport systems.

Two conditions are therefore compared. The disrupted condition represents the observed or modelled journey under service unreliability, including the resulting passenger exposure and digital activity. The counterfactual condition represents the corresponding journey if the service had operated normally. Importantly, the counterfactual does not assume that passengers would have stopped using their smartphones. They may instead have used them onboard, at another point in the journey, or for a different duration. The relevant quantity is therefore the difference between the two conditions.

At the individual passenger level, this relationship can be written as:

$$\Delta E_i = E_i^D - E_i^C$$

where E_i^D represents passenger-related digital electricity consumption for passenger under the disrupted condition, and E_i^C represents the corresponding electricity consumption under the normal-service counterfactual. This expression defines the quantity of interest at the individual level; it does not imply that both terms can be directly observed for each passenger. In practice, the counterfactual is unobserved, and passenger-level electricity measurements are generally unavailable in transport operational datasets. The empirical implementation therefore requires an aggregate representation based on passenger exposure, behavioural parameters, and electricity-intensity estimates, which is developed in the following subsections. Estimation of this baseline is subject to uncertainty because digital behaviour can differ between passengers, journey stages, activities, and waiting conditions. Instead of assigning a single deterministic value to this difference, the framework represents uncertain behavioural and electricity parameters through ranges and evaluates their influence through sensitivity analysis. This approach allows the estimated DPEU to reflect the available evidence without assuming a level of behavioural precision that the underlying data cannot support. This counterfactual structure prevents temporal displacement from being interpreted as additional electricity consumption. For example, if ten minutes of smartphone activity that would normally occur onboard instead occurs during an additional ten-minute wait, the timing and location of electricity consumption have changed, but the net change may remain close to zero. A positive DPEU requires a net increase relative to the counterfactual rather than the simple observation of smartphone activity during waiting. Conversely, DPEU may be negative if disrupted conditions reduce digital activity relative to normal service. The framework therefore does not impose the direction of the effect before the numerical analysis.

3.3. Dynamic Passenger Exposure

The number of passengers exposed to a disruption changes throughout the waiting period. Passengers may continue to arrive at a stop while a service is delayed, while others may leave the waiting population by boarding another service, changing route, or abandoning the trip. For this reason, passenger exposure cannot generally be represented by a single fixed passenger count multiplied by the duration of the delay. The revised framework instead treats the waiting population as a time-dependent quantity.

The basic passenger balance introduced in Section 2.2 is used as the starting point:

$$N(t) = N_0 + \int_0^t \lambda(\tau) d\tau - B(t) - R(t)$$

where $N(t)$ is the number of passengers waiting at time t, N_0 is the number present when the disruption period begins, and $\lambda(\tau)$ is the passenger arrival rate over time. $B(t)$ represents passengers who leave the waiting population by boarding, while $R(t)$ represents other departures from the queue, including rerouting or abandoning the wait. The expression is used as a passenger-balance representation rather than as a fully calibrated queueing model. Its purpose is to preserve the changing size of the exposed population without assuming that detailed passenger-level arrival and departure observations are available for every stop. Passenger arrival behaviour is not assumed to be identical across services. For lower-frequency or timetable-oriented services, some passengers may coordinate their arrival with a scheduled departure. In frequent services, arrivals can be less closely tied to individual timetable entries, making the relationship between passenger arrivals and headways more important. Consequently, the model allows $\lambda(\tau)$ to vary according to the service context rather than imposing a universal arrival pattern. Where empirical passenger-count or automatic passenger-counting data are available, these data can be used to estimate the arrival process more directly. Where they are unavailable, plausible arrival assumptions must be stated explicitly and tested in the sensitivity analysis rather than treated as observed behaviour. Service irregularity also affects the period over which passengers accumulate. For timetable-oriented services, exposure can be estimated over the additional waiting interval associated with the difference between scheduled and observed operation. For high-frequency services, the relevant interval is instead linked to the observed headway relative to the expected or reference headway. A longer-than-expected headway can allow more passengers to accumulate before the next vehicle arrives, while a short following headway may produce a substantially different waiting population. This approach therefore connects passenger exposure to the service definition established in Section 3.2 rather than treating every disruption as scheduled lateness.

Information conditions are included as a source of behavioural variation rather than as a fixed adjustment. Real-time passenger information may affect when passengers arrive, whether they continue waiting, or whether they choose another travel option. Recent evidence from disruption settings also shows that passengers can reconsider their travel choices as a disruption develops and that the information provided about disruption duration can influence whether they remain with the original service [16]. Accordingly, information-related responses can enter the framework through changes in $\lambda(\tau)$ or $R(t)$ when suitable evidence is available. They are not assigned a universal numerical effect.

Passenger accumulation may also produce crowding at stops or platforms. Because the evidence reviewed in Section 2.2 does not support a universal relationship between crowding and smartphone use, no fixed crowding reduction factor is imposed in the model. Its possible behavioural effect is instead incorporated through the disrupted digital-activity probabilities defined in Section 3.4 and examined through sensitivity analysis. To connect the changing waiting population with the later electricity calculation, cumulative passenger exposure during a disruption is represented as:

$$X = \int_0^T N(t) dt$$

where T is the duration of the disruption interval and X represents cumulative passenger-time exposure. When $N(t)$ is expressed as passengers and in minutes, X is measured in passenger-minutes. This quantity is more appropriate for the DPEU calculation than either delay duration or passenger count alone because it captures both how long the disruption lasts and how many passengers are exposed as the waiting population changes. Importantly, X represents exposure to disrupted waiting, not electricity consumption. It does not assume that every exposed passenger uses a smartphone, nor that every passenger-minute produces additional digital activity. Those behavioural differences are introduced separately in Section 3.4. Keeping passenger exposure separate from digital behaviour prevents the model from automatically converting additional waiting time into additional electricity demand.

3.4. Digital-Activity and Electricity Model

Passenger exposure alone does not determine DPEU. A passenger may spend an additional minute at a stop without using a smartphone, may continue an activity that would otherwise have occurred onboard, or may change the type and duration of digital activity during the disruption. The electricity component of the framework therefore begins with the change in digital activity relative to the normal-service counterfactual, rather than with waiting time itself.

For each type of digital activity, a, the behavioural difference between disrupted and normal-service conditions can be represented by:

$$\Delta p_a(t) = p_a^D(t) - p_a^C(t)$$

where $p_a^D(t)$ is the probability or proportion of exposed passengers engaged in activity *a* at time *t* under disrupted conditions, and $p_a^C(t)$ is the corresponding value under the normal-service counterfactual. The activity categories may include, for example, messaging, web browsing, social media, navigation, or video use. The framework does not require all passengers to undertake the same activity, and $\Delta p_a(t)$ may be positive, close to zero, or negative. This distinction is important because different applications and operating conditions can produce different device power demands. Recent experimental work by Groza et al. [17] shows that mobile-application characteristics can materially influence battery consumption and that changes in application implementation can produce measurable differences in energy use. Rather than assigning one universal electricity value to all smartphone activity, the present framework therefore represents device-side power for activity *a* using an activity-specific parameter P_a^{dev}. Where direct measurements are unavailable, this parameter should be defined from published measurements as a range rather than treated as an exact value.

The incremental device electricity associated with a disruption can then be represented as

$$\Delta E_{dev} = \int_0^T N(t) \sum_a \Delta p_a(t) P_a^{dev} dt$$

where $N(t)$ represents the dynamic waiting population defined in Section 3.3, T is the disruption interval, and P_a^{dev} represents the device power associated with activity a. When power is expressed in watts and time in hours, the resulting electricity is expressed in watt-hours. This expression links passenger exposure to electricity only through the difference in digital behaviour between the disrupted and counterfactual conditions. If $\Delta p_a(t) = 0$, exposure to additional waiting does not generate additional device electricity for that activity.

When P_a^{dev} is expressed in watts, the time basis of the integral must be expressed in hours for ΔE_{dev} to be obtained in watt-hours. In the numerical application, where passenger exposure is expressed in passenger-minutes, the corresponding exposure term is divided by 60 before multiplication by device power.

Device electricity, however, represents only one part of the operational boundary established in Section 2.6. Digital activities that exchange data may also be associated with communication-network and data-centre electricity. These components require particular caution because shared ICT infrastructure does not necessarily change its electricity consumption in direct proportion to the traffic generated by an individual user. The network and data-centre terms are therefore treated as incremental attributable components, rather than assigning a fraction of total infrastructure electricity to every passenger-minute.

Device, network, and data-centre electricity are therefore represented as separate components. Before aggregation, each component must be expressed on a consistent energy and activity basis. This distinction is necessary because device demand can be estimated from activity-specific power and duration, whereas network and data-centre estimates may be reported relative to data traffic or other service-specific units. The components are therefore calculated separately and combined only after their units and system boundaries have been harmonised in the integrated model developed in Section 3.5. These components are kept separate in the numerical analysis because their evidence bases and uncertainties are different. In particular, network electricity should not be estimated by assuming a simple proportional relationship between data volume and total network electricity. Evidence reviewed in Section 2.5 already shows why such allocation can overstate the marginal effect of additional traffic. The same caution applies to data-centre electricity, whose attribution depends on the digital service being used and the available measurement boundary. Crowding is retained as a potential behavioural influence rather than assigned a fixed numerical coefficient. Because the evidence reviewed in Section 2.2 does not establish a sufficiently general relationship between crowding and smartphone use, its possible effect is represented through changes in the disrupted activity probabilities $p_a^D(t)$, where supported, and otherwise examined through sensitivity analysis.

The resulting electricity estimate therefore depends on three distinct elements: how many passengers are exposed, how their digital behaviour differs from the counterfactual, and how electricity-intensive the relevant activities are. Keeping these elements separate prevents the model from treating waiting time itself as electricity consumption and makes the behavioural and technological assumptions visible for later sensitivity testing.

3.5. Integrated DPEU Model

The components developed in Sections 3.2–3.4 are combined to estimate the net change in passenger-related operational electricity consumption associated with public transport unreliability. Passenger exposure and changes in digital activity determine the device-side effect, while communication-network and data-centre electricity are treated as separate infrastructure components within the operational system boundary. As discussed in Section 2.5, these infrastructure components cannot be assumed to change proportionally with passenger data traffic. They are therefore included quantitatively only when an incremental electricity effect can be supported by an appropriate electricity-intensity estimate and a consistent system boundary. Where such attribution cannot be supported, the corresponding component is reported separately rather than assigned an arbitrary value.

The integrated operational definition of DPEU is:

$$DPEU_{net} = \Delta E_{dev} + \Delta E_{network} + \Delta E_{DC}$$

where ΔE_{dev} , $\Delta E_{network}$, and ΔE_{DC} denote the changes in device, communication-network, and data-centre electricity, respectively, between disrupted and corresponding normal-service conditions. Each component is included quantitatively only when it refers to the same assessment period and system boundary and can be expressed in compatible energy units. This formulation is distinct from the digital-electricity boundary defined in Section 2.5: the boundary identifies the operational electricity components considered in the framework, whereas DPEU represents the net counterfactual change in those components associated with the disruption.

The sign of DPEU is retained in the analysis. A positive value indicates higher passenger-related operational electricity consumption under disrupted conditions, while a value close to zero indicates little net change, including cases in which digital activity is mainly displaced between different stages of the journey. A negative value indicates lower electricity consumption under disrupted conditions. The model therefore allows the direction and magnitude of the effect to emerge from the analysis rather than assuming that unreliability necessarily increases electricity demand. The framework distinguishes between inputs obtained from transport data and those that remain uncertain. Service characteristics and normal-operation references can be derived from operational data, while disruption magnitudes may be either directly observed or explicitly specified as analytical perturbations, depending on data availability. Passenger exposure is then estimated using the approach described in Section 3.3. Behavioural differences and electricity-intensity parameters are obtained from available empirical evidence or represented through explicit ranges where direct observations are unavailable. Their influence on estimated DPEU is examined through the sensitivity and uncertainty analysis in Section 3.7.

The integrated model provides the basis for the real-system application in Section 3.6, where the possible magnitude of DPEU is estimated and compared with the corresponding scale of transport-system energy consumption. This comparison provides an order-of-magnitude perspective on the event-level effect without implying empirical validation or network-scale significance

3.6. Real-City Case Study and Data

To provide a real-system numerical application of the framework, Turin, Italy, is selected as the case study. Public transport in the metropolitan area is operated by Gruppo Torinese Trasporti (GTT), which provides bus, tram, and metro services. Turin provides a suitable setting for the analysis because GTT makes scheduled public transport data openly available and also provides real-time service information through its open-data infrastructure. Service information is obtained from the GTT datasets published through the City of Turin open-data portal. The static feed follows the General Transit Feed Specification (GTFS) and describes the scheduled service, including routes, trips, stops, stop sequences, and scheduled arrival and departure times. GTT also provides GTFS-Realtime information on vehicle passages and positions, together with service alerts [44,45]. The static GTFS provides the scheduled structure of the GTT network, including routes, trips, stops, stop sequences, and scheduled service times. For the numerical application, Line 4 was identified in the GTFS as route 4U, and weekday trips operating during the selected 09:00–20:00 period were extracted from the corresponding trip and stop-time records. Terminal departure times were ordered separately by direction and used to calculate consecutive scheduled headways. The resulting GTFS-derived headway distribution is used together with GTT's published service-frequency information to establish the normal-service reference for the case study. Although GTT provides GTFS-Realtime information, a matched archived sequence was not available for the selected analysis period. The present numerical application therefore does not reconstruct an observed disruption from real-time records. Static GTFS and published service-frequency information are used to establish the normal-service reference, while disruption magnitude is represented through explicitly defined analytical headway perturbations. The operational definition of unreliability follows the distinction established in Section 3.2. For timetable-based services, scheduled arrival or departure times provide the normal-service reference. For frequent services, expected headways provide the more appropriate baseline. The numerical application focuses on a frequency-based GTT service, allowing service irregularity to be represented as a deviation from the expected headway rather than as timetable lateness alone. Passenger exposure is estimated using the dynamic formulation described in Section 3.3. GTFS is used to characterize service operations but is not treated as a source of passenger counts. Where direct stop-level passenger observations are unavailable, passenger-flow inputs are obtained from documented demand information where possible and otherwise represented through explicit uncertainty ranges. This distinction prevents scheduled service information from being interpreted as evidence of the number of passengers actually waiting during a disruption. The operational inputs are combined with the behavioural and electricity parameters defined in Sections 3.4 and 3.5. Parameters that are not directly observed in the Turin transport data, particularly the difference between disrupted and counterfactual digital activity, are represented using evidence-based ranges and examined through the sensitivity analysis described in Section 3.7. The analysis therefore distinguishes observed or documented transport inputs from literature-derived parameters and explicitly uncertain quantities. To place the estimated DPEU in context, the results are compared with the energy scale of the GTT transport system. GTT reported total energy consumption of 296,936.07 MWh in 2025, approximately 55.0 million kilometres of service, and approximately 300.4 million passengers [46]. These system-level values are not interpreted as the energy consumption associated with an individual disruption. Instead, they provide an empirical reference for evaluating the order of magnitude of the estimated DPEU relative to the energy scale of the transport system. The case study is therefore designed as an order-of-magnitude application of the framework rather than as a claim of precise passenger-level electricity measurement. It combines a real transport-system baseline with transparent behavioural and electricity assumptions while preserving the distinction between observed, literature-derived, and uncertain inputs. This structure allows the magnitude of DPEU to be evaluated without assuming in advance that the effect is practically significant.

3.7. Sensitivity and Uncertainty Analysis

The DPEU estimate is affected by uncertainty in both transport-related and behavioural parameters. Some inputs, such as the duration and timing of service irregularities, can be derived directly from operational data, whereas others cannot be observed with the same level of precision. In particular, passenger arrival patterns, differences in digital activity between disrupted and normal-service conditions, activity-specific device power, and attributable ICT-infrastructure electricity may vary across passengers, locations, devices, and types of digital activity. These uncertainties are therefore retained explicitly rather than represented by a single set of fixed assumptions. Parameter ranges are defined according to the quality of the available evidence. Observed operational values are used where suitable data are available. For parameters obtained from empirical studies, the reported values or ranges are used where they are compatible with the model definition and system boundary. Where direct evidence is limited, the parameter is assigned a transparent plausible range and identified as uncertain rather than treated as an observed quantity. This distinction allows the analysis to separate uncertainty originating from transport operations from uncertainty associated with passenger behaviour and electricity intensity.

In this study, Monte Carlo simulation was selected because DPEU depends simultaneously on uncertain operational, behavioural, and electricity-related inputs whose combined effects are not adequately represented by a single deterministic scenario. The method allows uncertainty in these inputs to be propagated jointly through the model, producing a distribution of possible DPEU outcomes rather than a single point estimate. This approach is consistent with established uncertainty-analysis practice, in which uncertainty in model inputs is propagated to examine its influence on model outputs [47]. It is particularly appropriate here because empirical probability distributions are unavailable for several parameters and the objective is to examine the plausible magnitude and sensitivity of DPEU rather than to produce a probabilistic forecast. The Monte Carlo analysis was implemented in Python, with NumPy used for random sampling and numerical calculations and SciPy used to calculate Spearman rank correlations. A total of 300,000 Monte Carlo realizations were generated using the parameter ranges defined for the numerical analysis. Uncertain continuous parameters were sampled independently from uniform distributions over their specified ranges where empirical probability distributions were unavailable. These distributions are therefore exploratory assumptions and should not be interpreted as observed parameter frequencies. For each realization, passenger exposure and device-side DPEU were recalculated using the same analytical relationships applied in the deterministic calculations. The simulated output was summarized using the median and the 2.5th and 97.5th percentiles, with the latter reported as the central 95% of simulated outcomes rather than as a statistical confidence interval. Parameter influence was assessed using Spearman rank correlations between the sampled inputs and model output.

Particular attention is given to the behavioural difference, $\Delta p_a(t)$, because it determines whether disrupted conditions produce a net increase, decrease, or negligible change in digital electricity consumption relative to the counterfactual. Device power and passenger exposure are examined as influences on the magnitude of this effect. Crowding is retained within behavioural uncertainty rather than represented by a predetermined reduction coefficient, allowing lower, similar, and higher levels of disrupted digital activity to be considered without imposing a fixed direction of influence.

The analysis also includes a zero-difference behavioural condition in which, $\Delta p_a(t)$ =0. Under this condition, additional passenger waiting does not generate incremental device electricity for activity a. This provides an important reference case for testing the compensating effect identified in Section 3.2 and prevents the model from producing a positive DPEU solely because a disruption increases waiting time. Sensitivity results are interpreted together with the magnitude of the estimated DPEU. A parameter may strongly influence the relative variation of the model output while the absolute electricity effect remains very small. The analysis therefore considers both parameter influence and the resulting absolute range of DPEU. The subsequent comparison with transport-system energy consumption is used to place the uncertainty in an order-of-magnitude context without implying empirical validation or practical significance.

3.8. Aggregation, Magnitude Comparison and Validation

The event-level estimates produced by the DPEU model are aggregated only across disruption events for which the required operational and passenger-exposure information can be represented consistently. For a set of J disruption events, aggregate DPEU is expressed as:

$$DPEU_{agg} = \sum_{j=1}^{J} DPEU_j$$

where $DPEU_j$ is the net passenger-related electricity change associated with disruption event j. Aggregation can be performed across stops, routes, time periods, or the selected study area, provided that the events refer to a common assessment boundary. This structure allows event-level estimates to be aggregated when suitable disruption-specific data are available, without assuming that recurrence alone establishes practical significance at route or network scale. The absolute value of DPEU alone is insufficient to establish its practical significance. The aggregated estimate is therefore evaluated relative to the energy scale of the transport system over a comparable period. The system-level energy data introduced in Section 3.6 provide the reference for this comparison. Where the available transport-energy information is reported at a broader temporal or operational scale than the DPEU estimate, the difference in scale is stated explicitly rather than implying a direct event-level comparison. Results are reported both as absolute electricity values and as a relative magnitude, allowing the estimated effect to be interpreted in the context of conventional transport energy consumption. The comparison also considers uncertainty in the DPEU estimate itself. The range obtained from the uncertainty analysis in Section 3.7 is carried into the magnitude assessment rather than comparing only a central estimate with transport-system energy use. This distinction is important because a numerically detectable model output may still be too small, or too uncertain, to support claims of practical relevance. The interpretation therefore depends on both the estimated magnitude and the stability of that estimate across plausible parameter values. Validation is treated according to the type of input involved. Where matched GTFS and GTFS-Realtime observations are available, operational quantities can be checked for consistency between scheduled and observed service conditions, while passenger-flow inputs can be compared with independent counts or ridership information where these are available. Behavioural and electricity parameters require a different form of validation because they are not directly observed in the transport feeds. Their plausible ranges are therefore assessed against empirical evidence and their influence on the results is tested through the sensitivity analysis. This distinction avoids presenting parameter plausibility as equivalent to direct empirical validation.

The present application should consequently be interpreted as an order-of-magnitude real-system application of the framework rather than as a complete empirical validation of DPEU. Full validation would require matched observations of service disruption, passenger exposure, digital activity, and electricity use under both disrupted and comparable normal-service conditions. Such data would allow the behavioural counterfactual and electricity parameters to be calibrated directly and would provide a stronger test of whether the estimated net effect is reproduced under observed conditions. Until such evidence becomes available, conclusions are restricted to the magnitude and uncertainty supported by the documented system characteristics and parameter ranges used in the analysis.

4. Results

4.1. Case-Study Operational Conditions and Parameterisation

The numerical application focuses on GTT Line 4 in Turin. The GTT static GTFS feed provides the scheduled network and service structure used to identify the case-study route, while the normal-service headway is obtained from GTT's published Line 4 service-frequency information for the selected weekday period [48]. The service is treated as frequency-based for the present analysis, so the normal-service reference is defined by the applicable headway rather than by the lateness of an individual vehicle. Because an archived sequence of GTFS-Realtime observations is not available for the selected analysis period, the numerical example does not represent the tested service irregularities as observed GTT disruption events. Instead, headway perturbations are introduced analytically relative to the documented normal-service reference. This preserves the distinction between observed system characteristics and the analytical inputs used to examine the possible magnitude of DPEU.

For a disruption that extends the normal headway by minutes, and assuming an approximately constant passenger arrival rate during the short analysis interval, additional passenger exposure can be derived from the dynamic passenger formulation introduced in Section 3.3. At the time the vehicle would normally arrive, approximately passengers have accumulated, while additional passengers continue to arrive during the extended interval. For an isolated extended headway, the resulting additional passenger-time exposure is:

$$X_{\text{delay}} = \lambda\left(h\delta + \frac{\delta^2}{2}\right)$$

where X_{delay} is expressed in passenger-minutes, is the normal-service headway, is the additional headway associated with the disruption, and is the passenger arrival rate. This expression is a simplified application of the dynamic passenger-balance formulation in Section 3.3 for an isolated extended headway. It assumes approximately uniform passenger arrivals over the short analysis interval and no boarding before the delayed vehicle arrives. The behavioural component remains a major source of uncertainty. Existing empirical evidence shows that smartphone use is common during public-transport waiting and that passenger smartphone behaviour varies with waiting conditions [28]. However, the available evidence does not provide a directly transferable estimate of the difference between digital activity under disrupted and equivalent normal-service conditions required by the present counterfactual framework. Consequently, is treated as an uncertain behavioural parameter rather than assigned an empirically observed value for Turin.

Device electricity is parameterised separately from passenger behaviour. Experimental studies show that smartphone electricity consumption varies across applications, devices, and operating conditions [17,18]. For the order-of-magnitude application, however, individual digital activities are represented by an aggregate active-use state rather than modelled separately. Accordingly, Δp represents the net behavioural difference across active smartphone use, while P^{dev} represents an effective active-use power parameter rather than the power demand of a specific application. Their uncertainty is represented through the ranges reported in Table 2.

For the numerical application, the 09:00–20:00 weekday period is selected. Analysis of the GTT static GTFS for Line 4 identified 69 terminal departures in one direction and 70 in the other during this period on the applicable weekday service. Consecutive scheduled departures produce a median headway of 9 min in both directions, with individual intervals concentrated between 8 and 11 min. The corresponding mean headways are approximately 9.51 min in each direction. These GTFS-derived values are consistent with GTT's published service-frequency information, which reports a 9-min mean interval for Line 4 during the selected daytime period [48]. The normal-service reference is therefore set to h = 9 min. Using the median scheduled GTFS headway avoids introducing additional precision into an order-of-magnitude application while retaining a baseline directly supported by the observed service schedule. The operational perturbation is represented by an additional headway δ rather than an observed delay. Three perturbation levels of 3, 6, and 9 min are evaluated, corresponding to total headways of 12, 15, and 18 min. These values are analytical inputs used to examine the response of the model and should not be interpreted as observed disruptions on Line 4.

Using the passenger-exposure relationship defined above, the additional exposure for a given passenger arrival rate is:

$$X_{\text{delay}} = \lambda\left(9\delta + \frac{\delta^2}{2}\right)$$

For an illustrative arrival rate of one passenger per minute, additional headways of 3, 6, and 9 min produce passenger exposures of 31.5, 72, and 121.5 passenger-minutes, respectively. These values demonstrate the nonlinear increase in exposure as the disruption becomes longer, because passengers already waiting are delayed while additional passengers continue to arrive. The operational and uncertain inputs used in the Line 4 numerical application are summarized in Table 2.

Table 2. Operational inputs for the GTT Line 4 numerical application.

Input	Value/Range	Unit	Status
Normal headway, h	9	min	GTFS-derived median weekday headway; consistent with GTT's published interval
Additional headway, δ	3 to 9	min	Analytical perturbation levels
Passenger arrival rate, λ	0.5 to 2.0	passengers/min	Uncertain input; sensitivity analysis
Behavioural difference, Δp	−0.20 to 0.20	dimensionless	Uncertain behavioural input
Device power, P^{dev}	1 to 5	W	Literature-informed sensitivity range
GTT annual energy consumption	296,936.07	MWh	Reported 2025 value
GTT annual passengers	300,414,096	passengers	Reported 2025 value
GTT annual distance	55,016,101	km	Reported 2025 value

The 9-min normal-service reference is derived from scheduled GTFS terminal departures for Line 4 during the selected weekday period and is independently consistent with GTT's published service-frequency information. The three discrete perturbation levels are used to illustrate changes in passenger exposure, whereas the Monte Carlo analysis samples δ continuously over the 3 to 9 min interval to represent uncertainty in disruption magnitude. The device-power interval is used as a sensitivity range rather than as a universal empirical value for smartphone use. Experimental studies demonstrate substantial variation in smartphone electricity demand across applications, devices, communication protocols, and operating conditions [17,18,49]. Ali et al. [18], for example, measured marked differences in battery discharge across video-calling applications and smartphone models, while Groza et al. [17] showed that application characteristics and implementation choices can materially affect mobile-device power consumption. Caiazza et al. [49] further demonstrated that communication protocol and interaction pattern influence smartphone energy demand. On this basis, the 1 to 5 W interval is retained as a broad sensitivity range representing plausible active-use conditions rather than an empirical distribution or a typical power value for passengers. Device-power uncertainty is evaluated separately from the behavioural parameter Δp, preserving the distinction between whether digital activity changes and how electricity-intensive that activity is.

4.2. Device-Side DPEU Estimates

The device-side calculation combines additional passenger exposure with the difference in digital activity between disrupted and normal-service conditions. Because Δp may be positive, zero, or negative, the analysis retains all three possible outcomes rather than assuming that longer waiting necessarily increases smartphone electricity consumption. Passenger exposure increases with both the additional headway and the passenger arrival rate. For an additional headway of 3 min, X_{delay} ranges from 15.75 to 63 passenger-min as λ varies from 0.5 to 2 passengers/min. With an additional headway of 6 min, the corresponding range is 36–144 passenger-min, while an additional headway of 9 min produces 60.75–243 passenger-min. The increase is nonlinear because passengers already accumulated at the stop remain exposed during the extended interval while additional passengers continue to arrive.

For the numerical application, device-side DPEU is calculated as:

$$\Delta E_{dev} = \frac{X_{\text{delay}} \Delta p \, P^{dev}}{60}$$

where division by 60 converts passenger-minutes to passenger-hours when P^{dev} is expressed in watts. The calculation is evaluated across the parameter ranges reported in Table 2.

Across the full parameter space, the estimated device-side DPEU ranges from approximately −4.05 to +4.05 Wh per disruption event. The extreme values occur when the largest passenger exposure is combined with the largest absolute behavioural difference and the upper device-power value. The sign of the estimate depends on the behavioural difference: positive values indicate greater digital activity during the disrupted condition, whereas negative values indicate lower digital activity relative to the normal-service counterfactual. When $\Delta p = 0$, device-side DPEU is zero regardless of passenger exposure or disruption duration. This result is important because it demonstrates that additional waiting does not, by itself, generate additional electricity consumption. If smartphone activity is simply shifted from another stage of the journey to the waiting period, the net device-side effect can remain close to zero. The numerical application therefore supports the counterfactual distinction introduced in Section 3.2 and avoids interpreting all smartphone activity observed during a disruption as delay-induced electricity use.

Even at the upper boundary of the tested parameter space, the estimated electricity change associated with a single disruption remains on the order of a few watt-hours. The present event-level calculation does not establish whether such effects become relevant at route or network scale, because that assessment would additionally require observed distributions of disruption frequency and duration, passenger exposure, and behavioural response. The following sensitivity analysis therefore examines which uncertain inputs most strongly influence the event-level estimate before its magnitude is compared with the wider energy scale of the GTT system.

4.3. Sensitivity and Uncertainty Results

The sensitivity analysis examines how uncertainty in passenger arrival rate, disruption magnitude, behavioural change, and device power affects the estimated device-side DPEU. The parameter ranges reported in Table 2 are propagated jointly rather than varying one parameter while holding all others at a single reference value. This allows the combined influence of operational, behavioural, and electricity-related assumptions to be reflected in the resulting estimates. The analysis confirms that the behavioural difference, Δp , is the most influential parameter in determining the direction of DPEU. Because the tested range extends from negative to positive values, the estimated electricity change also spans both sides of zero. When $\Delta p = 0$, DPEU remains zero even under longer headways, higher passenger arrival rates, or greater device power. Increasing these other parameters therefore scales an existing behavioural difference but cannot independently determine whether the net effect is positive or negative.

For the absolute magnitude of DPEU, sensitivity is distributed across all four uncertain inputs. The absolute behavioural difference, $|\Delta p|$, has the strongest influence because it directly determines the proportion of passenger exposure associated with a net change in digital activity. Device power affects the electricity associated with that behavioural change, while passenger arrival rate and additional headway determine the amount of passenger exposure over which the change occurs. Longer disruptions have an additional accumulation effect because they both retain passengers who were already waiting and allow new passengers to arrive.

Across the complete parameter space, the theoretical bounds remain approximately −4.05 to +4.05 Wh per disruption event, as reported in Section 4.2. These bounds represent combinations of extreme parameter values rather than typical outcomes. Under independent uniform sampling of the ranges in Table 2, simulated estimates are concentrated substantially closer to zero. The 2.5th–97.5th percentile range of simulated device-side DPEU is approximately −1.37 to +1.36 Wh per event, with a median close to zero. The near-symmetry of this range follows from the deliberately symmetric behavioural range around zero and should therefore not be interpreted as evidence that positive and negative behavioural responses are equally likely among actual passengers. A rank-based sensitivity assessment was used to examine the relative influence of the uncertain inputs. For signed DPEU, the Spearman rank correlation between Δp and the model output is 0.928, substantially larger than the correlations associated with the other inputs. This confirms that the behavioural difference primarily determines whether DPEU is positive or negative. When the absolute magnitude of DPEU is considered instead, $|\Delta p|$ remains the strongest influence, with a Spearman rank correlation of 0.713. Device power has the next strongest association (0.396), followed by additional headway (0.347) and passenger arrival rate (0.347). These results indicate that improved operational data alone would not remove the principal uncertainty in DPEU if the counterfactual change in passenger digital activity remained poorly constrained. The relative influence of the uncertain parameters on the absolute magnitude of DPEU is shown in Figure 4. Overall, the sensitivity analysis does not support a single deterministic DPEU value for the GTT Line 4 application. Instead, it identifies a bounded distribution of outcomes whose sign and magnitude depend primarily on behavioural response and are subsequently scaled by passenger exposure and device power. The following analysis places effects of this order of magnitude against the energy scale of the GTT transport system to provide context for their relative magnitude. The principal uncertainty and sensitivity outcomes are summarized in Table 3.

Table 3. Sensitivity and uncertainty results for the GTT Line 4 numerical application.

Indicator	Result
Theoretical minimum DPEU	−4.05 Wh/event
Theoretical maximum DPEU	+4.05 Wh/event
Median simulated DPEU	≈0 Wh/event
2.5th percentile	−1.37 Wh/event
97.5th percentile	+1.36 Wh/event
Spearman rank correlation: behavioural difference → signed DPEU	0.928
Spearman rank correlation: magnitude of behavioural difference → absolute DPEU	0.713
Spearman rank correlation: device power → absolute DPEU	0.396
Spearman rank correlation: additional headway → absolute DPEU	0.347
Spearman rank correlation: passenger arrival rate → absolute DPEU	0.347

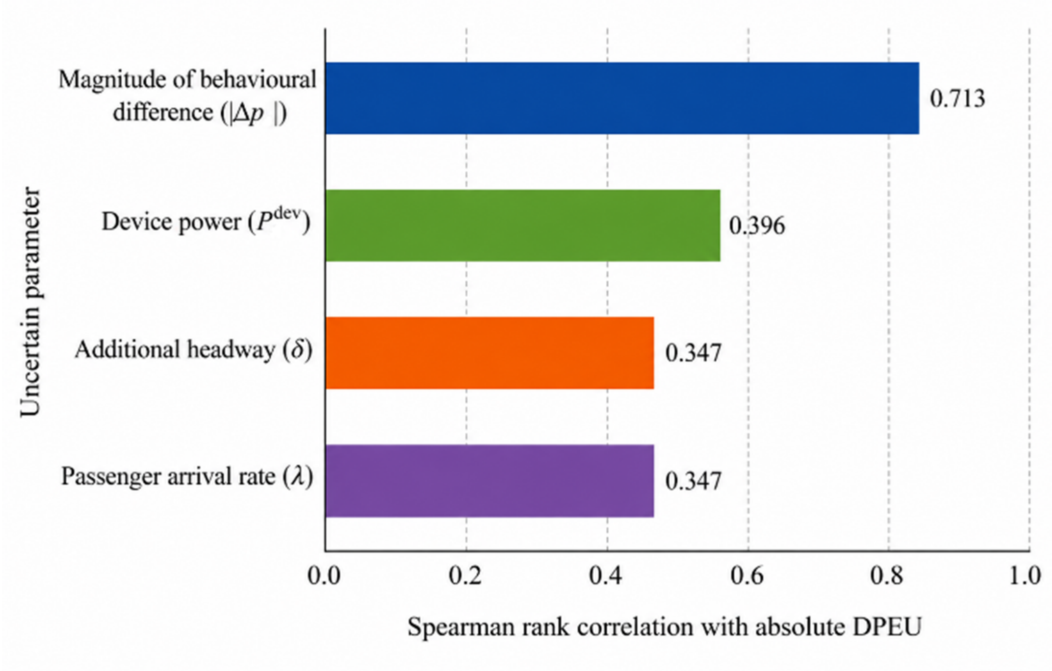

Figure 4. Spearman rank-based sensitivity of absolute device-side DPEU to uncertain model parameters.

4.4. Magnitude Relative to Transport-System Energy

GTT reported total energy consumption of 296,936.07 MWh in 2025 and 55,016,101 km of service across its operations. Based on these reported annual totals, the corresponding fleet-average energy intensity is approximately 5.397 MWh per thousand kilometres, equivalent to approximately 5.397 kWh per kilometre [46]. This system-level indicator provides a reference for interpreting the order of magnitude of the device-side DPEU estimates. The maximum absolute device-side DPEU obtained within the parameter space examined in this study is 4.05 Wh per disruption event, equivalent in energy magnitude to approximately 0.75 m of average fleet travel. The 97.5th-percentile estimate of approximately 1.36 Wh corresponds to approximately 0.25 m. These comparisons indicate that device-side DPEU is very small at the individual disruption-event scale relative to transport-system operational energy, but are intended only to communicate scale and do not imply a functional equivalence between passenger digital activity and vehicle operation.

The GTT report does not provide statistical uncertainty or measurement-error bounds for the reported annual energy consumption and service-distance values [46]. A formal test of whether DPEU exceeds the statistical error of transport-system energy consumption therefore cannot be performed without introducing an unsupported uncertainty assumption. The comparison is consequently restricted to the reported system-energy scale and the uncertainty quantified within the DPEU model.

These event-level results should not be extrapolated directly to annual network-scale DPEU. Such an estimate would require observed distributions of disruption frequency and duration, passenger exposure, and behavioural response across the network. The present results are therefore interpreted as an order-of-magnitude assessment of the proposed effect rather than an estimate of its annual network-wide magnitude.

5. Discussion

This study extends current understanding of public transport unreliability by examining an indirect consequence that lies outside conventional transport-energy accounting. DPEU connects three processes that are usually considered separately: service irregularity, passenger digital behaviour, and operational electricity demand associated with digital activity. In this sense, waiting is not treated simply as lost travel time, but as a period during which service conditions may alter how passengers interact with digital technologies. The contribution of the framework is therefore not the assumption that delays necessarily increase electricity consumption, but the identification of a measurable pathway through which such an effect may occur. The numerical application provides an important qualification to the original conceptual argument. Additional waiting increases passenger exposure, but greater exposure does not automatically imply positive DPEU. What matters is whether digital activity changes relative to an equivalent normal-service journey. Smartphone activity that would otherwise have occurred onboard or at another stage of the journey represents temporal displacement rather than necessarily additional electricity consumption. Conversely, disruption may increase digital engagement, leave it largely unchanged, or suppress it. The counterfactual baseline is therefore central to distinguishing genuinely delay-induced electricity use from activity that has merely changed in time or location. This distinction also helps connect the framework with existing evidence on passenger responses to waiting and digital information. Smartphone use is commonly observed during public-transport waiting, and empirical research has shown that such use can alter passengers' perception of waiting time, with heterogeneous effects across passengers and waiting conditions [28]. More recent evidence also shows that real-time information applications interact with objectively measured public-transport reliability and passengers' evaluation of service quality [50]. However, evidence that passengers use smartphones while waiting does not itself establish a net increase in digital activity over the complete journey. The present analysis therefore shifts the empirical question from whether passengers use smartphones during delays to whether, and by how much, their digital activity differs from what would have occurred under normal service conditions.

The sensitivity analysis reinforces the importance of this behavioural distinction. Operational conditions determine the extent of passenger exposure, while the behavioural difference primarily determines the direction of DPEU. Device power and passenger exposure subsequently influence its magnitude. This separation is particularly relevant because experimental evidence shows that smartphone electricity consumption varies according to communication protocol, application and device characteristics, and operating conditions [17,18,49]. Caiazza et al., for example, experimentally demonstrate differences in smartphone energy consumption across communication conditions and show that the relative energy performance can also change with the interaction pattern. Consequently, increasingly precise information on vehicle delays or headway irregularity would improve the operational component of the framework but would not resolve its principal uncertainty without corresponding evidence on passenger digital behaviour.

The Turin analysis provides an order-of-magnitude real-system application rather than an empirical validation of DPEU. At the disruption-event scale examined here, device-side DPEU is very small relative to the operational energy intensity of the transport system and should not be interpreted as an energy demand comparable with traction or other major operational uses. The present results also do not establish a route- or network-scale effect. Such estimation would require observed distributions of disruption frequency and duration, passenger exposure, and behavioural response across the relevant spatial and temporal boundary. Applying annual ridership or service distance directly to the event-level estimates would bypass these requirements and could substantially misrepresent the aggregate magnitude. The framework therefore provides a structure for future aggregation where suitable empirical data become available, without treating aggregation itself as evidence of practical significance.

Crowding adds another layer to this behavioural uncertainty. Passenger accumulation during unreliable service changes the physical and social conditions of waiting and may affect opportunities for smartphone use. However, the evidence reviewed in Section 2 does not support a sufficiently general numerical relationship between crowding and digital activity to transfer a fixed reduction factor across transport settings. Incorporating such a coefficient would therefore introduce unsupported precision. In the present framework, crowding is instead retained as a potential influence on disrupted behavioural probabilities and examined within the wider behavioural uncertainty.

The findings also refine the potential implications of DPEU for transport management. Improved reliability reduces excess waiting and passenger exposure, while recent empirical work confirms the importance of headway regularity to passenger experience even when real-time information is available [50]. However, the present results do not support the stronger claim that reliability improvements will necessarily reduce passenger smartphone electricity consumption, because the net effect also depends on what passengers would have done during the corresponding normal journey. Reliability improvements should therefore continue to be justified primarily through established transport benefits, while any reduction in indirect digital electricity demand should be treated as a possible secondary effect requiring empirical verification. Accordingly, DPEU is not proposed here as a dispatch-control or service-management metric; its immediate role is as an analytical and accounting framework for identifying cross-system electricity effects associated with transport unreliability.

From a broader urban-systems perspective, DPEU illustrates how digitalisation can create connections between sectors that are not visible when transport and ICT energy are examined independently. As passenger information, navigation, communication, and entertainment become increasingly integrated into everyday mobility, the boundary between transport behaviour and digital energy demand becomes less distinct. Recognising these interactions does not require treating every small electricity effect as environmentally significant. Instead, it provides a way to identify and quantify indirect effects and subsequently determine whether their magnitude warrants attention.

The revised framework also establishes a clearer pathway for empirical validation, with calibration of the behavioural difference as the immediate priority. The sensitivity analysis identifies Δp as the dominant determinant of signed DPEU in the numerical application, indicating that increasingly precise operational data alone would not resolve the principal uncertainty while the counterfactual behavioural response remains poorly constrained. Future field studies could therefore compare passenger digital activity under matched normal and disrupted service conditions, combining stop-level behavioural observations with archived GTFS-Realtime or automatic vehicle-location records and passenger counts. Where video-based observation is used, digital engagement could be recorded at repeated time intervals together with passenger density, allowing the empirical distribution of Δp to be estimated and its relationship with crowding to be tested rather than represented through an assumed universal reduction coefficient. This direction is increasingly feasible: recent public-transport research has combined GPS-derived headway-reliability measures with passenger responses to real-time information rather than relying exclusively on perceived service conditions [50]. Repeated observations across disruption intensities and waiting environments could then determine whether the behavioural response varies systematically with passenger density, disruption magnitude, service type, or other contextual conditions. Device-side measurements could subsequently be matched more closely to the observed activity mix, while communication-network and data-centre components could be incorporated where defensible marginal electricity intensities are available.

A further extension should move from the present event-level representation toward route- and network-level simulation of DPEU. The current framework evaluates passenger exposure associated with an isolated headway perturbation and therefore does not reproduce the propagation of irregularity through successive stops, vehicle bunching, service recovery, or spatially uneven passenger demand. A microscopic transport simulation could represent vehicle movements, passenger arrivals, boarding processes, stop-level accumulation, and changing headways jointly across a route. Platforms such as SUMO or PTV Vissim provide suitable environments for this development because they support microscopic and multimodal representation of transport operations and passenger or pedestrian flows [51]. Coupling such a simulation with empirically calibrated behavioural parameters would allow $N(t)$, passenger-time exposure, and DPEU to be estimated dynamically at successive stops rather than independently for a single disruption event. Route-level DPEU could then be aggregated from disruption-specific exposures while preserving spatial and temporal variation in passenger demand and service conditions. This extension would also permit investigation of whether an initial irregularity produces compensating effects later in the route, such as a shorter subsequent headway, rather than assuming that each disruption contributes independently to aggregate DPEU.

Overall, the findings position DPEU as a quantifiable but currently uncertain secondary consequence of public transport unreliability. Its contribution lies less in the magnitude obtained from the Turin example than in making the causal pathway explicit, defining the counterfactual required to distinguish additional from displaced electricity use, and identifying the operational, behavioural, and technological observations required for empirical estimation. This provides a basis for examining interactions between transport reliability and digital electricity demand without presuming either their direction or their practical significance.

6. Limitations

The numerical application is subject to limitations arising mainly from data availability. Although the normal-service characteristics of GTT Line 4 are based on published operational information, the analysed headway perturbations are not reconstructed historical disruption events. Stop-level passenger arrival data are also unavailable, so passenger flows are represented through uncertainty ranges rather than direct observations. The assumption of approximately uniform arrivals may therefore not capture variations associated with time of day, passenger arrival strategies, or the use of real-time information. The illustrative perturbation also treats the extended headway as an isolated event and does not model subsequent service recovery, bunching, or a compensating shorter headway. Behavioural parameters introduce a further limitation. Existing studies document smartphone use during public-transport waiting, but do not provide a directly transferable estimate of the counterfactual behavioural difference required by the DPEU framework. The range assigned Δp is consequently exploratory and has not been calibrated for Turin. Crowding is not estimated independently for the same reason: current evidence is insufficient to specify a transferable relationship between passenger density and changes in digital activity. The electricity estimates are likewise constrained by variation across devices and usage conditions. The device-power range represents plausible active-use conditions derived from experimental literature rather than the observed activity mix of Line 4 passengers [17,18,49]. Network and data-centre electricity are not quantified because a defensible marginal attribution to individual passenger activity could not be established from the available evidence. Finally, the Monte Carlo results depend on the specified parameter ranges and uniform sampling assumptions rather than empirically estimated probability distributions. The findings therefore characterize the behaviour and plausible order of magnitude of the framework under the conditions examined, rather than the observed distribution of DPEU in Turin. For the same reason, the event-level estimates are not extrapolated to an annual network total.

7. Conclusions

This study introduced Delay-Induced Passenger Electricity Use (DPEU) as a framework for examining whether public transport unreliability can indirectly alter passenger-related digital electricity consumption. By defining DPEU relative to a normal-service counterfactual, the framework distinguishes genuinely incremental electricity use from digital activity that is displaced between waiting and other stages of a journey or suppressed under disrupted conditions. This distinction is essential because additional waiting alone does not establish an increase in electricity consumption.

The Turin analysis provides an order-of-magnitude real-system application of the framework rather than an empirical validation of DPEU. It uses documented service characteristics as the normal-service baseline and analytical headway perturbations to examine how passenger exposure, behavioural change, and device power influence the estimated effect. Under the parameter space examined, device-side DPEU remains small at the individual disruption-event scale and can be positive, close to zero, or negative depending on the behavioural response. The analysis therefore does not support treating passenger digital activity during delays as automatically additional electricity demand. The sensitivity results further identify the counterfactual behavioural difference as the principal determinant of the direction of DPEU and the strongest influence on its absolute magnitude, indicating that behavioural measurement is the most important priority for reducing uncertainty in future applications.

DPEU should consequently be understood as a secondary interaction between transport reliability and digital electricity demand rather than as a major component of transport-system energy consumption. Its value lies in providing a transparent way to identify and quantify this cross-system interaction without presuming its magnitude or environmental significance. Future research should focus first on empirical calibration of the behavioural difference through repeated observations of passenger digital activity under comparable normal and disrupted service conditions, together with corresponding passenger-density and operational data. Combining these observations with historical operational data and stop-level passenger flows would allow the exploratory parameter ranges used here to be progressively replaced by empirically calibrated distributions and would support estimation across observed disruption events. Further work could examine whether and how crowding modifies digital behaviour and, where defensible marginal electricity intensities become available, extend the quantified boundary to communication networks and data centres. Beyond empirical calibration, future development could embed the DPEU framework within microscopic route- or network-level simulation to represent the propagation of service irregularity, uneven passenger demand, vehicle bunching, and changing passenger accumulation across successive stops. Applications across different service frequencies, transport modes, and urban contexts would then provide evidence on the transferability of DPEU. Whether individually small event-level effects remain negligible or acquire relevance when aggregated at route or network scale remains an empirical question requiring observed distributions of disruption frequency, passenger exposure, and behavioural response.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The public transport data used in this study were obtained from publicly available GTT sources, as cited in the manuscript. The numerical analysis was based on the parameter ranges and analytical formulations reported in the manuscript. No new empirical passenger-level dataset was generated during this study.

Conflicts of Interest

The author declares no conflict of interest.

Use of AI and AI-Assisted Technologies

The author used OpenAI ChatGPT and Grammarly platform during manuscript preparation to support language refinement, structural revision, and improvement of clarity and readability. The author critically reviewed, verified, and edited all AI-assisted content and takes full responsibility for the accuracy, interpretation, originality, and final content of the manuscript.

References

1. Anselmo, S.; Safaeianpour, A.; Moghadam, S.T.; et al. GIS-based solar radiation modelling for photovoltaic potential in cities: A sensitivity analysis for the evaluation of output variability range. *Energy Rep.* **2024**, *12*, 4656–4669. https://doi.org/10.1016/j.egyr.2024.10.031.
2. Safaeianpour, A. Application of an automated procedure for Solar Radiation estimation for the City of Turin A pilot application in a portion of District 6. Master of Science in Digital Skills for Sustainable Societal Transitions, Master's Thesis, Politecnico di Torino, Turin, Italy, 2024.
3. Abdeyazdan, H.; Safaeianpour, A.; Amini, M.A. Explainable machine learning for passive design: Early-stage building energy reduction in hot-arid climates. *Sustain. Energy Technol. Assess.* **2025**, *83*, 104589. https://doi.org/10.1016/j.seta.2025.104589.
4. Yan, H.; Lv, Z. A survey of sustainable development of intelligent transportation system based on urban travel demand. *Sustain. Society Dev.* **2024**, *2*, 2399. https://doi.org/10.54517/ssd.v2i1.2399.
5. Khalili, S.; Rantanen, E.; Bogdanov, D.; et al. Global Transportation Demand Development with Impacts on the Energy Demand and Greenhouse Gas Emissions in a Climate-Constrained World. *Energies* **2019**, *12*, 3870. https://doi.org/10.3390/en12203870.
6. Kisielewski, P.; Duda, J.; Karkula, M.; et al. Optimization of urban transport vehicle tasks for large, mixed fleet of vehicles and real-world constraints. *Arch. Transp.* **2024**, *70*, 65–78. https://doi.org/10.61089/aot2024.qnwb3h25.
7. Bolanle, A.S.; Oyedele, O.M.; Mariam, I.A.; et al. Internet of Things (IoT) Solutions for smart transportation infrastructure and fleet management. *Tuijin Jishu J. Propuls. Technol.* **2024**, *45*, 1492–1509.
8. Liu, K.; Feng, T.; Yamamoto, T.; et al. Electrification pathways for public transport systems. *Transp. Res. Part D Transp. Env.* **2024**, *126*, 103997. https://doi.org/10.1016/j.trd.2023.103997.
9. Kosmidis, I.; Müller-Eie, D. The synergy of bicycles and public transport: A systematic literature review. *Transp. Rev.* **2024**, *44*, 34–68. https://doi.org/10.1080/01441647.2023.2222911.
10. Zhang, N.; Yang, Q. Public transport inclusion and active aging: A systematic review on elderly mobility. *J. Traffic Transp. Eng. Engl. Ed.* **2024**, *11*, 312–347. https://doi.org/10.1016/j.jtte.2024.04.001.
11. Potter, S. Transport Energy and Emissions: Urban Public Transport. In *Handbook of Transport and the Environment*; Hensher, D.A., Button, K.J., Eds; Emerald Group Publishing Limited: Bingley, UK, 2003; pp. 247–262. https://doi.org/10.1108/9781786359513-013.
12. Barrero, R.; Mierlo, J.V.; Tackoen, X. Energy savings in public transport. *IEEE Veh. Technol. Mag.* **2008**, *3*, 26–36. https://doi.org/10.1109/mvt.2008.927485.
13. Malmodin, J.; Lövehagen, N.; Bergmark, P.; et al. ICT Sector Electricity Consumption and Greenhouse Gas Emissions—2020 Outcome. *Telecommun. Policy* **2024**, *48*, 102701. https://doi.org/10.1016/j.telpol.2023.102701.
14. Andrae, A.; Corcoran, P. *Emerging Trends in Electricity Consumption for Consumer ICT*; University of Galway Research Repository: Galway, Ireland, 2013. https://doi.org/10.13025/18707.
15. Watkins, K.E.; Ferris, B.; Borning, A.; et al. Where Is My Bus? Impact of mobile real-time information on the perceived and actual wait time of transit riders. *Transp. Res. Part A Policy Pract.* **2011**, *45*, 839–848. https://doi.org/10.1016/j.tra.2011.06.010.
16. Yu, D.; Yao, E.; Liu, S.; et al. The Impact of Disruption Information Strategies on the Dynamic Travel Choice Behaviour of Stranded Metro Passengers During Unplanned Service Disruptions. *IET Intell. Transp. Syst.* **2026**, *20*, e70220. https://doi.org/10.1049/itr2.70220.
17. Groza, C.; Dumitru-Cristian, A.; Marcu, M.; et al. A Developer-Oriented Framework for Assessing Power Consumption in Mobile Applications: Android Energy Smells Case Study. *Sensors* **2024**, *24*, 6469. https://doi.org/10.3390/s24196469.
18. Ali, H.; Khan, H.A.; Pecht, M. Evaluation of in-service smartphone battery drainage profile for video calling feature in major apps. *Sci. Rep.* **2023**, *13*, 11699. https://doi.org/10.1038/s41598-023-38859-3.
19. Istrate, R.; Tulus, V.; Grass, R.N.; et al. The environmental sustainability of digital content consumption. *Nat. Commun.* **2024**, *15*, 3724. https://doi.org/10.1038/s41467-024-47621-w.
20. Mytton, D.; Ashtine, M. Sources of data center energy estimates: A comprehensive review. *Joule* **2022**, *6*, 2032–2056. https://doi.org/10.1016/j.joule.2022.07.011.

21. Mytton, D.; Lundén, D.; Malmodin, J. Network energy use not directly proportional to data volume: The power model approach for more reliable network energy consumption calculations. *J. Ind. Ecol.* **2024**, *28*, 966–980. https://doi.org/10.1111/jiec.13512.
22. Soza-Parra, J.; Raveau, S.; Muñoz, J.C.; et al. The underlying effect of public transport reliability on users' satisfaction. *Transp. Res. Part A Policy Pract.* **2019**, *126*, 83–93. https://doi.org/10.1016/j.tra.2019.06.004.
23. Soza-Parra, J.; Raveau, S.; Muñoz, J.C. Travel preferences of public transport users under uneven headways. *Transp. Res. Part A Policy Pract.* **2021**, *147*, 61–75. https://doi.org/10.1016/j.tra.2021.02.012.
24. Fan, Y.; Guthrie, A.; Levinson, D. Waiting time perceptions at transit stops and stations: Effects of basic amenities, gender, and security. *Transp. Res. Part A Policy Pract.* **2016**, *88*, 251–264. https://doi.org/10.1016/j.tra.2016.04.012.
25. Liu, L.; Miller, H.J. Does real-time transit information reduce waiting time? An empirical analysis. *Transp. Res. Part A Policy Pract.* **2020**, *141*, 167–179. https://doi.org/10.1016/j.tra.2020.09.014.
26. Mishalani, R.G.; Lee, S.; McCord, M.R. Evaluating Real-Time Bus Arrival Information Systems. *Transp. Res. Rec.* **2000**, *1731*, 81–87. https://doi.org/10.3141/1731-10.
27. Mishalani, R.G.; McCord, M.M.; Wirtz, J. Passenger wait time perceptions at bus stops: Empirical results and impact on evaluating real-time bus arrival information. *J. Public Transp.* **2006**, *9*, 89–106. https://doi.org/10.5038/2375-0901.9.2.5.
28. Wang, P.C.; Hsu, Y.T.; Hsu, C.W. Analysis of waiting time perception of bus passengers provided with mobile service. *Transp. Res. Part A Policy Pract.* **2021**, *145*, 319–336. https://doi.org/10.1016/j.tra.2021.01.011.
29. Julsrud, T.E.; Denstadli, J.M. Smartphones, travel time-use, and attitudes to public transport services. Insights from an explorative study of urban dwellers in two Norwegian cities. *Int. J. Sustain. Transp.* **2017**, *11*, 602–610. https://doi.org/10.1080/15568318.2017.1292373.
30. Ohmori, N.; Harata, N. How different are activities while commuting by train? A case in Tokyo. *Tijdschr. Voor Econ. En Soc. Geogr.* **2008**, *99*, 547–561. https://doi.org/10.1111/j.1467-9663.2008.00491.x.
31. Wardman, M.; Chintakayala, P.; Heywood, C. The valuation and demand impacts of the worthwhile use of travel time with specific reference to the digital revolution and endogeneity. *Transportation* **2020**, *47*, 1515–1540. https://doi.org/10.1007/s11116-019-10059-x.
32. Timmermans, H.; Van der Waerden, P. Synchronicity of activity engagement and travel in time and space: Descriptors and correlates of field observations. *Transp. Res. Rec. J. Transp. Res. Board* **2008**, *2054*, 1–9. https://doi.org/10.3141/2054-01.
33. Zhang, L.; Tiwana, B.; Qian, Z.; et al. Accurate online power estimation and automatic battery behavior based power model generation for smartphones. In Proceedings of the CODES/ISSS '10: Eighth IEEE/ACM/IFIP International Conference on Hardware/Software Codesign and System Synthesis, Scottsdale, AZ, USA, 24–29 October 2010. https://doi.org/10.1145/1878961.1878982.
34. Duan, L.T.; Guo, B.; Shen, Y.; et al. Energy analysis and prediction for applications on smartphones. *J. Syst. Archit.* **2013**, *59*, 1375–1382. https://doi.org/10.1016/j.sysarc.2013.08.011.
35. Spachos, P.; James, M.; Gregori, S. Power tradeoffs in mobile video transmission for smartphones. *Comput. Commun.* **2018**, *118*, 163–170. https://doi.org/10.1016/j.comcom.2017.10.017.
36. Kim, Y.G.; Kim, M.; Kim, J.M.; et al. A novel GPU power model for accurate smartphone power breakdown. *ETRI J.* **2015**, *37*, 157–164. https://doi.org/10.4218/etrij.14.0113.1411.
37. Pasek, A.; Vaughan, H.; Starosielski, N. The world wide web of carbon: Toward a relational footprinting of information and communications technology's climate impacts. *Big Data Society* **2023**, *10*, 20539517231158994. https://doi.org/10.1177/20539517231158994.
38. International Telecommunication Union. *Recommendation ITU-T L.1410 (11/2024)—Methodology for Environmental Life Cycle Assessments of Information and Communication Technology Goods, Networks and Services*; ITU Publications: Geneva, Switzerland, 2024.
39. Bieser, J.C.T.; Hintemann, R.; Hilty, L.M.; et al. A review of assessments of the greenhouse gas footprint and abatement potential of information and communication technology. *Environ. Impact Assess. Rev.* **2023**, *99*, 107033. https://doi.org/10.1016/j.eiar.2022.107033.
40. Liu, X.; Schmöcker, J.D.; Zhao, J.; et al. How to make service better? A review on developing service-oriented public transit systems. *Transp. Rev.* **2025**, *45*, 672–695.
41. van Ardenne, M.T.; Cebecauer, M.; Cats, O.; et al. Personalised passenger information systems in public transport: A review and a 5-level personalisation taxonomy. *Transp. Rev.* **2025**, *45*, 1016–1047. https://doi.org/10.1080/01441647.2025.2537203.
42. Drabicki, A.; Cats, O.; Kucharski, R. Has the COVID-19 pandemic affected travellers' willingness to wait with real-time crowding information? *Travel Behav. Society* **2025**, *38*, 100895. https://doi.org/10.1016/j.tbs.2024.100895.
43. Grant, M.J.; Booth, A. A typology of reviews: An analysis of 14 review types and associated methodologies. *Health Inf. Libr. J.* **2009**, *26*, 91–108.

44. GTT—Gruppo Torinese Trasporti. Feed GTFS Trasporti GTT. 2020. Available online: https://aperto.comune.torino.it/dataset/feed-gtfs-trasporti-gtt (accessed on 8 August 2026).
45. GTT—Gruppo Torinese Trasporti. Feed GTFS Real-Time Trasporti GTT. Available online: https://aperto.comune.torino.it/dataset/feed-gtfs-real-time-trasporti-gtt (accessed on 8 August 2026).
46. GTT—Gruppo Torinese Trasporti. Rendicontazione di Sostenibilità 2025. 2026 Available online: https://aperto.comune.torino.it/dataset/feed-gtfs-real-time-trasporti-gtt (accessed on 8 August 2026).
47. Usher, W.; Barnes, T.; Moksnes, N.; et al. Global sensitivity analysis to enhance the transparency and rigour of energy system optimisation modelling. *Open Res. Eur.* **2023**, *3*, 30. https://doi.org/10.12688/openreseurope.15461.1.
48. GTT—Gruppo Torinese Trasporti. L'intervallo Indicato è Quello dei Tratti in Commune. 2026. Available online: https://www.gtt.to.it/cms/risorse/urbana/intervalli_sito.pdf (accessed on 15 August 2026).
49. Caiazza, C.; Luconi, V.; Vecchio, A. Energy consumption of smartphones and IoT devices when using different versions of the HTTP protocol. *Pervasive Mob. Comput.* **2024**, *97*, 101871. https://doi.org/10.1016/j.pmcj.2023.101871.
50. Henriquez-Jara, B.; Arriagada, J.; Tirachini, A. Impact of real-time information on passenger satisfaction across varying public transport quality levels in 13 Chilean cities. *Transp. Res. Part A Policy Pr.* **2025**, *200*, 104622. https://doi.org/10.1016/j.tra.2025.104622.
51. Lopez, P.A.; Behrisch, M.; Bieker-Walz, L.; et al. Microscopic Traffic Simulation using SUMO. In Proceedings of the 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Maui, HI, USA, 4–7 November 2018; pp. 2575–2582. https://doi.org/10.1109/itsc.2018.8569938.