

Automated GPS-Based Self-Ticketing and Fare Verification System for Urban Public Buses: A Review

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Abstract — Urban bus operators still rely on cash, paper tickets and card taps that slow boarding, leak revenue through fare evasion and reveal little about where passengers actually travel. Smartphones now carry the sensors needed to replace these steps with automatic, location-driven ticketing. This paper reviews the literature behind an automated, GPS-based self-ticketing and fare verification system for urban buses. Six recent IEEE papers form the primary corpus, supported by the works they cite. The review traces the shift from cash to check-in/check-out and be-in/be-out ticketing, examines how GPS trajectories matched against GTFS and vehicle-location feeds can identify the bus a passenger rode, and discusses fare-evasion control, fusion of vehicle-location and fare records, alighting-stop inference, and IoT and cloud architectures with their privacy safeguards. A layered reference architecture and a seven-step verification workflow are then synthesised from the reviewed evidence. Reported results show that dynamic time warping identified the correct bus for 92.9% of a small set of test trips, while fused vehicle-location and fare data placed 94.7% of boardings on the correct route and stop in a one-year city dataset. Open problems include short-trip detection, GPS degradation in dense areas, battery and privacy cost, and inclusion of riders without smartphones.

Keywords— Automated fare collection, GPS, self-ticketing, fare verification, fare evasion, be-in/be-out, urban bus transit.

I. INTRODUCTION

Buses form the backbone of public transport in many cities, yet their fare-collection model is often among the least modernised parts of the system. Fares are the main income of a transit operator, so every unpaid or mis-priced ride is a direct loss [1]. Operators also gain little insight from conventional ticketing: a cash sale or a card tap records, at best, a boarding event. Meanwhile, transport accounts for roughly a quarter of global CO₂ emissions [1], which makes a smoother, more attractive bus service a climate concern as well as a commercial one.

Fare evasion, whether deliberate or accidental, is the most visible weakness. Studies have quantified its financial impact and its spatial and temporal patterns [2], a literature review has synthesised more than a hundred works including psychological and criminological explanations [3], and predictive risk scores have been proposed to direct inspections toward the routes where evasion is most likely [4]. Traditional validation, such as checking a paper ticket or tapping a card, also forces physical interaction that delays boarding and is awkward for riders with disabilities [5].

A different approach is to let the passenger's own phone do the work. Almost every commuter carries a handset with a GPS receiver and motion sensors, and bus agencies already publish route geometry and live vehicle positions in the General Transit Feed Specification (GTFS). If the phone can detect that its

owner is on a bus, and the back end can work out which bus it was, then the ticket can be issued and the fare charged without any action by the rider [6], [5]. Verification then shifts from checking a physical token to confirming a digital journey record.

This paper reviews the evidence needed to design such a system. Its contributions are: (i) a structured account of how bus ticketing has moved from cash to automatic be-in/be-out models; (ii) a critical comparison of the GPS trajectory-matching and data-fusion methods reported in six recent IEEE papers; (iii) an examination of how fare verification and evasion control can be built on location evidence; and (iv) a reference architecture, a verification workflow and a list of open research gaps. The remainder of the paper is organised as follows. Section II states the scope of the review, Sections III and IV cover ticketing technologies and paradigms, Section V treats GPS-based journey recognition, Section VI addresses verification, Sections VII and VIII discuss analytics and architecture, Section IX presents the synthesised design, and Sections X to XII close with challenges, future directions and conclusions.

II. REVIEW SCOPE AND METHOD

The primary corpus consists of six IEEE journal papers supplied for this study: a survey of automated fare collection (AFC) solutions [6], a comprehensive review of technologies

for public-transport improvement [1], a GPS-based bus identification framework for frictionless fare collection [5], a method for integrating vehicle-location, fare and schedule data [7], a model for inferring bus origin–destination (OD) pairs from incomplete smart-card data [8], and a method for predicting OD distributions on an expanding metro network from AFC data [9]. Supporting studies were taken from the reference lists of these papers and are described only as far as the citing papers describe them.

The material was grouped into five themes: ticketing paradigms, location-based journey recognition, verification and evasion control, data fusion and analytics, and architecture with security. This is a narrative review rather than an exhaustive systematic search. Quantitative results are quoted as published; because the studies use different cities, sensors and sampling rates, the numbers illustrate feasibility and should not be read as a like-for-like benchmark.

III. EVOLUTION OF BUS FARE COLLECTION

1. Conventional Payment Methods

Cash remains the most accessible way to pay, but it is slow, exposes drivers to security risk and generates no usable data [1]. Transit passes suit regular riders and do little for occasional ones. Smart cards and RFID media allow fast contactless entry and offline validation, although they carry deployment cost, cloning risk and limited suitability for visitors [1]. Examples cited in the literature include the Oyster card in London and the OV-chipkaart in the Netherlands, all of which still depend on a physical interaction by the passenger [6].

2. Mobile and Contactless Ticketing

Early mobile solutions used voice calls or text messages. SMS tickets need an operator subscription, carry no location information and are easy to forge, and one study found that up to 5% of messages did not arrive in time [6]. QR codes are cheap and work on any camera phone, but scanning is slow and needs adequate light; a field study in Wuhan found that QR payment lengthened boarding service time relative to integrated-circuit cards and cash [10]. NFC phones emulate smart cards and so reuse existing readers, yet NFC works only as a tap-and-pay interaction and cannot support fully automatic fares [6]. Comparative trials of QR, NFC and BLE ticketing have been reported as well [11].

3. Biometric and Sensor-Based Methods

Face and fingerprint recognition remove the need for a token altogether. Prototypes include an edge-AI facial recognition

payment system and a fingerprint-based fare scheme, but storing and processing biometric data raises privacy and misuse concerns that have slowed adoption [5]. An IoT-based fare system aimed at visually impaired riders has also been reported; it combines RFID fare processing, infrared passenger counting, GPS distance measurement and audio guidance [12]. Table I condenses the trade-offs.

Table I: Fare Payment Technologies and Their Trade-Offs

Method	Strengths	Limitations
Cash	Universally accessible	Slow; security risk; no data
Transit pass	Convenient for regular riders	Inflexible for occasional riders
RFID / smart card	Fast contactless entry; offline validation	Cloning risk; deployment cost
QR code	Low cost; suits occasional users	Slow scan; needs light and a working device
SMS ticket	No app needed	Needs subscription; no location; forgeable
Biometric	Seamless; no token	Privacy and data-protection concerns
BLE beacon	Hands-free, in-vehicle presence	Beacons needed on every vehicle and stop

IV. TICKETING PARADIGMS

The survey by Bieler *et al.* [6] organises mobile ticketing into four paradigms, which also give a useful scale of automation.

- **Check-In (CI):** The rider selects and buys a ticket before departure and simply leaves the vehicle at the destination. The system learns nothing about the actual journey.
- **Check-In/Check-Out (CICO):** The rider registers at boarding and again on alighting through an app or reader, which allows the system to compute an optimised fare. This is a widely used mobile model [6], [13].
- **Check-In/Be-Out (CIBO):** The rider checks in actively, but location data collected during the trip are used to close the journey and price it on arrival.
- **Be-In/Be-Out (BIBO):** No active check-in or check-out is needed. The phone streams sensor readings to a central server while the rider travels; the server infers the transport mode and the destination and prices the trip from that

evidence. Bieler *et al.* judge BIBO the paradigm most likely to produce high customer satisfaction [6].

Bluetooth Low Energy (BLE) is the most frequently studied enabler of BIBO [14], [15]. In a BLE trial, 80% of users were highly satisfied [6], and a mobile fare-payment evaluation in Tallahassee reported comparable satisfaction among both riders and operators [13]. The drawback is infrastructure: beacons must be fitted at every facility and inside every vehicle, which makes BLE the costliest BIBO option to deploy [6]. Location-based BIBO, which needs only the passenger's phone and public transit data, is therefore attractive for cities with large, ageing bus fleets. This is the model examined in the next section.

V. GPS-BASED SELF-TICKETING

1. Sensing and Travel-Mode Detection

A self-ticketing app first has to know when the user is on a vehicle. Bieler *et al.* identify in-vehicle presence and transport-mode recognition as the crux of automatic ticketing [6]. Accelerometer-based classification of transport modes on smartphones is an established technique [16], and the framework of Ghorbankhani *et al.* assigns the job to an on-device Travel Mode Detector that wakes the location logger once a vehicle trip is detected [5]. GPS is the simplest positioning source, but it degrades among tall buildings because signals scatter [6]. Wi-Fi positioning has been explored as an alternative, with a three-year Australian data set suggesting it is useful for transit applications [6]. Cellular triangulation was used in early location-based ticketing, but Bieler *et al.* note that early GPS or network-only schemes cannot by themselves establish in-vehicle presence [6]. This is why recent work pairs phone GPS with bus-side data instead of relying on phone location alone.

2. Journey Recognition by Trajectory Matching

The Journey Recognition Module (JRM) proposed in [5] runs in the cloud and proceeds in three stages. First, the opening and closing points of the recorded trace are compared with known stop locations; if both fall within a threshold, the trip is treated as a potential bus ride, otherwise as a private-vehicle trip. Second, buses whose reported positions lay near the start stop around the boarding time, and near the end stop around the alighting time, are intersected to form a candidate list. Third, the user's trace is compared with the trajectory of every candidate and the best match is chosen.

Two similarity measures are compared. Let the user trajectory be $U = (u_1, \dots, u_m)$ and a candidate bus trajectory be $B = (b_1, \dots, b_n)$.

Dynamic time warping (DTW) aligns the two sequences elastically using the Haversine distance d between points, building a cumulative cost

$$D(i, j) = d(u_i, b_j) + \gamma(i, j), \quad (1)$$

where $\gamma(i, j) = \min \{D(i-1, j), D(i, j-1), D(i-1, j-1)\}$. The result is normalised by path length and converted to a similarity with a Gaussian kernel,

$$AD = D(m, n) / (m + n - 1), \quad (2)$$

$$S_{DTW}(U, B) = \exp(-AD^2 / 2\sigma^2). \quad (3)$$

The Longest Common Subsequence (LCSS) alternative counts points that match within a spatial threshold ϵ and a time threshold δ and is normalised by the shorter sequence,

$$S_{LCSS} = LCSS(m, n) / \min(m, n). \quad (4)$$

For N candidates with scores S_i , the probability of each bus is

$$P_i = S_i / \sum_{j=1}^N S_j, \quad (5)$$

and the bus with the highest P_i is accepted only if its score exceeds a threshold α [5]. Both measures tolerate irregular sampling and GPS noise, which is why they suit crowd-sourced phone traces.

3. Reported Performance

The framework was tested in Hamilton, Ontario with 51 trips (21 bus rides and 30 car journeys) recorded at 1 Hz from volunteers' phones and matched with GTFS real-time bus positions updated about once a minute [5]. Stop analysis removed 28 trips as private-vehicle journeys; the candidate-bus stage then rejected nine more, seven of which were in fact bus trips whose short duration and sparse bus-location data left the candidate list empty. Of the 14 bus trips that reached the similarity stage, DTW identified the correct bus with 92.9% accuracy against 64.3% for LCSS [5]. The authors conclude that DTW was both more accurate and more efficient, and that short trips need denser location data. An earlier study from the same group also reconstructs journeys from GPS and GTFS data [17].

Two points follow. The result supports the feasibility of purely location-based bus identification, with no extra hardware on the vehicle. But the evaluation is small, covers one city and loses one third of the bus trips (7 of 21) before similarity matching is

even attempted, so a production system would need larger trials and a fallback for the short, sparse trips that were missed.

4. Complementary Signals

GPS alone cannot separate two buses that share a corridor for many stops. Complementary signals can break such ties. BLE beacons placed in vehicles give a strong proximity cue [14], wireless scanning of passengers' devices has been used to detect end-to-end bus trips [18], and motion, pressure and gyroscopic readings can reinforce in-vehicle detection [6]. A hybrid design would use GPS as the default and invoke a cheaper secondary check only when the similarity scores of the top candidates are close.

VI. FARE VERIFICATION AND EVASION CONTROL

1. Why Verification Matters

Automatic ticketing removes the moment at which a conductor or reader traditionally confirms payment, so the system must supply a different form of assurance. Bieler *et al.* stress that the key innovation is establishing, with non-repudiation, that a traveller really was inside the vehicle [6]. Verification therefore has two jobs: protecting revenue from riders who avoid paying, and protecting honest riders from wrongful charges.

2. Measures Reported in Practice

A study of the New York City Transit Authority describes a layered response to evasion that includes security features built into the fare-collection infrastructure, cameras that identify repeat offenders and covert observers deployed at random intervals [19]. Risk-based approaches aim to concentrate inspection effort where it matters: evasion-risk scores for bus networks [4] and work on real-time deterrence [2] both point toward sending controllers where they are most useful. Krishnamoorthy and Venugopal list automatic ticket barriers, stored-value cards and QR codes among the standard defences and note that no single payment method is best on convenience, security, cost and inclusivity at once [1].

3. Verification in a GPS-Based Self-Ticketing System

The reviewed studies do not describe a complete verification subsystem for location-based ticketing, so the following design is a synthesis of their ingredients rather than a reported result. Three complementary checks can be combined.

Journey proof: The JRM output (matched bus identifier, boarding and alighting stops, similarity score and timestamps) is stored as the evidence of travel [5]. A trip that cannot be

matched with sufficient confidence is not silently dropped but flagged for a fallback such as QR validation.

Inspector check: On request, the rider's app displays a short-lived signed token tied to the bus and trip. An inspector's device validates it against the server, or locally using a public-key signature, so that checking works without a mobile signal. Public-key infrastructure is one of the security frameworks discussed for transit data in [1].

Post-trip audit: Server-side logs are reconciled with vehicle-location and fare events. Benavente *et al.* show how AVL and AFC streams can be merged to assign each ticketing event to the right bus visit [7]; the same logic could help expose tokens presented on a bus that never carried the rider.

A further concern is manipulation of the location data itself. Accuracy of trip recognition, not adversarial behaviour, is the focus of the studies reviewed here, so the effect of spoofed coordinates remains an open question for future evaluation.

VII. DATA FUSION AND ANALYTICS

1. Fusing Vehicle-Location and Fare Records

Raw operational data are rarely clean. Benavente *et al.* analysed one year of automated vehicle location (AVL), boardings-only AFC and schedule data from Santander, Spain, a city of about 174,000 inhabitants [7]. Their pipeline preprocesses each source, builds the expected stop sequence for every route, classifies AVL fragments, fits travel and dwell-time models, detects vehicles that change identifier mid-trip and attaches each ticketing event to the correct bus visit. Of all boarding groups, 94.7% were judged to report the right route and stop, 5% were reassigned to a different stop and 0.3% could not be linked to a trip; 92% of the raw AVL entries were ultimately used. A robustness test with only 25% of the real data and added synthetic errors showed that accuracy falls as real evidence thins out [7]. For a self-ticketing system the lesson is practical: the bus-side feed that the JRM relies on needs the same cleaning and cross-checking before it can be trusted for billing.

2. Inferring Where Passengers Alight

When riders do not tap out, which is typical of flat-fare buses, only the boarding point is recorded. Tang *et al.* address this with a two-layer model on two weeks of Chengdu data containing roughly 30 million records, of which 20,029,017 were boarding transactions [8]. Extended trip-chain rules supply high-confidence alighting labels, a Random Forest selects features and a CatBoost classifier predicts the alighting stop. Applied to a subway line with masked destinations (170,682 records), the

trip-chain rules recovered 93.6% of the hidden stops [8]. On the bus data, CatBoost reached a stop-level accuracy of 0.4614, ahead of XGBoost at 0.4403 and Random Forest at 0.4565, and reproduced the trip-distance distribution with R^2 up to 0.8382. The authors also introduce a Trend Consistency Index to validate results when no ground truth exists. Earlier work estimated journey destinations from AFC data with spatial validation [20].

Stop-level accuracy below 50% shows how hard destination inference is without a passenger-side signal. This is a strong argument for self-ticketing: a phone that records the whole trajectory observes the alighting stop directly instead of guessing it.

3. Network-Level Demand Estimation

Liu applies AFC data to metro planning by combining a disaggregate destination-choice model with an aggregate model of historical flows to predict OD distributions after a new line opens [9]. On Guangzhou Metro Line 18 the mean absolute error was 12.5 passengers for weekday flows and 11.5 for weekend flows. Although the setting is rail, the same fare-derived OD matrices help bus agencies in route design and in calibrating distance-based fares, and the combination of individual-level choice with aggregate patterns is relevant to estimating demand for new bus corridors. Table II summarises the primary studies.

Table 2: Summary of the Primary Studies

Study	Data and method	Principal outcome
Ghorbankhani et al. [5]	Phone GPS and GTFS-RT, Hamilton; DTW vs. LCSS	Bus ID accuracy 92.9% (DTW) vs. 64.3% (LCSS) on 14 trips
Benavente et al. [7]	One year of AVL, AFC and schedule data, Santander	94.7% of boardings on correct route and stop
Tang et al. [8]	Chengdu smart-card and bus GPS; RF + CatBoost	R^2 up to 0.8382; accuracy 0.4614 vs. 0.4403 (XGBoost)
Liu [9]	Guangzhou Metro AFC; disaggregate + aggregate models	MAE 12.5 (weekday) and 11.5 (weekend) passengers

Study	Data and method	Principal outcome
Bieler et al. [6]	Survey of mobile ticketing, IoT and machine learning	BIBO judged most suited to high satisfaction; presence detection and privacy remain open
Krishnamoorthy and Venugopal [1]	Review of ITS technologies	Trade-offs of payment methods; value of integrating IoT, big data, ML, cloud and edge

VIII. ARCHITECTURE, SECURITY AND PRIVACY

1. Layered IoT Architecture

Bieler *et al.* describe public-transport IoT as three layers: a perception layer of sensors and devices, a network layer that carries their data, and an application layer that processes it [6]. Sensors and on-board hubs sit inside the vehicle and connect to the internet over Wi-Fi or cellular links. Message transport options include publish/subscribe brokers using MQTT, which give low coupling and many-to-many delivery, and CoAP, which a public-transport comparison found to reach full reliability like MQTT while using noticeably less overhead for confirmed messages [6]. For long-range telemetry from vehicles, LoRaWAN has been proposed, with one compression scheme shrinking a GPS record from 280 bits to 49 [6].

2. Cloud and Edge Processing

Krishnamoorthy and Venugopal argue that cloud and edge computing complement each other in transit systems: the cloud provides scalable storage and retraining of models, while edge nodes in vehicles or local control points give low-latency decisions [1]. For a self-ticketing system this suggests lightweight mode detection and buffering on the phone, trajectory matching and fare calculation in the cloud, and the possibility of an edge function on the bus for offline validation. Bieler *et al.* likewise recommend on-device or federated learning to reduce energy use and keep raw data local [6].

3. Security and Privacy

Continuous location tracking is inherently sensitive. Reported safeguards include public-key infrastructure, ticketing on a

blockchain, privacy-by-design practices aligned with the GDPR, and federated learning [1], although the authors note that these remain hard to deploy in large networks and that standard federated learning can itself be attacked by dishonest participants. Bieler *et al.* add that anonymisation alone may not suffice, since even basic NFC exchanges can contain identifiers that allow customers to be re-identified, and that granular mobility data create their own privacy risk [6]. Practical consequences are to collect location only while a vehicle trip is detected, to retain raw traces for the shortest period consistent with dispute handling, and to separate identity from trip data wherever possible.

IX. SYNTHESISED REFERENCE DESIGN

Combining the evidence above gives the layered design in Fig. 1. The sensing layer pairs the passenger's phone with a bus unit that reports vehicle positions. The network layer carries encrypted, batched uploads. The cloud layer performs journey recognition, fare calculation and token issuing, and the application layer serves riders, inspectors and operators. This design is a conceptual synthesis; it has not been implemented or tested as a whole.

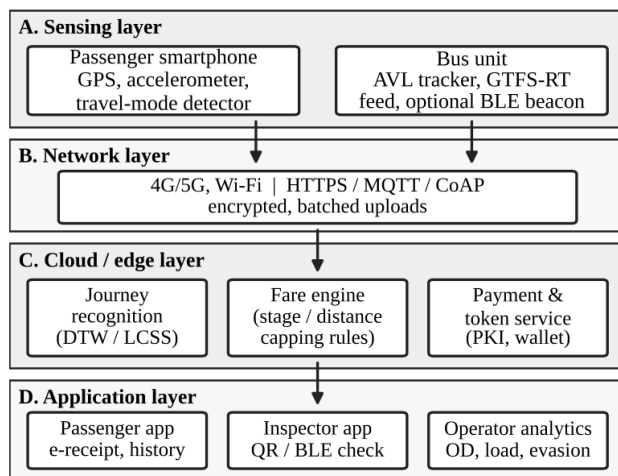


Fig.1. Layered reference architecture for GPS-based self-ticketing and fare verification (synthesised from the reviewed literature)

The operational flow is shown in Fig. 2. The mode detector starts logging when vehicle motion is sensed; start and end points are matched to stops; candidate buses are drawn from the live AVL feed; DTW selects the most probable bus subject to the acceptance threshold; the fare engine prices the trip from the boarding and alighting stops; and a signed token is issued

for inspection. Failure handling is part of the design: if no candidate bus exists or the best score falls below the threshold, the trip is not charged automatically but is routed to a fallback such as manual QR validation or review. This directly addresses the short-trip weakness reported in [5].

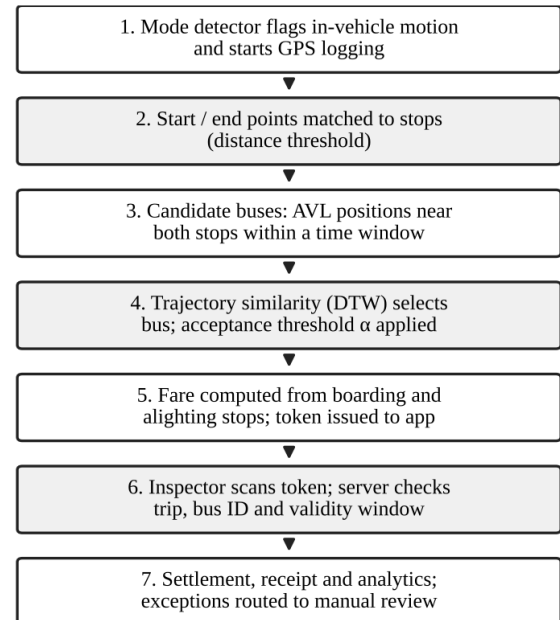


Fig.2. Seven-step workflow from boarding detection to settlement and exception handling

Challenges and Research Gaps

- **Short trips and sparse sampling:** Short rides yield few GPS points, and low-frequency bus-location feeds left some trips without any candidate bus in [5]. Higher sampling rates on both sides, or a secondary sensor, are needed.
- **Urban-canyon positioning:** GPS error grows near tall buildings [6], exactly where dense bus corridors lie. Map matching and sensor fusion are therefore important.
- **Data quality:** Missing, duplicated or inconsistent vehicle identifiers and mismatched trip codes across subsystems are common and demand explicit correction [7].
- **Validation without ground truth:** Large-scale labelled trips are scarce; Tang *et al.* propose indirect indices [8], but they need to be tested on self-ticketing data.
- **Battery and compute cost:** Continuous GPS and machine-learning inference are energy-intensive on

phones, which motivates event-triggered sensing and edge or federated processing [6].

- **Privacy and trust:** Location histories are personal data. Governance, consent and minimal retention must be designed in from the start [1].
- **Inclusion:** Smartphone-dependent systems may exclude low-income and elderly riders, so low-cost alternatives and simple interactions are needed [6]. Dynamic fare schemes should also be examined for fairness, because short-trip riders may be disadvantaged by flat or entry fares.
- **Evidence base:** Published evaluations of location-based bus identification are small and city-specific [5]. Multi-city field trials with audited ground truth are the most pressing gap.

Future Directions

Several lines of work follow from the review. First, richer sensing: accelerometer and gyroscope signals, higher GPS frequency and complementary BLE or Wi-Fi cues should be evaluated against the DTW baseline [5], [6]. Second, learning-based matchers, including deep and graph-based models, deserve benchmarking against trajectory-similarity methods [5]. Third, risk-aware verification can adapt inspection intensity using evasion-risk scores [4], [2]. Fourth, federated and on-device learning can protect privacy while improving mode detection [6]. Finally, extending the approach to trams, metros and demand-responsive services would support the integrated mobility envisioned in [1].

X. CONCLUSION

This review examined how GPS-based self-ticketing and fare verification can modernise urban bus fare collection. The literature shows a clear path from cash and card taps toward be-in/be-out ticketing, and the first location-only bus identification results are encouraging: DTW matched the correct bus for 92.9% of the test trips that reached the similarity stage, and fused AVL and fare data tied 94.7% of boardings to the right route and stop. Yet the evidence is thin, short trips remain troublesome, and verification, privacy and inclusion need as much attention as accuracy. The layered architecture and seven-step workflow proposed here offer a starting point for pilots that couple automatic trip recognition with signed tokens, inspector checks and post-trip audit.

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