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DISCUSSION PAPER 06/25 | 30 DECEMBER 2025

Assessing Bus Performance in Greater Kuala Lumpur

Kelvin Ling Shyan Seng & Gregory Ho Wai Son

Khazanah Research Institute

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Authors' Email Addresses: consultant.kelvin@krinstitute.org and gregory.ho@krinstitute.org.

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Assessing Bus Performance in Greater Kuala Lumpur.

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Summary

- **Bus reliability in Greater Kuala Lumpur remains uneven, contributing to commuter distrust in bus services.** Using high-frequency GTFS static and real-time data, we show that while many routes achieve acceptable punctuality scores on average, a non-trivial subset of Rapid KL bus routes exhibit large and unpredictable deviations. These deviations undermine commuters' ability to plan daily travel and erode confidence in busses as a dependable mode of transport.

- **We develop a Bus Performance Index (BPI) that integrates punctuality with the severity of service deviations.** By combining on-time performance with a normalized measure of deviation magnitude, the BPI distinguishes between routes that are occasionally late, and those that fail severely when they happen to be late. This allows the index to more closely reflect commuter experience.

- **MRT Feeder services consistently outperform Rapid KL bus routes both in reliability and predictability.** Across the study period, MRT Feeder routes record higher BPI scores, tighter performance distributions, and near-zero collapse rates. In contrast, while the specific Rapid KL bus routes with very low scores vary from day to day and week to week, the proportion of such low-performing routes remain relatively stable over time. This pattern points to a systemic reliability issue embedded in the network.

- **Meaningful near-term improvements in reliability can be achieved through targeted operational reforms, even within existing infrastructural constraints.** The results point to practical interventions such as timetable recalibration using real-time data, improving real-time passenger information, and bus control strategies such as conditional transit signal priority. These measures directly address reliability failures that commuters experience today, while also strengthening the effectiveness and resilience of future infrastructural investments when capacity expansion becomes necessary.

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1. Introduction

Urban transportation systems is best understood as a complex system, where the actions of heterogeneous actors interact across space and time. A disruption in one segment, be it in delays, inefficiencies, or bottlenecks cascades across the network and expose systemic fragilities.

For many working adults in Malaysia, private cars remain indispensable despite their high cost[1]. Private cars offer greater comfort and protection compared to a motorcycle even though motorcycle is generally more affordable. However, motorcycle carries higher commuting accident risk among workers in Malaysia[2]. Hence, private cars are often the only reliable means to ensure timely arrival at work, schools, essential appointments, or to run other essential errands in the city. The alternative – chiefly public transport is somewhat of a mixed-bag. A journey that should take 20-minutes can easily stretch into an hour if bus frequencies are erratic for a variety of reasons, for example, due to unexpected delays, breakdowns, traffic condition or failure to adhere to published schedules. With the uncomfortable experience of waiting at bus stop and low predictability, commuter would gradually lose patience and opt for private vehicles as a more convenient alternative.

Malaysia's reliance on private vehicles is well established. Malaysia records 18.1 million registered cars, and 17.5 million motorcycles, against a population of 34.1 million people[3, 4]. Most households own at least one vehicle, making the switch to public transportation a difficult proposition. Even among those open to alternative modes, poor service reliability often pushes them back towards the use of private vehicles. The question then is whether public transportation can deliver the dependability required for everyday urban life.

In theory, multimodal integration offers a pathway toward more sustainable urban mobility. Feeder busses, Demand-Responsive Transit can potentially bridge first- and last- mile gaps, reduce car usage, and support higher levels of use in the broader rail network. This vision aligns with the United Nations Sustainable Development Goal (SDG) 11.2 which calls for:

> *"By 2030, provide access to safe, affordable, accessible and sustainable transport systems for all, improving road safety, notably by expanding public transport, with special attention to the needs of those in vulnerable situations, women, children, persons with disabilities and older persons." – UNSDG 11.2*

Yet, Malaysia's experience underscores the challenge put forth by the UN. The Auditor General's Report highlights, that both the MRT Kajang and Putrajaya lines have failed to meet their projected ridership levels, with combined accumulated losses exceeding RM50 billion as of 2024[5]. This shortfall is not for the lack of frequency or quality of service. The MRT's headway in the central

[1] Sinar Daily (2025)
[2] Rusli and Salam (2021)
[3] MOT (2025)
[4] DOSM (2025)
[5] Choy (2024)

business district area range between 3 to 4 minutes during peak hours, indicating world class quality of service[6]. Rather, many suggest that the real issue is first- and last- mile connectivity. While urban commuters experience walkability barriers such as poor infrastructure and environmental exposure, suburban commuters face longer journeys and fewer alternative public transportation options, resulting in disproportionate financial and time burdens[7].

Compounding the problem is the negative public perception that public transportation is unreliable, unsafe and uncomfortable. Such perceptions disincentivizes modal shift[8], pushing commuters towards purchasing their own private vehicles, and by extension eroding the potential social returns of MRT investments[9]. If left unaddressed, this dynamic risks entrenching a self-reinforcing cycle, where losses continue to accumulate, service quality deteriorates and ridership could decline further. This is a self-reinforcing feedback loop.

Against this backdrop, the paper develops and applies a Bus Performance Index (BPI) to systematically investigate the performance of Greater Kuala Lumpur's urban bus system[10]. By focusing on both punctuality and variability, the BPI provides a commuter-centered metric to assess whether busses can serve as a reliable driver of sustainable mobility and as a primary mode of transport.

The paper is structured as follows. Section 2 reviews the literature on the quality of service and metrics of punctuality. Section 3 outlines our methodology, including the use of GTFS static and real-time feeds, and the derivation of two indicators, On-Time Performance (OTP) and Magnitude of Deviation. Section 4 presents the Bus Performance Index (BPI), a composite metric that combines these indicators. Section 5 presents the results of our analysis, including daily and monthly performance summaries, ternary plots of punctuality, comparative insights between MRT Feeder and Rapid KL services. Section 6 concludes by discussing overall results, potential refinements for future research, the study's limitations and broader implications for transport policy and service planning in Malaysia.

2. Literature Review

2.1. Quality of Service

To meaningfully assess the performance of public bus systems, it is essential to define what constitutes 'quality' from both the commuter and operator perspectives. Drawing from the Transit Cooperative Research Program (TCRP)'s *Transit Capacity and Quality of Service Manual 3rd Edition* (TCQSM)[11], we highlight two broad domains: 'availability' and 'comfort and convenience' as central to the commuter experience.

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[6] "Rapid Rail Performance Update" (2024)
[7] Scheurer, Curtis, and McLoed (2017)
[8] Hu, Zhou, and Wang (2015)
[9] Social Return on Investment is a framework for measuring for social, environmental and economic value created by an intervention. Source: Lawlor et al. (2009)
[10] Based on Fourth National Physical Plan, Greater Kuala Lumpur refers to the whole territory of Kuala Lumpur, Selangor, Putrajaya and some parts of Perak (Tanjung Malim) and Negeri Sembilan (Seremban).
[11] National Academies of Sciences, Engineering, and Medicine (2013)

The first domain, **Availability** captures the structural features of a bus system that determines if commuters can access the service when and where they need it. This includes:

- **Frequency**: the number of services provided to commuters within a given timeframe. From the commuters' perspective, busses typically offer less flexibility compared to private vehicles, which can be operated entirely at a user's discretion.
- **Service span**: the period throughout the day a transit service is available along a particular route.
- **Accessibility**: whether transit services are operated near commuter's origin and destination points and whether the service is easily reachable by foot or through other feeder modes.

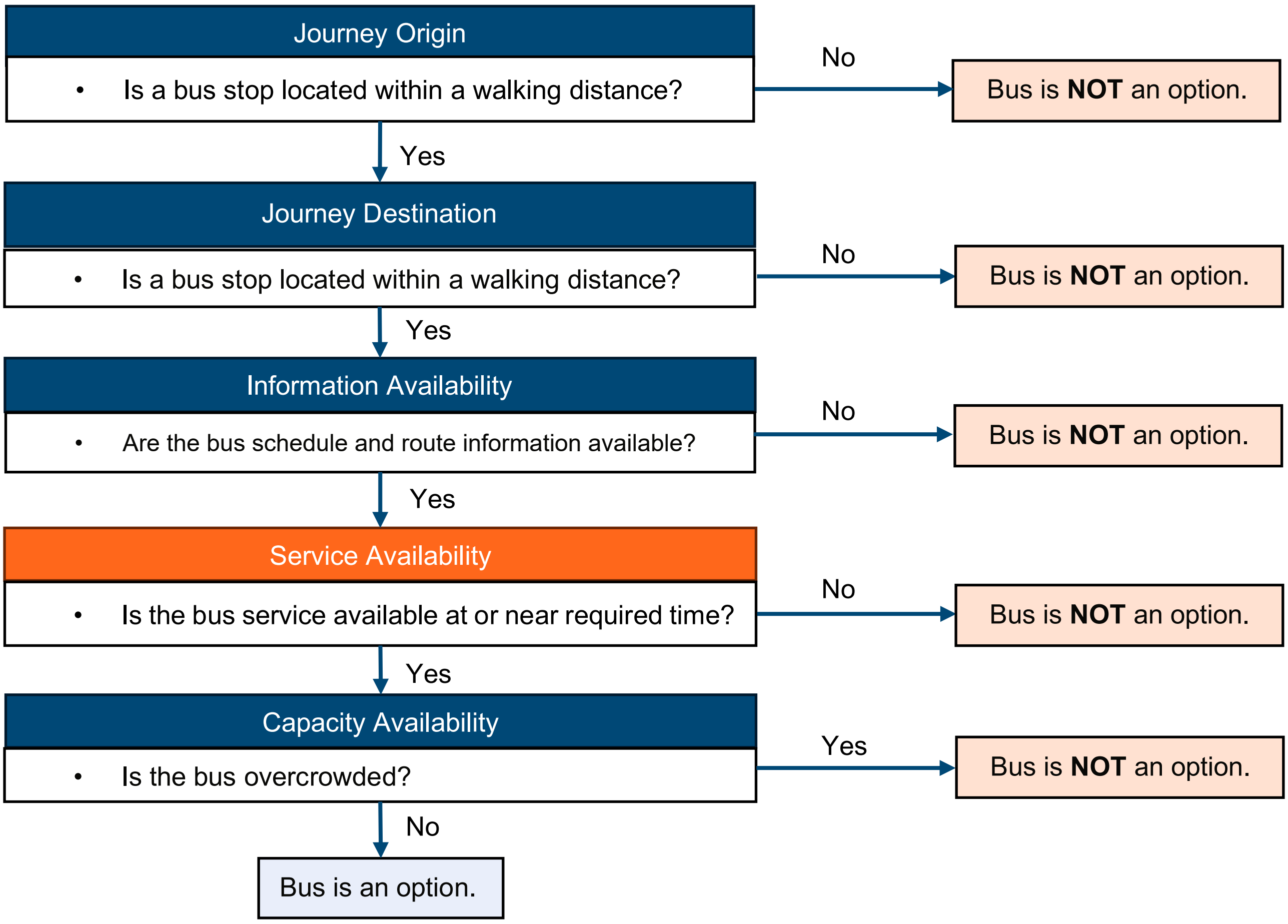
On the other hand, **comfort and convenience** describe the subjective experience of using the system. This includes:

- **Passenger load**: Overcrowding affects the comfort of a travel. An overcrowded buses may discourage a commuter from using the service, leading them to wait for the next vehicle or consider other modes of transportation.
- **Reliability**: measured through metrics like on-time performance and headway adherence (the time between vehicle). Irregular intervals undermine trust in service.
- **Travel time:**. Commuters often compare time required to complete a journey using the bus, against the time taken using private vehicles especially for time sensitive trips.

However, identifying these service qualities is only the first step. It is also equally important to consider how people make decisions about which mode of transportation to use. Figure 1 is a decision-making process flowchart summarised from the general framework proposed in TCQSM[12], focused on bus services. In this study, the notion of reliability is a one of the key factors influencing commuter choice. The flowchart underscores the need for a commuter-centred evaluation framework, which not only measures punctuality, but also help identifies operational issues that affect satisfaction.

[12] National Academies of Sciences, Engineering, and Medicine (2013)

Figure 1: Flowchart of decision-making process.



Source: National Academies of Sciences, Engineering, and Medicine (2013)

Note: Within this framework, our study attempts to evaluate service availability of public buses.

2.2. On-time Performance

Among the various service quality metrics, *On-Time Performance (OTP)* is one of the most visible and influential from the perspective of the commuter. OTP serves as a main proxy for reliability. When riders cannot anticipate with reasonable certainty that their bus will arrive, and that they will be able to reach their destinations on time, their next best alternative is to use private vehicles or other modes of transport, even when public transportation is otherwise available.

Yet, what counts as 'on-time' varies widely between agencies in different countries, often depending on operational constraints and policy standards. Based on a survey of U.S. transit agencies conducted in the mid-90s, 42% of respondents accepted that busses can be up to five minutes late and still be considered "on-time," while 24% thought that early departures also qualify as "on-time"[13]. On the other hand, a survey conducted in Canada in 2000 found that out of 17 agencies, 11 agencies agreed to define "on-time" as no more than three to four minutes late, 6

[13] Benn (1995)

agencies suggested no later than five minutes and only 2 agencies agreed to some early departing buses are considered "on-time"[14].

From the commuter's perspective, however, early departures cannot reasonably be considered on-time. A commuter arriving at the stop just before the scheduled time, anticipates taking the bus, but loses access **IF** the bus departs early and ahead of schedule. Commuters who are affected by early departures have to either wait for the next bus, which can be more than 30 minutes, or resort to an alternate mode of transportation. In high-frequency systems like MRTs, missing a train typically means waiting for another 4-7 minutes and an annoyance for commuter at most. But in the case of low-frequency scenarios like bus and KTM, waiting times could be 30 minutes to 45 minutes long. Hence, many commuters plan their arrival at the bus stop closer with the scheduled bus arrival time to minimise their waiting time[15].

Therefore, most agencies include a note in their timetables indicating that the vehicle may depart up to one minute early[16]. Understanding this difference in perspective is important, as perceptions of punctuality can differ between operators and commuters. Nevertheless, perceptions diverge. What is operationally acceptable for the operator could still be experienced as failure by commuters.

The following table presents a comparison of how on-time performance is perceived by both commuters and operators in United States, as proposed in TCQSM[17].

Table 1: On-time performance perceived by stakeholders.

On-time Performance	Commuter Perspective	Operator Perspective
95% - 100%	Commuters taking one bus trip per weekday without transfers are likely to encounter just **one delayed bus every two weeks**.	Feasible for buses to run below capacity on **physically separated lanes** that are free from other traffic, with minimal infrastructure or vehicle issues.
90% - 95%	Commuters taking one bus trip per weekday without transfers may encounter **one delayed bus per week**.	Feasible for buses to run below capacity on **physically separated lanes** that are free from other traffic.
80% - 90%	Commuters taking one bus trip per weekday without transfers may encounter **two delayed buses per week**.	Feasible by bus services operating in **small to medium-sized cities**.
70% - 80%	Commuters taking one bus trip per weekday could face up to **three delayed buses per week**, possibly experiencing **one delayed bus every day** with multiple trips.	Feasible by bus services operating in **larger cities**.

[14] Canadian Urban Transit Association (2001)
[15] Barabino, Di Francesco, and Mozzoni (2015)
[16] National Academies of Sciences, Engineering, and Medicine (2013)
[17] Ibid.

<70%	The bus is highly **unreliable**.	May represent the **best achievable results** in **congested Central Business Districts (CBDs)** where buses must share lanes with other traffic.

Source: National Academies of Sciences, Engineering, and Medicine (2013)

In the Malaysian context, to the best of our ability, we were not able to find a study in Malaysia on what the commuter perceives as "on-time." On the other hand, MyRapid KL defines and reports punctuality based on the scheduled arrival and departure times from the terminal (representing the first bus stop in a route), rather than arrival or departure times at each subsequent stop[18].

2.3. Magnitude of Deviation

While OTP provides an answer to the question of 'How frequently do buses arrive on time?', this is only one part of the picture. An equally important aspect of reliability has to do with the severity of deviation when a bus is not punctual. In other words, **"How far off are busses when they fail?"**

For example, a bus that is regularly 1-2 minutes, or even 5 minutes late may be manageable for most riders, but an unexpected 20-minute delay can result in a missed appointment, being late for work or picking up children from school. This is an outcome that can at times be far more damaging to commuter trust. Thus, even when overall punctuality seems acceptable, the unpredictability of outlier events can significantly erode confidence in the system.

In bus travel time forecasting studies, mean absolute error (MAE) is commonly used to evaluate the accuracy of predictions by measuring the average differences between forecasted values and actual observations[19, 20, 21]. Other commonly used methods include root mean squared error (RMSE) and mean absolute percentage error (MAPE).

While RMSE is sensitive to large errors, which is useful to identify outliers, MAPE expresses errors as percentage, which might be misleading when actual values are close to zero. In contrast, MAE offers interpretable estimate of average deviation in absolute time units. Although current literature does not implicitly use MAE as a component of quality of bus services[22, 23, 24], it serves as a valuable complement to on-time performance by capturing the magnitude of deviations which allow a more complete evaluation of bus service quality.

[18] "Rapid Bus Performance Update" (2024)
[19] Mete, Çelik, and Gül (2023)
[20] Ma et al. (2019)
[21] Comi and Polimeni (2020)
[22] Muhammad Fadhlullah Abu Bakar et al. (2023)
[23] Norhisham et al. (2022)
[24] Shuhairy Norhisham et al. (2018)

3. Methodology

3.1. Data

The primary dataset for this study is the General Transit Feed Specification (GTFS), accessed through Malaysia's Official OpenAPI platform[25]. GTFS provides a standardized format widely used in urban mobility research. This allows us to integrate scheduled and real-time operational data. Two complementary components are employed:

- **GTFS-static (GTFS-s)**: the digital equivalent of printed timetables, containing route structures, stop identifiers, geolocations, and scheduled arrival and departure times.
- **GTFS-realtime (GTFS-r)**: continuous position updates that record the actual progress of busses along their routes, including vehicle identifiers, trip start times, and timestamps. Realtime data on bus locations are continuously recorded every 15 seconds from 5am to 11pm every day.

These feeds enable the alignment of scheduled expectations with actual real-time service delivery. Data for this study was restricted to regular weekdays in the second quarter of 2025 (April – June) as this study focuses on public transport as a means of commuting to work. Furthermore, multiple studies have shown positive correlation between accessibility of public transport and access to employment[26, 27]. Hence, weekends and public holidays were excluded to ensure consistency in service patterns, as operational frequencies and demand profiles differ substantially outside the working week.

The resulting dataset provides a representative view of weekday commuting conditions during the study period. Table 2 summarizes the information contained in GTFS-s and GTFS-r.

Table 2: Summary of available data from GTFS

GTFS	Information	Descriptions
GTFS-s	Agency	Contains information on the bus provider such as official agency name, official websites and agency official phone number.
	Calendar	Contains information on services provided by the bus operator, including the service ID and indicators for operation on Monday, Tuesday, and other days of the week (0 = no service, 1 = service available), start date and end date.
	Routes	Contains the bus provider's name and detailed information for all routes, including their IDs, short names, and long names.

[25] https://developer.data.gov.my/
[26] Bastiaanssen, Johnson, and Lucas (2022)
[27] Blumenberg and Pierce (2014)

	Stop times	Contains information for every route cycle, including the type of day (weekday or weekend/public holiday), scheduled bus arrival and departure times at each bus stop (identified by stop IDs), and the sequence of bus stops along the route.
	Stops	Contains information for every bus stop, including its ID, name, and geolocation (latitude and longitude).
	Trips	Contains information for trips provided by the bus operator such as route ID, service ID, and trip ID.
GTFS-r	Trip IDs	The identifier linking the record to the scheduled cycle.
	Route IDs	The route on which the bus is operating.
	Geolocation	The real time geographic coordinates (latitude and longitude) of the bus.
	Vehicle IDs	The unique identifier for each bus.
	Start time	The date and time when each bus cycle begins.
	Malaysia time	The exact timestamp (in Malaysia local time) when the real time data was recorded.

Source: Malaysian Government's official OpenAPI platform

While the GTFS provides a high-resolution record of bus operations, the dataset that we have constructed is not without its limitations. Our automated retrieval process (via cronjobs) has been subjected to occasional interruptions. On such days, the real-time feed is incomplete, preventing reliable reconstruction of bus cycles. In Q2-2025, there were 60 non-public holiday weekdays. Among these, 12 days for Rapid KL Bus services and 17 days for Rapid KL MRT Feeder had partial or missing data, while the remaining 48 days (Rapid KL Bus) and 43 days (MRT Feeder) had complete data. To safeguard the integrity of our analysis, all days with partial or missing data were excluded. This filtering step ensures that only days with full GTFS-s and GTFS-r coverage are included in the construction of the Bus Performance Index. In practice, this means that the index reflects a conservative but reliable representation of bus services on weekdays during Q2-2025.

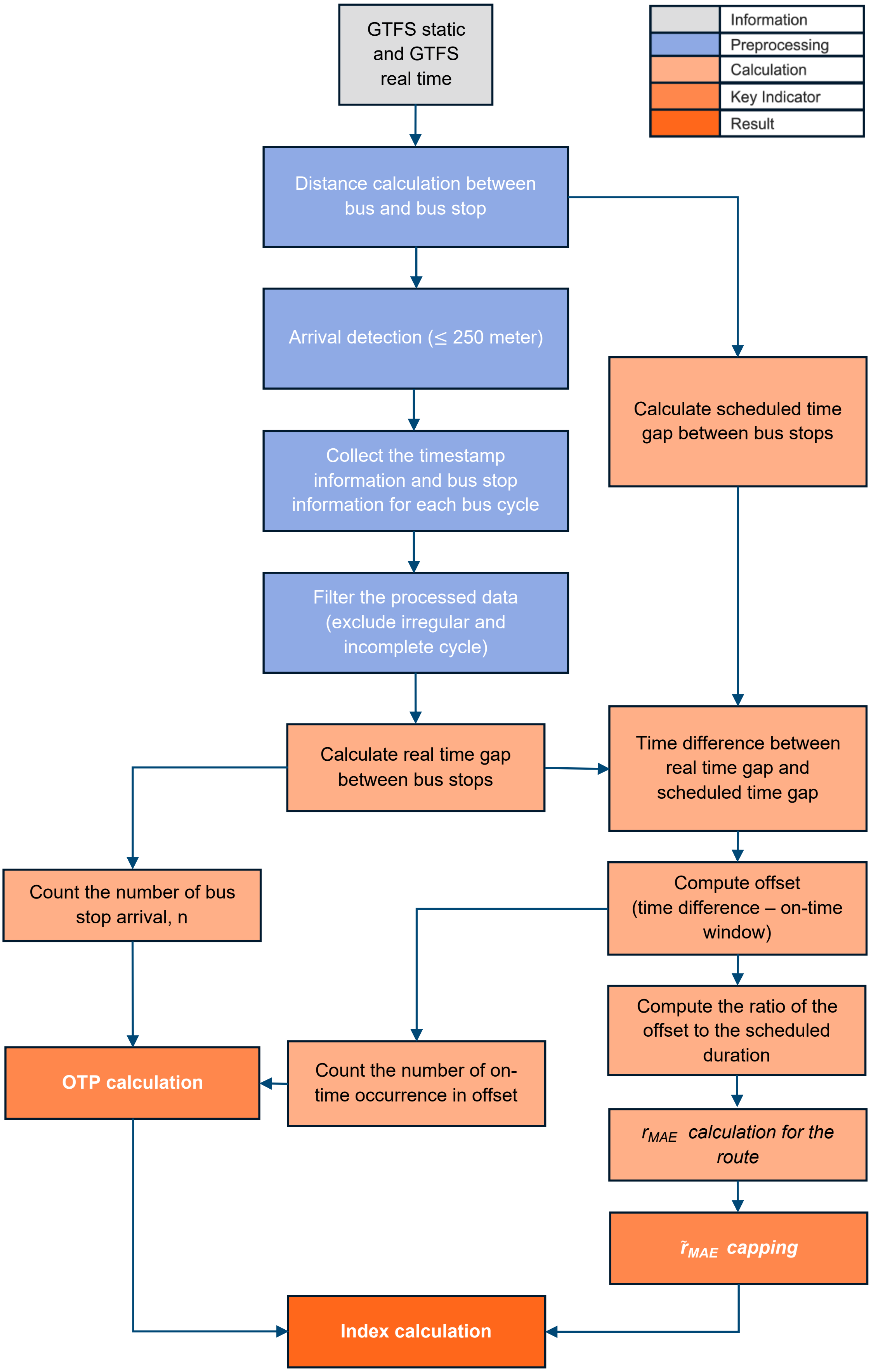
3.2. Operational Definitions and Metrics

To evaluate bus efficiency, we operationalize two complementary dimensions: **punctuality** and **reliability.** Punctuality captures whether buses arrive within an acceptable window, while reliability measures how severe and unpredictable the deviations are when they fall outside this window. Together, these dimensions reflect part of the commuter's lived experience and form the foundation of the Bus Performance Index (BPI).

Framework Overview

Figure 3.2.1 below presents our computation framework.

Figure 3.2.1 The Bus Performance Index (BPI) computation framework.



The process begins with detecting bus arrivals by aligning GTFS-static (scheduled) and GTFS-r (real-time positions) data. An arrival is recorded when a bus comes within 250 meters of a stop. Each cycle is validated, and irregular or incomplete cycles (e.g. due to diversions, road closures, or breakdowns) are excluded from our analysis. This is so that our resultant assessment of bus performance yields only results representing a bus system that is working normally.

From valid cycles, we extract timestamps, and compute scheduled durations, and observed deviations, which are then used to compute two indicators:

1. **On Time Performance (OTP):** the proportion of arrivals that occur within an acceptable window.
2. **Normalized relative mean absolute error ($\tilde{r}_{MAE}$):** the average size of deviations relative to scheduled duration.

Number of Observed Bus Stop Arrivals (*n*)

The analysis begins with us categorizing the number of *valid* bus stop arrivals, denoted n. We categorize a cycle as *valid* if the bus progresses through at least two stops, ensuring measurable differences in scheduled and actual times. Certain anomalies (e.g. events like the ASEAN Summit 2025 or road closures) can invalidate cycles. These were systematically excluded.

For context, Table 3.1 presents descriptive information for Rapid KL Bus and Rapid KL MRT Feeder service, while Table 3.2 illustrates the extremes in cycle duration and stop counts across both routes.

Table 3.1: Descriptive information of Rapid KL Bus and Rapid KL MRT Feeder services.

Information	Rapid KL Bus	Rapid KL MRT Feeder	Total
Average routes	138	98	236
Average number of buses	556	253	809
Average number of bus cycles	3,811	2,851	6,662
Average cycle duration (in minutes)	50.16	31.53	-

Note: computed based on authors' calculation.

Based on the GTFS real time observed in this period, Rapid KL Bus on average operates 138 routes and 556 active buses, while Rapid KL MRT Feeder operates 98 routes and 253 active buses. In general, a route in Rapid KL Bus has about four buses while MRT Feeder has only three buses per route. On average, a cycle in Rapid KL Bus takes approximately 50.16 minutes, while Rapid KL MRT Feeder takes 31.16 minutes, reflecting their different roles, as feeder services complete shorter loops compared to the main bus services. Overall, Rapid KL Bus cover larger part of Greater Kuala Lumpur compared to Rapid KL MRT Feeder.

Table 3.2.: Extremes routes across Rapid KL Bus and Rapid KL MRT Feeder.

Route	Operator	Descriptions	Number of Stops	Scheduled Durations (in minute)
T464	MRT Feeder	Longest cycle duration and largest number of stop.	58	105
MPS1	Rapid KL	Longest cycle duration and largest number of stops.	111	230
T112	MRT Feeder	Shortest cycle duration	11	15
T113	MRT Feeder	Shortest cycle duration	11	15
T454	MRT Feeder	Shortest cycle duration	12	15
T810	MRT Feeder	Shortest number of stops	9	20
MENARA PRASARANA	Rapid KL	Shortest cycle duration and shortest number of stops	2	3

For instance, route MPS1 spans 111 stops and 230 scheduled minutes, while Menara Prasarana shuttle covers just 2 stops in 3 minutes. Delays on long routes amplify commuter disruption, underscoring why the dataset focuses only on valid, fully observed cycles.

Arrival (a_i) and Time Deviations (d_i)

For each bus arrival, we define the arrival deviation as difference between the actual duration taken to reach the *i*-th bus stop and the scheduled duration for that same bus stop:

$$a_i = \text{actual duration of the } i\text{-th stop} - \text{scheduled duration of the } i\text{-th stop.}$$

A bus is considered **on time** if:

$$-1 \leq a_i \leq 5$$

The definition follows TCQSM standards[28], allowing departures up to one minute early, and arrivals up to five minutes late. The tolerance reflects operational realities while keeping standards of punctuality, service oriented. Following arrivals, the time deviation of the *i*-th bus arrival, d_i, is defined as:

$$d_i = \begin{cases} 0, & if\ -1 \leq a_i \leq 5 \\ -1 - a_i, & if\ a_i \leq -1 \\ a_i - 5, & if\ a_i \geq 5 \end{cases}$$

[28] National Academies of Sciences, Engineering, and Medicine (2013)

A value of $\boldsymbol{a_i} < \mathbf{-1}$ indicates that the bus departed **earlier than the acceptable on-time window**, while $\boldsymbol{a_i} > \mathbf{5}$ indicates that **the bus arrived later than the acceptable on-time window**. An $-1 \leq a_i \leq 5$ indicates that the bus arrived on time. Note that here, at the extremes, we consider busses that depart 1 minute early and arriving 5 minutes later than the appointed schedule as 'on-time'.

On-Time Performance (OTP)

Secondly, we compute *On-Time Performance (OTP)*, as a measure of punctuality. OTP is defined as the share of arrivals that falls within the on-time window[29], and is defined as follows:

$$\text{OTP} = \frac{\text{Number of on-time arrivals}}{\text{Total number of arrivals in the route}}$$

Using the previously defined d_i, where a bus is considered on-time if $-1 \leq a_i \leq 5$, the OTP can be reformulated as:

$$\text{OTP} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}(-1 \leq a_i \leq 5)$$

where the indicator function, $\mathbf{1}(\cdot)$, returns 1 when the actual deviation, a_i, is 'on-time' and 0 otherwise.

OTP is intuitive and widely used in transit operations. It answers a simple question, *"How often do busses arrive on time?".* Yet, OTP alone is limited. It treats a bus that is 6 minutes late the same as one that is 30 minutes, or even 45 minutes late.

Normalised Relative Mean Absolute Error ($\tilde{r}_{\text{MAE}}$)

To capture the severity of deviations, we calculate the cycle level deviation ratio:

$$\text{r} = \frac{\sum_{\text{i}=1}^{\text{n}} |d_i|}{\sum_{\text{i}=1}^{\text{n}} \text{s}_\text{i}}$$

Where the numerator is the total deviation in a cycle and the denominator is the total scheduled duration of that cycle. To capture the severity of deviations, we calculate Mean Absolute Error (MAE):

$$\text{r}_{\text{MAE}} = \frac{1}{\text{m}} \sum_{\text{i}=1}^{\text{m}} \text{r}_i$$

An $\text{r}_{\text{MAE}} > 1$ implies that the normalized deviation is at least as large as the cycle itself. This effectively means that busses are so late (or so early) that they cancel the utility of the schedule.

[29] National Academies of Sciences, Engineering, and Medicine (2013)

For all intents and purposes, one might just disregard the schedule entirely in these cases, because your wait time for the bus could be longer than the average headway.

To preserve interpretability, we cap the measure:

$$\tilde{r}_{MAE} = \min(r_{MAE}, 1)$$

where $\tilde{r}_{MAE}$ returns r_{MAE} when $r_{MAE} < 1$, and is capped at 1 otherwise.

We also compute the standard deviation of r_{MAE}, $\sigma_{r_{MAE}}$, to distinguish between systematic deviations (low variability, suggesting timetables need adjustment) and erratic deviations (high variability, signalling operational unpredictability).

From the commuter's perspective, r_{MAE} addresses not just how often busses are off schedule, but how badly.

Bus Performance Index (BPI)

As we have argued before, while the literature often uses On-Time Performance (OTP) to assess the performance of bus services, OTP does not account for how late or early if the buses arrive when they are not on-time[30, 31, 32]. This means that two routes with similar OTP scores might offer very different experience to commuters if one route has more severe delays in arrival or early departures. Studies also highlight that OTP do not fully capture the commuter experience, especially in situations where unexpected delay is high[33, 34]. Therefore, to integrate punctuality and reliability into a unified measure, we define:

$$f(\mathrm{OTP}, \tilde{r}_{MAE}) = \mathrm{OTP} \text{ x } (1 - \tilde{r}_{MAE})$$

The Bus Performance Index is then:

$$\mathrm{BPI}(\mathrm{OTP}, \tilde{r}_{MAE}) = \begin{cases} 0, & if\ either\ \mathrm{OTP} = 0\ or\ \tilde{r}_{MAE} = 1 \\ f(\mathrm{OTP}, \tilde{r}_{MAE}), & otherwise. \end{cases}$$

This formulation ensures interpretability: if no busses arrive on time, or if deviations are as large as cycle durations, the index is set to 0, reflecting a service that is effectively useless to commuters. Consistent with the TCQSM's classification of an unreliable service has an OTP of less than 70%. In our study, we classify a Bus Performance Index (BPI) value of below 0.7 as unreliable, following the TCQSM's classification. This is because our BPI extends the OTP to include a measure of reliability when services do not arrive on-time. This is an indication that services fail to meet the acceptable levels of punctuality OR the temporal consistency when it does not arrive on-time.

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30 Muhammad Fadhlullah Abu Bakar et al. (2023)
31 Norhisham et al. (2022)
32 Shuhairy Norhisham et al. (2018)
33 Ait-Ali (2024)
34 Wood (2015)

3.3. Technical Estimation and Validation

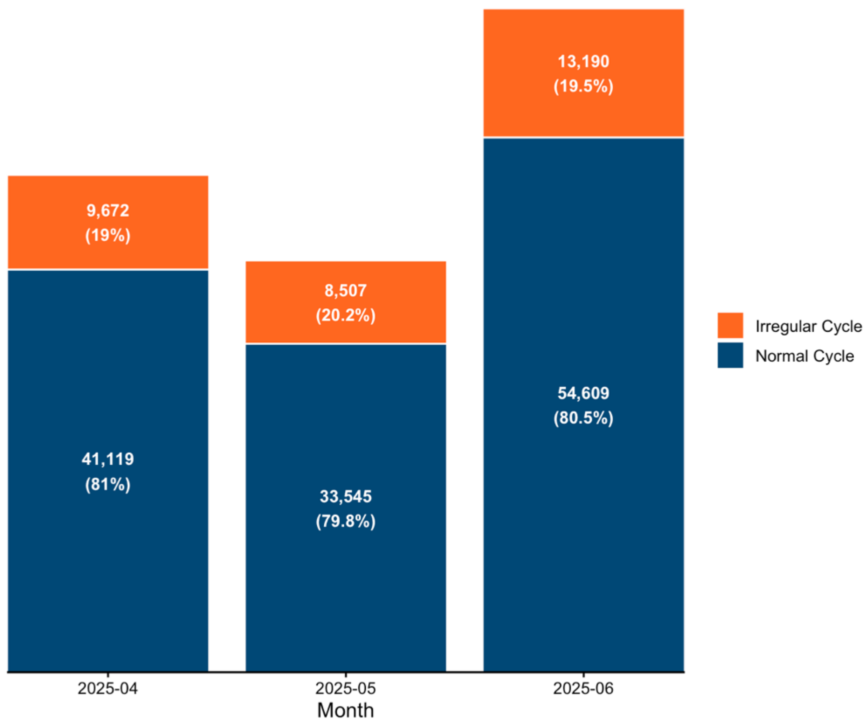
Complete Cycle Extraction

The first step in constructing the index is to extract and validate bus cycles from the GTFS-r dataset. A cycle is defined as the complete journey of a bus from its first stop to its final stop in a service run. In practice, however, not every detected cycle reflects normal service conditions. GTFS data may capture re-routes, partial journeys, or anomalies caused by system or even human errors. If left unfiltered, these irregularities may distort the measures for punctuality and reliability.

To address this, we distinguish between **normal cycles** and **irregular cycles**. Normal cycles adhere to the stop sequence and timing expectations in the GTFS-s schedule. This represents planned operations. On the other hand, irregular cycles deviate substantially in one of two ways:

- **Stop jumps**, when a substantial number of consecutive bus stops are skipped (5 by our estimates). These typically reflect road closures, diversions or deliberate short-turning practices;
- **Time gaps**, when travel between two consecutive stops exceeds a significant amount of time (one hour by our estimates). This is often the result of vehicle breakdowns, or driver changes[35].

Figure 3.1 The number and percentage of normal cycles out of extractable cycle obtained each month.



[35] The choice of thresholds for both the time gap and stop jump parameters will be discussed in Appendix 8.2.

Figure 3.1 shows the distribution of extractable bus cycles for Rapid KL Bus identified by the algorithm developed in this study, categorised into normal and irregular cycles for each month from April to June 2025. Approximately 80% of extracted cycles were classified as normal, with the proportion stable across months despite fluctuations in service volume[36]. This consistency suggests that the dataset captures an operational environment where majority of services adheres to published schedules, even amid the disruptions typical of an urban bus system

Figure 3.2 The number and percentage of complete cycles out of normal cycle obtained each month.

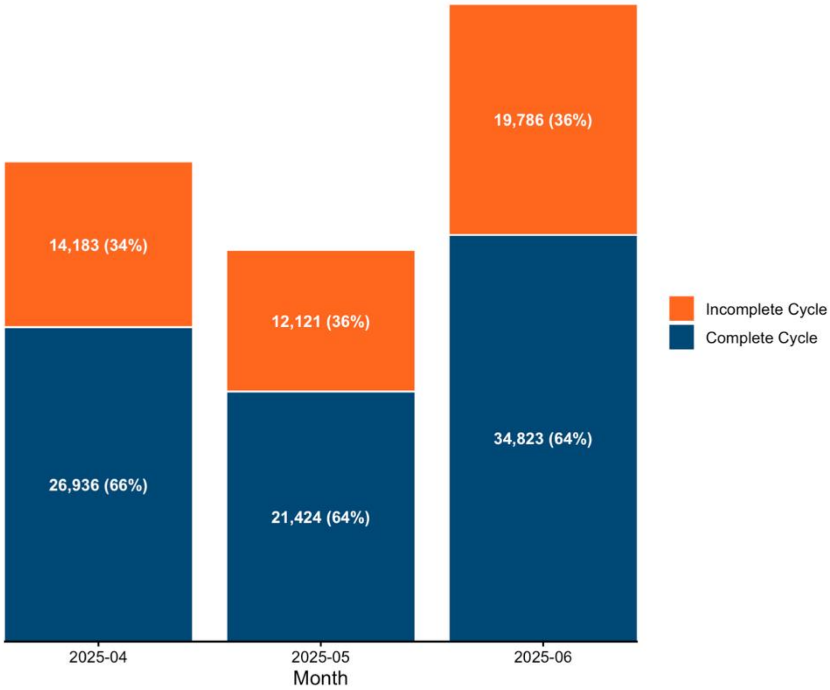


Figure 3.2 presents the distribution of valid and invalid cycles out of normal cycles for Rapid KL Bus identified for each month from April to June 2025.

From the pool of normal cycles, we then identify complete cycles. A cycle must include at least two stops to permit meaningful analysis of stop-to-stop travel times. Single-stop cycles, often artifacts of GPS malfunction, missing API signals, or other errors were excluded. Valid cycles accounted for 64% to 66% of all normal cycles. While this filtering may appear strict, it ensures analytical integrity. The final dataset reflects journeys commuters could realistically experience, rather than noise from technical failures.

Properties of Composite Index

Constructing a composite measure of bus performance requires balancing mathematical rigor with commuter experience. To guide formulation, we identified three properties that the index should satisfy:

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[36] The number of extractable cycles depends on the number of days observed in a particular month. Each month has a varying number of days to maintain consistency in service patterns, which is reflected in the number of rows in each GTFS-r file.

1. **Monotonicity**: The index should move in the expected direction. If punctuality (OTP) improves, or deviations (rMAE) decrease, the index should not fall.
2. **Boundedness**: The index must remain interpretable by being restricted to values between 0 and 1, with 0 representing complete inefficiency and 1 representing ideal service where the bus arrives on time for **ALL** of its scheduled arrivals.
3. **Penalty Severity**: Poor reliability should be penalized more heavily when punctuality is low. From a commuter's standpoint, the frustration of an already unreliable service is magnified when very few busses are on time.

These principles embed commuter priorities into the mathematics of the index. Rather than being an abstract performance score, the BPI is designed as a commuter-centred diagnostic tool, translating reliability into terms that mater for public trust and policy accountability.

The BPI was conceptually defined as a rule-based composite of OTP and rMAE guided by the four properties above. The following regression model was not used to statistically estimate index weights. Instead, its purpose was:

- To test whether the proposed mathematical form of the index behaves consistently with these conceptual properties, and
- To validate the sensitivity and functional relationship between punctuality (OTP) and reliability (rMAE) across operators.

Regression-based Estimation

To operationalize these properties, we employ a regression-based formulation of the index. Specifically, we estimate:

$$\log\big(f(\mathrm{OTP},\ \tilde{r}_{\mathrm{MAE}})\big) = \beta_0 + \beta_1 \cdot \log(\mathrm{OTP}) + \beta_2 \cdot (1 - \tilde{r}_{\mathrm{MAE}}) + \beta_3 \cdot (1 - \tilde{r}_{\mathrm{MAE}})^2 + \varepsilon$$

where ε is the standard error term.

The model allows for non-linear interactions between punctuality and reliability. The log transformation of OTP captures diminishing returns. As punctuality approaches 100%, marginal improvements matter less. The squared term for reliability deviations allow the model to capture curvature, acknowledging that modest deviations might be tolerated by commuters, but large deviations disproportionately erode at efficiency.

Expected coefficient signs follow commuter intuition:

- $\beta_1 > 0$, indicating that higher OTP raises efficiency
- $\beta_3 < 0$, indicating that higher deviations lower efficiency

The estimated function then defines the BPI as:

$$\mathrm{BPI}(\mathrm{OTP},\ \tilde{r}_{\mathrm{MAE}}) = \begin{cases} exp(\ \beta_0 + \beta_1 \cdot \log(\mathrm{OTP}) + \ \beta_2 \cdot (1 - \tilde{r}_{\mathrm{MAE}}) + \ \beta_3 \cdot (1 - \tilde{r}_{\mathrm{MAE}})^2 + \ \varepsilon\ ), & if\ OTP\ > 0\ and\ \tilde{r}_{\mathrm{MAE}} < 1 \\ 0, & if\ either\ \mathrm{OTP} = 0\ \ or\ \tilde{r}_{\mathrm{MAE}} = 1 \end{cases}$$

Estimation and Validation

Table 3 describes the coefficients of our regression. Coefficients were estimated separately for Rapid KL Bus and Rapid KL MRT Feeders to reflect operator-specific conditions. This approach acknowledges that service environments (or the objective) differ. Rapid KL MRT Feeder routes are typically shorter and more frequent, while Rapid KL Bus serve a wider, more heterogeneous network. Operator-specific estimation enables tailored analysis while retaining comparability through the common index framework.

Table 3: Rapid KL Bus service and Rapid KL MRT Feeder service

	Dependent variable:	
	$\log(f(\text{OTP}, \tilde{r}_{\text{MAE}}))$	
	Rapid KL Bus service	Rapid KL MRT Feeder service
log(OTP)	1.026***	1.156***
	(0.006)	(0.023)
$\tilde{r}^2_{\text{MAE}}$	−2.737***	−2.706***
	(0.036)	(0.043)
$\tilde{r}_{\text{MAE}}$	5.453***	5.566***
	(0.046)	(0.059)
Constant	−2.782***	−2.881***
	(0.014)	(0.019)
Observations	2,782	2,400
R^2	0.971	0.941
Adjusted R^2	0.971	0.941
Residual Std. Error	0.092 (df = 2778)	0.065 (df = 2396)
F Statistic	31,191.990*** (df = 3; 2778)	12,708.150*** (df = 3; 2396)
Note:		*p<0.1; **p<0.05; ***p<0.01

Random Holdout Validation

To evaluate predictive performance and avoid overfitting, the first approach is a random 60/40 split of the dataset into estimation and validation subsets. Coefficients were estimated on the 60% estimation sample and then applies to the 40% validation sample. This procedure tests whether the functional form of the index as cross-sections, to evaluate whether it is robust to sampling variability across different routes and service cycles. While this approach does not respect the time series nature of the data, it provides reassurance that the model is not overly sensitive to idiosyncrasies in any particular subset of observations.

Randomized train-test split: 60% of the data were used for model training, while 40% were reserved for testing. The models demonstrated high explanatory power and low prediction errors in both sets (refer to Table 5 and 6), suggesting that the functional. The following tables present results from error metric to assess the accuracy of predictions.

Table 4: Error metric for Rapid KL Bus service and Rapid KL MRT Feeder service

	Metric	Rapid KL Bus service	Rapid KL MRT Feeder service
1	MAE	0.024	0.014
2	RMSE	0.028	0.018
3	MAPE (%)	4.366	2.793
4	R-squared	0.984	0.984

The results indicate that both models perform well on both training and test sets, with high R^2 values and low prediction errors.

Regression Coefficients

Based on the estimated parameters, the Bus Performance Index for Rapid KL Bus service can be expressed as follows:

$$BPI_{Rapid\ KL\ Bus}(\text{OTP}, \tilde{r}_{\text{MAE}}) = \begin{cases} exp(\ \beta_0 + \beta_1 \cdot \log(\text{OTP}) + \ \beta_2 \cdot (1 - \tilde{r}_{\text{MAE}}) \ + \ \beta_3 \cdot (1 - \tilde{r}_{\text{MAE}})^2 \ ), & OTP \ > 0 \ and \ \tilde{r}_{\text{MAE}} \ < \ 1 \\ 0, & if\ either\ \text{OTP} = 0 \ or\ \tilde{r}_{\text{MAE}} \ = \ 1 \end{cases}$$

with $\beta_0 = -2.782,\ \beta_1 = 1.026,\ \beta_2 = 5.453$ and $\beta_3 = -2.782$. Similarly, the Bus Performance Index for Rapid KL MRT Feeder service can be expressed as:

$$BPI_{MRT\ Feeder}(\text{OTP}, \tilde{r}_{\text{MAE}}) = \begin{cases} exp(\ \beta_0 + \beta_1 \cdot \log(\text{OTP}) + \ \beta_2 \cdot (1 - \tilde{r}_{\text{MAE}}) \ + \ \beta_3 \cdot (1 - \tilde{r}_{\text{MAE}})^2 \ ), & OTP \ > 0 \ and \ \tilde{r}_{\text{MAE}} \ < \ 1 \\ 0, & if\ either\ \text{OTP} = 0 \ or\ \tilde{r}_{\text{MAE}} \ = \ 1 \end{cases}$$

with $\beta_0 = -2.881,\ \beta_1 = 1.156,\ \beta_2 = 5.566$ and $\beta_3 = -2.881$. This index will be applied in section 4.1 to examine the perspective of commuters waiting to board the bus[37].

4. Findings and Policy Implications

This segment interprets the Bus Performance Index (BPI) and its components from the perspective of commuters waiting to board the bus. This perspective reflects whether busses arrive as promised, and how frequently they don't.

Our analysis, which combines a ternary visualisation plot and distributional analysis to access punctuality patterns using the Bus Performance Index (BPI), offers both a granular route-level view and a system-wide perspective on service reliability. From a system-design standpoint, the analysis shows that small punctuality gaps are not local. Instead, it exists throughout the network, affecting overall reliability and commuters' perception. Together, these findings help explain why public trust in bus services remains fragile and highlight where improvements would have the greatest impact.

4.1. Commuter Perspective: Experience Waiting to Board

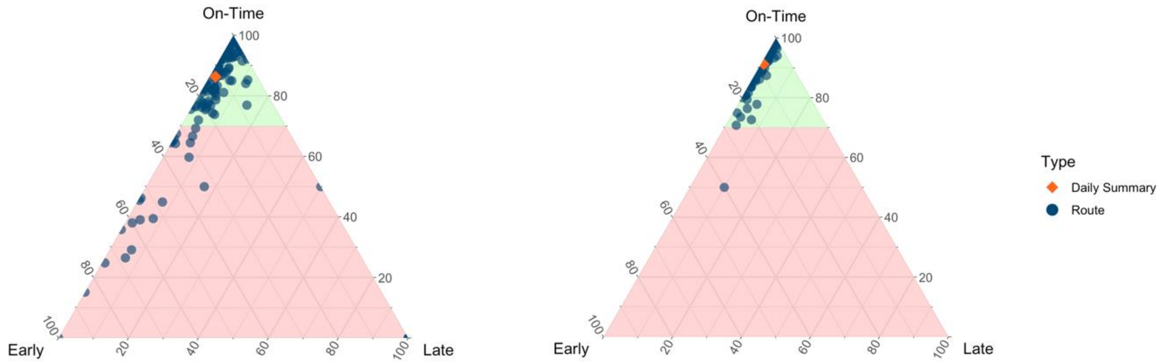
For commuters at the bus stop, punctuality is experienced in real-time. Does the bus arrive within the expected window? Using 2 April 2025 as an illustrative day, Figures 4.1.1 **(A)** and 4.1.2 **(B)** show ternary plots of both the Rapid KL Bus and Rapid KL MRT Feeder services, categorizing arrivals as early, on-time, or late. Each point corresponds to a route; the orange marker aggregates and summarizes all arrivals on that day.

Figure 4.1.1 (A): The ternary plot of On-Time Performance for Rapid KL Bus routes on 2nd April.

Figure 4.1.2 (B): The ternary plot of On-Time Performance for Rapid KL MRT Feeder routes on 2nd April.

[37] The temporal holdout validation will be discussed in Appendix 8.3.

(A) (B)



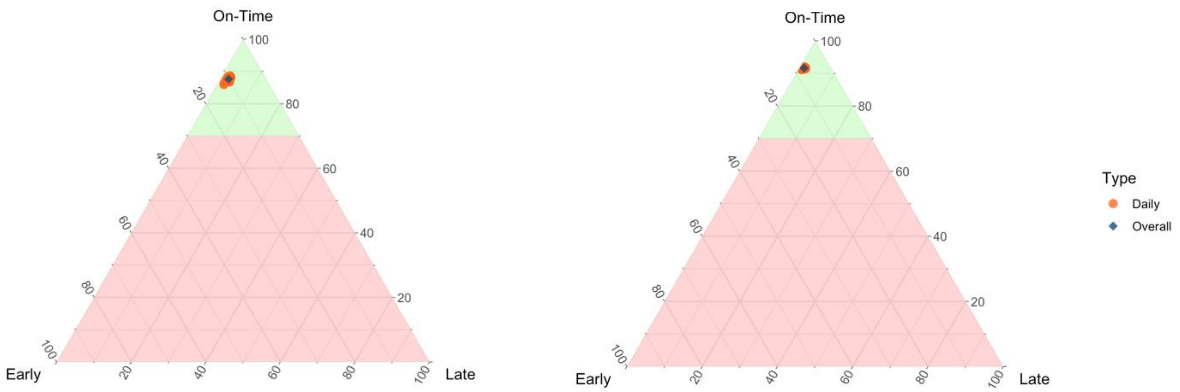
Most services cluster near the on-time corner, with Rapid KL Bus recording 86% and Rapid KL MRT Feeders 91% of arrivals within the acceptable window. Variability differs sharply. Rapid KL Bus points were more scattered, while Rapid KL MRT Feeder points are tightly clustered, indicating a more consistent performance. This suggests that Rapid KL MRT Feeder services exhibit higher predictability in arriving on-time, likely due to shorter distances and lower exposure to external disruptions.

Extending this across the full quarter, Figures 4.1.3 **(A)** and 4.1.4 **(B)** plot daily summaries for April-June 2025, to determine whether the single day patterns persist consistently across the quarter.

Figure 4.1.3 (A): Ternary plot of On-Time Performance for Rapid KL Bus routes (daily summary).

Figure 4.1.4 (B): Ternary plot of On-Time Performance for Rapid KL MRT Feeder routes (daily summary).

(A) (B)

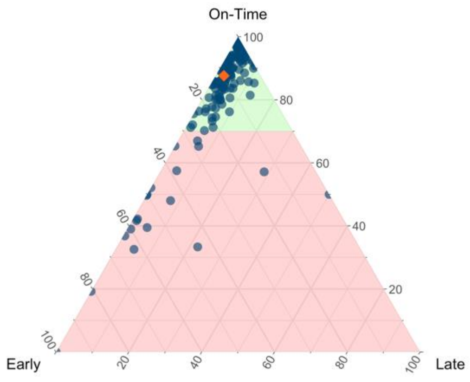


At the monthly level, Figures 4.1.5 **(A)** and 4.1.6 **(B)** present medoids[38] of route-level OTP.

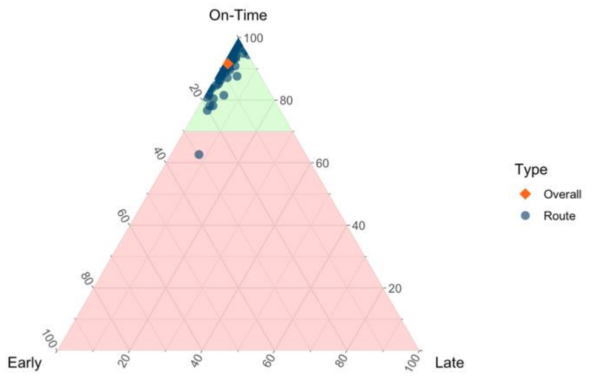
Figure 4.1.5 (A): Ternary plot of On-Time Performance for Rapid KL Bus routes (April).

Figure 4.1.6 (B): Ternary plot of On-Time Performance for Rapid KL MRT Feeder routes (April).

(A)



(B)



These typical values confirm the persistence of patterns – Rapid KL MRT Feeders are mostly punctual, while Rapid KL Bus routes exhibits more wider spread. Notably, 11-12% of Rapid KL Bus routes are registered as early departure, where buses on these route depart earlier than 1 minute ahead of the schedule. In such cases, commuters who arrive on time but miss the bus may have to wait 20–40 minutes for the next scheduled trip to continue their journey.

Figure 4.1.7: Scheduled duration of each cycle of T789.

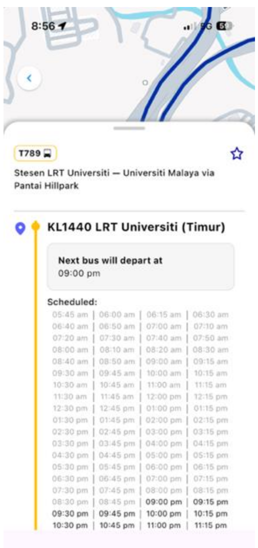
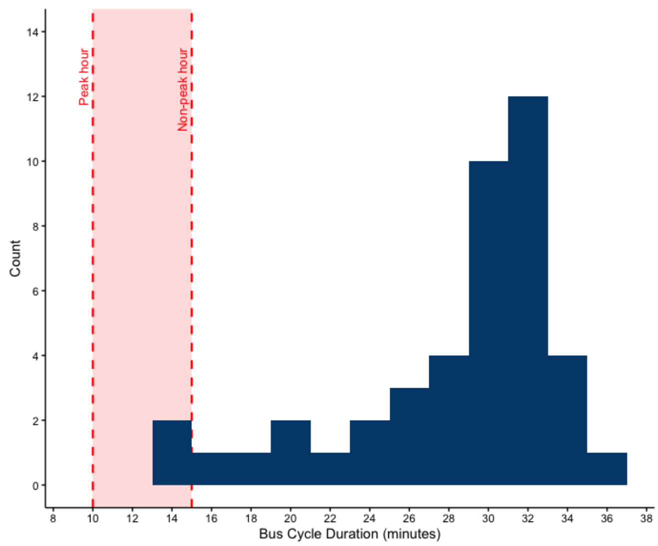


Figure 4.1.8: Distribution of daily median bus cycle duration for complete cycle. (Route T789)



Source: Screenshots from MyRapid Pulse app, authors' own compilation. Note: Computed based on authors' calculation.

[38] Unlike median, which summarise a distribution by its central value, the medoid is an actual observation from dataset that minimise the total distance to all other points. Using medoid instead of median ensures that the representative value corresponds to an actual day's bus journey.

Additionally, there is a mismatch between the scheduled bus cycle duration and the observed bus cycle duration. Take Route T789 (Stesen LRT Universiti ~ Universiti Malaya via Pantai Hillpark) for example, while the published timetable for Route T789 indicates an average headway of 10 minutes during peak hours and 15 minutes during non-peak hours. However, observed data suggests that actual cycle durations are closer to 30 minutes. Persisting with unrealistic schedules widens the gap between expectation and reality, resulting in an even more frustrating experience for commuters.

Yet, OTP alone is incomplete. Two routes with identical OTP can differ in how extreme their deviations are. While OTP measures frequency of punctual arrivals, Bus Performance Index (BPI) integrate both punctuality and variability, offering a fuller reliability picture. To account for this, Figures 4.1.9 and Figure 4.1.10 examines the share of routes with a zero[39] Bus Performance Index (BPI).

Figure 4.1.9: Monthly proportion of Rapid KL Bus routes with zero Bus Performance Index (BPI).

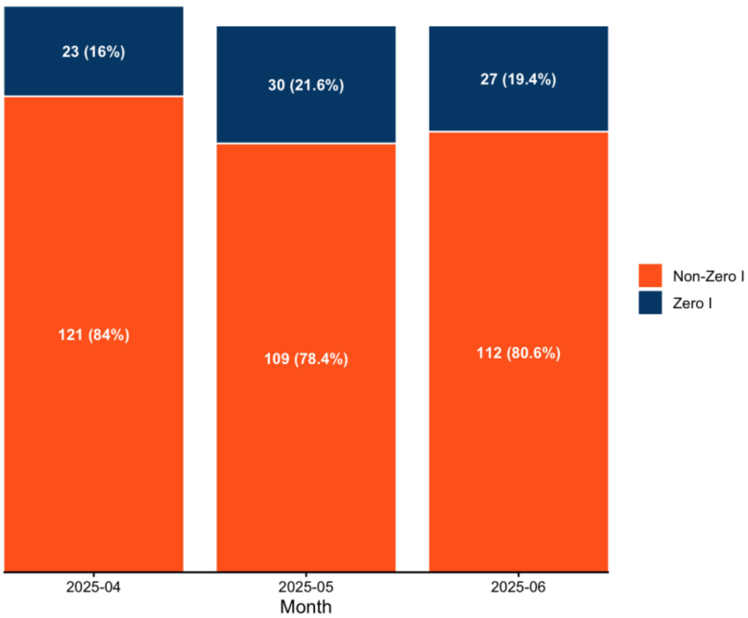
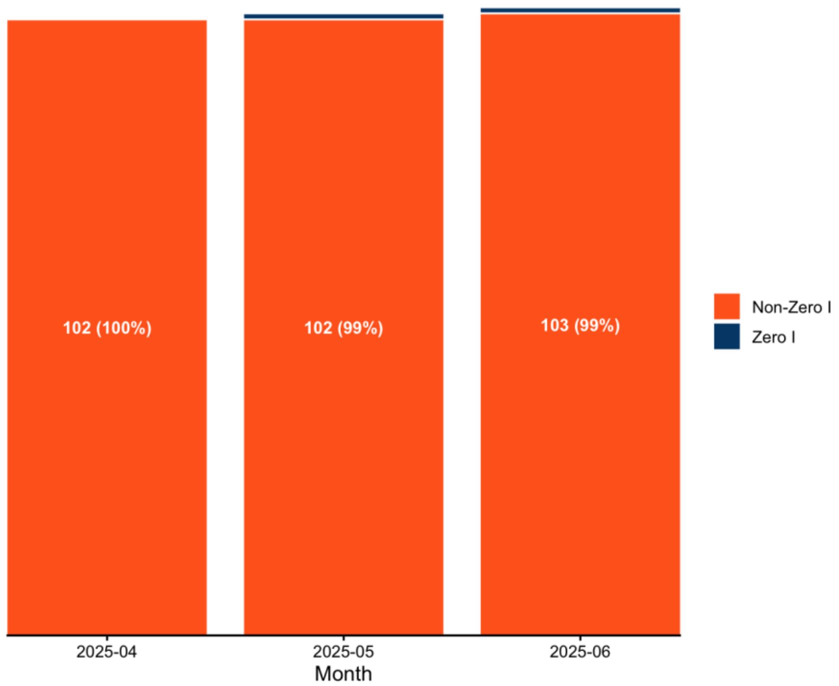


Figure 4.1.10: Monthly proportion of Rapid KL MRT Feeder routes with zero Bus Performance Index (BPI).

[39] A zero BPI implies that the route has no busses arrive on time, or the deviations are as large as cycle durations when busses are not on-time.



Effectively, these represent services that fail entirely. Roughly 20% of Rapid KL Bus routes fall into this category each month, while Rapid KL MRT Feeders avoids these collapses almost entirely. Figures 4.1.11 show the full distribution of I values while Figure 4.1.12 show the distribution of I values for non-zero routes.

Figure 4.1.11: Distribution of Bus Performance Index (BPI) for Rapid KL Bus routes and Rapid KL MRT Feeder routes, from April to June.

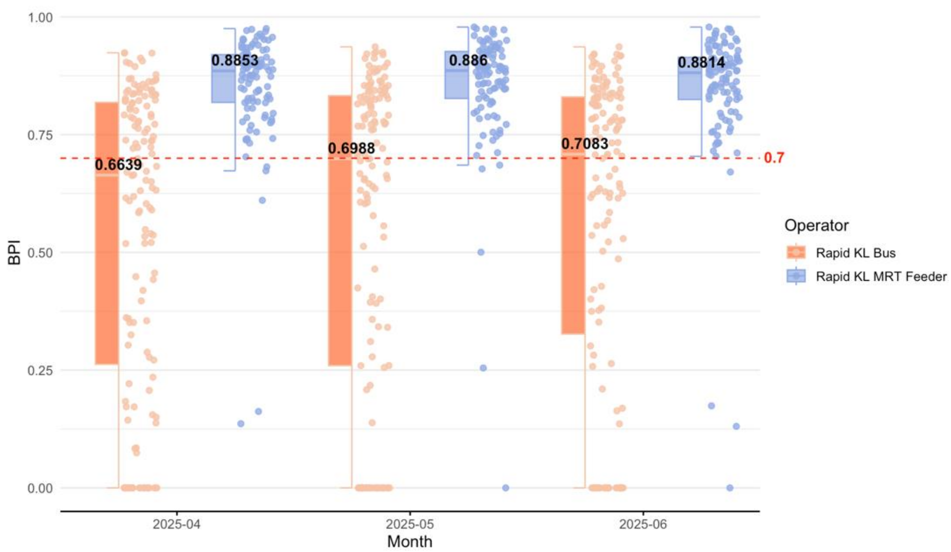
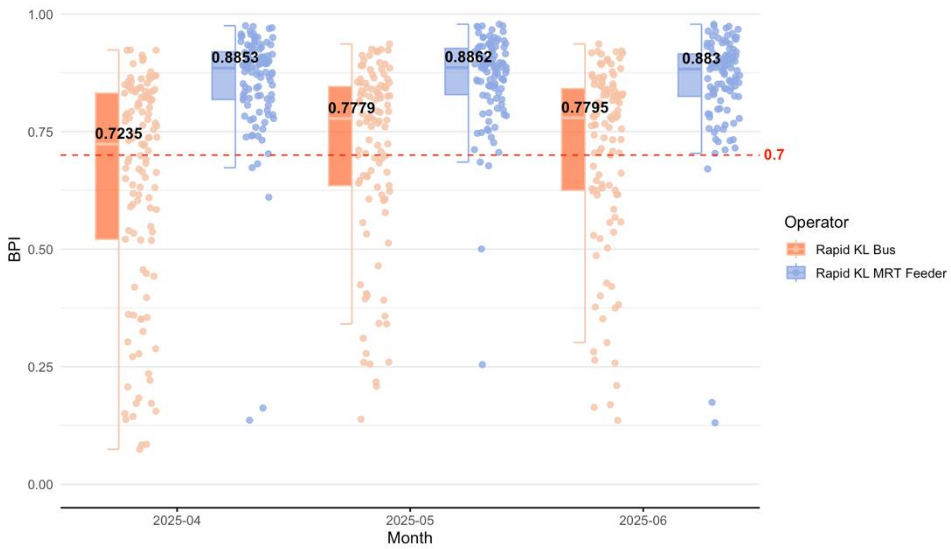


Figure 4.1.12: Distribution of Bus Performance Index (BPI) for non-zero scoring Rapid KL Bus routes and Rapid KL MRT Feeder routes, from April to June – Boarding Perspective.



Median performance is higher for Rapid KL MRT Feeders (~0.88) than for Rapid KL Bus (0.72-0.78), and Rapid KL Bus exhibits a much longer tail. For commuters, this means that while most routes are serviceable, certain Rapid KL Bus routes remain fundamentally unreliable.

Notably, the majority of routes cluster towards the higher end of BPI throughout the observation period, indicating that after excluding the zero scores, both Rapid KL Bus and Rapid KL MRT Feeder network to exhibit relatively high efficiency when both punctuality and variability in bus arrivals are considered. These findings are consistent with Table 1, which shows that performance levels of 70% to 80% are typically achievable in large cities mainly served by Rapid KL Bus, while levels of 80% to 90% are more common in small to medium-sized cities, aligning with the Rapid KL MRT Feeder's role of bridging people to MRT stations. Additionally, the inter-quartile ranges are relatively thicker compared to Rapid KL MRT Feeder services, reflecting greater variability in performance across routes.

Although the median and overall spread of Rapid KL Bus performance remained largely stable over the observation period, the interquartile range has slightly narrowed, indicating that most routes have become more similar in performance. However, the long tail on the lower end of *I* persists, implying that a portion of the routes continue to exhibit low performance.

The wider scatter in Rapid KL Bus routes likely stems from several structural factors, including longer route lengths, and greater exposure to mixed-traffic congestion. By contrast, Rapid KL MRT Feeder routes are shorter, more tightly integrated with rail stations, and often run or corridors with better operational control. These institutional and infrastructural differences explain why punctuality and variability differ despite overall system averages appearing close to one another.

5. Limitations

The study faces several important limitations. First, we rely on GTFS datasets as our primary data source. While these data provide detailed operational logs, they are also susceptible to technical errors such as irregular signal loss or missing records for certain cycles. Such issues can compromise the precise identification of arrival times. Although filtering and preprocessing were applied to mitigate these errors, some residual errors may persist in timestamp accuracy. Additionally, the accuracy of GPS coordinates can vary across space. In dense urban areas, signal obstruction from surrounding structures may reduce positional precision.

Second, the framework assumes that each route contains a sufficient number of operating cycles to support robust analysis. The computation of Bus Performance Index (I) depends heavily on stop-level data, but in practice, some routes lack adequate recorded arrivals due to data gaps. As a result, performance estimates for those routes may not fully reflect operational realities. For example, on 23-04-2025, the lack of adequate arrivals impeded the calculation of BPI for many routes.

Third, the scope of the index is restricted to two systems under MyRapid: Rapid KL Bus and Rapid KL MRT Feeder services. Other providers such as GoKL and SmartSelangor, were excluded due to data access limitations. In addition, incomplete daily records for some routes during the observation period further limit the comprehensiveness of the analysis.

Finally, the index focuses on punctuality and variability. It does not incorporate other crucial dimensions of service quality such as passenger comfort, load factor, waiting-time variability, or perceptions of safety and comfort. For that, refer to our working paper titled "Greater Kuala Lumpur's Public Transportation and its Viability: A Qualitative Study[40]."

6. Key Finding and Discussion

6.1. Summary of Key Findings

The study demonstrates that from the perspective of commuters waiting to board, Rapid KL Bus services performs less reliably than Rapid KL MRT Feeder services. Although certain Rapid KL Bus routes achieve relatively high BPI, significant inconsistencies persist across the service network. For commuters, these inconsistencies translate into unreliable journeys, longer waiting times, and the need to allocate buffer time. This reinforces the perception that busses are not dependable.

The BPI provides a replicable and scalable framework to measure these patterns. Despite limitations, the index captures both punctuality and variability for moments when bus services operate normally, offering a wider view of reliability that extends beyond traditional OTP measures.

6.2. Policy Implications

Three tiers of implications follow from these findings. First, **Institutionalize reliability monitoring**. The BPI provides authorities with a practical diagnostic tool that can be embedded into dashboards. Regular monitoring at the route level would allow early detection of deteriorating services, enabling corrective action before commuter trust erodes such as using

[40] Shukri Mohamed Khairi and Gregory Ho Wai Son (2025)

demand control strategy whereby the buses are being control by applying both real time information and schedule.

Second, **target weaker routes with operational reforms.** Roughly one-third of Rapid KL Bus routes collapse into zero performance. These should be prioritized for targeted interventions. Three operational strategies stand out:

(i) Timetable revision using real-time data: Aligning schedules with actual observed conditions can correct systemic under- or overestimation of travel times on part of the commuter. This helps diffuse commuter tension and stress that arise from their plans falling apart.

(ii) Real-time passenger information: Providing live updates via apps and bus stop displays reduces uncertainty and gives commuters a sense of control.

(iii) Conditional Transit Signal Priority (TSP) + Designated Bus lanes: Adjusting traffic lights when busses approach intersections can substantially reduce travel times and lateness, with minimal impact on general traffic. This effectively makes the bus operate like a train.

Finally, **Integrating with wider transport planning**. Rapid KL MRT feeder services show that shorter routes, tightly coupled with rail, can achieve higher reliability. Scaling this principle through stronger feeder coverage, integrated scheduling and potential BRT expansion would maximize returns on Malaysia's rail investment and support a national shift away from car dependence.

6.3. Broader Relevance

The findings underscore that reliability is not merely a technical metric, but a determinant of public confidence. Malaysia's progress towards SDG11.2 depends as much on the predictability of everyday services as on infrastructure expansion. By embedding reliability monitoring into planning and deploying targeted reforms, policymakers can strengthen commuter trust, improve inclusivity for peri-urban riders and ensure that Malaysia's urban transport investments deliver on their intended goals

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8. Appendix

8.1. Appendix 1: Filtering and Preprocessing Cycle for Rapid KL MRT Feeder

This section presents the preliminary results of cycle extraction for Rapid KL MRT Feeder. Similar to Rapid KL Bus, the analysis began by identifying all extractable bus cycles from the GTFS real-time (GTFS-r) data, defined as the sequence of a bus's movement from its first stop to its final stop within a single service cycle.

Figure 8.1.1: The number and percentage of normal cycles out of extractable cycle obtained each month (Rapid KL MRT Feeder).

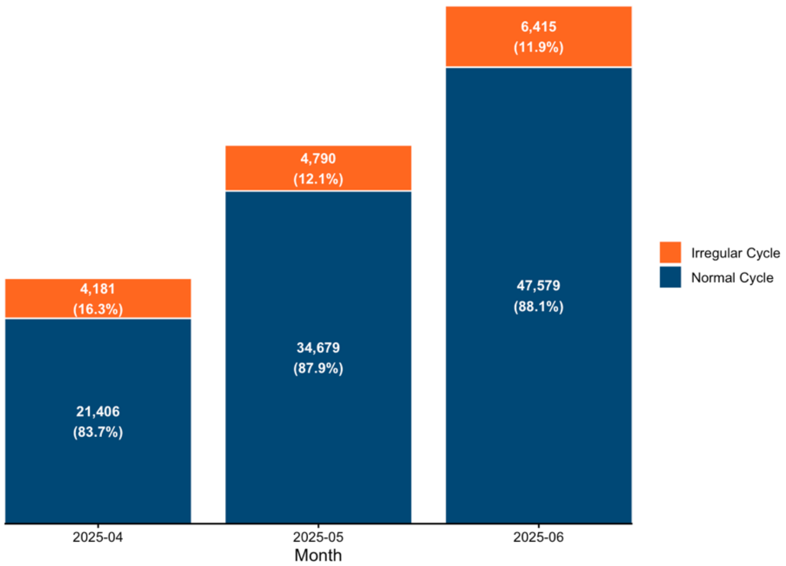


Figure 8.1.1 shows the distribution of extractable bus cycles for Rapid KL MRT Feeder identified by the algorithm developed in this study. Unlike Rapid KL Bus, the Rapid KL MRT Feeder exhibits a different pattern in the GTFS real-time (GTFS-r) dataset. As a result, the days selected for the observation period differ from those for Rapid KL Bus in order to capture representative service cycles while maintaining consistency in the analysis. These normal cycles consistently make up more than 80% of all identified cycles each month similarly to Rapid KL Bus, indicating that the majority of bus movements adhere to scheduled patterns. While the total number of extractable cycles varied each month, the proportion of normal cycles remained stable. From these, only normal cycles which are those that follow the expected stop sequence and timing based on the GTFS-static (GTFS-s) stop times, to determine the number of valid cycles for further analysis.

Figure 8.1.2: The number and percentage of valid cycles out of normal cycle obtained each month (Rapid KL MRT Feeder).

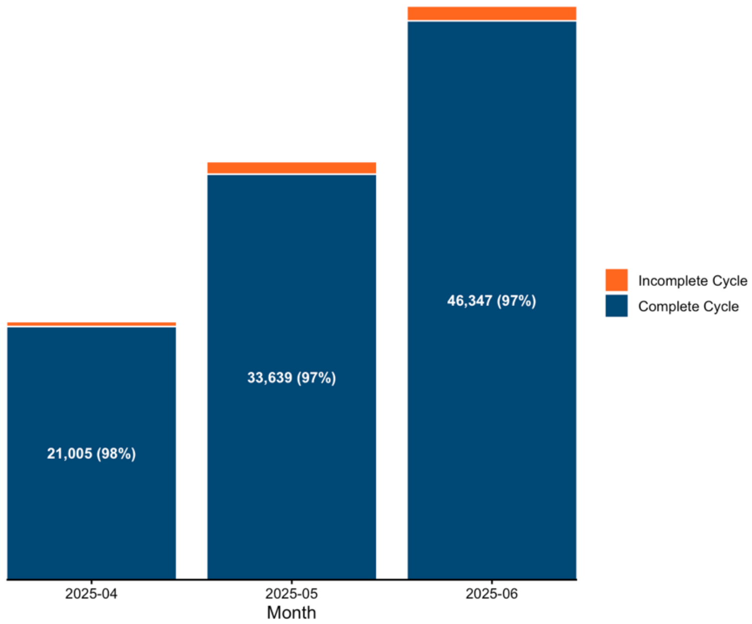
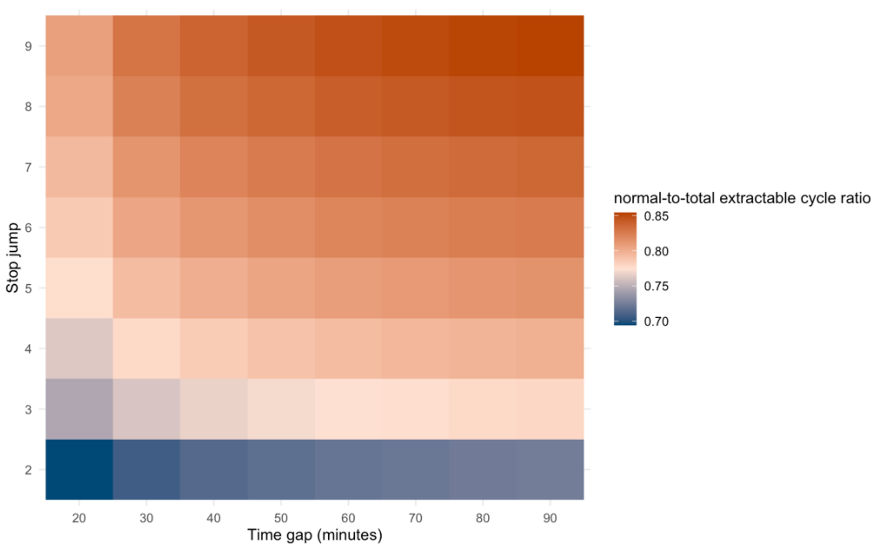


Figure 8.1.2 presents the distribution of complete and incomplete cycles out of normal cycles for Rapid KL MRT Feeder buses identified during the observation period. Overall, Rapid KL MRT Feeder contained at most 3% incomplete cycles, performing significantly better than Rapid KL Bus, which saw incomplete cycles spike up to 36%.

8.2. Appendix 2: Threshold analysis on time gap and stop jump parameters

Figure 8.2.1 presents a sensitivity analysis of the threshold parameters used in bus cycle classification, showing normal to total cycle ratio across different combination of time gap and stops jump thresholds. For small stop jump thresholds (≤ 4), the normal ratio is low, suggesting that these value are overly restrictive and may misclassify normal bus cycle as irregular. Similarly, for larger time gap threshold (> 60 minutes), the normal ratio inflates, which may mask genuinely irregular cycle. Hence, a stop jump threshold of 5 and time gap 60 minutes to balance both sensitivity and robustness.

Figure 8.2.1: Sensitivity Analysis of Time Gap and Stop Jump Thresholds.



8.3. Appendix 3: Temporal holdout validation of Bus Performance Index (BPI)

Table 5 describes the coefficients of our regression for temporal holdout validation. Similarly, coefficients were estimated separately for Rapid KL Bus and Rapid KL MRT Feeders to reflect operator-specific conditions.

Table 5: Rapid KL Bus service and Rapid KL MRT Feeder service (Temporal)

	Dependent variable:	
	$\log(f(\mathrm{OTP}, \tilde{r}_{\mathrm{MAE}}))$	
	Rapid KL Bus service	Rapid KL MRT Feeder service
log(OTP)	1.019***	1.175***
	(0.006)	(0.028)
$\tilde{r}^2_{\mathrm{MAE}}$	−2.594***	−3.274***
	(0.031)	(0.053)
$\tilde{r}_{\mathrm{MAE}}$	5.247***	6.511***
	(0.040)	(0.074)
Constant	−2.713***	−3.264***
	(0.012)	(0.026)
Observations	2,792	2,174
R^2	0.978	0.922
Adjusted R^2	0.978	0.922
Residual Std. Error	0.081 (df = 2788)	0.074 (df = 2170)
F Statistic	41,686.980*** (df = 3; 2788)	8,587.105*** (df = 3; 2170)
Note:		*p<0.1; **p<0.05; ***p<0.01

Temporal Holdout Validation

To evaluate predictive performance and avoid overfitting, the second approach is to validate using monthly dataset into estimation and validation subsets. Coefficients were estimated using April and May dataset as estimation sample and then applies to June dataset as validation sample. This procedure evaluates whether the functional form of BPI remains stable over time when applied to future data, providing evidence that the model generalizes beyond the estimation period. The following tables present results from error metric to assess the accuracy of predictions.

Table 6: Error metric for Rapid KL Bus service and Rapid KL MRT Feeder service

	Metric	Rapid KL Bus service	Rapid KL MRT Feeder service
1	MAE	0.021	0.018
2	RMSE	0.025	0.024
3	MAPE (%)	4.460	3.059
4	R-squared	0.987	0.975

The results indicate that both models perform well on both training and test sets, with high R^2 values and low prediction errors.

8.4. Appendix 4: Further analysis on the impact of peak and non-peak hour on bus performance

Figure 8.4.1, 8.4.2, and 8.4.3 presents the distribution of BPI values for both services from the perspective of commuter waiting to board a bus on morning peak hour, evening peak hour, off peak hour, respectively. Here, morning peak hour are defined from 6 A.M. to 9 A.M, while evening peak hour are considered from 5 P.M. to 8 P.M., otherwise it is considered as off peak hour. Interestingly, there are no significant differences between the performance of both bus service during peak hour or non-peak hour, suggesting that it is network wide issue rather than time specific issue.

Figure 8.4.1: Distribution of Bus Performance Index (BPI) for non-zero scoring Rapid KL Bus routes and Rapid KL MRT Feeder routes, from April to June (morning peak).

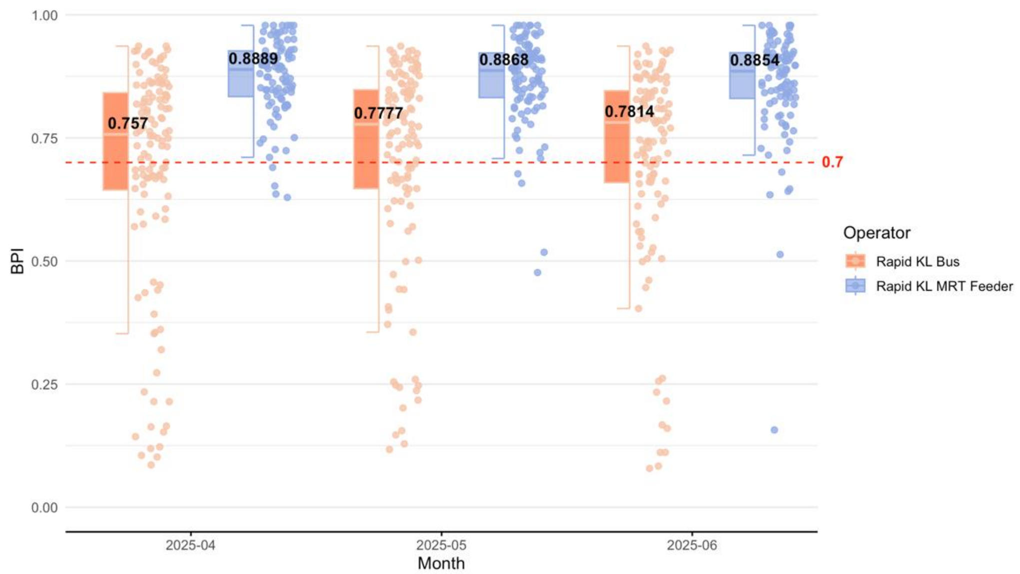


Figure 8.4.2: Distribution of Bus Performance Index (BPI) for non-zero scoring Rapid KL Bus routes and Rapid KL MRT Feeder routes, from April to June (evening peak).

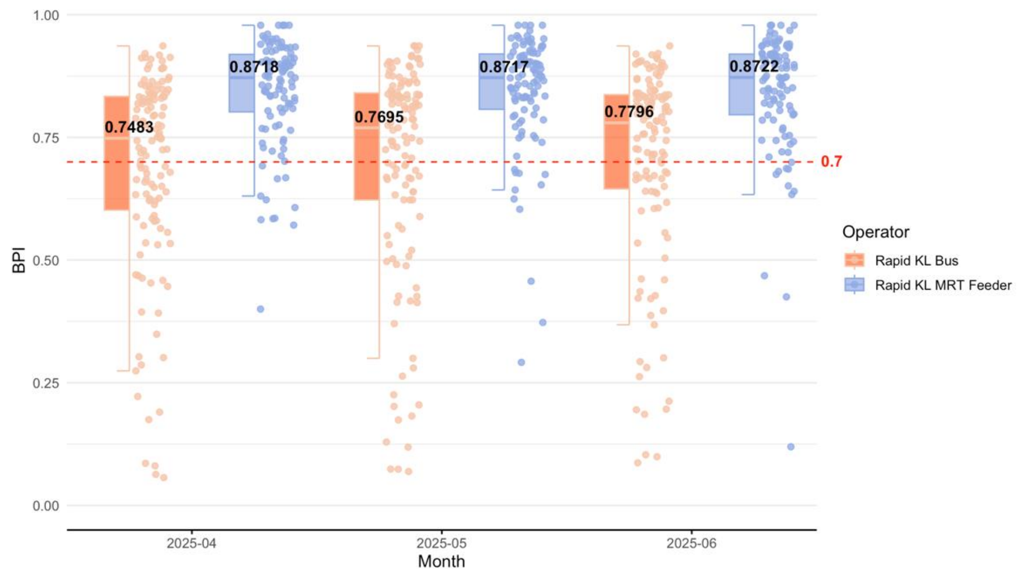


Figure 8.4.3: Distribution of Bus Performance Index (BPI) for non-zero scoring Rapid KL Bus routes and Rapid KL MRT Feeder routes, from April to June (off peak).