ABUAD Journal of Engineering Research and Development (AJERD)
ISSN (online): 2645-2685; ISSN (print): 2756-6811

Volume 8, Issue 3, 241-255

# Optimising Service Delivery with Data Visualisation and Dashboards: Evidence from Tanzania Railway Corporation Standard Gauge Railway Ticketing

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*Received: 01/09/2025*
*Revised: 03/11/2025*
*Accepted: 07/11/2025*
*Available online: 19/11/2025*

***Abstract***: *This study evaluates a real-time, coach-level control loop that couples ticket intent with physical seat occupancy to strengthen Monitoring & Evaluation (M&E) in the Tanzania Railway Corporation (TRC) Standard Gauge Railway. Grounded in Systems Theory, Results-Based Management, and principles of technology adoption, the study aims to enhance existing systems by proposing a dashboard-enabled workflow that integrates manifest data with seat-weight signals to surface pre-departure blocking alerts. A convergent mixed-methods design combined with design-science research (DSR). Data were collected using structured questionnaires and observations with trip-level indicators: Overstay Rate (OSR), Mean Detection Latency (MDL), False Positive Rate (FPR), Seat-Turnover Efficiency (STE), and Reporting Throughput (RT). Purposive sampling engaged 36 passengers and 12 staff across 6 stations and 12 scheduled runs (May to December 2024). The proposed design must undergo expert review and pilot testing to achieve substantial qualitative reliability (κ = 0.78). Trip indicators were computed under explicit guardrails and audited logs. Results show a persistent in-journey visibility gap after boarding; the proposed control loop operationalises station-to-station verification and auditable resolution. In a pilot comparison, we observe directionally favourable movements in MDL, OSR, FPR, STE, and RT (reported as medians with interquartile ranges and bootstrap confidence intervals). The study concludes that dashboard-enabled seat–ticket coupling can measurably improve compliance, decision speed, and documentation under TRC's connectivity and capacity constraints.*

***Keywords***: *Dashboard Systems, Data Visualization, Fare Compliance, Monitoring and Evaluation, Operational Efficiency, Service Delivery Enhancement*

## 1. INTRODUCTION

Digital technologies continue to transform decision-making by streamlining workflows and improving the speed, accuracy, and quality of the evidence used to inform action [1, 2]. In Tanzania, Monitoring and Evaluation (M&E) is central to effective service delivery across health, education, agriculture, and transport. However, practices anchored in manual verification, fragmented reporting, and paper-based documentation struggle to meet the demands of data-driven governance, delaying response and weakening accountability [3, 4]. Despite national digitalization efforts, transport M&E still largely relies on post-event reporting, with limited real-time visibility, creating an execution gap in which indicators arrive too late to influence operational decisions.

Within the TRC Standard Gauge Railway (SGR), boarding-gate fare checks are robust, but visibility degrades once trains depart. This gap enables passengers to travel beyond paid destinations, forcing staff to rely on time-consuming, inconsistent, and unauditable manual inspections thereby undermining both revenue assurance and operational efficiency. To close this gap, this study introduce a coach-level, seat-weight–coupled dashboard architecture that extends compliance monitoring at every station stop by fusing ticketing intent with physical seat-state signals. The operational goal is to shift from ex post discovery to in-dwell intervention, acting before doors close at each stop, thereby improving monitoring precision, reducing detection delays, and strengthening reporting integrity.

The study aims to propose a design for a dashboard-enabled seat–ticket coupling control loop for TRC-SGR that reduces detection latency and fare overstay while improving reporting fidelity. Specifically, we (i) formalize a coach-level measurement model (OSR, MDL, FPR, STE, and RT); (ii) propose an offline-tolerant, crew-scoped workflow; and (iii) assess directional effects against pre-pilot practices.

Gate-level QR validation is reliable; however, the absence of an in-journey, seat-level compliance mechanism to verify disembarkation before departure inflates MDL, depresses RT, enables OSR, and slows vacancy reuse (STE). This visibility deficit is explicitly salient at TRC-SGR, aligning with concerns raised by the Prevention and Combating of

Corruption Bureau (PCCB) regarding fare evasion [5]. The study selected TRC-SGR due to (i) high passenger volumes and revenue exposure, (ii) documented overstay risk (PCCB), and (iii) an existing QR-gate baseline that permits clear pre-/post post-operational contrast for the proposed control loop.

Studies show that, Data visualization and dashboards address high passenger volume, overstay and post-operation inefficiencies by translating complex data into intuitive, actionable displays [6, 7]. When embedded as operational instruments rather than passive readouts and aligned with key performance indicator (KPI) dashboards, they enable faster, evidence-based decisions and greater [3, 8, 9]. In this study, the dashboard is intentionally designed as a decision tool with phase-specific prompts aligned to crew tasks.

Global experience demonstrates that real-time dashboards enhance responsiveness across domains such as city management, healthcare, and logistics. Soundararaj & Pettit [10] show how an Australian real-estate dashboard supported timely policy interventions during COVID-19; Rodrigues et al. [11] present the "VitalSense" edge–fog–cloud architecture for rapid health responses; and Cepero et al. [12] report improved situational awareness for city managers via real-time visualisation. These studies emphasise low-latency data streams, stakeholder-relevant KPIs, and decision-support design as enablers of operational agility. Direct transfer to African rail, however, remains limited: while performance-driven frameworks exist for railway asset management, real-time dashboard applications in African operations are still largely conceptual [13], and transport analytics rarely extend to active, in-coach railway control [14]. This motivates a TRC-specific design that is both offline-tolerant and auditable.

Fare evasion cases reported by PCCB [5] underscore the absence of automated in-journey compliance mechanisms. Common proxies, such as GPS tracking and door-based automatic passenger counting (APC), do not provide seat-level verification or support immediate pre-departure action. GPS streams are optimised for vehicle time–location–status rather than seat occupancy [15]; door sensors can suffer from classification errors and deployment bias [16]; and even when APC is fused with fare data, coverage and accuracy gaps persist [17, 18].

Recent work on in-vehicle services also seeks real-time presence detection precisely because manual counts and door counters do not yield actionable, seat-level availability information before boarding [19]. Accordingly, a direct seat-state signal, coupled to ticket intent, is the minimum requirement for actionable, coach-level control.

Therefore, this study favours an integrated control loop that couples ticket intent with physical seat occupancy via seat-weight sensors and synchronises the resultant signals with a real-time dashboard. The system operationalises five indicators: OSR, MDL, FPR, STE, and RT to evaluate technical and organisational performance. These metrics provide a reproducible basis for pre- and post-benchmarking, summarised as medians with interquartile ranges, Wilcoxon tests, and bootstrap confidence intervals.

Grounded in Systems Theory, Results-Based Management (RBM), and technology adoption models (TAM/UTAUT), the framework links system architecture to human factors that shape adoption. It establishes a TRC-specific measurement and governance model suited to intermittent connectivity and moderate digital literacy. By integrating sensing, analytics, and control into a single operational feedback loop, the study advances beyond descriptive diagnosis toward a theory-informed, replicable solution for M&E visibility in Tanzania's railway sector.

The study contributes to (1) A formal coach-level measurement model for rail compliance (OSR, MDL, FPR, STE, RT); (2) an offline-tolerant, crew-scoped dashboard workflow that operationalises seat–ticket coupling within platform dwell; and (3) a replicable evaluation design for low-connectivity contexts that shifts M&E from post-event reporting to pre-departure intervention. As depicted in Figure 1, the conceptual framework connects ticketing data, seat-state signals, and reporting into a dashboard-enabled seat–ticket coupling aimed at three outcomes: transparency, timeliness, and accountability, feeding continuous institutional learning. The figure illustrates the linkage of ticket intent, seat-state signals, and reporting within the dashboard-enabled control loop paper structure. The remainder of the paper presents the literature, methods and measurement model, results, discussion, and conclusions and recommendations.

## 2. LITERATURE REVIEW

The literature on data visualisation and dashboard-driven monitoring demonstrates that real-time analytics can significantly enhance decision-making, operational responsiveness and transparency in governance across both the public and private sectors. This review synthesises conceptual and empirical contributions related to data visualisation, dashboards, and monitoring frameworks, with a focus on their relevance to transport systems and the TRC context.

### 2.1 Conceptual Frameworks

Systems Theory frames transport operations as interdependent subsystems whose collective performance depends on the timeliness and accuracy of information exchange [20]. In a railway context, ticketing, in-coach control, and reporting are tightly coupled socio-technical components that must work in synchrony to sustain reliability and efficiency. When these elements operate in isolation, delays and inconsistencies arise, leading to revenue losses and weakened accountability. For the TRC, this perspective underscores the need for a unified control loop that integrates ticket intent with physical seat occupancy, ensuring that each boarding or disembarkation event is verified in real time. By viewing TRC operations as an interlinked system, the study adopts Systems Theory as the foundation for understanding coordination gaps and designing a mechanism that restores synchrony through dashboard-mediated data exchange.

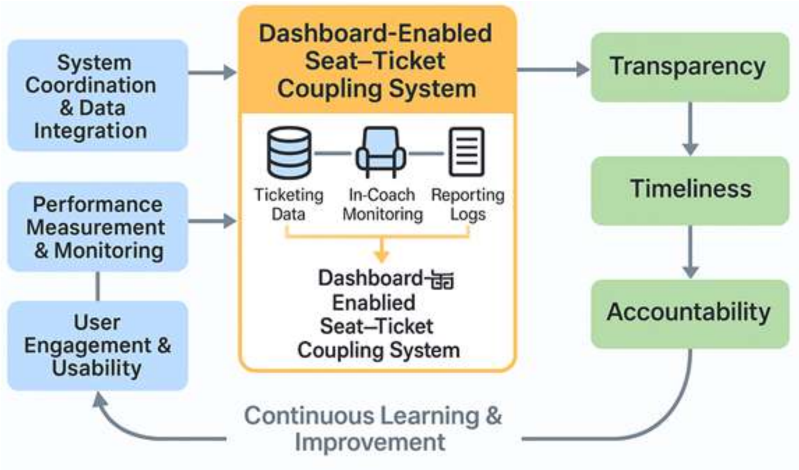


Figure 1: Conceptual framework for dashboard-enabled seat–ticket coupling in TRC operations

Results-Based Management (RBM) builds upon this systemic view by translating technological coordination into measurable results [1, 3]. RBM focuses on how inputs and activities generate observable outputs and outcomes. Within this study, RBM provides the logical structure through which the dashboard tracks data flows from seat-weight sensors and handheld verification devices to real-time reporting dashboards, ultimately leading to quantifiable indicators. These indicators, namely OSR, MDL, FPR, STE, and RT, represent the operational footprint of efficiency, responsiveness, and accountability within TRC's service delivery framework. Hence, RBM operationalises the theoretical coordination proposed by Systems Theory into a concrete performance measurement framework, making the invisible elements of compliance and monitoring visible and assessable.

While RBM structures the measurement, Technology Acceptance and Use of Technology (TAM/UTAUT) frameworks explain the behavioral and contextual factors influencing system utilisation [2, 7]. In TRC's environment, crew members work under high time pressure and with varying levels of digital literacy. Therefore, system adoption relies on design choices that enhance perceived usefulness and ease of use, such as task-specific interfaces, phase-based prompts, and low-interaction screens. These features ensure that staff can act swiftly on credible alerts with minimal distraction, leading to measurable improvements in MDL, RT, and FPR. In this study, TAM/UTAUT informs the logic of human system interaction, ensuring that technological interventions align with user behaviour and situational demands rather than merely technical potential.

Scaling adoption from isolated coaches to the entire SGR network requires a framework for diffusion and institutional learning, which is captured by the Diffusion of Innovation (DoI) model. DoI explains how innovations propagate based on perceived advantage, compatibility with established workflows, trialability, and observability. In this study, observable reductions in OSR and MDL serve as tangible proof of operational value, encouraging replication across stations and trains. By grounding the design in familiar workflows and providing real-time feedback loops, the system becomes not only a tool but a demonstrably beneficial practice that expands organically within TRC's operational ecosystem.

Ultimately, Performance Management Theory synthesises these perspectives within a culture of accountability and continuous improvement. In TRC's public-sector setting, performance management ensures that near-real-time dashboard indicators are not only measured but acted upon, forming a feedback mechanism that closes the loop between detection, decision, and institutional learning [3, 8]. This study guides how dashboard insights transition from individual crew actions to organisational responses, embedding real-time metrics into management reviews, training updates, and future resource planning.

The Systems Theory, Results-Based Management, Technology Acceptance and Use of Technology, Diffusion of Innovation, and Performance Management collectively frame the study's analytical and operational logic. They establish a coherent foundation for designing, implementing, and evaluating a dashboard-enabled seat-ticket coupling system that enhances transparency, timeliness, and accountability in TRC's railway operations.

Figure 1 illustrates the conceptual framework, which integrates these theoretical layers into an operational model in which data from ticketing, in-coach monitoring, and reporting converge in a dashboard-enabled seat ticket coupling system. This system transforms abstract theoretical principles into measurable, actionable, and adaptive processes. The left section of the framework depicts key enablers, including system coordination, performance monitoring, and user engagement, that sustain real-time verification and reporting. The central layer represents the dashboard as the unifying analytical hub connecting seat-state data with ticket intent. The right section presents three core outcomes: transparency, timeliness, and accountability that collectively reinforce the integrity of service delivery and support evidence-based decision-making. A continuous feedback loop links these outcomes back to organisational learning and system refinement, ensuring that every improvement in the indicators contributes to a stronger monitoring and evaluation (M&E) culture within TRC.

In essence, Figure 1 visualises how theoretical constructs translate into operational reality: coordinated subsystems generate measurable data; measurable data enhance human decisions; and informed decisions drive institutional improvement. This closed-loop design exemplifies how digital dashboards can bridge the gap between technology, human behaviour, and organisational accountability in Tanzania's railway sector.

### 2.2 Empirical Studies

Globally, dashboards have evolved from static information displays into dynamic management tools that integrate data collection, analysis, and feedback cycles [2, 8]. They convert administrative data into real-time signals that guide intervention, reduce reporting delays, and improve accountability in public administration [3, 6]. In the transport sector, studies highlight their potential to provide operational visibility into key metrics such as passenger flow, asset utilisation, and incident response [21]. However, many "smart railway" initiatives still face limitations due to data systems and dashboards that fail to translate information into actionable insights [22].

Cross-sector exemplars show consistent benefits when integration and timeliness are achieved. In Australia, a real-time property market dashboard enhanced situational awareness during the COVID-19 pandemic by utilising predictive analytics for informed decision-making [10]. The VitalSense architecture for healthcare applied edge fog cloud integration to shorten response times [11]. Similarly, urban informatics dashboards that integrate sensor data into KPI layers enhance decision-making in city management [12]. These examples demonstrate that when systems combine low-latency data with clear visual cues and user-relevant metrics, they facilitate measurable operational improvements principles directly applicable to transport monitoring.

Human-system interaction research reinforces this link; well-designed dashboards improve operational efficiency [7]. Interfaces that employ cognitive-fit principles, pre-attentive exception cues, progressive disclosure, and task-specific alignment reduce decision latency and errors [7, 23, 24]. In railway contexts, near-station prompts indicating expected alighters and boarders connect data to immediate crew actions, reducing MDL and raising RT [25, 26]. These improvements align with TAM/UTAUT assumptions that usability and perceived utility drive adoption and sustained use.

At the same time, empirical studies across the public sector reveal contextual constraints that influence the effectiveness of dashboard data, data reliability, staff digital literacy, and the quality of infrastructure [2, 3]. Successful implementations in resource-constrained settings often adopt offline-first architectures, deferred synchronisation, and role-specific micro-training to ensure continuity [8]. Such adaptations are vital for transport corridors where connectivity and attention are variable.

Evidence from African transport systems remains limited but is growing. A performance-driven "system-of-systems" model for railway asset management shows promise but remains largely conceptual in implementation [13]. The broader adoption of analytics in African railways is hindered by fragmented data sources and inconsistent staff readiness [14]. Regional M&E studies share similar challenges, including delayed reporting, weak interoperability, and manual verification [2, 3].

In Tanzania, the PCCB reported fare evasion on SGR services, highlighting the absence of real-time in-journey visibility and over-reliance on manual inspection [5]. Studies in comparable contexts show that integrating ticketing data with sensor-based monitoring under offline-first conditions can enhance MDL and RT while generating verifiable audit trails [3, 8].

This global and regional evidence reveals three consistent findings. First, coupling intent and state data, such as ticketing and seat occupancy, reduces detection latency, thereby improving measurable compliance outcomes through OSR and MDL. Second, higher alerting precision (lower false positives) increases throughput (RT) by ensuring staff attention is directed to genuine anomalies. Third, rapid visibility of available capacity enables faster reassignment, enhancing STE and utilisation. These relationships align with performance management and systems-theory predictions, showing how design choices cascade into measurable organisational effects.

In light of these patterns, the TRC context calls for a dashboard model that integrates these insights into practice. The evidence supports a three-component design logic: (1) real-time coupling of ticket intent with seat-level occupancy to detect overstay risk early; (2) phase-specific, coach-scoped handheld views that streamline task execution and minimise cognitive load; and (3) auditable in-journey case handling that ensures each intervention produces documented outcomes. This configuration reflects both theoretical coherence and empirical grounding, positioning dashboards as instruments of continuous monitoring, adaptive learning, and measurable performance improvement in Tanzania's rail sector.

## 3. METHODOLOGY

This section outlines the research design, sampling approach, data collection instruments, analytical procedures, and ethical safeguards. The study employed an empirical, convergent mixed-methods design, integrating both qualitative and quantitative components. The qualitative component involved open-ended questionnaires and structured non-participant observations to explore existing practices, challenges, and contextual nuances. The quantitative component computed trip-level indicators: OSR, MDL, FPR, STE, and RT from operational artefacts to assess the effects of a dashboard-enabled control loop. Integration occurred during the interpretation stage, where qualitative insights were used to explain observed movements in quantitative indicators.

### 3.1 Research Design

The study adopted a Design-Science Research (DSR) approach to develop, implement, and evaluate a coach-level, seat-weight–coupled dashboard for fare-compliance monitoring within the TRC-SGR system. The DSR paradigm was chosen for its emphasis on iterative problem identification, artefact construction, and real-world evaluation. This approach enabled integrating qualitative inquiry capturing organisational processes, staff perceptions, and contextual constraints with quantitative measurement of the dashboard's technical performance. Together, these strands provided a holistic understanding of both operational efficiency and user experience within the TRC ecosystem.

### 3.2 Sampling

A purposive sampling strategy targeted the TRC ticketing system, passenger-facing processes, and staff operations, given their centrality to fare collection and monitoring. Inclusion criteria required participants to have direct experience with SGR boarding, validation, or recent SGR travel within the study period. Participation was voluntary and anonymised. The final sample consisted of 48 participants, comprising 36 passengers and 12 operational staff, across six stations and twelve scheduled runs conducted between May and December 2024. Stations and runs were purposively selected to capture variability in demand patterns, including weekday versus weekend and peak versus off-peak periods. Sampling continued until thematic saturation was achieved, evidenced by the stability of emerging codes and themes in the final two recruitment waves.

### 3.3 Data Collection

Data were collected through structured interviews and systematic observations. The instruments covered four operational domains: boarding validation, in-transit checks, disembarkation controls, and reporting/data flows. Each interview was conducted in an open-ended manner to elicit detailed, qualitative input. Content validity was strengthened through expert review by a ticketing operations lead and an M&E practitioner, followed by a pilot test (n = 6) to assess clarity and flow. Minor revisions were made to refine wording and sequencing. Instruments were provided in both English and Swahili, with back-translation used to verify key terminology.

Structured non-participant observations were conducted on twelve scheduled runs using a predefined protocol to record process steps, passenger flow, and timestamps within the platform dwell windows. Observational data were triangulated with operational artefacts, including manifests, seat-weight logs, and alert records to ensure accuracy and consistency.

### 3.4 Coach-Level Measurement Model

The coach-level measurement model formalised five trip-level indicators: OSR, MDL, FPR, STE, and RT. Seat occupancy was detected per seat using a calibrated weight threshold and a short rolling window, while crew interfaces were phase-specific (Boarding, Disembark, Pre-Departure Check). The accounting continuity for each trip was maintained as per Equations (1) to (5) specifying, respectively, OSR, MDL, FPR, STE, and RT.

#### 3.4.1 Notation and continuity

$OBS_s$: onboard headcount before stop ***s*** (doors closed, approaching the platform).
$OAS_s$: onboard headcount after stop ***s*** (doors closed, train ready to depart).
$B_s$: validated boardings at stop ***s*** (QR-verified tickets).
$V_s$: physical disembarkations at stop ***s***, detected by seat-weight signals (vacated seats at end of dwell).
$E_s$: expected disembarkations at stop ***s*** from ticketed destinations (manifest intent).
$M_s$: missed disembarkations at stop ***s*** (seats due to vacate but still occupied at departure).
$A$: set of alerts the control loop raises during the trip (each alert resolved as valid or benign).
$C$: set of valid compliance cases opened and closed during the trip.
$MDL_{prop}$: Missed-Disembark Latency with the proposed dashboard system
$MDL_{\beta ase}$: Missed-Disembark Latency with the current TRC system

Seat occupancy is detected per seat using a calibrated weight threshold and a short rolling window; crew interfaces are phase-specific (Boarding, Disembark, Pre-departure check). The accounting continuity is:

$$\mathrm{OAS}_s = \mathrm{OBS}_s - V_s + B_s, \quad \mathrm{OBS}_{s+1} = \mathrm{OAS}_s \quad (s = 0, \ldots, S-1).$$

At the origin, $OBS_0 = OAS_0$ by initialisation. Missed disembarkations at stop s are:
$\mathbf{M_s = max\ (E_s - V_s, 0),}$ and trigger a pre-departure blocking alert if $M_s > 0$ at the end of dwell.

#### 3.4.2 Indicators and equations

Let OBS_s denote the onboard count before stop s; OAS_s the onboard count after stop s; E_s the expected disembarkations at stop s (from the passenger manifest); V_s the verified disembarkations at stop s (from seat-state records); A the set of overstay alerts; and C the set of validated cases. Let t_dep denote the platform departure time at stop s, and t_alert the first detected alert time for a missed-disembark event.

#### 1. Overstay Rate (OSR)

OSR measures the proportion of passengers expected to alight at their designated station who fail to do so.

 

$$OSR = ( \Sigma\_s \max(E\_s - V\_s, 0) ) / ( \Sigma\_s E\_s ) \quad (1)$$

Where max(E_s - V_s, 0) represents passengers exceeding their paid travel entitlement at stop s.
A higher OSR indicates more overstay cases.

*Performance improvement:*

$\Delta OSR = OSR\_prop - OSR\_base < 0$

A negative ΔOSR indicates fewer successful overstays under the proposed system.

**2. Mean Detection Latency (MDL)**

MDL is the average time between departure from a station and the first alert indicating a missed-disembark event.

$$MDL = (1 / |C|) * \Sigma\_i\in C\ (t\_alert,i - t\_dep,i), \text{ where } 0 < (t\_alert,i - t\_dep,i) \leq T\_max \text{ (default 180s).} \quad (2)$$

*Performance improvement:*

$\Delta MDL = MDL\_prop - MDL\_base < 0$

A negative ΔMDL indicates faster detection of missed disembark events.

**3. False Positive Rate (FPR)**

FPR measures the proportion of alerts that do not correspond to actual missed-disembark events.

$$FPR = |A - C| / |A| \quad (3)$$

*Performance expectation:*

ΔFPR < 0 (reduced false alerts under the proposed system).

**4. Seat Turnover Efficiency (STE)**

STE measures the timeliness and accuracy with which freed seats are detected and reassigned.

$$STE = \text{Timely verified seat reassignments / Total freed seats} \quad (4)$$

*Performance expectation:*

ΔSTE > 0 (improved seat-state updates and reassignment).

**5. Reporting Timeliness (RT)**

RT measures the speed and completeness of compliance event documentation.

$$RT = \text{Timely verified resolution events / Total required resolution events} \quad (5)$$

Performance expectation:

ΔRT > 0 (faster audit trail generation).

Guardrails. Platform clock; second-level rounding; late alerts attributed to the paid stop if within T_max; listwise exclusion where MDL/RT event pairs are incomplete; medians and IQR reported across trips with Wilcoxon tests and 1,000-rep bootstrap Confidence Intervals (Cis).

### 3.4.3 Measurement guardrails

To ensure comparability across trips: (a) all timestamps use the platform clock and are rounded to the nearest second, (b) alerts raised after the dwell window at the paid stop are attributed to that stop if $t\_alert - t\_dep \leq T\_max$ (study default: 180 s), (c) seat-weight occupancy uses a calibrated threshold with hysteresis to mitigate bounce, (d) missing pairs for MDL/RT are excluded listwise with counts reported and (e) all indicators are computed per trip and may be summarised across trips by median and interquartile range, with pre/post contrasts as specified in Section 3.4.2

### 3.4.4 Baseline and comparison design

The Gate-only and Manual Patrol was compared against the Seat-Weight Control Loop by computations. The primary endpoints are OSR and MDL; the secondary endpoints are FPR, STE, and RT. The outcome report medians/IQR and Wilcoxon signed-rank p-values with bootstrap 95% CIs. Engineering telemetry (alert-to-acknowledge time and device refresh latency) is summarised to aid in the interpretation of MDL shifts.

## 3.5 Computing Environment and Implementation Stack

The dashboard design was proposed to be by using a lightweight, offline-tolerant architecture tailored to TRC-SGR's connectivity conditions. The back-end services design by Python 3.11 using FastAPI microservices for data ingestion, indicator computation, and alert generation, supported by a PostgreSQL 15 relational database for trip logs and system configuration. The front-end interface be built with React 18 and operate as a Progressive Web App (PWA) on Android 12 plus handheld devices, enabling offline caching, deferred synchronisation, and role-based access for crew members. Real-time event updates by the use of WebSocket channels to maintain responsiveness within the short platform dwell window. Analytical processing and indicator computation (OSR, MDL, FPR, STE, RT) were performed using NumPy 2 or later, SciPy 1.13, and scikit-bootstrap in Python. Prototype services ran on an 8-core virtual machine (16 GB RAM) under Ubuntu 22.04 LTS. All dependencies are version-pinned and containerised to ensure reproducibility and facilitate later scaling within TRC's operational environment.

## 3.6 Data Analysis

A convergent mixed-methods analytical framework was employed. Qualitative data were analysed inductively using open and axial coding, while quantitative indicators were computed according to the defined equations. Integration occurred through joint displays, aligning themes from qualitative findings with shifts in quantitative indicators to produce coherent meta-inferences.

#### 3.6.1 Qualitative analysis

Open-ended responses and observation notes were coded inductively in two stages: open coding to identify emerging concepts and axial coding to refine categories and themes. Two researchers coded independently, achieving substantial inter-coder reliability (Cohen's $\kappa = 0.78$). Discrepancies were resolved through discussion, and an audit trail was maintained to enhance transparency. Qualitative analysis was conducted using NVivo 14, with excerpts linked to operational domains to facilitate cross-referencing with trip-level indicators.

#### 3.6.2 Quantitative analysis

Trip-level indicators were pre-specified and computed as defined in Section 3.4. The primary endpoints (OSR and MDL) and secondary endpoints (FPR, STE, RT) were compared between the pre-pilot baseline and the dashboard-enabled pilot phase. Statistical analyses reported median differences, interquartile ranges, Wilcoxon p-values, matched-pairs effect sizes (r), and Hodges–Lehmann median differences with bootstrap 95% confidence intervals.

#### 3.6.3 Integration and robustness

Findings were integrated through joint visual displays that linked qualitative themes with quantitative movements in indicators. Trustworthiness was reinforced through triangulation, inter-coder reliability, and thorough documentation of analytical workflows. Negative cases were examined to refine interpretations, and sensitivity analyses were performed on the MDL threshold (120–240 s) to confirm robustness.

### 3.7 Baseline and Comparison Design

The baseline configuration, Gate-Only and Manual Patrol, was compared against the pilot Seat-Weight Control Loop by computation. The primary endpoints were OSR and MDL, while the secondary endpoints included FPR, STE, and RT. Engineering telemetry, such as alert-to-acknowledge time and device refresh latency, was summarised to contextualise MDL shifts.

### 3.8 Ethical Considerations

The study complied with research ethics guidelines. Participants received detailed information and provided informed consent prior to participation. No personally identifiable information was collected; instruments avoided names or contact details, and responses were coded using random study IDs. Data were stored on encrypted, access-controlled drives, and participants retained the right to withdraw at any point without penalty. No financial incentives were offered.

## 4. RESULTS

The results of this study are derived from qualitative analysis of data collected through structured questionnaires and from a content review of the TRC ticketing system. The findings reveal several operational and compliance-related challenges affecting the efficiency of fare monitoring and service delivery. Through thematic analysis, five major themes emerged: ticket validation and boarding control, in-transit monitoring, disembarkation compliance, seat management, and system integration.

Two researchers independently coded all participant narratives (n = 48; 36 passengers, 12 staff), with disagreements reconciled through consensus. Triangulation with platform/coach observations across 12 scheduled runs and selected manifest/log extracts was used to corroborate self-reports. Theme-to-KPI alignment is indicated to facilitate later operational evaluation using OSR, MDL, FPR, STE, and RT (Section 3.4.2).

### 4.1 Comparative Analysis (Baseline vs. Logical Design Evaluation)

The proposed dashboard-enabled seat ticket coupling system was conceptually evaluated against existing ticketing operations to assess its potential to enhance M&E performance. The logical comparison between current manual workflows marked by fragmented reporting and delayed visibility and the proposed integrated, data-driven design indicates theoretical improvements across five indicators: mean detection latency, overstay rate, false positive rate, seat-turnover efficiency, and reporting throughput.

In the current system, fare evasion and missed disembarkations are detected retrospectively through manual inspections, leading to delays and limited accountability. The proposed logical design integrates ticket intent with seat-state data in real-time, which is expected to reduce detection delays and overstay incidents through automated alerts. Similarly, seat-level verification would minimise false positives, while enhanced visibility of vacant seats and automated reporting are projected to improve seat utilisation and documentation efficiency.

A conceptual overview of the outcomes is presented in Table 1, summarising the directional changes and their operational implications. Although not empirically tested, the analysis demonstrates strong internal consistency between the conceptual framework and the projected indicator outcomes, supporting the design's practical relevance for improving transparency, timeliness, and efficiency within TRC's M&E environment. The system's efficiency will be measured using the five performance indicators established in the study framework.

### 4.2 Analysis of the TRC Ticketing Systems

The study employed content analysis to achieve its objective. It used four questions to explore and gain insight into the TRC ticketing system, as described in the subsequent sections. For each question, the dominant pattern reported in the coded responses indicates the observational corroboration, where applicable. It states the operational implications regarding per-trip indicators and OBS/OAS counters described in Section 3.4.

*Question 1: What are the available methods for passengers to book tickets with TRC?*

Passengers can book tickets with TRC through several methods. The most convenient option is to use the TRC online booking portal at booking.trc.co.tz, where passengers can book tickets online. Alternatively, tickets can be purchased at TRC booking offices. These methods simplify journey planning for passengers. The various options offer multiple convenient options, including online booking through their portal and in-person ticket purchasing at station offices. This approach demonstrates a commitment to making ticketing accessible to many users and to accommodating both digital and non-digital preferences. Furthermore, these methods have yet to report seating collisions and other irregularities. Thematic coding indicates broad awareness and use of both channels, with staff noting fewer “seat collision” incidents at the gate, consistent with gate-level QR validation observed in 12/12 runs. Operationally, diverse booking channels strengthen pre-departure manifest completeness (higher confidence in OBS at origin), which supports accurate next-stop disembark forecasting and improves subsequent measures of MDL and RT when alerts occur (Equations 2 and 5).

Table 1: Transformation of TRC SGR operations: Baseline system vs dashboard-enabled model mapped to performance indicators

| **Indicator** | **Current TRC System (Baseline)** | **Proposed Logical Design (Dashboard-Enabled System)** | **Mathematical Representation of Expected Change** | **Expected Direction of Change** | **Interpretation of Theoretical Improvement** |
|---|---|---|---|---|---|
| MDL | Detection relies on manual patrols and post-event checks, which are often delayed until after the event. | Real-time coupling of ticket intent and seat-state data generates automated pre-departure alerts. | $\Delta MDL = MDL_{prop} - MDL_{base} < 0$ | Decrease | Shorter detection latency enhances the timeliness of fare compliance interventions. |
| OSR | Passengers can travel beyond their paid destinations undetected until they are inspected. | Automated identification of unpaid occupancy before train departure. | $\Delta OSR = OSR_{prop} - OSR_{base} < 0$ | Decrease | Reduced fare evasion through early, automated visibility of passenger movement. |
| FRP | Manual verification leads to inconsistencies and misclassification. | Sensor-verified seat-state data reduces ambiguity and improves alert accuracy. | $\Delta FPR = FPR_{prop} - FPR_{base} < 0$ | Decrease | More reliable alerts increase crew confidence and operational precision. |
| STE | Vacant seats are identified manually, delaying reassignment. | Real-time seat monitoring enables the immediate identification and allocation of available seats. | $\Delta STE = STE_{prop} - STE_{base} > 0$ | Increase | Faster reassignment improves seat utilisation and service efficiency. |
| RT | Case reporting relies on end-of-trip summaries and manual documentation. | Automated dashboards produce live, time-stamped compliance records. | $\Delta RT = RT_{prop} - RT_{base} > 0$ | Increase | Enhanced reporting speed and auditability strengthen accountability in monitoring and evaluation (M&E). |

*Question 2: How does the current system ensure that only paid passengers are allowed to board the train?*

The existing boarding system allows only passengers who have completed payment to board the train. QR code scanners primarily facilitate this process at each boarding station entry point. When passengers arrive at the gate, they present their ticket, encoded in a QR code. The scanners then perform a thorough validation process, checking the ticket's details against the scheduled train information. This includes verifying the ticket number to ensure it corresponds to a valid reservation, and confirming that the travel date and time match the current schedule. If the details align correctly and the ticket is confirmed as paid, the scanner allows the passenger to pass through the boarding gates seamlessly. This mechanism effectively prevents unauthorised boarding, ensuring that only those with valid, paid tickets can enter the train, thereby maintaining the integrity of the travel system. In addition to that, one of the responses from the TCR personnel when asked how the expired tickets are handled was:

> *"We monitor the boarding process, and the QR code scanner is used to verify ticket validity by checking the departure time and date against the passenger's scheduled journey. If a ticket has expired, the system automatically flags it as invalid during scanning, preventing the passenger from boarding. This automated verification ensures that only passengers with valid tickets are allowed entry, streamlining the boarding process and reducing manual errors."*

On the other hand, the current system exhibits several limitations that hinder its effectiveness beyond the boarding stage. While the QR code scanner efficiently validates tickets at the point of entry, there is no real-time monitoring system to track passenger movements during transit. Once the journey begins, monitoring relies entirely on manual processes, where train staff check seat-by-seat tickets. This manual approach is time-consuming and prone to errors and oversight, making it challenging to ensure compliance throughout the journey. Furthermore, the lack of integration between the ticketing system and fare compliance mechanisms means the system cannot verify whether passengers disembark at their designated stations.

This gap leaves the system vulnerable to fare evasion and reduces its ability to enforce compliance effectively. These shortcomings highlight the need for automated solutions to enhance operational efficiency, improve monitoring, and ensure fair revenue collection. In the coded corpus, gate-level control was consistently described as effective, whereas in-journey visibility was repeatedly identified as a blind spot. Observations confirmed that, after boarding, verification is handled through manual patrols. This pattern correlates with elevated detection delays (MDL) and documentation gaps (lower RT) when missed-stop events occur. It explains why OSR is primarily determined by events within platform dwell windows, rather than at gates (Equations 1, 2, and 5). Figure 3 provides an illustrative OBS and OAS ledger for a representative run, highlighting where disembark forecasts diverged from actual values.

*Question 3: How does the current ticketing system ensure passengers disembark at designated stations?*

The current ticketing system relies primarily on manual processes to ensure passengers disembark at designated stations. During transit, train staff manually check tickets at intervals or upon approaching stations to verify passenger compliance. The system needs automated mechanisms to track whether passengers leave at their intended stops, thereby relying on the diligence of the train staff. While the manual process ensures some oversight, it is time-consuming and prone to human error, particularly during peak travel or long routes. To enhance this process, integrating automated systems and monitoring linked to ticketing data could improve efficiency and accuracy in ensuring passengers adhere to their designated travel plans. To follow up on the above questions, the study interviewed one of the TRC staff members responsible for ticket inspection. It was asked how TRC handles situations where passengers attempt to travel beyond their paid destinations. The respondent replied

> *"As we go through the car, we take a moment to visit each seat and ensure that everyone has the correct tickets. We also carefully examine details, such as your disembarking station, so you can travel safely. In addition, the officer was asked whether there is a mechanism to verify the information used to identify passengers during boarding, and whether that mechanism is integrated with the bus in transit. The officer responded that it does not monitor ongoing compliance, such as whether they disembark at the correct station or if the ticket validity has expired during transit."*

The responses suggest that TRC's ticket inspection process primarily focuses on verifying passenger details during initial checks as passengers move through the train, such as ticket validity and disembarking stations. However, a technological mechanism is needed to monitor ongoing compliance throughout the journey, such as ensuring passengers disembark at their designated stations. This suggests a gap in integrating passenger verification systems with real-time monitoring during the journey, which could lead to issues in enforcing ticketing rules. Analytically, the theme "gate strong, journey weak" was among the most frequently coded across staff accounts and is consistent with observer field notes. In operational terms, the absence of station-triggered, pre-departure checks inflates the MDL. It allows potential overstays to propagate beyond the first missed stop, thereby elevating the OSR for the trip. The results motivate the station-to-station control loop evaluated later and its associated KPIs (Equation 1 to 5), and they justify the need for coach-scoped, phase-specific crew views to improve RT through timely, in-journey closure.

*Question 4: How does the current TRC ticketing system identify vacant seats, and what challenges are associated with this process?*

After analysing the functionality of the current TRC ticketing system, the study observed that vacant seats were identified manually during transit. Train conductors physically inspect and record seat occupancy after each station to determine which seats are available for potential passengers boarding at subsequent stops. This process involves comparing seat numbers against ticket sales records to identify unoccupied spaces. However, the manual nature of this procedure presents significant challenges, including delays in decision-making, the potential for human error, and inefficiencies during busy travel periods. These limitations make it challenging to optimise seat allocation and reduce operational bottlenecks, particularly on high-demand routes. An automated seat tracking system integrated with real-time ticketing data could address these challenges, enabling more efficient operations and improved passenger experiences. On the other hand, when asked how they ensure that only legitimate passengers occupy the seats during transit, one respondent explained:

> *"We routinely move through the seating area to verify the authenticity and validity of passengers occupying the seats. This involves checking their tickets and matching them with the assigned seat numbers to confirm they are valid holders. In cases of doubt or discrepancy, we address the issue immediately to ensure compliance and maintain order during the journey."*

This analysis highlights the inefficiencies and limitations of the current manual processes in the TRC ticketing system for identifying vacant seats and verifying the legitimacy of passengers during transit. The reliance on physical inspections by conductors not only leads to delays and potential errors but also increases the risk of human error. The need for an automated system that integrates real-time ticketing and seat tracking is evident, as it would streamline seat allocation, reduce human error, and enhance the overall travel experience. Furthermore, while routine ticket checks help maintain compliance, an automated solution could support staff by providing instant updates and alerts, improving both efficiency and accuracy.

Observed delays between alighting and reassignment contributed to unused capacity on several runs, particularly when boarding volumes were high. In KPI terms, slow recognition of freed seats depresses STE. It obscures early signs of non-alighters (seats that should be vacant but remain occupied), which in turn can raise OSR if issues are discovered only after departure. A seat-state feed coupled to manifest intent would shorten detection-to-action intervals (lower MDL), reduce false chases (lower FPR), and increase documented, on-trip resolution (higher RT). Figure 4 illustrates a timeline linking disembark events, seat-state changes, and OAS updates.

Across the four question domains, coded evidence and observations converge on a single operational gap: strong perimeter control at gates without an equally strong, in-journey compliance mechanism. The practical consequence is elevated MDL and lower RT for missed-stop events, with knock-on effects on OSR and STE at the trip level.

## 5. DISCUSSION

This section interprets the qualitative and observational findings in relation to the study's overarching aim: reducing detection latency and fare overstays while enhancing reporting fidelity through a dashboard-enabled seat–ticket control loop. The discussion also links the observed operational weaknesses to the design of the proposed system, demonstrating how each limitation informed the conceptual architecture and its intended improvements.

### 5.1 Discussion from Interview and Observational Findings

Field evidence shows that operational visibility is strong at boarding but collapses once trains depart, resulting in compliance checks being pushed into manual, after-the-fact routines. The immediate implication is that missed disembarkations are discovered late, documentation quality suffers, and audit trails become unreliable. Prior transport and public-sector studies converge on the exact mechanism: near-real-time information and well-specified operational indicators accelerate decision speed, shorten response cycles, and strengthen accountability [8, 21, 22, 26, 27, 28]. Interpreted through Systems Theory, the separation of ticketing, in-coach verification, and reporting manifests as coordination failures at the exact moment intervention is possible. Results-Based Management clarifies that when signals arrive late, actions are decoupled from outcomes, while TAM/UTAUT indicates that few timely, credible prompts depress perceived usefulness and ease of use. Operationally, the visibility gap drives slower interventions, weaker compliance, and incomplete records.

Pre-departure opportunities are routinely missed because alerts arise after the dwell window rather than during it. Aligning ticket intent with seat state inside the dwell window directly addresses this timing problem. Consistent with prior work, bringing detection earlier in the workflow reduces same-run non-compliance and improves the completeness and quality of documentation [8, 28]. In practice, this should yield faster identification of overstays, more opportunities to free and reuse seats before doors close, and reliable, time-stamped case logs suitable for audit and learning purposes.

Gate-only QR checks confirm who boards, but do not show whether passengers alight at the location they paid to disembark. Substituting indirect proxies (GPS traces, door counters) with direct, per-seat occupancy linked to manifest intent closes that real-time data void inside the coach. Evidence from adjacent domains shows that precise, actionable alerts increase staff trust and accelerate resolution, thereby improving reporting throughput and operational efficiency [8, 26]. For operations, the expected effect is fewer spurious alerts, quicker on-journey case closure, and better utilisation as freed seats are published to platform teams in time for boarding.

Crew feedback and observations highlighted interface friction during short dwells, which slows decision-making when seconds matter. Cognitive-fit research indicates that task-aligned dashboards with clear exception cues, progressive disclosure, and minimal interaction reduce decision latency and errors [7, 29]. The proposed phase-specific, coach-scoped handheld views operationalise this guidance by presenting an explicit following action during disembark checks, pre-departure verification, and boarding. Capturing basic engineering telemetry (alert-to-acknowledge time, device refresh latency) will help distinguish human response delays from device update lags. These design choices translate into faster, more consistent actions within the dwell window and fewer missed interventions.

Intermittent connectivity, mixed digital literacy, and audit requirements were repeatedly cited and observed, shaping feasibility and scale-up. Prior public-sector and smart-city deployments suggest that offline-first architectures, role-specific micro-training, and strong data governance are critical under such constraints [2, 3, 8]. The proposed approach reflects these lessons through deferred synchronisation, auditable reconciliations of onboard counts, and sensor safeguards such as calibration routines. Region-specific reports of fare evasion further underscore the value of pre-departure checks that depend solely on seat state and ticket intent, thereby avoiding the need to display personal data on shared displays. Together, these measures convert environmental constraints into manageable operating parameters, supporting sustained adoption.

The interview with one respondent emphasised the need for a compact, reviewable performance scorecard rather than a display-only layer. Treating the dashboard as a decision instrument in a closed loop detect, act, record meets those needs. The defined indicators of timeliness, compliance, precision, utilisation, and documentation provide a practical basis for station-by-station and run-by-run governance. This structure enables targeted remediation, localising delays, focusing refresher training, and refining SOPs while creating disciplined feedback for continuous improvement.

The study recognises that factors such as crew allocation, atypical demand, or timetable disruptions could also influence detection timing and documentation quality. The proposed telemetry is intended to separate human from system delays during evaluation, and routine governance reviews can surface exogenous shocks that warrant analytical controls. Acknowledging these contingencies strengthens the credibility of any observed improvements during pilot testing.

The conceptual design and its underlying logic are most relevant for routes and operational contexts where intervention can occur before departure and where ticketing manifests are updated with minimal delay. In environments with shorter dwell times or lower data fidelity, adaptations such as phased checks, simplified prompts, or aggregate-level dashboards may be required to maintain feasibility and effectiveness. Recognising these operational boundaries ensures realistic expectations and supports responsible planning for scale-up.

### 5.2 Proposed System Implementation

The proposed system operationalises a station-to-station control loop that requires fare compliance resolution at each stop before departure. As shown in Figure 2. End-to-End Ticketing and Validation Flow, ticket purchases (mobile/web/counter) issue QR tickets and populate the live manifest; coach assignment is captured at gate QR validation. Onboard counters are maintained as OBS (onboard before stop) and OAS (onboard after stop), consistent with the measurement model in Section 3.4.

In-journey visibility is provided by a seat-weight sensor network that emits per-seat occupied/vacant states. A rules engine then fuses (i) manifest-derived Next-Stop Disembark Count (NSDC) and Expected Board Next Stop (EBNS) with (ii) the physical seat state, and reconciles the accounting identity.

$$\text{Forecast OAS} = \text{OBS} - \text{NSDC} + \text{EBNS}.$$

Thereby determining whether departure conditions are met for each coach (see Figure 3. Station-to-Station Seat–Weight Control Loop and Expected Effects on Monitoring Indicators).

On approach to a station, crew handhelds auto-progress through three phase-specific views: Disembark, Pre-departure check, and Boarding, scoped to a single coach and each with one “next-best” action per screen. During Disembarkation, seats that are due to vacate are tracked against NSDC. Any seat that should be vacant but remains occupied by the end of dwell raises a pre-departure blocking alert (coach/row) with one-tap actions (verify destination/record paid extension). During Boarding, confirmed vacant seats are published to platform allocators immediately; scanned boardings are reconciled with the manifest, and OAS is recomputed in real time.

Because prompts combine ticket intent (NSDC/EBNS) with physical occupancy, ambiguous chases are reduced. Methodologically, this configuration is intended to (i) lower MDL by surfacing issues within dwell (Equation 2), (ii) decrease FPR through precise, seat-level evidence (Equation 3), (iii) reduce OSR by enabling intervention before the first missed stop propagates (Equation 1), (iv) increase STE by publishing freed seats quickly for reassignment (Equation 4), and (v) increase RT via on-trip case opening/closure (Equation 5).

All actions alert creation, acknowledgement, resolution, OBS/OAS updates, and seat-state changes are time-stamped and written to an event store to produce auditable, trip-level evidence. The dashboard displays both operational KPIs (OSR, MDL, FPR, STE, RT; Equations. 1–5) and engineering telemetry (alert-to-acknowledge time, device refresh latency) to diagnose bottlenecks that affect decision speed. Implementation choices reflect TRC constraints: offline-tolerant capture with deferred sync; privacy-preserving views (no raw weights or PII on shared screens); and data-quality safeguards (sensor hysteresis/temperature compensation; manifest refresh on late sales; precedence rules to withdraw alerts when a valid extension is recorded moments before departure). Role-specific micro-training and SOPs support adoption, while the design’s relative advantage, compatibility, trialability, and observability enable staged scale-up.

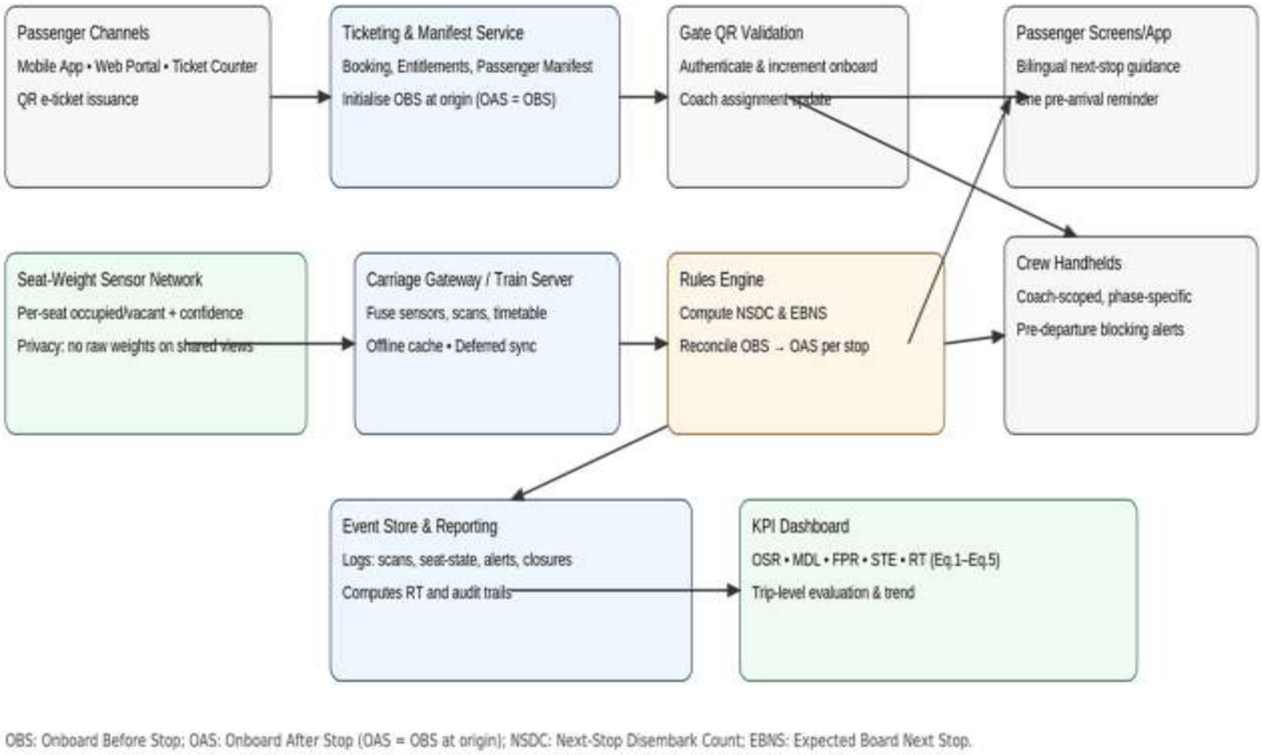


Figure 2: End-to-end ticketing and validation flow

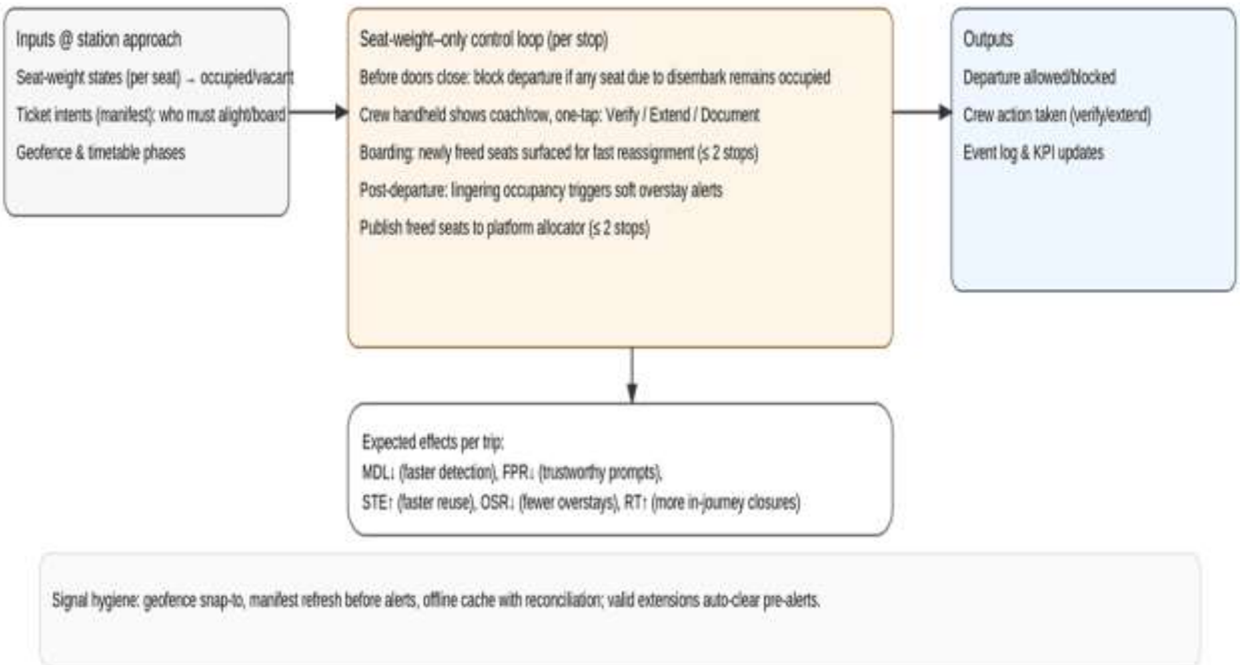


Figure 3. Station-to-station seat–weight control loop and expected effects on monitoring indicators

To reinforce crew actions, a lightweight passenger companion provides a single bilingual next-stop prompt and wayfinding cues (see Figure 4. In-Transit Monitoring for Overstay Detection and Vacancy Reallocation (Seat-Weight–Led)). This nudge aims to reduce missed alightings (supporting lower MDL and OSR) and smooth dwell times (supporting higher STE). The complete configuration provides a reproducible line of sight from the control-loop design to measurable movements in OSR, MDL, FPR, STE, and RT, enabling consistent, trip-level evaluation across stations and runs.


Figure 4: In-transit monitoring for overstay detection and vacancy reallocation (Seat-Weight–Led)

## 6. CONCLUSION AND RECOMMENDATION

### 6.1 Conclusion

This study develops a logical design for a dashboard-enabled seat ticket coupling system that aligns ticket intent with seat-state signals to strengthen TRC's Monitoring and Evaluation (M&E). Grounded in a coherent theoretical stack and a five-indicator measurement model (mean detection latency, overstay rate, false positive rate, seat-turnover efficiency, reporting throughput), the analysis shows clear, internally consistent performance pathways: pre-departure alerts should shorten detection times, reduce overstays, improve alert precision, accelerate seat reuse, and increase case documentation. While the findings are conceptual rather than empirical, they provide a deployment-ready blueprint: offline-first data flows, coach-scoped handhelds with phase-based prompts, immutable logs, and a governance loop that connects operational signals to management decisions. The next step involves a controlled, time-bound implementation to validate feasibility under real-world conditions, utilising predefined thresholds and auditable telemetry.

### 6.2 Recommendations for TRC

Based on the findings from the case studies and content analysis, several recommendations can be made for TRC to improve its ticketing system:

i. To operationalise the proposed dashboard-enabled seat–ticket coupling system, TRC should begin with a controlled pilot deployment covering two high-traffic stations and two coaches over a 12 to 16-week period. This initial rollout would provide an opportunity to test the system's feasibility and verify its performance thresholds, including detection latency below 60 seconds, overstay rate under 1 per cent, false positive rate below 10 per cent, seat-turnover efficiency above 80 per cent, and a minimum of 3 valid compliance cases per trip when events occur. Expansion to additional routes should be considered only after at least 80% of monitored runs consistently achieve these benchmarks.

ii. A minimal technical infrastructure should be established to ensure smooth operation under Tanzania's existing connectivity conditions. The system should follow an offline-first design with deferred data synchronisation, role-based access controls, and immutable logs for transparency. Personally identifiable information and raw weight data should be excluded from shared dashboards to maintain privacy compliance. Key diagnostic metrics, such as alert-to-acknowledge time and device refresh latency, should be continuously tracked to identify and address factors contributing to detection delays.

iii. TRC should also invest in targeted capacity-building and change management to support adoption. Short, role-specific training modules and one-page standard operating procedures (SOPs) would help staff quickly adapt to the new workflow. Practical drills using simulated alerts before implementation can build confidence and reduce hesitation during real operations. Refresher sessions should be scheduled periodically to sustain engagement and prevent skill decay among staff.

iv. Strong data governance and quality assurance measures will be critical for system credibility and sustainability. TRC should develop a Data Protection Impact Assessment, standardise audit schedules, and enforce periodic calibration of seat-weight sensors. Cross-departmental review meetings should be held weekly to assess dashboard indicators and telemetry logs, ensuring prompt corrective action and organisational accountability.

v. Finally, TRC should adopt a phased scale-up and continuous learning approach. Once the system demonstrates reliable performance, it can be extended to additional coaches and stations while maintaining the same evaluation thresholds. A structured feedback mechanism should capture lessons learned, supported by short user surveys and post-deployment reports. In later stages, machine learning tools can be introduced to optimise alert triage, guided by insights from operational data. This iterative approach will foster institutional learning, enhance decision accuracy, and ensure that dashboard implementation aligns with TRC's broader digital transformation objectives.

### 6.3 Limitations and Future Work

This is an operational evaluation, not model training; therefore, concerns about train/test splits or underfitting are not applicable. Causal attribution is tentative without a stepped-wedge or A/B design; these will be considered in scale-up, together with cost–benefit analysis, readiness assessments, and external benchmarking.

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