MnDOT's Mobility-as-a-Service Platform: Assessing User Behavior and Measuring System's Benefits

Final Report

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A Mobility-as-a-Service (MaaS) platform was implemented in Southern Minnesota to streamline transit use and promote rural transit use, incorporating features like interactive trip planning and mobile payment. The project commenced with an area analysis, followed by a literature review highlighting MaaS’s potential benefits for rural regions. Pre-deployment ridership data analysis revealed the impact of COVID-19 and seasonal variations on mid- and long-term ridership trends. Analysis of reservation and ride data provided insights into transit use patterns and user/operator experiences, informing areas for improvement through MaaS deployment. The post-deployment analysis employed a time series model to estimate MaaS’s impact on ridership, showing a notable average monthly increase of 4.2% for demand-responsive transit (DRT) and paratransit services over nine months, compared to a marginal 0.2% rise in the control group. In addition, a before-and-after study of trip location data demonstrated MaaS’s efficacy in boosting transit service rates in areas with socioeconomically disadvantaged populations, underscoring its equity-driven effectiveness.

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MNDOT’S MOBILITY-AS-A-SERVICE PLATFORM: ASSESSING USER BEHAVIOR AND MEASURING SYSTEM’S BENEFITS

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EXECUTIVE SUMMARY

In March 2023, a Mobility-as-a-Service (MaaS) platform was implemented in rural areas of Southern Minnesota. This innovative platform integrates interactive trip planning, mobile payment, and demand response transit (DRT) booking features, aiming to enhance the rural transit user experience and encourage more use of transit. This study begins by outlining the study area and delineating the types of transit services provided by various operators in the region. Subsequently, a comprehensive literature review identifies the positioning of the Southern Minnesota MaaS platform within the broader context of MaaS conceptualization, elucidating the anticipated impacts of its implementation in the study area.

Central to the study is a before-and-after analysis evaluating the efficacy of the MaaS deployment. This assessment leverages two primary datasets collected before and after the MaaS rollout. The first dataset comprises monthly ridership statistics from the National Transit Database (NTD), offering insights into ridership trends across different transit service types and agencies. The second dataset, named the origin, destination, and reservation (ODR) data, provides detailed observations of transit reservations and trips over two one-week periods, spanning both pre- and post-MaaS deployment phases. These datasets serve as crucial analytical tools in gauging the tangible benefits and outcomes of the MaaS initiative on rural transit operations and user behavior.

SUMMARY OF MAAS PRE-DEPLOYMENT ANALYSES

The analysis of pre-deployment NTD ridership data provides valuable insights into the long-term trends in transit ridership within the region, with particular consideration of the disruptive impact of the COVID-19 pandemic. Post-pandemic, overall transit ridership decreased while the average distance traveled per trip increased. This pandemic effect varied across different service types, with bus-based transit, including fixed routes (-55%) and route deviation services (-25%) experiencing more substantial ridership losses compared to DRT, which saw a modest decline of -11% compared to pre-pandemic levels. In addition, a comparison at the transit agency level reveals varying degrees of recovery, with some agencies nearly reaching or exceeding pre-pandemic ridership levels. Statistical tests were employed to discern whether the observed long- and mid-term ridership changes differed significantly by agency and service type, underscoring the necessity of independent analyses for different service types and an adjustment of seasonal ridership variations to isolate the pure impact of MaaS deployment.

Conversely, the examination of pre-deployment ODR data focused on elucidating user and operator experiences prior to the MaaS platform launch, identifying areas for improvement and potential enhancements with MaaS integration. Analysis of demand patterns revealed distinct hourly demand distributions. The demand for DRT services exhibited patterns with no clear morning peak; only 12% of trips occurred between 7 and 10 AM. Conversely, the midday period (10 AM – 2 PM) accounted for 54% of total DRT travel. In comparison, bus-based transit services showed a morning peak concentration of 27%, with midday demand comprising 41%. Analyzing the reservation experience for DRT users using ODR data revealed significant insights. This dataset includes timestamps such as the Preferred Departure Time (PDT) submitted by passengers and the Scheduled Departure Time (SDT) assigned by agencies. Schedule displacement, calculated as SDT subtracted from PDT, highlights user inconvenience when trips do not align with their desired times. Analysis indicated that approximately 32% of users experienced schedule displacement exceeding 30 minutes, underscoring a notable area for improvement in service delivery.

Moreover, by examining the temporal gap between reservation/cancelation and actual trip dates, we discovered that same-day DRT dispatch requests constituted over a third of all reservations. Similarly, trip cancellation requests were concentrated on earlier dates, with more than three-quarters targeting same-day trips. This drive another potential of MaaS, which lies in its ability to automate real-time requests, allieviates the burden on transit agencies, especially in efficiently handling imminent trip requests with shorter preparation times.

Further analyses of the pre-deployment ODR dataset encompassed various aspects, including the distribution of DRT users' waiting times, comparison of DRT service speeds to personal car travel, day-of-week distribution of trip requests, trip distances, and the proximity of DRT pick-up and drop-off locations to existing bus stops. These analyses identified several opportunities for MaaS deployment in rural areas, highlighted by the potential to enhance convenience and efficiency through automated vehicle dispatching and trip cancellation processes, provision of real-time information and on-trip notifications, and facilitation of intermodal connections to streamline rural transit operations.

SUMMARY OF MAAS POST-DEPLOYMENT ANALYSES

Following the extension of NTD ridership data collection to months post-MaaS deployment, our methodology initially involved defining a control group comprising transit agencies in Minnesota without access to a MaaS platform. Collectively, these agencies represented the ridership characteristics of the target group, consisting of the Southern Minnesota transit agencies where MaaS had been deployed. Through ridership standardization and creating seasonal plots, we identified the time point from which monthly ridership trends began to mirror pre-deployment seasonal patterns and stabilized. Using the time-filtered data inputs, we applied seasonal-trend decomposition to adjust for predictable variation. The seasonality-adjusted ridership revealed that the target group experienced increases in DRT and paratransit ridership following MaaS feature deployments, whereas the control group exhibited no such trend. These findings strongly suggest a positive correlation between MaaS implementation and ridership growth, a conclusion bolstered by a statistical time series model. Analysis of the model's output revealed a notable net impact of MaaS deployment, with DRT and paratransit experiencing a significant average seasonality-adjusted monthly ridership increase of 4.2% over nine months post-deployment, in contrast to the control group's marginal 0.2% rise.

Due to the MaaS platform's incomplete functionality at the time of post-deployment analyses, the comparison of the pre-and post-ODR dataset's user experience provided limited insights. However, certain implications were discerned. The trip-planning feature of MaaS notably altered the hourly distribution of agency call-in times; post-deployment, there was less concentration of calls in the early morning, coinciding with the transit agency's daily operations commencement and contrasting with the high concentration observed in the pre-deployment period. Moreover, when using origin-destination locations stored in the ODR datasets, it was noted that several equity scores experienced improvement after the MaaS deployment. Of particular significance was the substantial increase in equity scores related to language barriers, indicating MaaS's potential in addressing communication challenges within transit services. Conversely, as anticipated, the equity score concerning service for individuals with limited internet access demonstrated the least improvement, given MaaS's reliance on a stable internet connection.

While the deployed MaaS platform has demonstrated success in increasing ridership, there is still ample room for improvement. To maximize social benefits, additional features and integration of social goals within the system are necessary. Rural MaaS initiatives present numerous untapped opportunities awaiting further exploration and development.

CHAPTER 1: INTRODUCTION

The advent of smartphone technology and the emergence of internet-of-things have made new and integrated transportation options available. A significant breakthrough in this domain is the rise of Mobility-as-a-Service (MaaS). This integrated platform presents multiple available transportation options and allows their booking/e-ticketing with a smartphone application (app). While MaaS has primarily been developed and deployed in urban areas, it also has potential benefits for rural areas [1-3].

First, MaaS can improve access to transportation options and reduce the isolation of rural communities. Relatively less extensive transit infrastructure in rural areas makes it difficult for residents to access essential services such as healthcare, education, and grocery shopping. This expected benefit of MaaS can also be observed from an equity perspective, as it is more challenging for people who do not have access to a personal vehicle or who cannot drive.

Second, MaaS can improve the passenger experience when planning trips and rides. The app can reserve an optimal, tailored transit itinerary and process electronic fare payments, requiring less passenger input and effort. Without a MaaS platform, rural transit users may actively acquire timetables, service areas, and fare schemes, buy transit tokens in advance, and then book some of their trip legs with phone calls. These steps become significantly more difficult if they want to plan a transfer from one agency's service to another.

Third, MaaS can offer cost savings and decrease burdens for transit agencies by automating reservations, distributing call demands, and dispatching vehicles with higher coordination to increase vehicle use rates and/or the number of trips served to passengers. For example, a MaaS app can recommend a transit path that is partially served by demand response transit (DRT), and then the remaining trip leg to be facilitated by a fixed-route bus. The shortened DRT operation with the saved travel time can then be used to pick up another passenger in the queue. These would make the DRT services available to more passengers and can collectively reduce the total vehicle miles traveled (VMT) systemwide.

This study aims to assess the benefits of deploying a MaaS app in Southern Minnesota, where the app deployment is expected to impact people's travel behavior and transit use experience. The study area is served by seven different transit agencies, covering two medium-sized cities (Rochester and Mankato) with multiple fixed bus routes, five small-sized cities with one or two fixed bus routes available within each city, and the surrounding rural areas.

In the two medium-sized cities, fixed-route buses operate with varying frequencies, ranging from a 20-minute headway to only a few daily services. In contrast, all small-sized cities have fixed bus routes with circular vehicle itineraries that operate on an hour's headway. For the bus routes of small-sized cities, passengers can request slight deviations from the route if the request does not significantly affect the bus schedule (route deviation service). Transit agencies in our study area also provide reservation-based DRT services that offer door-to-door transportation for passengers with some service area restrictions.

The service area or geographical coverage of each transit agency's DRT services and the cities with fixed bus routes are presented in Figure 1-1.

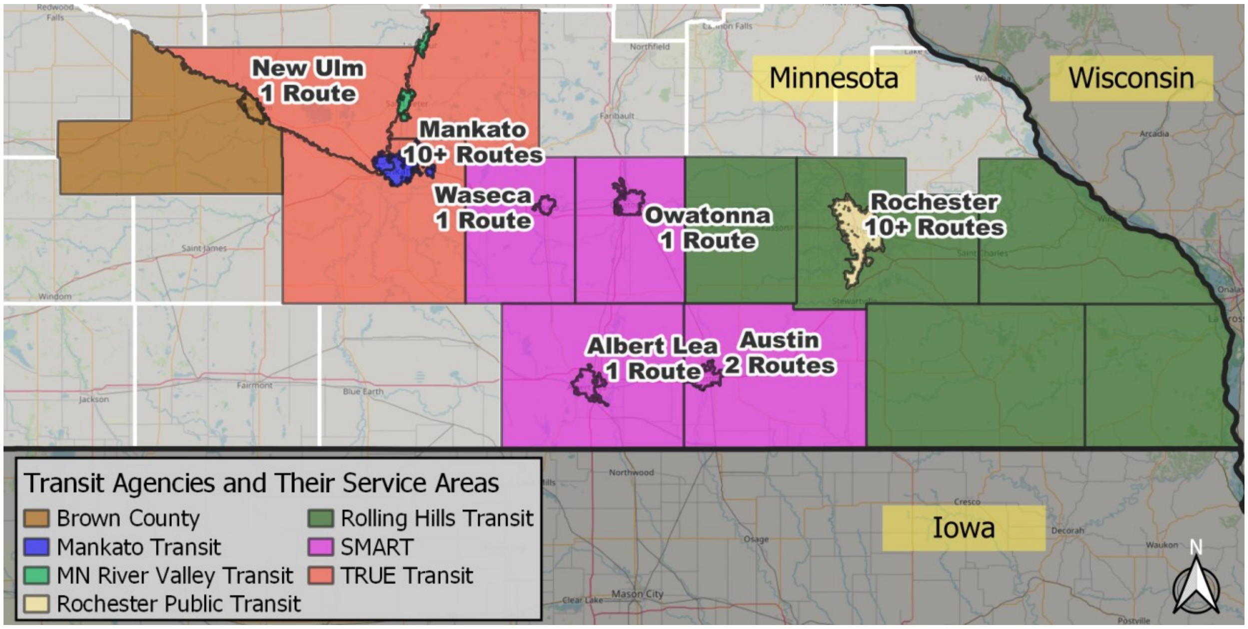


Figure 1-1 Service area of the participating transit agencies and cities with bus services

The passenger experience for most DRT and route deviation services can be divided into the Reservation and Ride stages. Before the MaaS app deployment, passengers would first search which transit agency serves their origin and to what extent their services cover. They then call the transit agency to request a ride in the reservation step. We define the call-in time as "reservation request time" or RRT. During the phone call, the passenger submits their origin, destination (OD), and preferred departure time (PDT) to the agency's call receptionist. Depending on the agency's policies and dispatch capability, they might immediately notify passengers of the scheduled departure time (SDT) at their origin, which could differ from the PDT. Alternatively, agencies might collect multiple requests from multiple calls, optimize future dispatches, and notify passengers of the confirmed departure schedule later. In the ride stage, passengers typically arrive at their requested origin around the PDT and sometimes have to wait for additional time due to delays. They would board the vehicle at the actual pickup time (APT), make a payment, and alight at the actual dropoff time (ADT). These typical passenger experiences before MaaS are illustrated in Figure 1-2.

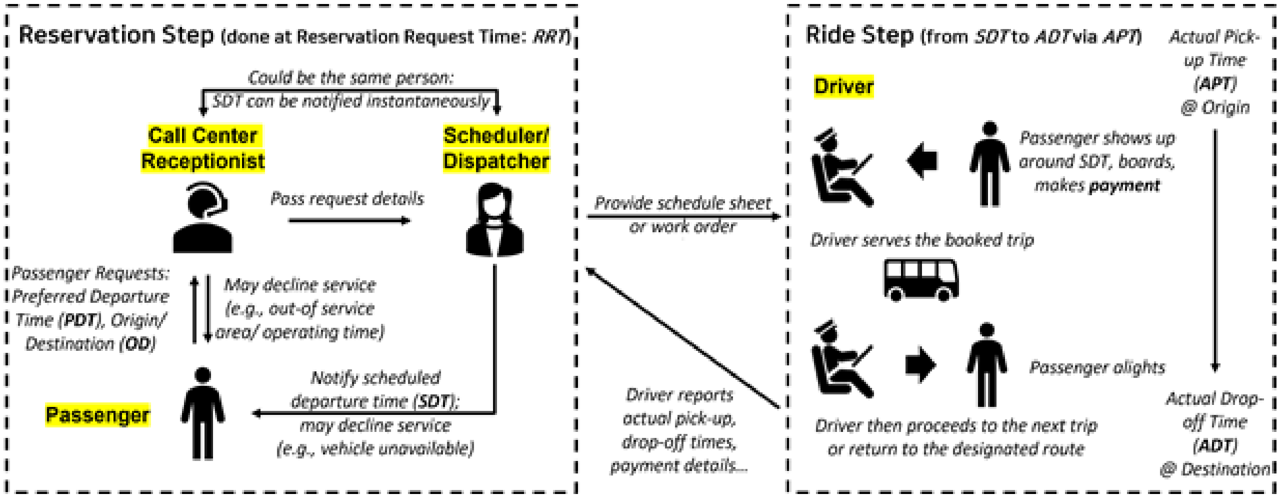


Figure 1-2 Typical steps of using DRT and route deviation services

Conceptually, the MaaS platform can simplify finding and reserving transportation services through a passenger's smartphone or website by providing information on transit service areas, operating times, and dispatch availability. This eliminates the need for lengthy phone calls and decentralized internet searches. Passengers can also enjoy features such as travel summaries, electronic payments, and real-time vehicle locations, enhancing their transit experience.

In the study area, the deployment of the MaaS platform, along with its respective features, occurred at different times and locations. Table 1-1 provides an overview of the deployment calendar, highlighting the activation dates for each feature across the agencies. Among different transit services, conventional rural transit services (DRT, fixed route, route deviation) and Rochester's ADA paratransit service are available on the platform. Additionally, by partnering with bike/scooter sharing services and intercity bus lines, the app offers tailored trip plan functionality for some cities, significantly improving accessibility. For instance, one can plan an intermodal trip with MaaS consisting of taking a DRT from a rural origin to a nearby intercity bus stop and then transferring to the regional bus to get to places such as Minneapolis-St. Paul International Airport or the Twin Cities Area.

Table 1-1 MaaS activation date by agency and feature

Agency Name	App Trip Planner	Ticket Sales	Web Trip Planner	DRT Booking in the App
Rochester Public Transit (fixed routes, paratransit)	4/15/2023	NA	8/1/2023	1/3/2024
Lime bike/scooter (City of Rochester only)	5/1/2023	NA	NA	NA
Mankato Public Transit (fixed routes, DRT)	3/1/2023	5/1/2023	8/1/2023	NA

SMART (DRT, route deviation)	3/1/2023	3/1/2023	8/1/2023	NA
Brown County (DRT, route deviation)	3/1/2023	NA	8/1/2023	NA
MRVT (DRT)	3/1/2023	NA	8/1/2023	NA
TRUE Transit (DRT)	3/1/2023	NA	8/1/2023	NA
Rolling Hills (DRT)	3/1/2023	3/1/2023	8/1/2023	1/3/2024
Land-to-Air (Intercity routes)	10/31/2023	NA	10/31/2023	NA

Based on the context provided, the subsequent sections of the report encompass a literature review on MaaS, detailing the anticipated benefits of its deployment. This is followed by a pre-deployment analysis using two distinct data sources to elucidate the current transit trip patterns within the study area and identify avenues where MaaS adoption and advancement could benefit residents. Finally, in the post-deployment before-and-after analysis, we leverage the same data sources for the post-MaaS deployment period and present quantitative assessments of the ridership gains brought by MaaS and its impact on equity measures.

CHAPTER 2: LITERATURE REVIEW

The definition of MaaS has been a topic of debate, and MaaS services conceptualized/deployed around the world varied in terms of characteristics of service areas, multimodal coverage, level of integration, and app features. To understand the expected benefits of the deployment, it is crucial to identify which type of MaaS it is. Sampo Hietanen, the inventor and pioneer of MaaS, defined MaaS as “A mobility model in which a customer’s major transportation needs are met over one interface and are offered by a service provider, where the services tend to be bundled into a package” [4]. The more recent MaaS definitions include “Digital platforms through which people can access transportation using a system that integrates planning, booking, and paying” [5] and “A framework for delivering a portfolio of multimodal mobility that can operate at any spatial scale, cover any combination of service offerings” [6]. There are tens of more definitions available in the field, which can be found in Hensher [7].

As there is no universal consensus on the definition of MaaS, the MaaS topology and looser notions have been proposed for broader service inclusion and better classification. Sochor et al. [8] proposed a MaaS classification method that assesses the level of service integration (Figure 2-1). Also, Holmberg et al. [9] suggested that a transport platform or app can be considered MaaS if it contains one or both of the following constituents: (1) a Combined Mobility Service that provides a subscription and packaging of included services, (2) Integrated public transport gives the users the possibility to plan, book, and pay for the whole journey.

Figure 2-1 Proposed topology of MaaS, with integration levels 0-4 (Sochor et al., 2018)

The general expectation of MaaS deployment benefits can be stated as follows: The use of MaaS can encourage customers to use services they would not normally use [10] and lead to an increase in the frequency of sustainable transport [11], by presenting alternatives in the highly complex decision-making system, which a large number of existing local transit operators are currently unable to provide [12]. The categorized, detailed benefits of MaaS deployments can be found in the extensive review paper by Maas [13]. They classified studies on MaaS into 19 categories, where each of the 127 studies can be a member of multiple categories. The following are some findings about user characteristics, willingness-to-pay, impacts, and benefits of MaaS suggested in Maas [13].

- Younger and middle-aged groups mainly used MaaS (5 studies).
- Families with children used MaaS significantly less frequently (3 studies).
- Users with multimodal platform experience are more likely to adopt MaaS (2 studies).
- Users' higher education level, frequency of car sharing usage, environment-friendly attitude, and desire to reduce car use positively affected the MaaS usage (3 studies).
- If users are satisfied with their existing mobility situation, there is no motivation to shift their behavior, especially for private car users or frequent transit users (5 studies).
- A general tendency towards subscriptions in the transport sector is low; sometimes, bike/e-bike sharing and taxis were related to a negative willingness to pay when included in a MaaS bundle or subscription (2 studies).
- There was little or no willingness to pay for the use of a transport app per se, but it provides incentives to use alternative modes (2 studies).
- MaaS is commonly referred to as an instrument used to solve first- and last-mile problems in the literature (1 study).
- The integration of carpooling and MaaS shows promising results for areas with little access to public transport (1 study).
- The introduction of MaaS could result in a shift from a private vehicle, especially for commuting/repeated trips (2 studies).
- MaaS should rather be marketed as a replacement for the second car in a household/complementary service (1 study).
- Deploying a MaaS platform is not enough to achieve significant changes in user behavior (2 studies).

However, the majority of conceptual/actual MaaS systems analyzed above are cases postulated/deployed for urban settings. Meanwhile, researchers and practitioners agree that the lack of existing infrastructure in rural areas poses great challenges for MaaS deployment [14]. Even so, some studies focused on MaaS in rural areas and distinguished it from urban MaaS. Eckhardt et al. and Barreto et al. [2, 15] suggested that rural MaaS would look different than urban or suburban areas, and DRT services would be the main components of rural MaaS. Other rural MaaS deployment cases and their level of integration are summarized in Mulley et al. [16].

The Southern Minnesota MaaS platform (app) allows users to plan, book, and pay for transit trips in small cities and rural areas, focusing on DRT and route deviation services. Applying the precise MaaS definitions, it could not be a full-featured MaaS as it does not have private modes integrated, and no subscriptions/bundling is available due to the existing transport infrastructure in the region (e.g., limited numbers or inexistence of car/bike/scooter sharing). Nevertheless, the Southern Minnesota MaaS can still be classified as level 2 rural MaaS based on the definition suggested by many papers. We could evaluate its impact by criteria the literature suggests for such MaaS deployments: how it improves residents’ accessibility, how it increases transit ridership, and how the features of the platform are efficiently designed.

CHAPTER 3: PRE-DEPLOYMENT ANALYSIS

The primary goal of the MaaS pre-deployment analysis is to identify the potential benefits of MaaS deployment by documenting historical/recent transit travel patterns in the Southern Minnesota region. Some of the results will be compared with post-deployment analysis in the subsequent section to measure the impact of MaaS.

3.1 DATA

Two datasets have been acquired in preparation for the pre-deployment and before-and-after studies. One dataset is from the National Transit Database (NTD) administered by the Federal Transit Administration (FTA). The other dataset is manually collected field data by transit agencies for a few weeks of pre- and post-MaaS deployment phase as part of this study. We named it the Origin, Destination, and Reservation (ODR) dataset.

3.1.1 National Transit Database (NTD)

The NTD is a centralized database that contains financial, operating, and asset information for public transit systems across the United States, including urban, rural, and specialized systems. Among many available data tables in NTD, this project utilized Service Level Ridership tables, which group each agency's monthly transit ridership and mileages by route or service. We collected the seven agencies' service level ridership tables from January 2018 to January 2023. By doing so, we could track ridership levels both in the short term and the long term, with and without considering the impact of COVID-19. Table 3-1 summarizes NTD's January 2023 monthly aggregated statistics of each agency's routes whose monthly ridership exceeds 20 passengers.

Table 3-1 Summary of January 2023 NTD service level ridership tables in the study area

Transit Agency	Service Type	Number of Passenger Trips	Vehicle Miles Traveled with Passengers	Vehicle Hours Traveled with Passengers
Brown County	DRT	3,411	15,740	978
	Route Deviation	296	3,394	234
Mankato Transit*	DRT	569	4,363	242
	Fixed Route	41,104	29,368	2,503
	ADA Paratransit	2,247	12,021	833
MN River Valley Transit (MRVT)	DRT	5,562	9,620	1,167
Rochester Public Transit	Fixed Route	83,741	127,395	8,501

	ADA Paratransit	3,054	22,069	1,601
Rolling Hills Transit	DRT	4,535	23,249	2,282
Southern MN Area Rural Transit (SMART)	DRT	10,757	34,350	2,939
	Route Deviation	10,076	21,624	1,920
TRUE Transit	DRT	908	16,051	750

**Note: Mankato Transit's ADA paratransit services were not integrated into the Southern Minnesota MaaS platform, but the analysis of this service type is included in this pre-deployment analysis chapter for a general understanding of transit usage patterns in the study area*

3.1.2 Origin, Destination, and Reservation (ODR) Data

To better understand the microscopic level of transit usage behavior and passenger experience associated with rides, we requested transit agencies to conduct a manual data collection to retrieve each ride's origin, destination, and reservation information. We named the results the ODR dataset. For the data collection, we designed a standardized worksheet for each transit service type. We asked the agencies to collect as many features as possible, considering their operational constraints, not to compromise the safety and quality of their services. Also, we gave transit agencies the flexibility to choose the data collection participating days selectively to minimize service interruption due to the data collection.

The collected features for the reservation-based services— DRT and route deviation— included the following: date and time of phone call (ride requests) received or reservation reception time (RRT), the request's intended trip date, preferred departure time (PDT), scheduled departure time (SDT), actual pickup time (APT), actual dropoff time (ADT), origin & destination (OD), fare type (cash, token, etc.), service type (paratransit, student, etc.), and some information on trip cancellations. Data collection activity for each feature varied on the existing systems of each agency. In some cases, reservation call receptionists or vehicle drivers manually collected certain features, while in others, data administrators pulled data from their agency's automated storage systems.

Meanwhile, we designed a different version of the worksheet to collect data on passengers' origin (boarding) and destination (alighting) stops for fixed-route buses. Bus drivers surveyed the alighting locations of every boarding passenger at each stop. The timestamps of boarding and alighting activities are attached later using the vehicle trip identifier and predefined timetables. Agency staff conducted the above "active" or manual data collection for some days from January 23rd to February 12th, 2023, for the post-deployment analysis. Additionally, we encouraged transit agencies to provide the "passively" collected or pullable data available in their automated data storages; it gave some agencies' ODR data collection results richer or more extensive time windows.

However, as the data collection sometimes required digitizing the information manually, there were many illogical or unreasonable records in the raw ODR data. For example, a record may have its SDT precede its RRT, which cannot happen because a scheduler/dispatcher cannot assign vehicles to the past. To fix these illogical timestamps, we identified records with impossible or impractical combinations of timestamps and then implemented a data-cleansing process. The process was devised with assumptions that (1) agencies tend to record SDT more accurately than RRT or PDT since SDT is crucial for scheduling vehicle dispatches and driver assignments, and (2) APT/ADT is more reliable than SDT because many vehicles are equipped with location tracker, and drivers are required to report them. The cleansing process was implemented in the following sequence:

- If any timestamp was in the out-of-service hour, we swapped its AM/PM designator.
- If PDT preceded the RRT, we discarded PDT.
- If SDT preceded the RRT, we discarded the RRT.
- If the time difference between PDT and SDT exceeded two hours, we deleted the PDT.
- If ADT preceded APT by less than an hour, we swapped ADT and APT.
- If in-vehicle travel time (ADT-APT) exceeded two hours, we swapped either timestamp's AM/PM. If the resultant time difference still exceeded two hours, we deleted ADT.
- If the time difference between APT and SDT was more than 30 minutes, we deleted SDT.

A total of 3,201 DRT records, including reservation or ride information or both, were collected from five of the seven participating transit agencies. Additionally, we collected 236 reservation-based route deviation requests from SMART, which had almost the same data feature specification as the DRT records. For fixed routes, 517 OD pairs from SMART (including the realized route deviation requests) and 476 daily boarding locations from Brown County were collected. The origin and destination locations are consistently recorded for nearly all reservation or ride instances, and actual departure/arrival times are for realized trips; the availability of RRT, PDT, and SDT varies across agencies and days. Table 3-2 provides an agency and service level overview of the data count, intended trip date (with the addition of "intended" to account for unrealized reservations), and availability of timestamps in the cleansed ODR dataset.

Table 3-2 Pre-deployment ODR data collection and timestamps availability summary

Transit Agency	Service Type	Data Counts	Trip-intended Dates (2023)	RRT	PDT	SDT
Brown County	DRT	158	1/30 – 2/3	74%	0%	100%
	Fixed Route/ Route Deviation*	476*	1/1 – 2/13	NA	NA	100%
Mankato Transit	ADA Paratransit	1,566	1/30 – 2/12	25%	6%	87%
	DRT	383	1/30 – 2/10	15%	9%	87%
	Fixed Route	*Not Collected*				
MRVT	DRT	1,333	2/6 – 2/14	100%	90%	90%

Rochester	Fixed Route	*Not Collected*				
	ADA Paratransit	*Not Collected*				
Rolling Hills	DRT	258	1/29 – 2/10	59%	4%	98%
SMART	DRT	833	1/30 – 2/10	71%	55%	75%
	Route Deviation	236	1/30 – 2/3	0%	100%	100%
	Fixed Route/Route Deviation*	517*	1/30 – 2/3	NA	NA	100%
TRUE Transit	DRT	*Not Collected*				

** Brown County and SMART's fixed route count includes the realized route deviation request where Brown County's route deviation reservation data itself was not collected.*

After fixing the timestamps, we implemented data anonymization for the DRT and route deviation requests, which included the exact addresses of pickup and dropoff locations. The addresses were first converted to decimal coordinates using Google Cloud Geocoding API and then rounded to the nearest ten-thousandth. The original address and the anonymized point could be displaced up to 230 ft after anonymization, making it impossible to identify the exact original location.

3.2 PRE-DEPLOYMENT MACROSCOPIC ANALYSIS WITH THE NTD

To properly assess the impact of MaaS deployment, it is crucial to track both long- and short-term fluctuations in the region's transit ridership and predict their extent in the future. This helps to account for changes in ridership due to seasonal effects and other factors that may affect ridership during the study period, even in the absence of MaaS. It should be noted that Mankato's DRT and Brown County's route deviation services began their operations in June 2019 and October 2022, respectively, while Minnesota River Valley Transit (MRVT) 's fixed route services were discontinued in March 2020. Figure 3-1 provides a summary of the region's long-term (five-year) transit monthly average ridership trends from January 2018 to December 2022, as reported by the transit agencies to NTD. The vehicle Miles Per Trip (MPT) statistics from DRT and ADA paratransit services averaged are also presented.

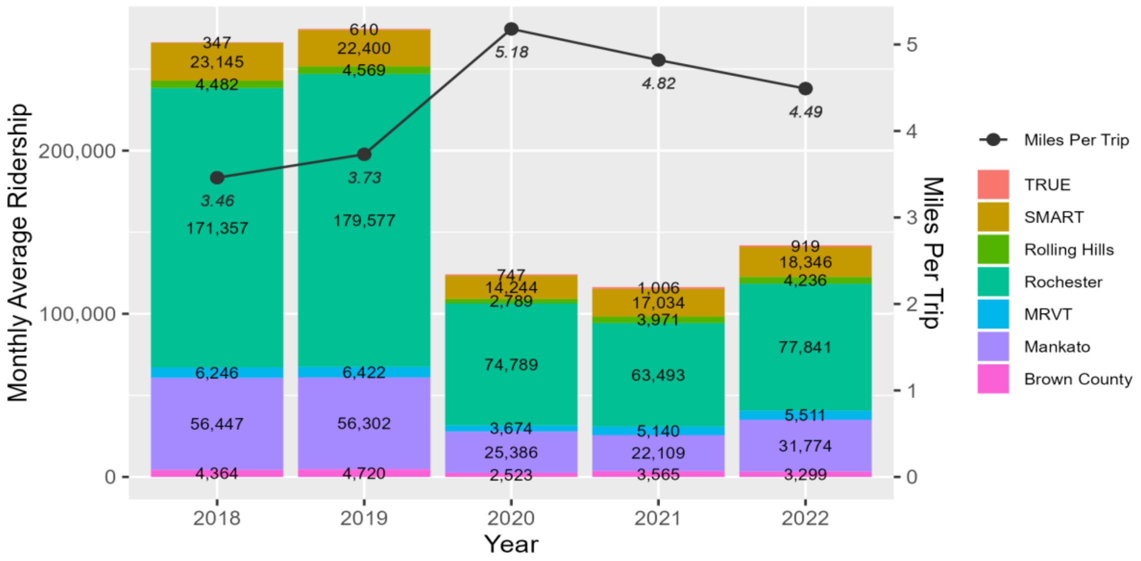


Figure 3-1 Monthly average transit ridership and MPT by agency (2018 – 2022)

The overall transit ridership of the region experienced a sharp decline during the COVID-19 pandemic (2020, 2021), whereas MPT peaked during the pandemic. While the region's total ridership slightly rebounded in 2022, it has not yet fully recovered to pre-pandemic levels. Nonetheless, TRUE Transit, Rolling Hills, and MRVT saw steady or even increased ridership, surpassing their pre-pandemic records.

On the other hand, Figure 3-2 provides more insight into these discrepancies by illustrating the same data grouped by transit service type. The increased MPT statistics in 2020 reveal that, during the pandemic, people were less likely to make short-distance transit trips with DRT and paratransit services. The figure also indicates that ridership on fixed routes decreased significantly while DRT services almost recovered from their pre-pandemic level.

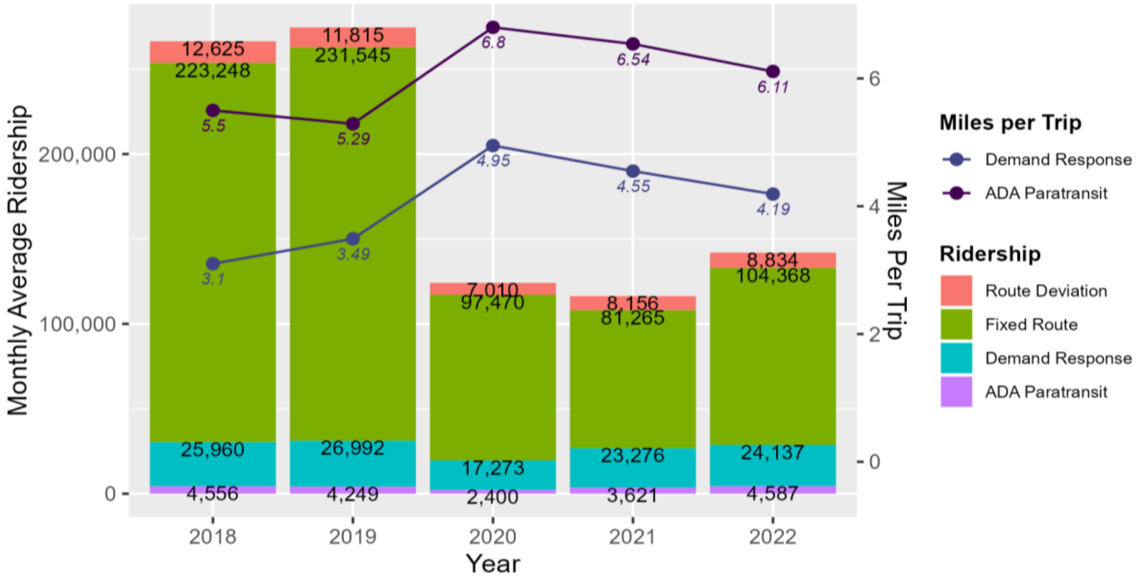


Figure 3-2 Monthly average transit ridership and MPT by service type (2018 – 2022)

It is also well-known that transit ridership varies throughout the year due to various factors, including holidays, school breaks, and vacations. Therefore, to accurately evaluate the impact of the MaaS deployment in a before-and-after analysis, it is necessary to adjust transit ridership using historical data that could be found in the NTD to control for seasonal effects and isolate the pure impact of MaaS. On the other hand, the COVID-19 pandemic has significantly affected residents' travel behavior since early 2020, and many transit agencies worldwide have not recovered the pre-pandemic ridership even in 2024.

The above seasonality and pandemic effect on ridership are elaborated in the post-deployment analysis following this section. For this pre-pandemic analysis, we examined the existence of seasonality in our study area and how they differ between a one-year period before the pandemic and the same length period right before the MaaS pre-deployment. Table 3-3 provides agency and service-type level NTD ridership comparisons between 2019 (pre-pandemic) and 2022 (pre-MaaS deployment), with the change rates. Notably, DRT in 2022 showed around 90% of pre-pandemic ridership, while fixed route ridership remained at only half the amount.

Table 3-3 NTD ridership and their changes between 2019 and 2022

Agency	2019 Ridership	2022 Ridership	'18 – '22 Change	Service Type	2019 Ridership	2022 Ridership	'18 – '22 Change
Brown County	4,720	3,299	-30.1%	**DRT**	26,992	24,137	-10.6%
Mankato	56,302	31,774	-43.6%				

MRVT	6,422	5,511	-14.2%	**Route Deviation**	11,815	8,834	-25.2%
Rochester	179,577	77,841	-56.7%				
Rolling Hills	4,569	4,236	-7.3%	**Fixed Route**	231,545	104,368	-54.9%
SMART	22,400	18,346	-18.1%				
TRUE	610	919	+50.7%	**Paratransit**	11,815	8,834	-25.2%

In more detail, Figure 3-3 depicts monthly NTD ridership with the two periods' comparisons. The upper panel shows the data from February 2019 to January 2020, and the lower panel from February 2022 to January 2023. Inspecting those two years, we can confirm that the directions of monthly ridership and MPT fluctuations were similar between both years from April to January of the following year, with only one exception for June to July. For the period between February and April, however, the results cannot be directly compared due to the impact of the COVID-19 Omicron Variant that affected early 2022. Meanwhile, months with summer school break or vacation concentration (May-August) had significantly lower ridership but higher MPTs than the other months, and months with relatively mild weather yet with fewer vacation demands (March, April, and October) had the highest ridership concentration.

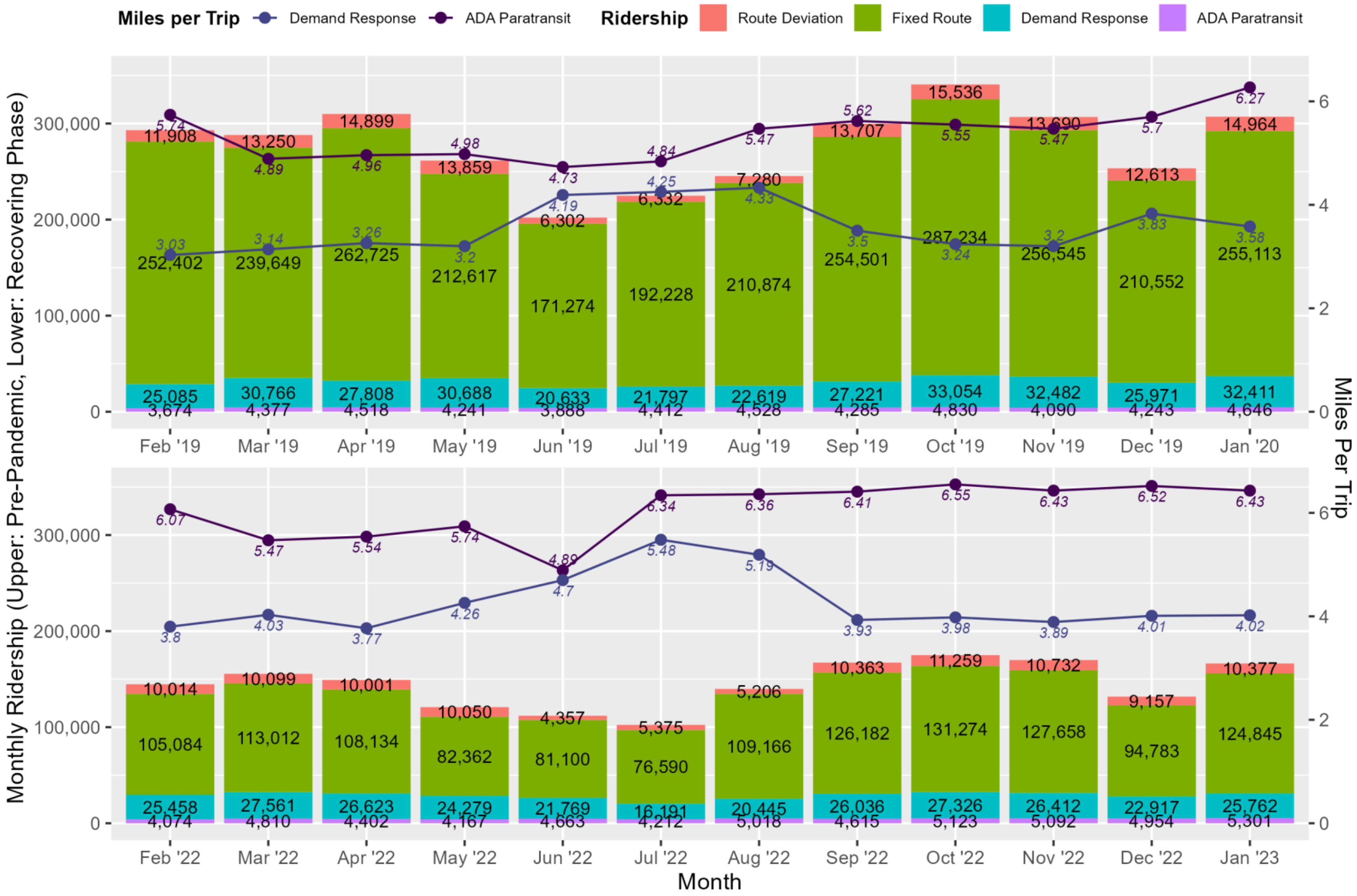


Figure 3-3 Monthly transit ridership and vehicle miles per trip trends (Upper: pre-pandemic; Lower: pre-MaaS deployment)

Motivated by the trends identified from our analyses, we conducted chi-square (χ^2) tests to determine whether there were significant associations between two categorical variables by which we can group the NTD data. For example, suppose we divided ridership counts by month and service type. If the test results show a statistical association between them (indicated by a low P-value or high χ^2 value), it recommends adjusting the seasonality by service type for a fair comparison. Table 3-4 shows the test results implemented on contingency tables generated, excluding the special category of ADA paratransit service type whose users are believed to have different travel behaviors.

Table 3-4 Chi-square independence tests of the NTD ridership

Variable 1 (# of classes)	Variable 2 (# of classes)	χ^2 Value	Degree of Freedom	P-Value
Years (5)	Agencies (7)	15,565	24	$<0.0001^{***}$
Years (5)	Service Types (3)	15,707	8	$<0.0001^{***}$
Months (12)	Service Types (3)	27,272	22	$<0.0001^{***}$
Months (12)	Years (5)	594,362	44	$<0.0001^{***}$

The results of the first and second tests (the first two rows of the table) demonstrate significant differences in yearly ridership across agencies and service types, indicated by the infinitesimal P-values. Notably, the yearly differences or trends in service types seem more plausible to be attributed to the variations observed than agency differences, as indicated by the higher χ^2 value. Similarly, the third test reveals that monthly ridership varied significantly depending on service types. Finally, the last test suggests monthly ridership variations across different years—long-term seasonal travel behavior changes exist. Using the statistics and test of this section, we can draw the following conclusions for the NTD comparison in post-deployment analysis:

- The pandemic significantly decreased transit ridership, with the largest decline observed in fixed routes, followed by route deviation and DRT services.
- As the pandemic recovers, transit ridership is rebounding, so there probably be a potential for continued momentum of ridership recovery during the study period
- The metric of vehicle miles per trip available in DRT and ADA paratransit showed an opposite trend to that of ridership, indicating less short-distance transit travels during the pandemic, with a gradual recovery to a lower MPT after 2021.
- Differences in ridership trends among agencies can be attributed to the different service types provided by each agency. An agency with only DRT services is recovering its ridership better than an agency with mixed services.
- Monthly ridership fluctuations were observed, indicating the effects of seasonal behavior changes or seasonality exist in the trend and need to be adjusted for further analyses.

Based on the above conclusions, we propose a methodology to identify stable data periods less affected by COVID-19-related fluctuations and techniques for adjusting seasonality. In the subsequent section, where before-and-after studies are conducted with the NTD ridership, our χ^2 test results imply the necessity for distinct adjustments based on service type rather than agency. This approach enables us to determine the appropriate NTD ridership input for statistical time series models aimed at forecasting ridership in our study area under the hypothetical scenario of no MaaS presence while accounting for seasonal fluctuations. This step is crucial for estimating the net impact of MaaS deployment on ridership by subtracting forecasted numbers from observed NTD ridership during the post-deployment period. Further elaboration on this process is provided in the subsequent section.

3.3 PRE-DEPLOYMENT MICROSCOPIC ANALYSIS WITH THE ODR

This section used the ODR data to analyze the study area's transit user experience and geographical aspects. While the NTD data offers a general understanding of long-term trends in ridership changes, the ODR data focuses on trip-level information for the pre-MaaS deployment phase. That is, we can derive deeper insights from the ODR data in terms of which aspects of the MaaS can enhance the users' experience for transit reservations and rides.

However, as noted in the previous section, the quantity and quality of the collected ODR data vary based on the transit agency. Due to our record-all-you-can policy for the data collection worksheet and uniform data cleansing steps, some sets of records missed specific columns or information, as already shown in Table 3-2. More undistinguishable yet equally undesirable cases exist as well: missing features in some records can be correlated to who recorded the data, making them be fixed/deleted systematically in the data cleaning step, whereas other records, even from the same agency and date, would have been not. Unfortunately, dividing every analysis into agency/data collector levels to mitigate the biases was not an option for this study, and the section's objective was to analyze the study area's overall transit usage patterns as well. As a result, readers must exercise caution when interpreting the tables and figures presented in this subsection, which are created based on different subsets of collected records.

3.3.1 Analyses of Temporal Factors of Transit Trips

Transit demand is influenced by people's activities, and it varies by time and location. In urban areas with many fixed-route transit systems, demand is typically highest during the morning and evening peaks due to the high volume of commuters, whereas in-between "midday" hours show significantly lower volumes. However, the hourly distribution of the trip departure timestamps in ODR (Figure 3-4) showed different hourly dynamics in the region.

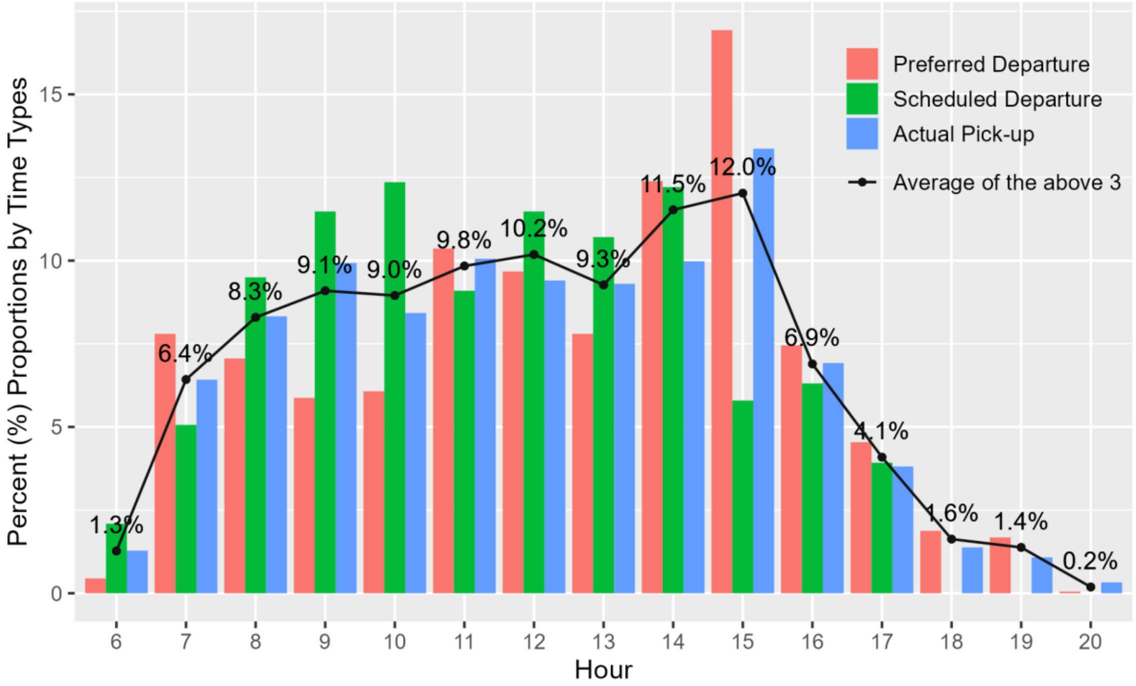


Figure 3-4 ODR departure-related timestamps' hourly proportions and statistics
(Data: records from every agency and service type; N=5,284)

Note again that PDT and SDT are not available for fixed routes, and each of the collected 5,284 records can miss specific timestamps almost randomly. This is the reason why the figure's bars represent hourly proportions among their timestamp group ("hour") rather than absolute counts. The figure also has the average values of the proportions (illustrated as lines) associated with each hour. For example, if we have 50 total PDTs, 100 SDTs, and 120 APTs available, where 5 (10%), 15 (15%), and 6 (5%) records of each have their values between 11:00 and 11:59, the average percentage of "11 AM group" becomes 10%, which are computed from the three example proportions above.

Several aspects can be observed from the figure. First, there was a prominent afternoon peak around 2 – 3 PM, whereas no distinct morning peak was observed. Those are comparable to the transit usage patterns of the nearby metropolitan area (Twin Cities, Minnesota), where the trip concentration in the morning peak (7 – 8 AM) was the highest, and the afternoon peak was located around 4 – 5 PM [17]. Second, we can observe a plateau across "midday" hours from 10 AM to 2 PM. Those five consecutive hours take around 50% of the total trips, whereas the Twin Cities area had only 25% of transit trips for the midday.

However, due to the non-exhaustive nature of the ODR dataset, Figure 3-4 has limitations. For example, PDT may primarily indicate a specific agency's values, whereas SDT indicates another's. Furthermore, trips of all four types of transit services are mixed in the bars and lines. Therefore, we also present Figure 3-5 and Figure 3-6 to break down the hourly statistics by service type with more controlled records. The former was plotted using ODR's "complete" DRT records that are not missing any of the four timestamps. Only eight records from Rolling Hills Transit and 216 from SMART fell in that criteria. The latter figure shows the route deviation and fixed route services' ADT histogram, as PDT and SDT are not applicable for the fixed routes.

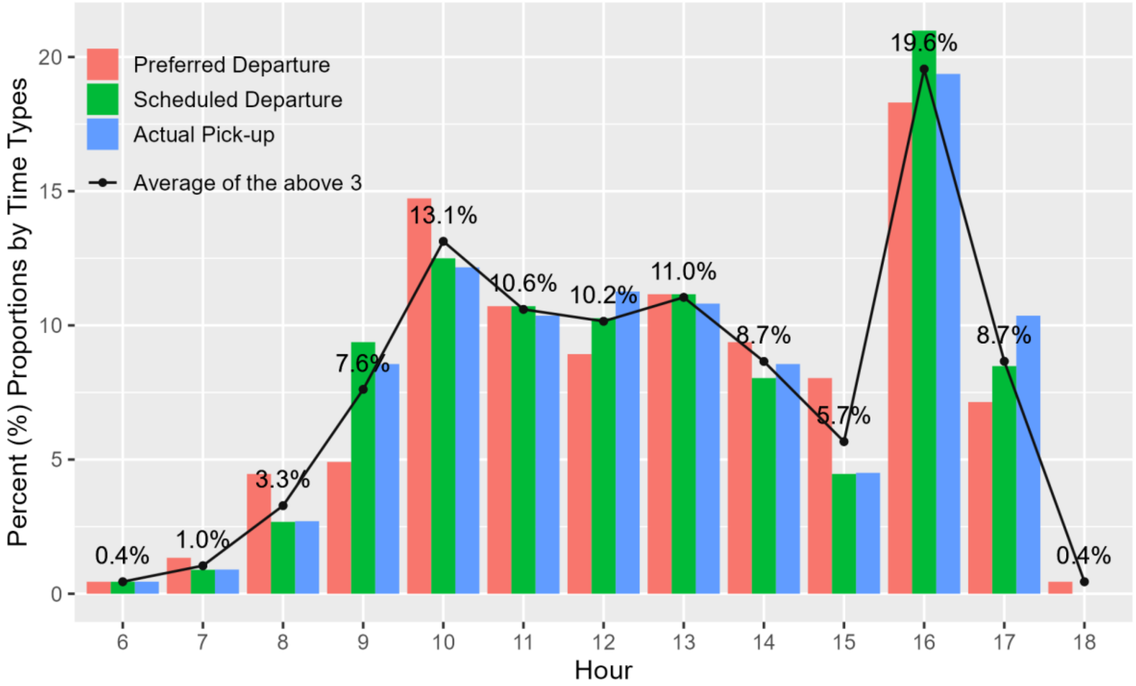


Figure 3-5 ODR trip timestamps' hourly proportions for selected DRT services

(Data: records from DRT with all three timestamps available; N=224)

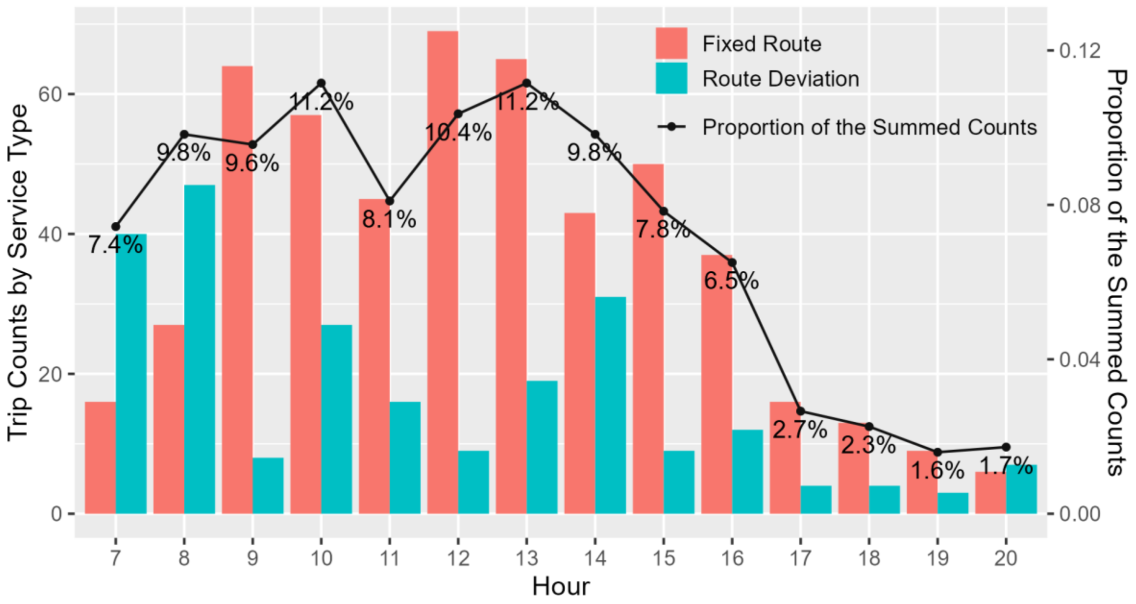


Figure 3-6 ODR trip timestamps' hourly proportions for selected bus services
(Data: boarding time records of fixed route and route deviation from SMART; N=752)

Figure 3-5 reconfirms the previous observations: no distinct morning peak, the midday concentration from 10 AM to 2 PM made up 54% of total travel, and higher dispersions between SDT and PDT differences than differences between APT and SDT. Interestingly, Figure 3-6 indicates route deviation and fixed route services have moderate ridership concentrations (26.8% total) in the conventional morning peak times (7 – 10 AM), differentiating it from the DRT usage pattern observed in Figure 3-5 (11.9% for the same window). Keep in mind that the data for both figures came from the same agency, meaning there are little issues when comparing those two results directly.

From the ODR's hourly statistics, we can conclude that Southern Minnesota's transit travel behavior is different from those of typical metro areas: no outstanding morning rush hours, earlier afternoon peak, and steadily high demands in midday. That was particularly the case in DRT usage. Fixed and route deviation services for small-sized cities also showed the second and third unique attributes of the above, whereas it had a light yet visible morning peak.

Enlarging the scope, we present day-of-week statistics of the collected ODR dataset. Figure 3-7 shows the entire dataset's records regardless of whether each trip really happened (i.e., including trip cancellations and future reservation data). Because ridership for DRT and paratransit services was way higher than those of the others, we divided the geometries in the graphs into two axes. One is for DRT and paratransit services (bars), and the other is for the remaining high-occupancy services (lines). Note that some agencies in the region do not offer weekend transit services. Therefore, Saturday and Sunday numbers are significantly lower.

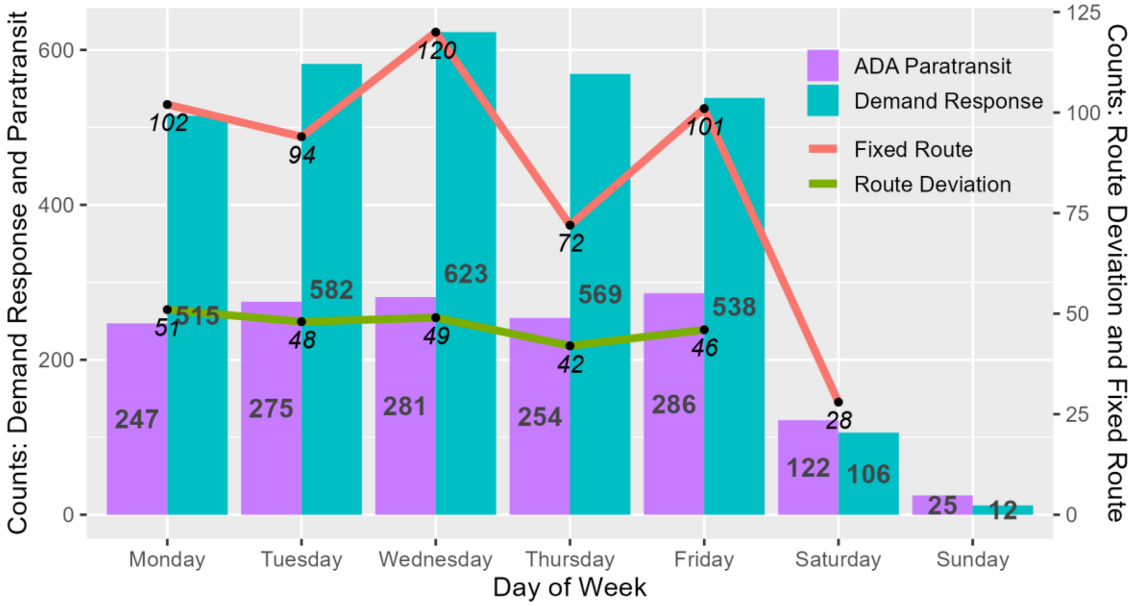


Figure 3-7 Day of week ridership histogram of ODR by service type
(Data: records with ADT available; N=5,188)

More detailed breakdowns are shown in Figure 3-8, which illustrates agency-level day-of-week ridership with system-wide daily proportions. For a more controlled comparison, we only used actual trip data that happened during the active ODR data collection period (two weeks, from Monday, 1/30/2023, to Sunday, 2/12/2023). Note that we only have paratransit data from Mankato and fixed/route deviation data from SMART, both of which already fell in the data selection period. Notably, both day-of-week figures indicated that among weekdays, Monday and Friday were the least busy days for DRT and fixed route services. Those patterns are also observed elsewhere, including the Twin Cities Metro Area.

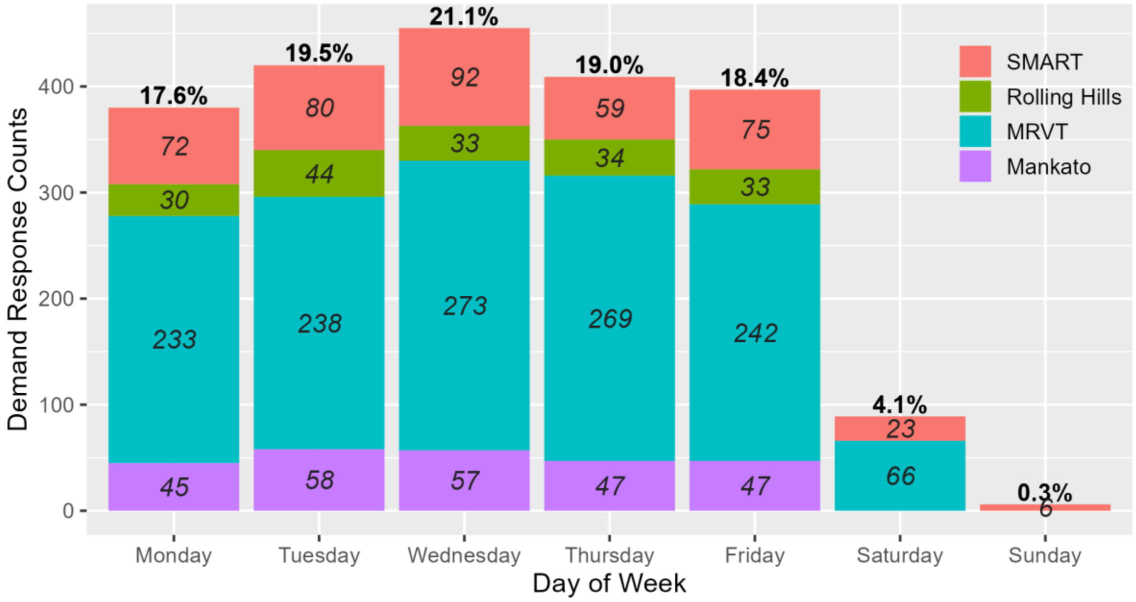


Figure 3-8 Day of week ridership histogram and daily proportions of ODR for DRT

(Data: DRT records with ADT available from 1/30 to 2/10, 2023; N=2,156)

3.3.2 Analyses of Trip Reservation and Agency/Passenger Experience

This subsection examines statistics focused on agency/passenger experience primarily for non-fixed-route services using the various timestamps recorded in the ODR. In ODR, there are reservation reception time (RRT) and preferred departure time (PDT) obtained from passenger requests, as well as the scheduled departure time (SDT) from agencies and actual pickup time (APT) recorded at the passenger origin (not vehicle "dispatch time"). Those times can significantly affect user experience even before they board the vehicle. Furthermore, the dataset also contains the actual dropoff time (ADT), allowing for the calculation of the in-vehicle time (IVT) by subtracting APT from ADT. Additionally, since we have the exact origin and destination for each request in the dataset, we were able to retrieve the expected travel time (ETT) and distance by utilizing OpenStreetMap's "driving direction" tool [18].

After presenting the distributions (hour, day of week) of the various types of timestamps collected in the ODR, we compared the time differences between some of them to recover transit agencies' or passengers' experiences. For example, the agency can decline a vehicle dispatch if the RRT is too close to the PDT. Also, comparing SDT with APT allows us to capture passengers' additional waiting time, and comparing IVT with ETT can be used to infer user perception. Finally, though limited, we present recorded payment or passenger types in the ODR to better understand passenger demographics.

First, Figure 3-9 shows the hourly distribution of RRT by transit agency (bars) and service types (lines). It also includes the total hourly proportion (text). Unlike the hourly statistics of the ridership presented in the previous subsection, there were obvious peak times in reservation calls in the morning (8 – 9 AM). Therefore, one expectation of MaaS is that it can alleviate the concentration of the calls during the opening hours to decrease the workload for the agency/staff if the platform allows online reservations during out-of-service hours.

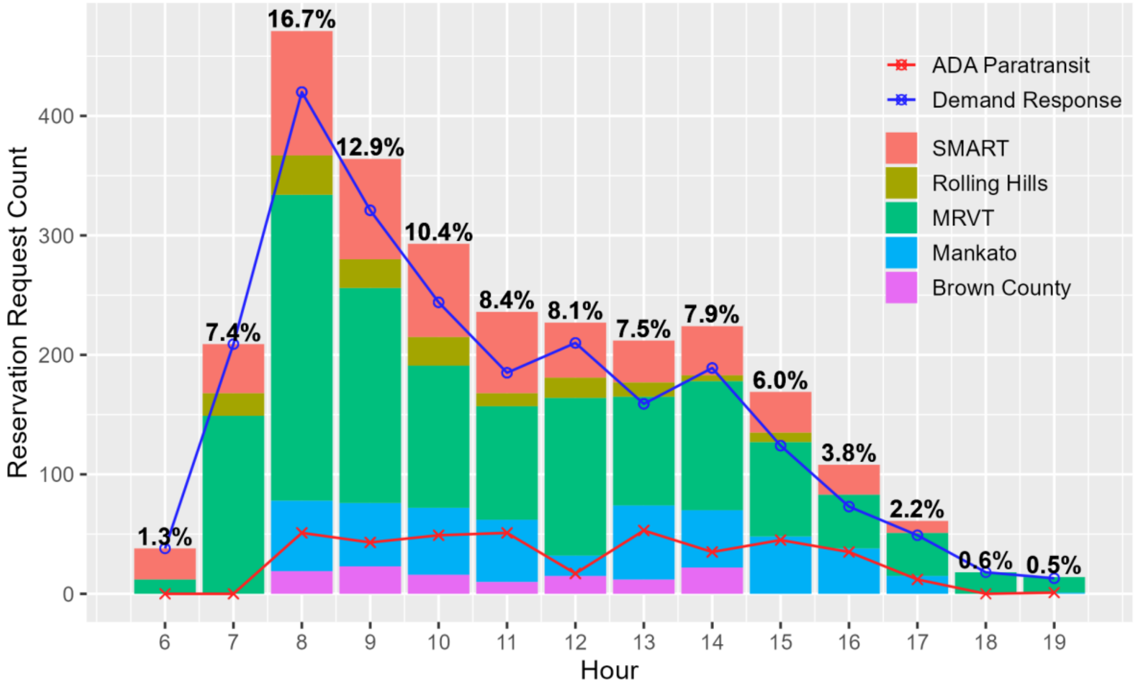


Figure 3-9 ODR reservation timestamps' hourly counts and aggregated proportions
(Data: DRT and ADA paratransit reservation records with timestamps; N=2,644)

Figure 3-10 and Figure 3-11show time differences associated with DRT and ADA paratransit services' reservations and trips. The former shows how early people made reservations before their trip. It used the entire ODR dataset record with RRT and trip-intended date. The latter illustrates how early cancellations were made for Mankato Transit, as the agency was the only agency that collected cancellation timestamps. About a third of trips were booked on the same day, and the proportions dropped exponentially until it reached six days before the trip. Interestingly, the “booking-a-week (7 days) before” behavior was more popular than booking five or six days prior to the ride. In addition, there was a nonnegligible proportion of bookings more than two weeks away. Meanwhile, about 80% of passenger cancellations were made on the same day. It is expected that those distributions will be changed after MaaS becomes capable of handling reservations on the platform.

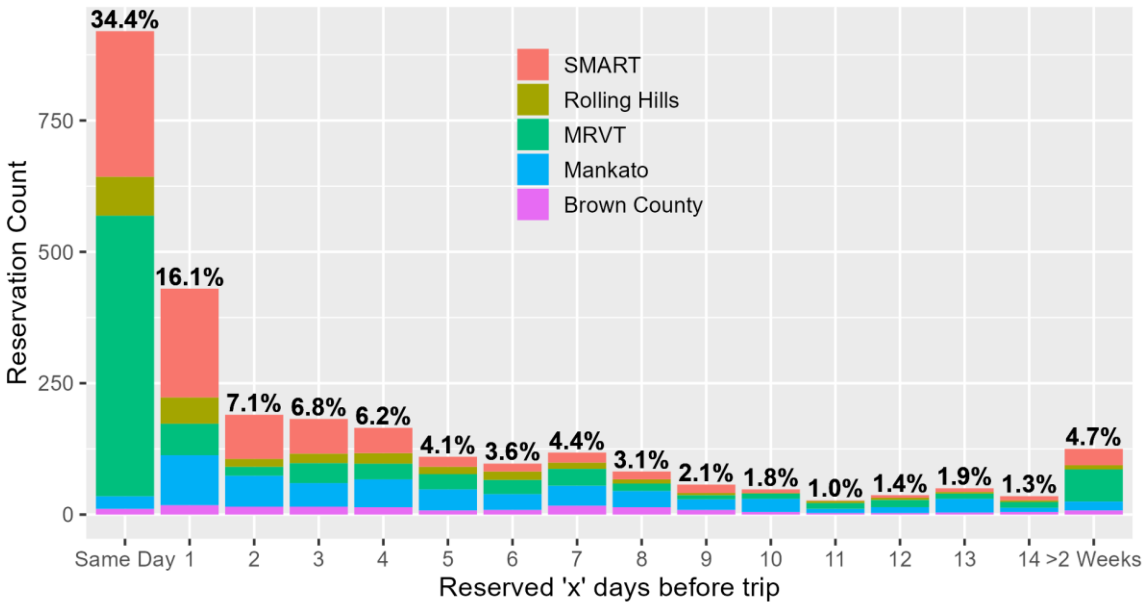


Figure 3-10 The day differences between reservation and trip

(Data: DRT and paratransit records with reservation request day information; N=2,673)

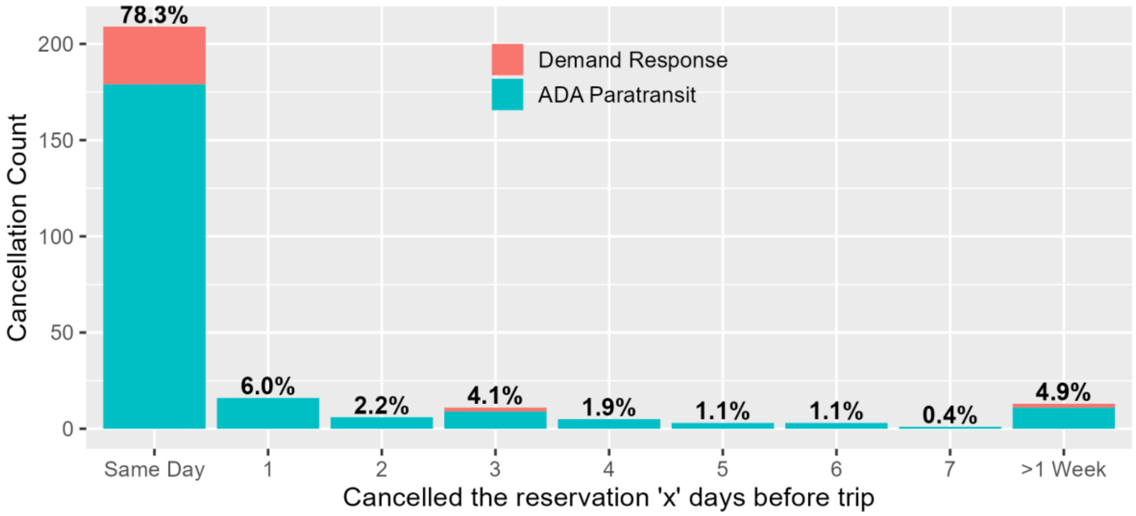


Figure 3-11 The day differences between user cancellation and trip

(Data: Mankato Transit's DRT records with cancelation information; N=267)

Zooming in to the first column of Figure 3-11, there were 920 same-day DRT reservations identified in the ODR dataset. Among them, 726 records had PDT available. Figure 3-12 inspected those same-day trips and measured how early the trip was reserved on a minute scale. Among them, there was a fifth of "imminent" vehicle dispatch requests (RRT less than 10 minutes before PDT). For those requests, there could have been burdens for agency call receptionists to find alternative SDTs and/or to persuade passengers to await more, where the MaaS app is expected to mitigate those inconveniences if they are equipped with an automated or real-time reservation/dispatch feature.

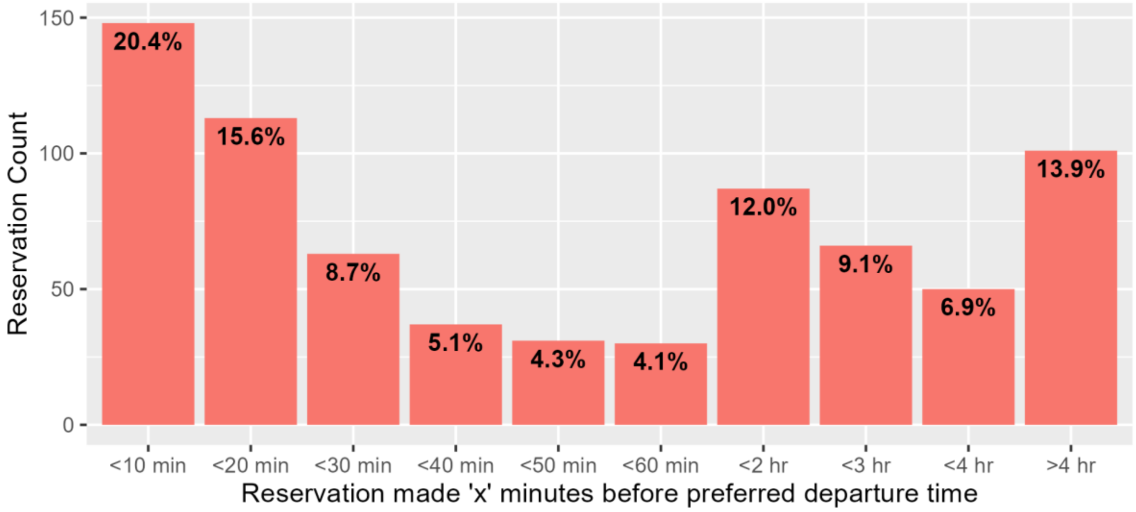


Figure 3-12 The minute differences between reservation and preferred departure time
(Data: Same-day trip requests for DRT in Mnakato, SMART, and Rolling Hills; N=726)

The next two aspects we examined are scheduled departure time displacements. Schedule time displacement (shown in Figure 3-13) was calculated by subtracting the preferred departure time (PDT) from the scheduled departure time (SDT), which represents the amount of unexpected or unfavorable time (in minutes) that passengers experienced between their requested PDT and the agency-notified SDT.

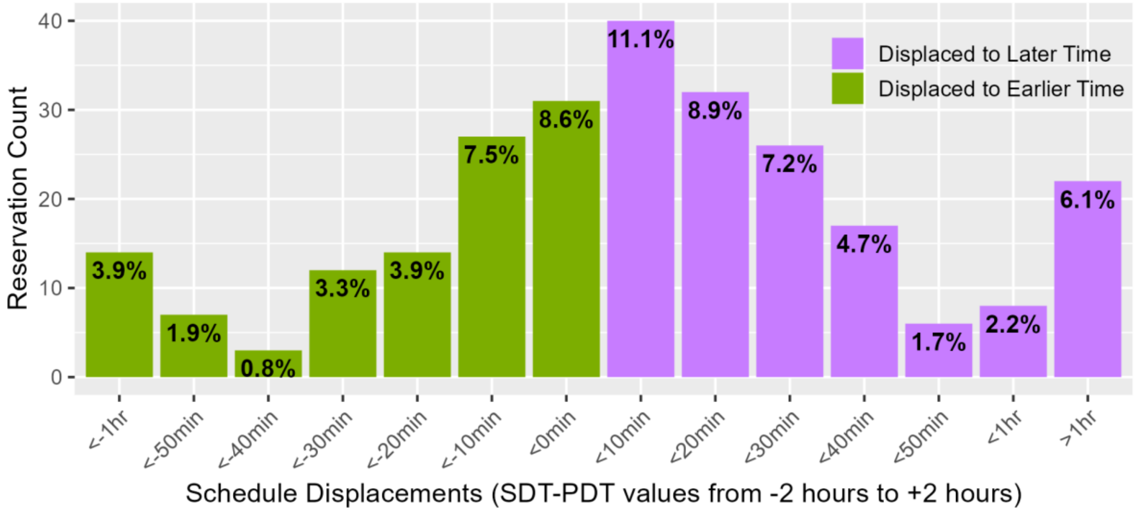


Figure 3-13 Schedule displacement distribution excluding the on-time value 0
(Data: Records with SDT and PDT; N=259 excluding the value 0 amounted to 28%)

After data cleansing, we found that 358 records had both PDT and SDT available. Among them, 99 (28%) had no schedule displacements (i.e., the same PDT and SDT values), while 259 (72%) had negotiated for or been notified of rescheduled departure times. Of these, 151 (42%) had later (positive SDT-PDT), while 108 (30%) had earlier (negative SDT-PDT) pickup assignments. The overall grand mean of the displacement was 3.31 minutes of later rescheduling, and the standard deviation was 33.6 minutes.

Similarly, we also examined the departure time displacement (Figure 3-14) or early departure/ waiting times, which measures how closely the DRT services' dispatch schedules were observed. Specifically, we calculated the difference between the scheduled departure time (SDT) and the actual pickup time (APT) and identified whether the passenger experienced a waiting time or an earlier departure. Out of 1,988 records with both SDT and APT available, 237 (12%) had the same values, indicating that the DRT vehicle picked up the passenger exactly at the scheduled time. The remaining records were identified as early departure or waiting time-generated, with 1,216 (61%) experiencing an early departure and 535 (27%) experiencing waiting time.

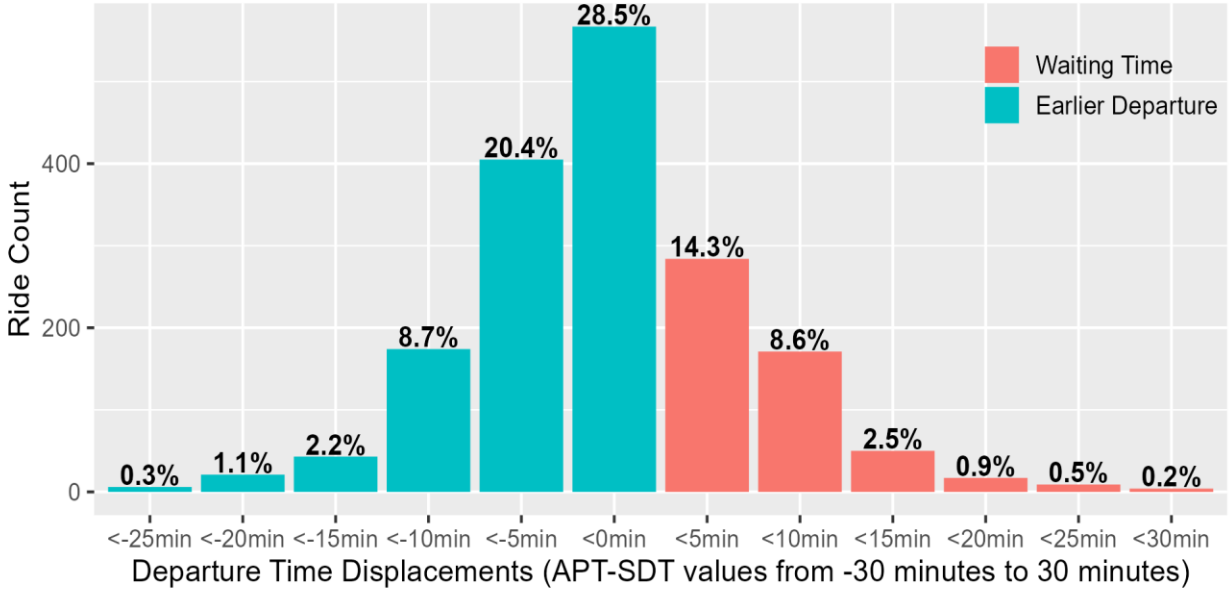


Figure 3-14 Departure time displacement distribution

(Data: Records with APT and SDT; N=1,751 excluding the value 0 amounted to 12%)

There are two points to consider when interpreting these results. Firstly, some passengers may have a tolerance for small amounts of departure time displacement. For example, some may not even consider 3 minutes of additional waiting time to be any disturbance, and others may even welcome the earlier departure. Secondly, we can group passengers by the type of experience they had in terms of APT and SDT differences. To this end, we regrouped the passengers into more practical categories of "Early Departure," (a broader notion of) "On-Time," and "Awaited" and summarized the descriptive statistics in Table 3-5. The table revealed that 33% of the early departure group experienced a pickup time that was earlier than their SDT by an average of 11 minutes, while the awaited group had an average waiting time of 10 minutes. Overall, the interquartile range (the range between the first and the third quartiles) and standard deviations were lower than those observed in the above schedule displacements.

Table 3-5 Passenger group statistics by departure time displacement
(Data: Records with APT and SDT; N=1,988 including the value 0)

Displacement Group	Early Departure (APT-SDT< -5 min)	On-Time*	Late Departure (APT-SDT > 5 min)
Counts (Proportion)	649 (33%)	1146 (57%)	193 (10%)
Average	-10.7 min	-0.7 min	10.2 min
Standard Deviation	4.3 min	2.87 min	4.7 min
1st Quartile	-13 min	-3 min	7 min
Median	-10 min	0 min	9 min
3rd Quartile	-10 min	0 min	9 min
Aggregated	The average was 2.9 minutes early departure (standard deviation: 7.2 minutes)		

**Negative values represent early departure amount, whereas positives represent (additional) waiting time*

The third time difference value we examined is in-vehicle time (IVT), calculated by subtracting APT from ADT. We grouped the data points by service type and agency to which they belonged. A total of 3,888 records with APT and ADT available were used to create descriptive statistics in Table 3-6, box plots in Figure 3-15, and a 5-minute-grouped histogram in Figure 3-16. Note that although the nominal service type of SMART's non-DRT bus is route deviation (e.g., in the NTD), we divide SMART buses' ODR records into two categories based on passenger activity: records from passengers who requested deviations are aggregated under "route deviation," while the others (i.e., from hop-on and hop-off passengers) are categorized as "fixed route."

Table 3-6 In-vehicle time statistics (in minutes) grouped by agency and service type
(Data: Records with ADT; N=3,888)

Agency	Service Type	Count	Average	1st Quartile	Median	3rd Quartile	Standard Deviation
Mankato	AP	1069	17.5	9	13	19	14.6
Mankato	DR	254	12.4	8	10	14	8.5
MRVT	DR	1260	11.2	5	8	15	10.8
Rolling Hills	DR	174	12.0	4	6	15	12.1

SMART	DR	378	9.5	6	8	11	8.0
SMART	FR	517	27.1	15	26	38	14.6
SMART	RD	236	20.9	10	18	30	14.6

**Service types: AP = ADA Paratransit, DR = Demand Response, FR = Fixed Route, RD = Route Deviation*

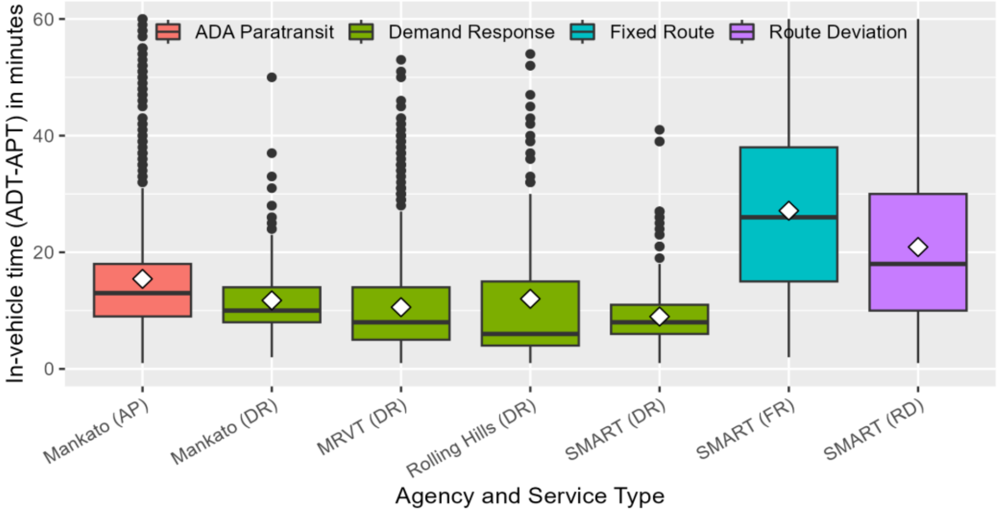


Figure 3-15 In-vehicle time box plots by agency/service type (Data: same as Table 3-6)

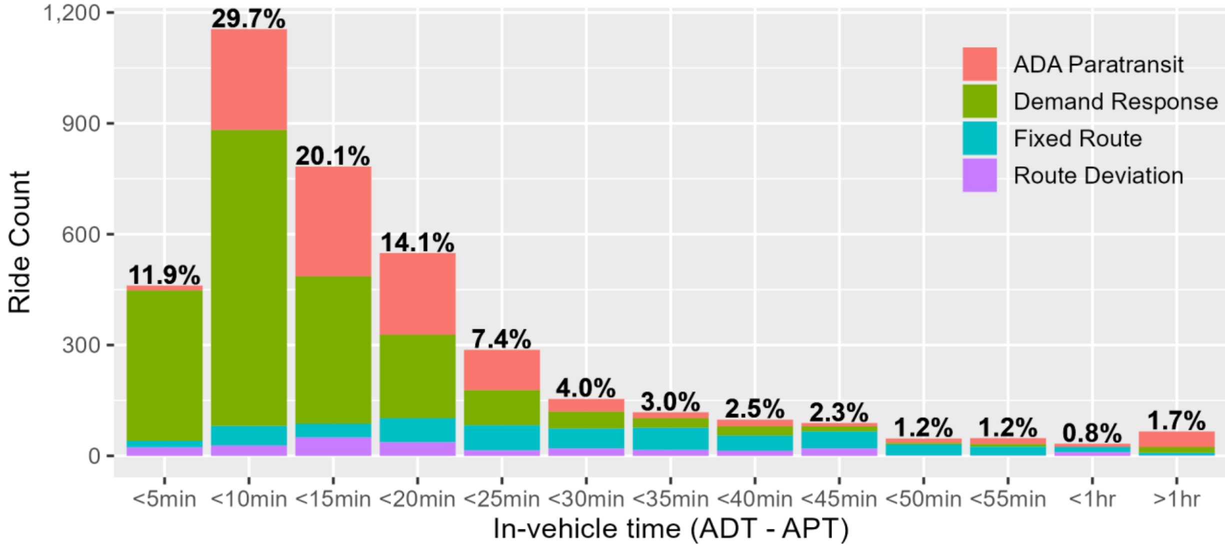


Figure 3-16 In-vehicle time histogram by the agency (Data: same as Table 3-6)

The in-vehicle time observations are as follows. First, we observed from the table that the fixed route and route deviation services of SMART had significantly higher IVT than their DRT service. This can be attributed to the fact that the inevitable design of low-demanded fixed routes in rural areas made routes have unidirectional circular itineraries. This adds excessive travel time for trips whose alighting stop is located upstream of the boarding stop because they have to travel along more than half of the circle's circumference. In contrast, the limitation can be mitigated by offering route deviation service as passengers can request reverse deviation if their destination is near the origin. This seemed to have affected the lower travel time average of route deviation compared to the fixed route rides in the table.

Similarly, the box plot in Figure 3-15 provides a visual representation of the above summary table's statistics, displaying the interquartile range and outliers as black dots and the mean as white diamond symbols. Figure 3-16, the associated histogram of IVT, indicates that most trips had an IVT between 5 and 15 minutes, with about 50% falling in this range and 85% having an IVT of less than 30 minutes. After that, as travel duration increased, the proportion of trips decreased.

On the other hand, Figure 3-17 shows a distance histogram estimated by OpenStreetMap's "direction" tool for each record's OD pair. Note that these are, in many cases, shorter than the actual distance transit vehicles took or passengers experienced, even for the DRT services, as they came from the open-source shortest path routing algorithm. The graph reconfirms the findings of Figure 3-16, with fewer trips under 0.5 miles compared to the next three bars, followed by a gradual decrease in counts after 2 miles. Interestingly, though it could not be found in the figures, Mankato's paratransit services had an average distance of 3.4 miles, while its DRT services had an average distance of 4.5 miles. However, we have already investigated that the average travel times for those service types were 17.5 and 12.4 minutes, respectively. Those two sets of observations collectively indicate that some portion of ADA paratransit's IVT could have been spent on other activities, such as assisting passengers' boarding and alighting.

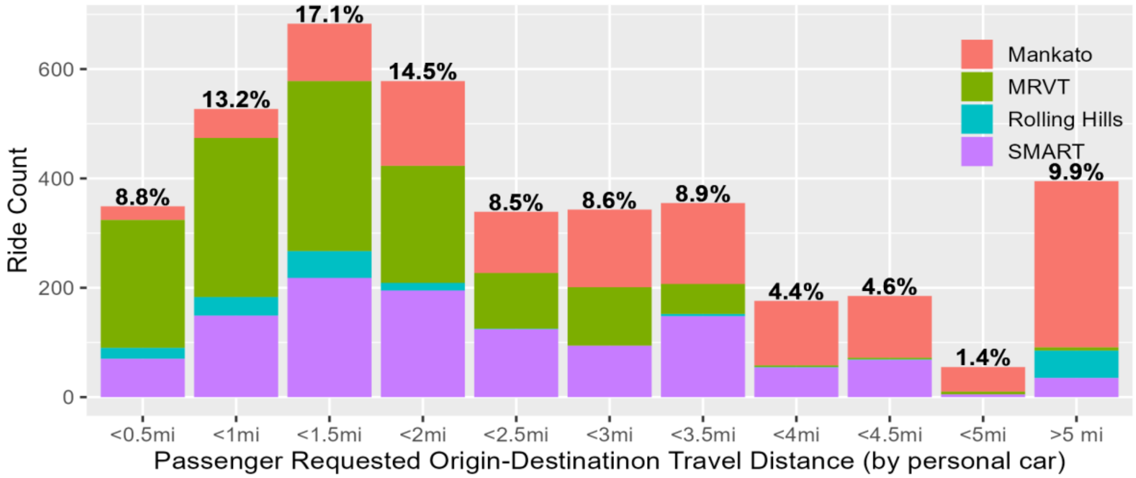


Figure 3-17 Estimated travel distance retrieved from OpenStreetMap's Direction tool
(Data: all origin-destination pairs in ODR except ADA paratransit; N=2,918)

Finally, we compared the observed IVT with the expected auto travel time (ETT) calculated from OpenStreetMap to determine how transit services in the region are comparable to personal vehicle drives (on the shortest path) regarding travel time. Table 3-7 presents descriptive statistics and box plots for the difference between IVT and ETT by service types except for ADA paratransit, which we excluded as the time data for boarding/alighting assistance of paratransit services were unavailable. All values of IVT-ETT were positive, indicating that transit rides' in-vehicle time is longer than that of the shortest path traveled by private vehicle rides. The IVT/ETT proportions were calculated only for records whose ETT is more than 5 minutes. The proportion ranged from 117% to 388%, but it is worth noting that the values are sensitive to short-distance trips whose ETT is small, making the denominator small.

Table 3-7 Transit and private car drive in-vehicle time differences in minutes (IVT-ETT)
(Data: Records with APT and ADT available excluding paratransit; N=2,818)

Agency	Service Type*	Count	Average	1st Quartile	Median	3rd Quartile	Mean IVT/ETT
Manakto	DR	253	3.57	0.31	1.71	4.15	140%
MRVT	DR	1,260	7.50	1.03	4.39	10.77	206%
Rolling Hills	DR	174	2.78	0.82	1.90	3.42	117%
SMART	DR	378	3.76	0.98	2.38	4.48	154%
SMART	FR	517	21.40	10.34	18.30	29.59	388%
SMART	RD	236	16.06	5.42	11.88	24.69	367%

**Service types: AP = ADA Paratransit, DR = Demand Response, FR = Fixed Route, RD = Route Deviation*

The table shows that DRT services that mainly operate as door-to-door straight OD connections had significantly lower difference values between ETT and IVT compared to those of fixed route and route deviation services. However, the differences in the IVT-ETT values between the route deviation and fixed route services were small. Fortunately, the first quartile value for route deviation was only 5 minutes, indicating that the deviation scheme works in terms of improving accessibility and mitigating the excessive travel times associated with the unidirectional circular design of the fixed routes. The detailed distribution of the above observations is illustrated as box plots in Figure 3-18.

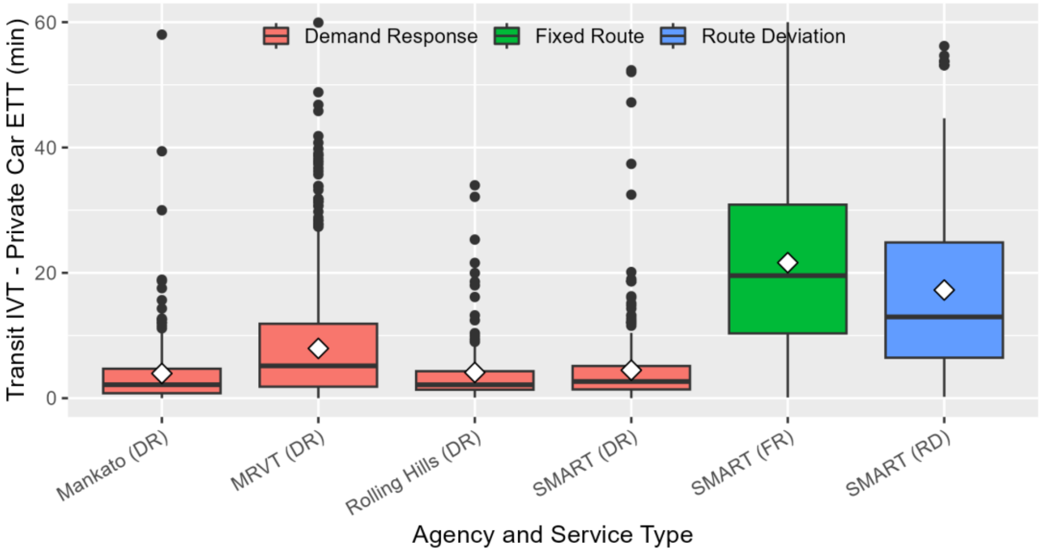


Figure 3-18 Transit and private car in-vehicle time differences (Data: same as Table 3-7)

So far, we have examined various time and agency- or passenger-experience related data available in ODR. However, we have not conducted any demographic-related marginal analyses as only a few agencies collected payment and/or passenger types for DRT services, and their classification methods varied. Nevertheless, it is worth noting the people who used which service, as shown in Figure 3-19, which summarizes the available demographic-related information for DRT.

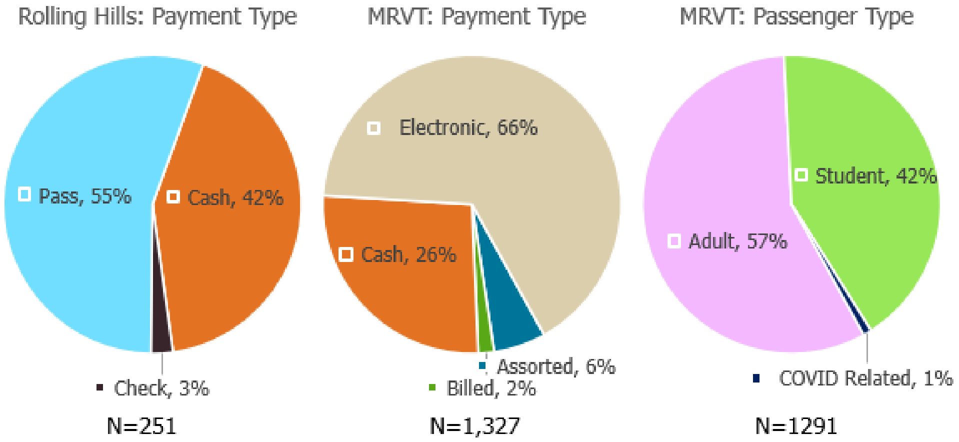


Figure 3-19 Available demographic-related information in the ODR dataset (DRT only)

3.3.3 Spatial Ridership Analysis Using Geographic Information System

The ODR dataset contains location information for each record, which includes the origin and destination points for passenger trips on fixed routes, ADA paratransit, DRT, and route deviation services. The locations for fixed route services were recorded for each passenger trip's boarding and alighting bus stops, while for paratransit and DRT services, passengers submitted both their origin and destination to the agency. For route deviation services, either the origin or destination (or both) was booked or requested, and then the data collectors recorded it. All locations associated with each trip or reservation were converted to coordinates that geographic information system (GIS) software could handle.

Figure 3-20 shows a map of all origin and destination points for all service types. Almost all of the available locations (94.4% collectively) were in the nine cities (labeled as boldface: New Ulm, Mankato/North Mankato, St. Peter, Le Sueur, Waseca, Albert Lea, Owatonna, Austin, and Rochester) that have or once had fixed route services (Le Sueur and St. Peter, both in MRVT service area, discontinued their fixed route services in 2020). Although the ODR data for Rochester Public Transit was not collected, we can observe that many trips from other agencies were headed to the city of Rochester.

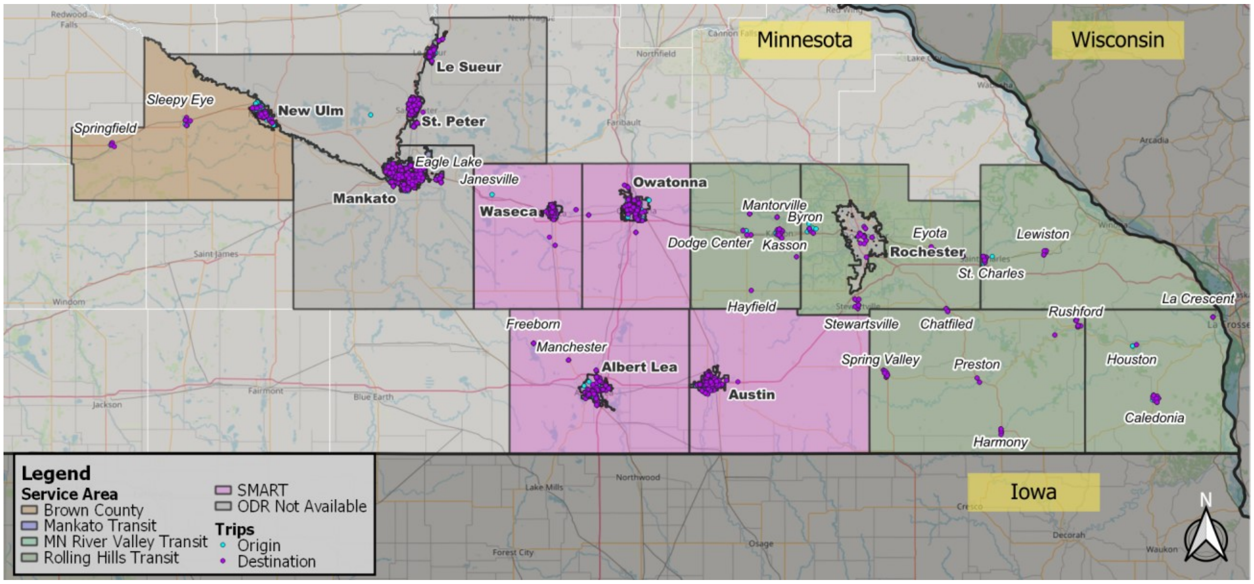


Figure 3-20 Origin/Destination locations in the ODR Dataset (N=5,281)

Another map, Figure 3-21, was created that zoomed in on the nine cities. This map only included DRT service data, as paratransit users may not consider other services as an alternative mode of transportation, and the other two services were examined in different ways later in this subsection. To make a fair comparison, we filtered data depending on the trip date. For Mankato, Brown County, and SMART, we used the one-week trip records from Jan 30 to Feb 5, 2023. Because of different data collection periods, we used data from Feb 6 to Feb 12 for MRVT. An exception was Rolling Hills Transit's data, as they primarily serve in the out-of-the-nine-cities area and lack the absolute number of records. Therefore, we used the full two weeks of data for Rolling Hills from Jan 30 to Feb 12. Heat maps (darker backgrounds plotted where more points exist) were also added to the detailed map to consider location duplications. We can observe that a significant proportion of origin or destination locations of DRT services were located near fixed route services, and the areas near some intercity bus (Jefferson Lines, Land to Air Express) lines' stops were popular demand points.

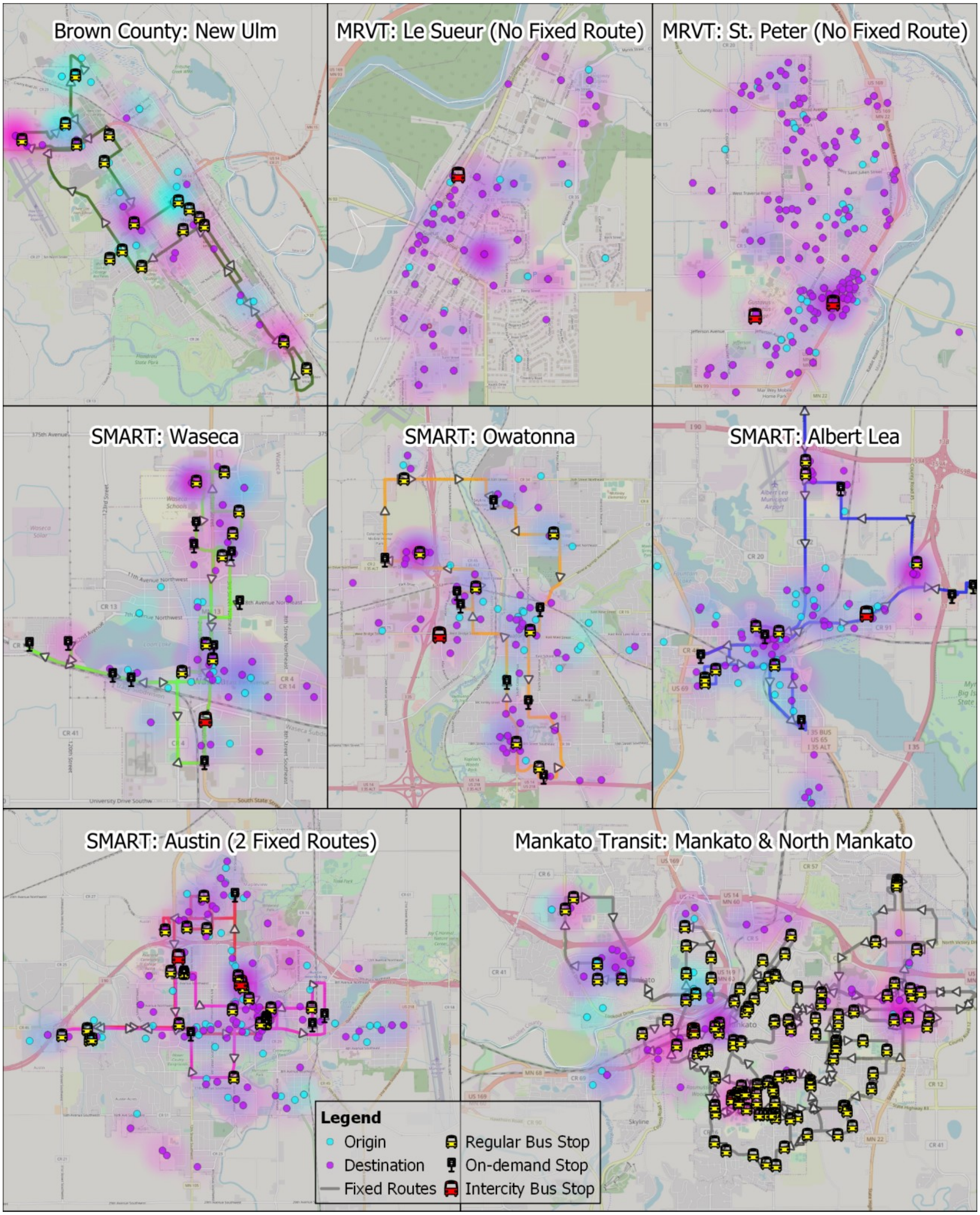


Figure 3-21 DRT trip/reservation records' origin and destination in ODR (eight cities)

(Data: OD pairs for the selected dates, excluding ADA paratransit; N=2,239 pairs)

The spatial patterns of DRT trips that require further clarification are summarized in Table 3-8. To summarize the statistics, each record was grouped based on whether its origin or destination was within the nine cities. For instance, an intra-Mankato trip or a trip from St. Peter to Le Sueur was classified as an "Urban ↔ Urban" trip. On the other hand, a trip originating from Kasson, Dodge County, and going to Rochester was classified as an "Urban ↔ Rural" trip. Similarly, a trip with the reverse origin and destination of the previous case was classified as "Urban ↔ Rural" as well. The observed IVT's average value was the highest in the second group, followed by the first and the third groups. However, the estimated average travel distance was higher in the third group than in the first group despite having a lower IVT average. As shown in Figure 3-22, the average distance to the nearest bus stop for the first group was walkable (0.26 miles).

Table 3-8 DRT trip statistics by urban/rural OD classification (Data: same as Figure 3-21)

Item	Agency	Urban ↔ Urban Trips	Urban ↔ Rural Trips	Rural ↔ Rural Trips
Data Counts	**Aggregated Statistics**	**1,821 (81%)**	**209 (9%)**	**218 (10%)**
	Brown County	42	9	6
	Mankato Transit	72	41	*0*
	MRVT	1,231	88	2
	Rolling Hills	*0*	48	210
	SMART	467	23	*0*
Average Observed In-vehicle Times (minutes)	**Aggregated Statistics**	**9.57**	**16.7**	**9.13**
	Mankato Transit	11.5	13.0	*NA*
	MRVT	9.9	12.8	15.0
	Rolling Hills	*NA*	31.5	9.1
	SMART	7.77	29.4	*NA*
Average Estimated Travel Distance Retrieved from OpenStreetMap (miles)	**Aggregated Statistics**	**1.62**	**8.28**	**3.32**
	Brown County	1.9	15.9	3.2
	Mankato Transit	3.8	6.0	*NA*
	MRVT	1.3	2.4	4.6
	Rolling Hills	*NA*	19.3	3.3

	SMART	2.1	8.7	*NA*
Average Estimated Travel Speed (mph, distances from OpenStreetMap)	**Aggregated Statistics**	**12.6**	**25.5**	**17.0**
	Mankato Transit	21.9	30.7	*NA*
	MRVT	11.2	16.9	18.2
	Rolling Hills	*NA*	40.9	17.0
	SMART	16.8	35.9	*NA*
Average Euclidean Distance to the Nearest Fixed Route Bus Stop from Origin (mi)	**Aggregated Statistics**	0.26	2.28	11.1
	Brown County	0.22	3.75	11.1
	Mankato Transit	0.18	1.53	*NA*
	SMART	0.28	3.05	*NA*

** Brown County's IVT was unavailable; thus, no travel speed calculations were conducted*

On the other hand, Figure 3-22 also displays the weekly fixed route ridership—boarding and alighting counts summed—for each bus stop, as well as the popular points for route deviation requests, regardless of them being the origin or destination point. There appears to be some correlation between the usage rate of nearby bus stops and popular deviation points.

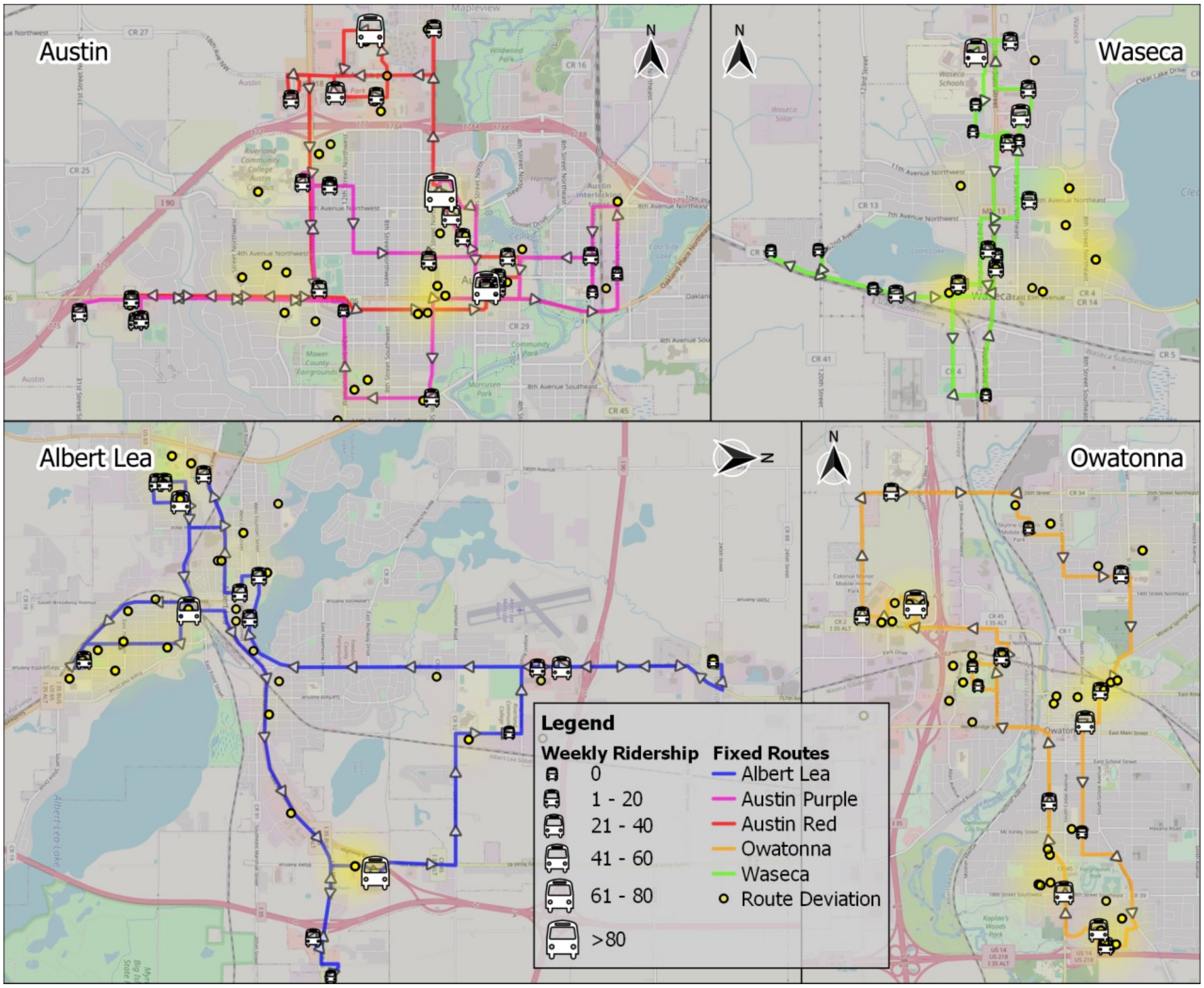


Figure 3-22 Weekly ridership of each fixed route stop and route deviation points
(Data: SMART's fixed route and route deviation records; N=753)

Finally, Figure 3-23 shows the straight lines connecting the origin and destination locations for long-distance DRT trips whose estimated travel distance exceeded 10 miles. There were only a few trips between the four cities in SMART's service area, while many Rolling Hills Transit trips headed to Rochester. If TRUE Transit's data were available for analysis, we would likely observe similar trends of trips from rural areas heading to Mankato, Le Sueur, St. Peter, or New Ulm.

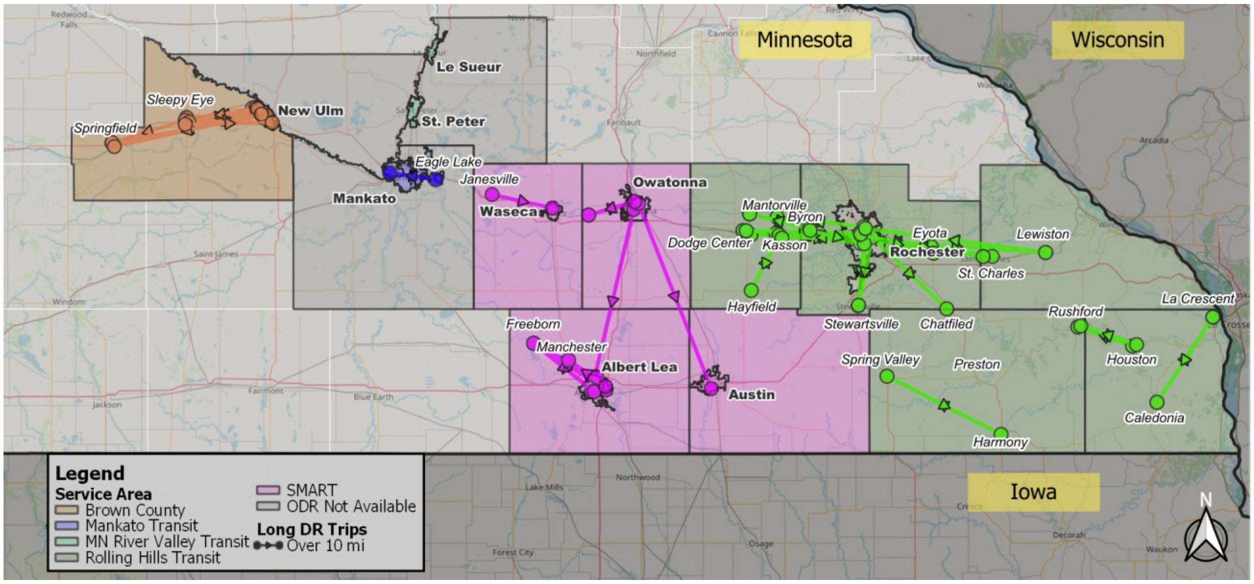


Figure 3-23 Long-distance DRT trip paths with Euclidean distance over 10 mi (N=120)

The ODR analyses conducted in the pre-deployment analysis section provided insights into the transit travel patterns within the study area, offering implications for estimating the benefits of MaaS post-deployment and guiding the direction of MaaS advancements. The summarized findings are as follows:

- Hourly ridership indicates that no distinct morning peaks were identified, steadily high demand concentration existed during midday, and afternoon peaks occurred around 3 – 4 PM, which was earlier than in Metropolitan Areas with higher transit supplies.
- Day-of-week ridership variances were small during weekdays, with slightly fewer concentrations on Mondays and Fridays and significantly lower counts for weekends.
- Reservation calls, unlike the ridership, were highly concentrated in the morning.
- About a third of reservations and 80% of cancellations were made on the same day the trips were supposed to happen.
- About half of the same-day trip requests had their preferred departure time less than 30 minutes from the call timestamps.
- About 72% of trip requests experienced more than 5 minutes of their departure schedules being displaced compared to the preferred departure times, either to earlier or later time.
- About 43% of trips had their actual pickup time more than 5 minutes away from the scheduled departure, with more proportions having experienced earlier departures.
- Transit trips less than 2 miles or 20 minutes constituted more than half of the total trips.
- Differences between the observed in-vehicle times and expected (shortest) auto travel times were highest in fixed routes, followed by route deviation, and significantly lower in demand response trips.
- Most transit trips happened in the nine municipalities of the region, and many demand response requests' origin/destinations are located near a fixed-route bus stop.

- Intermodal connections can be facilitated through MaaS primarily for the above cases and rural-to-urban trips—less popular yet important in terms of accessibility.

CHAPTER 4: POST-DEPLOYMENT ANALYSIS

Considering the deployment timeline outlined in Table 1-1, our post-deployment analysis continues to utilize two primary data sources. Firstly, the NTD monthly ridership tables are employed for a comprehensive macroscopic assessment spanning periods before, during, and after MaaS deployment. As highlighted in the preceding pre-deployment analysis section, we observed greater variation in ridership by service type rather than agency over time. Consequently, we primarily utilize service-type aggregated ridership for this analysis. Furthermore, we address the identified COVID-19 impact and seasonality from the pre-deployment analysis to facilitate the proper utilization of NTD data in time series modeling for estimating the impact of the MaaS platform.

Secondly, another round of ODR data collected by the research team serves as a foundational element for analyzing trip or reservation-level statistics and transit trip locations. Specifically, we compare user experiences regarding trip reservations assumed to be enhanced by MaaS. Additionally, leveraging the ODR's location information, we conduct equity impact analyses. The disparity in data collection frequency and resolution between the NTD ridership tables and ODR data aligns with the diverse analytical needs, enabling a thorough exploration of both macroscopic and microscopic aspects of the MaaS deployment impact.

4.1 TIME-SERIES ANALYSIS WITH NTD RIDERSHIP DATA

Continuing the exploration initiated in the pre-deployment analysis, which utilized the NTD service-level ridership data table up to January 2023, we extended our data collection to include the same tables until January 2024, coinciding with the deployment of the MaaS app and the initiation of the in-app DRT booking. Unlike the pre-deployment analysis, which concentrated on long-term yearly ridership changes, the post-deployment ridership analysis aims to:

- Examine monthly ridership patterns to identify when ridership variations stabilized following the initial impact of the COVID-19 outbreak.
- Utilize data from these stable periods to develop time series models capable of estimating post-deployment ridership under the assumption of MaaS absence.
- Validate ridership changes by comparing them with similar estimates from the selected control group.

4.1.1 Monthly Ridership Trends and Seasonality

In Figure 4-1, the monthly ridership recorded in the NTD is depicted for every agency-service type combination that was available in any form in the MaaS as of January 2024—the latest NTD available at the time of conducting the analysis. The first two plots illustrate total ridership from fixed routes and DRTs summed across agencies, excluding paratransit and route deviation total ridership, as valid observations for those two types are limited to Rochester and SMART, respectively, which already have their own plots. As evidenced in the pre-deployment analyses, there were significant ridership declines immediately following the COVID-19 state emergency in March 2020. A sharp ridership recovery followed this and then had a regression to a stable status, where seasonal variations appeared to affect more than the recovery momentum. To extract a valid time range of inputs for time series modeling, we must pick ridership data that shows stationarity or stability by excluding the periods with extensive external shock of COVID. This necessitates delineating pre- and post- (or under-) pandemic periods and incorporating observations only from the latter in the modeling.

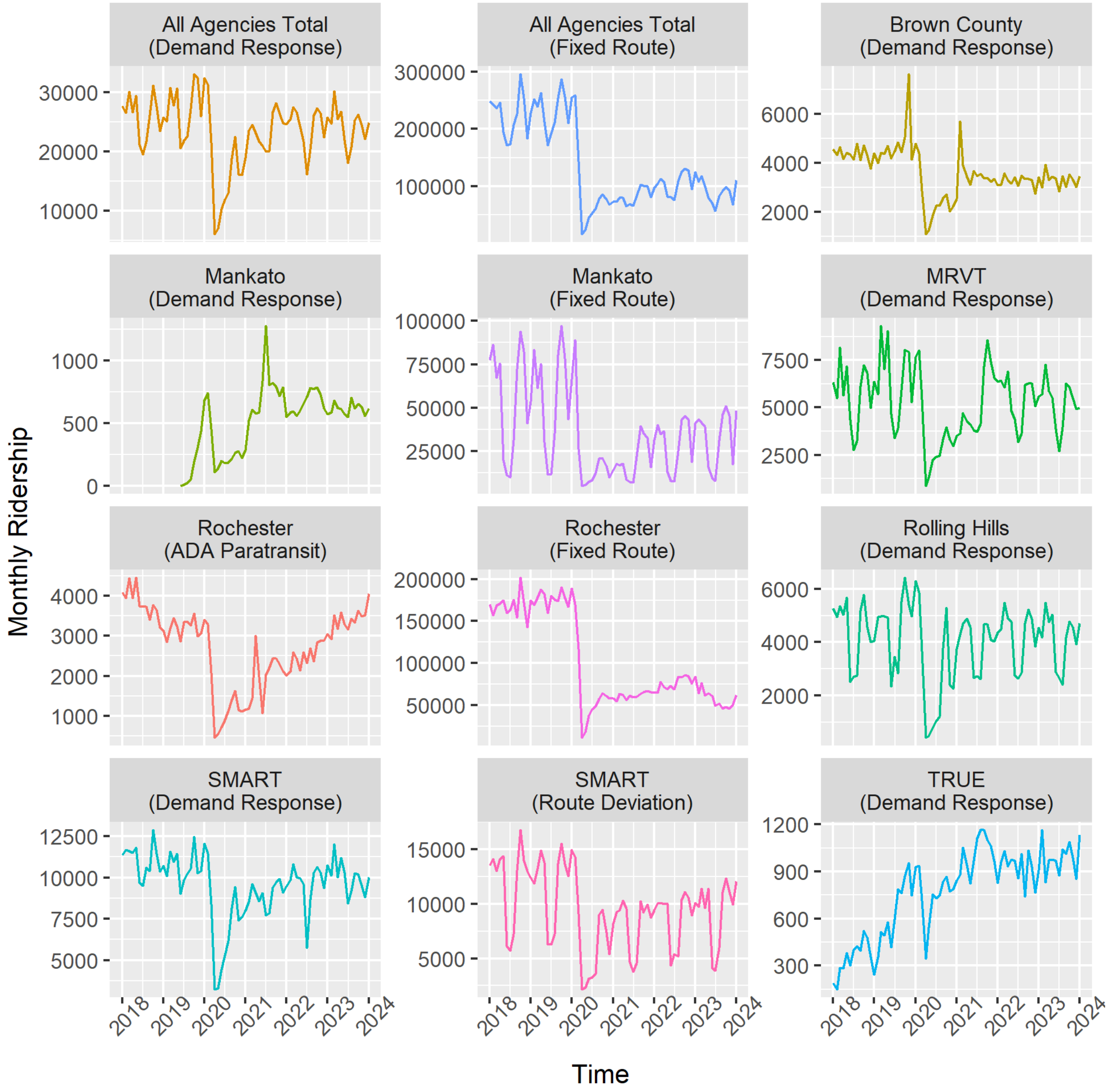


Figure 4-1 Six-year NTD ridership of the MaaS-impacted services (Jan 2018 – Jan 2024)

On the other hand, Figure 4-2 illustrates the seasonal plot for the averaged standardized ridership, the transformed value from the original ridership series. The transformation is required considering the extensive variations in the scales of each agency, which help to capture general fluctuations that have influenced the entire Southern Minnesota region. Standardized ridership or z-score of a month t, denoted z_t, is computed by subtracting a ridership series' mean (μ) from the original value (y_t) and then dividing the result by its standard deviation (σ); i.e., $z_t = (y_t - \mu)/\sigma$. This transformation aligns the ridership series with the standard normal distribution, facilitating meaningful comparisons or combinations of multiple standardized series across different contexts. The standardized series derived from each of the agency-specific plots in Figure 4-1 from the same month are averaged and presented in Figure 4-2.

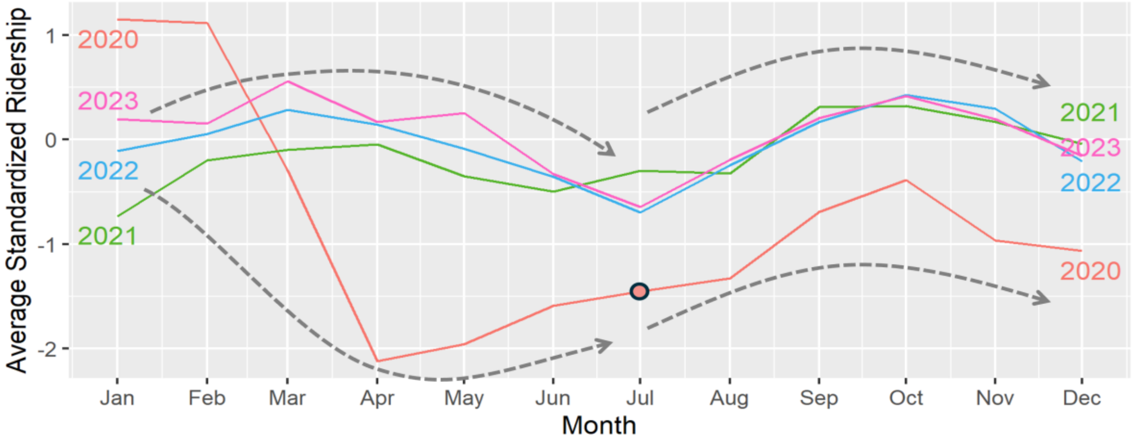


Figure 4-2 Seasonal plot of average monthly standardized NTD ridership (2020 – 2023)

The figure shows that July 2020 marks when the seasonal pattern or monthly variation in ridership changes stabilized. Although the ridership-recovery momentum continued to influence the data until late 2021, the direction of ups and downs from July 2020 became similar to those of the later years. Consequently, we designate July 2020 as the starting point for our time series modeling introduced in the later section. The purpose of this delineation is because the time series models can systematically incorporate increasing or steady trends—i.e., since April 2020—but do not encompass the unstable seasonality during the early pandemic.

Moving to the selection of control groups for the ridership time series *analysis*, we aimed to identify agencies with characteristics similar to the seven "target" agencies before the MaaS deployment but did not benefit from the MaaS. Considering the diverse areas covered by the target agencies with different service types, the control group agencies' NTD ridership was carefully selected to represent the target group collectively with the following steps.

- Collected NTD ridership data for each transit agency in Minnesota by service type.
- Excluded transit agencies operating within the Twin Cities Metro Area or partially covering out-of-state areas. (e.g., MVTA, Moorhead-Fargo Transit)
- Excluded transit agencies already with similar apps. (e.g., Duluth, Tri-Cap Transit)
- Matched each target group's service type occurrence by the size of cities they serve.

The selected control group transit agencies are Arrowhead Transit, St. Cloud Metro Transit, and Winona Transit Service. Arrowhead Transit covers 11 northeastern Minnesota counties with various-sized towns, representing DRT operations by MRVT, Rolling Hills, and TRUE Transit. St. Cloud Metro Transit mirrors Rochester Public Transit with similar yearly fixed route ridership and a comparable operation scheme: multiple fixed routes, a paratransit service, no route deviation, and no DRT service targeted at the general population. Winona Transit Service represents Mankato Transit and SMART, which operate a few bus routes with DRT services.

After collecting and filtering NTD data for the control group, their averaged standardized ridership is plotted alongside the target group in Figure 4-3. Despite a few deviations, the target and control groups exhibit similar fluctuation for the post-pandemic period. Notably, the control group appears to have gained a higher ridership increase that coincided with the MaaS feature deployments. However, more than this observation is needed to derive any conclusion about the MaaS's impact. To estimate the effect of MaaS precisely, we must control for seasonality and trends using the time series modeling introduced in the following section.

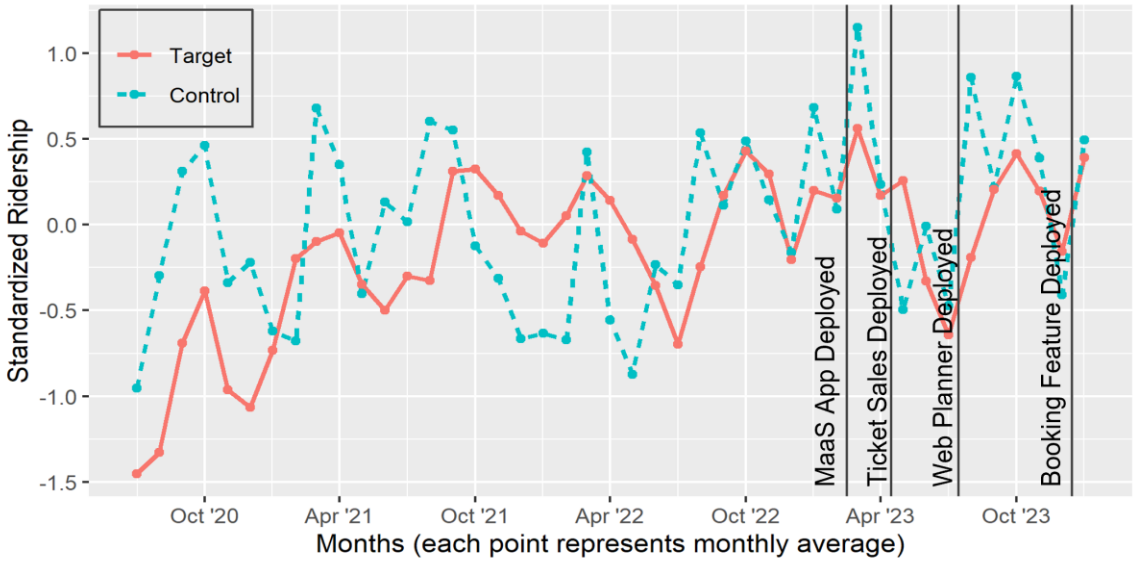


Figure 4-3 Average monthly standardized NTD ridership of the target and control groups

4.1.2 Time Series Analysis to Estimate MaaS Deployment Benefits

The preceding figures highlight the impact of seasonal variation or seasonality on transit ridership in Minnesota, influenced by factors such as holidays and weather. Given the inherent seasonality, accurately estimating the effect of a policy intervention—the deployment of the MaaS system for our case—on ridership is intricate. This complexity underscores the need to control for seasonality to derive the pure effect of the deployment [1-3].

Assessing seasonality involves decomposing the time series into distinct components, including seasonal components, trend-cycle components, and the remainder. In our analysis, we categorized the series introduced in Figure 4-1 into four categories: one dimension based on MaaS deployment (control and target groups) and the other based on two service types (paratransit & DRT and fixed route & route deviation). Our target group includes only one paratransit and route deviation service, leading us to group the former with DRTs, given their common door-to-door service scheme, and the latter with fixed routes, as both are bus-based services. Subsequently, we averaged the standardized ridership within each category. The Seasonal-Trend decomposition using Loess (STL) [22] was then applied to these series, and the resulting seasonality-adjusted time series from each group are visualized in Figure 4-4.

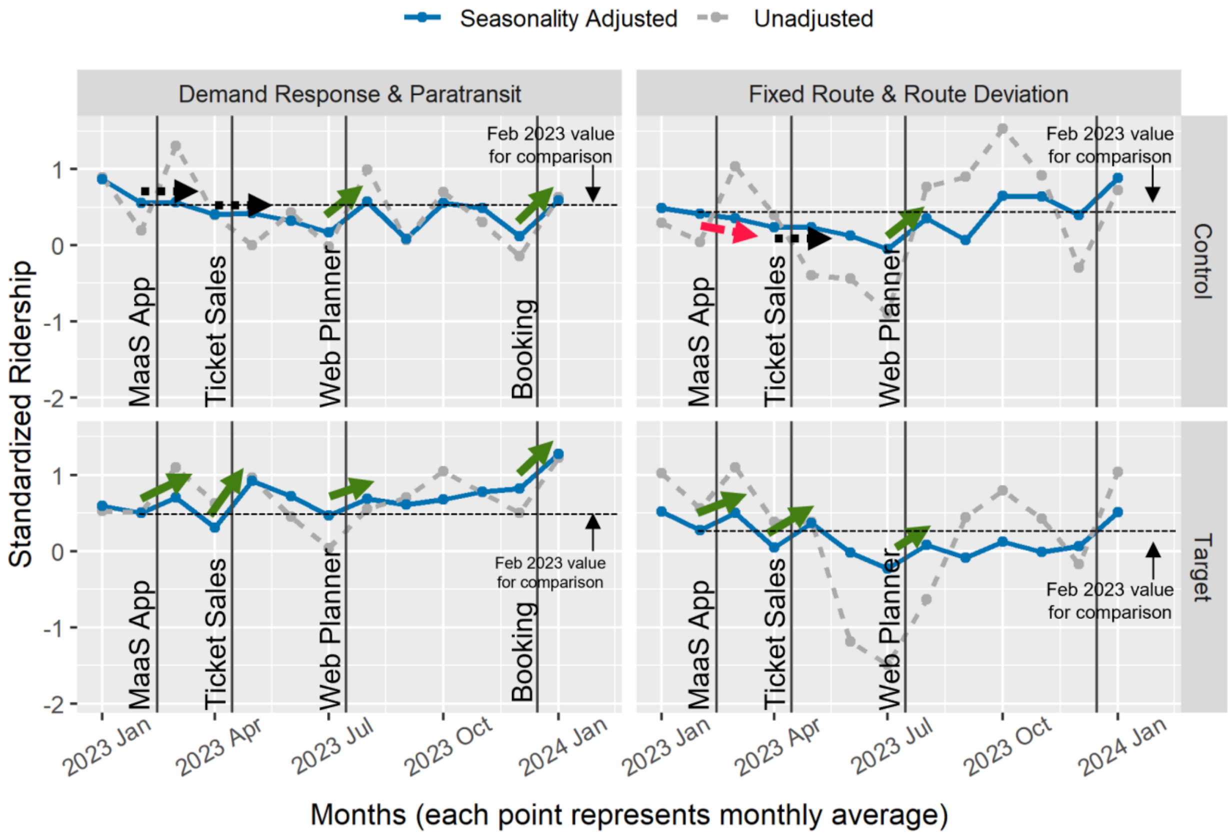


Figure 4-4 Seasonality-adjusted NTD ridership from STL decomposition

The solid blue lines in Figure 4-4 depict the seasonality-adjusted time series, providing a more suitable basis for comparing ridership changes before and after the external intervention [23], namely the deployment of the MaaS features. In contrast to the raw ridership, the adjusted ridership lines show that target group agencies experienced ridership increases following each feature deployment, whereas the control group does not exhibit evident changes. Notably, in the lower left panel depicting the trend for the target group's DRT and paratransit, the blue solid line consistently remains above the reference line representing the pre-deployment ridership (Feb 2023). Conversely, such a distinct rise above the reference line was not observed for the target group's fixed-route and route deviation services and the two control group occasions. Given that these two transit service types are not inherently complementary, it is possible that certain demands may have transitioned between them.

Moving forward, statistical time series models offer a valuable approach to time series forecasting. When appropriately designed, these models enable the estimation of "would-have-been" ridership, assuming the unavailability of MaaS during the periods even after its actual deployment. By comparing the model "forecast" estimates with the observed ridership, we can derive the impact of MaaS on ridership. Specifically, a time series model can selectively have autoregressive (AR) and/or moving average (MA) components depending on which temporal relationship is assumed among observations. An AR-only model forecasts future values based on past observations, while an MA-only model uses a weighted average of past forecast errors for forecasts. The combination of both components results in an ARMA model, and a more advanced model of ARMA, called the ARIMA (I: Integrated) model, adds differencing to stabilize the mean and variance of the time series, enhancing the accuracy. As introduced in the STL decomposition, the ARIMA framework can also account for seasonality with add-on terms.

The ARIMA model with a seasonal effect is characterized by seven parameters, denoted as $SARIMA(p,d,q)(P,D,Q)_m$. Here, p, d, and q represent the order of AR, integration, and MA terms, respectively, where their seasonal counterparts are denoted as P, D, and Q. Finally, m represents the assumed length of the season (for a monthly series with yearly patterns, we normally set m to 12). For instance, a $SARIMA(1,1,1)(1,1,1)_4$ can be expressed using the following equation, where ε_t denotes the error term and B is the backward shift operator: $B^n x_t = x_{t-n}$. Here, ϕ_k and θ_k represent the model coefficients to be estimated for AR and MA terms for the time lag k, while Φ_k and Θ_k represent their analogous seasonal counterparts. The terms within the parentheses in the order as stated in the equation signify the terms defined by p, P, d, D, q, Q, respectively.

$$SARIMA(1,1,1)(1,1,1)_4\colon (1-\phi_1 B)(1-\Phi_1 B^4)(1-B)(1-B^4)y_t = (1+\theta_1 B)(1+\Phi_1 B^4)\varepsilon_t$$

Given any time series data, the R package *tsibble* [24] automatically selects the most suitable ARIMA specification—iteratively adjusting AR, MA, differencing, and seasonal components—that best describes the data. We used the package to acquire the automatically fitted time series model by feeding the control group's ridership, and the resultant models' validity was checked. The model for DRT and paratransit combined yielded statistically significant parameter estimates and passed the Ljung-Box test [25], indicating the model's residuals or unexplainable parts resemble random white noise (i.e., the models forecasted the known ridership well). The fitted model for DRT and paratransit ridership estimation can be expressed as the following equation, and future ridership can be computed from previous observations and assuming ε_t being 0. The ϕ_1 value for the control and target groups are 0.894 and 0.890, respectively.

$$SARIMA(1,0,0)(0,1,0)_{12}\colon (1-\phi_1 B)(1-B^{12})y_t = \varepsilon_t;\ \varepsilon_t \sim N(0,\sigma_\varepsilon^2)$$

As the above equation implies, each estimate is not a precise figure but represents a “range” that follows a distribution. This structure enables the calculation of confidence intervals, indicating the range within which the model determines the true value lies. As we forecast further into the future beyond the data used to build our model, the range of possibilities widens because uncertainties accumulate over time. Consequently, relying on time series estimates for extended periods is discouraged due to the increasing uncertainty associated with distant forecasts. We observed that starting from December 2023, the 75% confidence interval for the estimates exceeded 5,000. Furthermore, since October 2023, we noticed a tendency for the model to overestimate ridership for the control group compared to the observed figures. This discrepancy is concerning, as it suggests a potential issue with the model’s accuracy. Therefore, we opted to report results using the model estimates up to November 2023.

Figure 4-5 illustrates the comparison between observed and the mean forecasted ridership calculated using the aforementioned equation, representing the combined projected ridership for DRT and paratransit services. The figure exhibits that for the control group, the two lines intersect multiple times, with positive and negative vertical differences along the time canceling each other when summed. In contrast, for the target group, the observed ridership line consistently lies above or near the forecasted line until October 2023, suggesting there were ridership gains in the study period after adjusting for seasonality. These differences are indicative of the MaaS platform’s effectiveness in increasing ridership. The figure’s numerical values are presented in Table 4-1, including observations, forecasts, and ridership gains. The column summarizing the gains shows that after the MaaS deployment, the services experienced an additional 1,114 riders per month, representing a 4.2% ridership gain. In contrast, the control group saw only a modest additional 55 riders per month, amounting to a 0.2% gain over the same period. The stability of the control group and the overall increases in the target group suggest a correlation between MaaS deployment and seasonally-adjusted ridership gains.

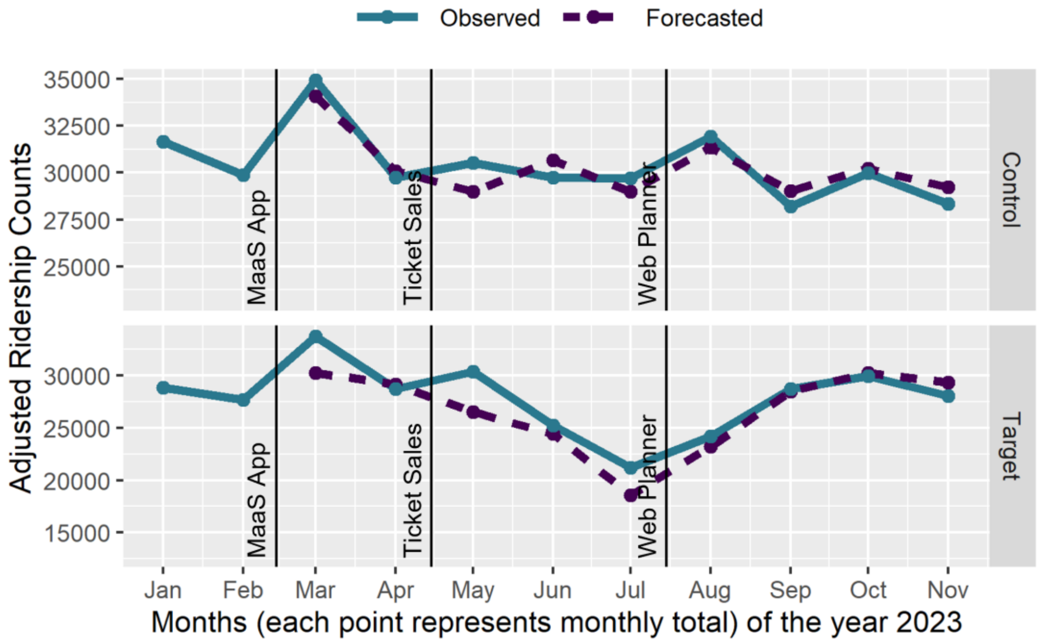


Figure 4-5 The observed and forecasted DRT/paratransit ridership from the ARIMA model

Table 4-1 DRT and paratransit ARIMA model results for seasonality-adjusted ridership

MaaS	Month	Forecasted Ridership (F)	Observed Ridership(O)	Ridership Gain (G: O-F)	Increment (G/F)
Target Group (with MaaS)	**Mar 2023: MaaS App (Trip Planner) Deployed**	30,253	33,729	3,476	11.5%
	Apr 2023	29,146	28,687	-459	-1.6%
	May 2023: MaaS Ticket Sales Deployed	26,502	30,374	3,872	14.6%
	Jun 2023	24,439	25,254	815	3.3%
	Jul 2023	18,574	21,215	2,641	14.2%
	Aug 2023: Web Trip Planner Deployed	23,195	24,202	1,007	4.3%
	Sep 2023	28,456	28,689	233	0.8%
	Oct 2023	30,214	29,939	-275	-0.9%
	Nov 2023	29,330	28,047	-1,283	-4.4%

	The monthly mean of the gain and increment			**1,114**	**4.2%**
Control Group (without MaaS)	Mar 2023	34,065	34,929	864	2.5%
	Apr 2023	30,095	29,738	-357	-1.2%
	May 2023	28,987	30,517	1530	5.3%
	Jun 2023	30,647	29,748	-899	-2.9%
	Jul 2023	29,004	29,701	697	2.4%
	Aug 2023	31,356	31,941	585	1.9%
	Sep 2023	29,027	28,208	-819	-2.8%
	Oct 2023	30,204	29,989	-215	-0.7%
	Nov 2023	29,245	28,351	-894	-3.1%
	The monthly mean of the gain and increment			**55**	**0.2%**

Additionally, Figure 4-6 illustrates the pairwise differences in the increment column from Table 4-1, where each month's value is calculated by subtracting the increment of the target group from that of the control group. These percentage point differences are significant as they are the results of controlling macroeconomic impacts (e.g., gas price) affecting ridership for both groups but could not be captured by the time series modeling framework. The positive percentage points observed for most months post-deployment further support the influence of MaaS deployment. Meanwhile, the diminishing differences after July can partially be attributed to the "regression to the mean effect," implying that unusually high numbers in the first few months of the external effect tend to normalize in subsequent months, smoothing the long-term trend and yielding more robust figures [26].

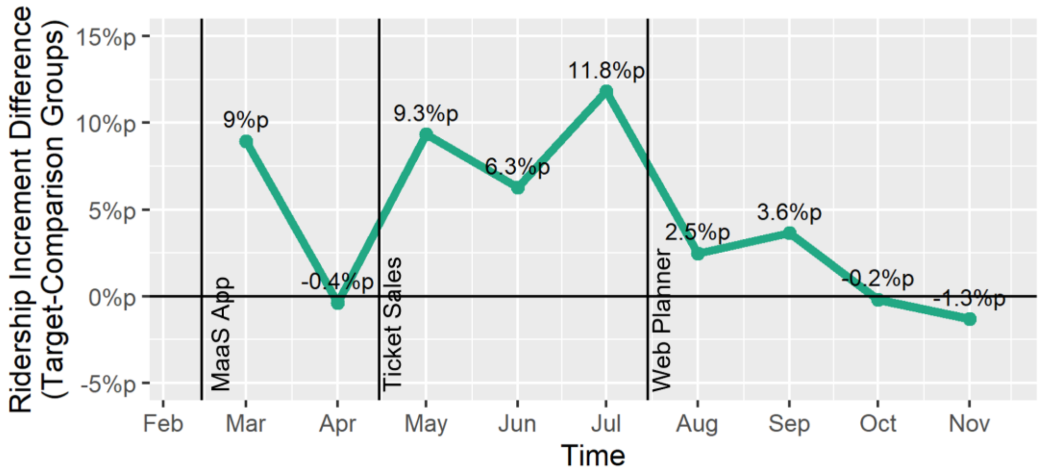


Figure 4-6 Ridership increment differences between the target and comparison groups

Nevertheless, it is important to note the limitations when focusing on monthly forecasted ridership, gains, and increments. Firstly, these numbers are seasonally adjusted estimates, not raw figures. Secondly, ARIMA models may struggle to account for macroeconomic changes effectively. Thirdly, to reiterate, as the forecasting horizon extends, the confidence interval of the estimates widens. Therefore, for interpretations and comparisons, it is advisable to use the mean value rather than individual monthly estimates.

On the other hand, the time series model automatically fitted for the bus-based services (fixed route and route deviation) failed the Ljung-Box test, indicating the residual part of the model—the numbers that cannot be explained by ARIMA systematic part of the model—still has significant autocorrelation along the time. Because of this, they had either statistically insignificant or illogical coefficient estimates, suggesting that ARIMA modeling for them may not be suitable. Therefore, we reject the model for the fixed route and route deviation services, concluding that no statistically significant numerical changes in seasonality-adjusted ridership after the MaaS deployment are observed for the two transit service types for the target group.

4.2 ODR DATA COMPARISON: RESERVATION AND EQUITY

Continuing the ODR data collection initiated in the pre-deployment phase (Jan – Feb 2023), we extended our efforts to gather data targeting transit rides and associated reservations that occurred in mid-October 2023. Table 4-2 presents the outcome of our post-deployment data collection. It is essential to note that no agencies had implemented in-app reservations during this data collection period. Consequently, the reservation segment of the data was solely comprised of call-in reservations, mirroring the structure of the pre-deployment ODR data.

Table 4-2 Post-deployment ODR data collection and timestamps availability summary

Transit Agency	Service Type	Data Counts	Trip-intended Dates (2023)	RRT	PDT	SDT
Brown County	DRT	107	10/16 – 10/19	0%	0%	100%
Mankato Transit	DRT	209	10/16 – 10/19	38%	38%	NA
MRVT	DRT	733	10/17 – 10/21	100%	100%	0%
Rochester	ADA Paratransit	99	10/16 – 10/20	0%	0%	90%
Rolling Hills	DRT	115	10/16 – 10/20	100%	15%	100%
SMART	DRT	286	10/16 – 10/20	62%	16%	100%
	Route Deviation	225	10/16 – 10/20	0%	100% by definition	
TRUE Transit	DRT	*Not Collecetd*				

Note: Fixed route ODR is not collected for the post-deployment phase

4.2.1 Reservation Behavior Comparison

To visualize the evolution of reservation behaviors for MaaS-powered DRT users (the only service type our data allows to analyze the before-and-after reservation behavior), we utilized reservation-related features (reception time, PDT, and SDT) from both pre-and post-deployment ODR datasets. Figure 4-7 provides insight into the hourly reservation call-in time histograms. An apparent peak at 8 AM is observed for the pre-deployment phase. However, during the post-deployment phase, the hourly call-in time distribution between 8 AM and 2 PM became notably flattened or more evenly distributed. One plausible explanation is that before the MaaS deployment, passengers faced limitations in accessing information and planning trips during the out-of-service hours of call centers (typically 5 PM – 8 AM). Consequently, calls might have been concentrated at the beginning of the service hour. The MaaS deployment likely addressed this inconvenience, leading to a more evenly distributed call-in time.

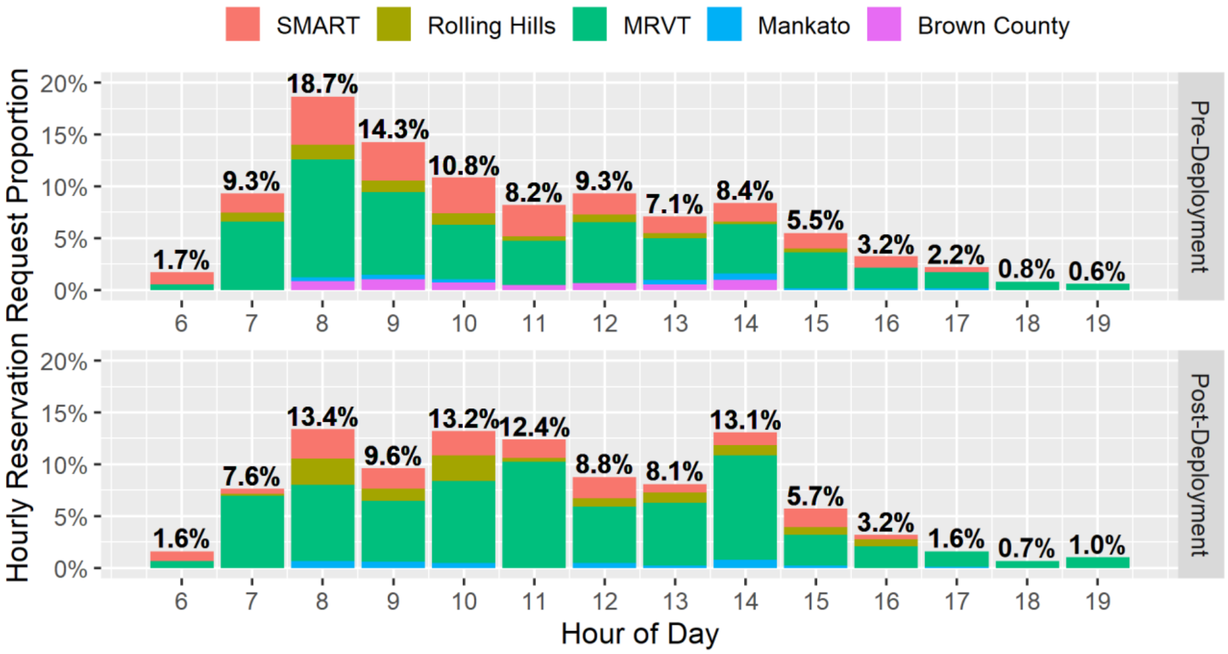


Figure 4-7 A comparison of the hourly distribution of reservation call-in time

In contrast, Figure 4-8 highlights a more extreme difference in the date gap between reservation call-in and the actual trip during the post-deployment phase. The ease of real-time information acquisition through MaaS, or simply not having to call for an inquiry, may have contributed to an increase in same-day trip requests. Additionally, the availability of looking up the future transit schedule with the “depart at” feature in the app could have led to a higher frequency of far-future (> ten days) trip requests.

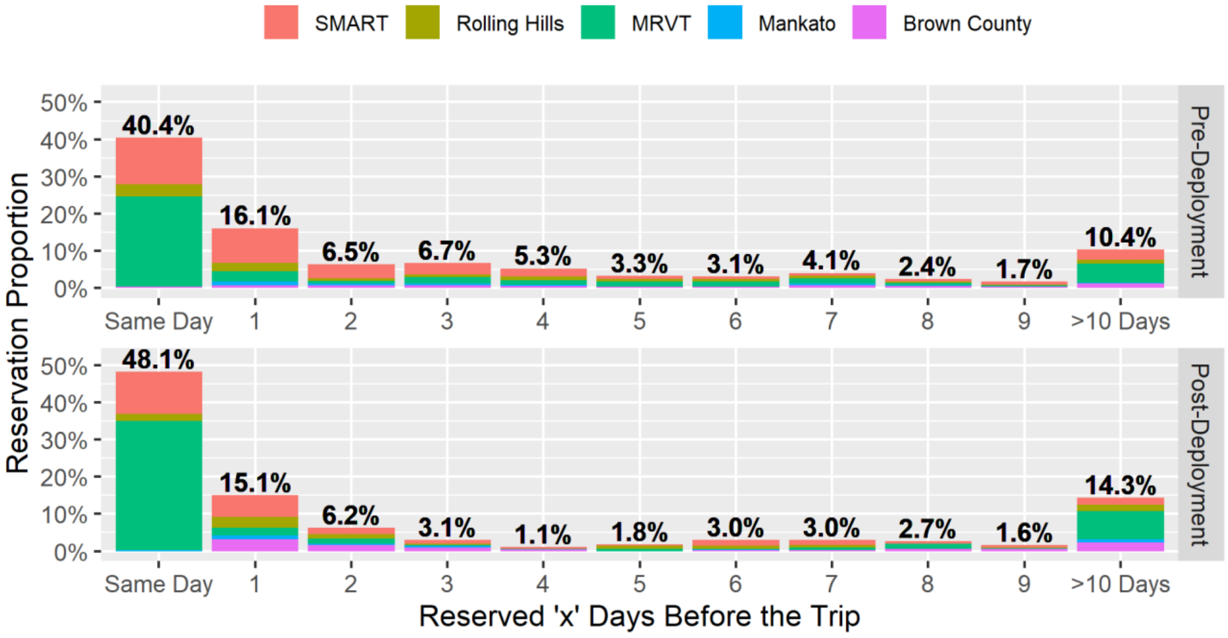


Figure 4-8 A comparison of the difference between reservation and trip dates

It is crucial to note that at the time of this analysis and ODR data collection, not all features of MaaS had been deployed, with the in-app reservation being notably absent. Consequently, no significantly observable differences were identified between the pre- and post-deployment periods for features other than those related to reservations. These include user behaviors concerning ride cancellation, hourly/weekly ridership distribution, and ride-related statistics such as schedule/departure time displacements, ride duration, and distance. They exhibited minimal changes compared to the pre-deployment periods.

4.2.2 Equity Analysis with ODR and Census Data

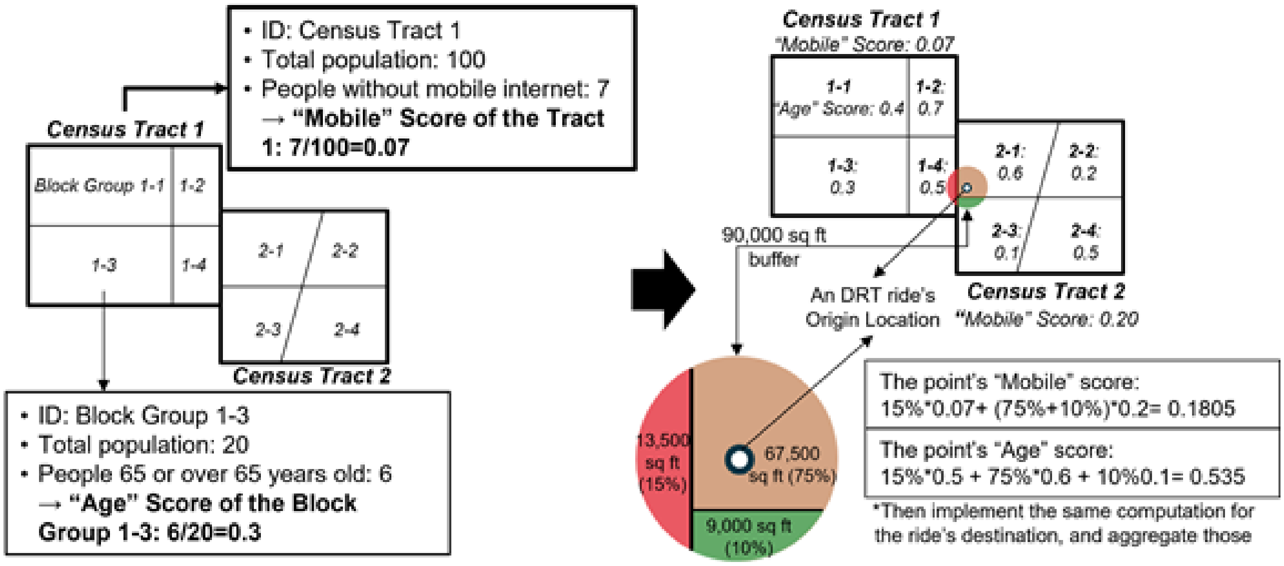
Ensuring equitable access to MaaS is essential for individuals facing challenges in undertaking trips for personal and social activities. In this context, the Minnesota Department of Transportation (MnDOT) has established the Equity Lens Framework to identify demographic groups potentially encountering barriers in accessing MaaS services. We utilized pre- and post-deployment ODR datasets to investigate how many transit rides originated and terminated in locations where populations facing barriers predominantly reside. The equity analysis with ODR involved leveraging datasets from the United States Census Bureau, with the addressed equity measures and utilized Census data sources are summarized in Table 4-3.

Table 4-3 Equity measures and Census dataset source (Data Year: 2022)

Measure	Census Dataset	Minimum Geographical Unit
1. People without mobile data plans	S2801: Types of Computers and Internet Subscriptions	Census Tract
2. People with physical disabilities	B23024: Poverty Status in the Past 12 Months by Disability Status by Employment Status for the Population 20 to 64 Years	Census Tract's Block Group
3. People whose income was below the poverty level		
4. People whose primary language is not English	B16004: Age by Language Spoken at Home by Ability to Speak English for the Population 5 Years and Over	Census Tract's Block Group
5. Households without a usable vehicle	B08201: Household Size by Vehicles Available	Census Tract
6. People 65 or more years old	B01001: Sex by Age	Census Tract's Block Group

Note: Another measure of "Unbankedness" proposed by MnDOT Equity Lens was excluded due to the Census data limitation

We defined an "Equity Score" for this analysis, representing each measure introduced in the above table. We designed each agency and each service type to have its own Equity Score for each period. The computation of the Equity Score involves multiple steps: compute by area and then aggregate based on DRT-used locations. Initially, we calculated the Equity Score for each Census geographical unit (either census tract or block group) by assessing the proportion of people of interest residing within the unit. Subsequently, for each ODR record's origin and destination, we created a 90,000 sq ft circle (the minimum area of the Census block) around it. We then calculated the proportion of the circle's area intersecting with each overlaying Census geographical unit. The Equity Score for the origin or destination was then computed by multiplying the Census unit's Equity Score by the area-overlaying proportion and summing those values. Finally, the system-wide Equity Score was determined by averaging all the ODR demand points' Equity Scores calculated in the previous step. Figure 4-9 illustrates the computation steps of the census unit-level and the ODR record's origin and destination-level Equity Score calculation processes.



(a) Equity score of each census geographical unit (b) Equity score of each ODR record

Figure 4-9 Equity score calculation steps and example

Table 4-4 presents the changes in Equity Scores between MaaS's pre-deployment and post-deployment phases. While there are some local decreases, the last row indicates that, across all equity measures, there have been increases in overall Equity Scores. Notably, the increments are smallest in mobile data, which is reasonable given that MaaS often requires a passenger with a mobile data plan or at least an internet connection. The second smallest increase pertains to age, a phenomenon explainable by the younger demographic being more smartphone app-friendly. The measure showing the most significant rise in Equity Score is language barriers, potentially reflecting a preference for using the app over making oral inquiries among populations facing language challenges.

Table 4-4 Equity Scores by each measure

Agency/ Type	Deployment Phase	Mobile Data	Disability	Income	Language	Vehicle	Age
Brown County/ DRT	Pre	0.1202	0.0560	0.0490	0.0047	0.0281	0.1229
	Post	0.1226	0.0576	0.0519	0.0048	0.0296	0.1278
MRVT/ DRT	Pre	0.1086	0.0620	0.0597	0.0041	0.0227	0.0922
	Post	0.1073	0.0689	0.0670	0.0042	0.0231	0.0945
Mankato/ DRT	Pre	0.0949	0.0491	0.1060	0.0027	0.0391	0.0842
	Post	0.1068	0.0522	0.0954	0.0034	0.0413	0.0879
	Pre	0.1071	0.0451	0.0364	0.0055	0.0291	0.0949

Rolling Hills/ DRT	Post	0.1078	0.0441	0.0451	0.0053	0.0365	0.1044
SMART/ DRT	Pre	0.1143	0.0649	0.0698	0.0177	0.0438	0.1042
	Post	0.1148	0.0660	0.0708	0.0268	0.0480	0.1025
SMART/ Route Deviation	Pre	0.1200	0.0687	0.0709	0.0161	0.0483	0.1123
	Post	0.1202	0.0696	0.0749	0.0175	0.0485	0.1193
Overall/ Total	**Pre**	**0.1098**	**0.0601**	**0.0663**	**0.0085**	**0.0328**	**0.0976**
	Post	**0.1113**	**0.0640**	**0.0698**	**0.0099**	**0.0343**	**0.1012**
	Changes	**1.37%**	**6.55%**	**5.30%**	**15.75%**	**4.63%**	**3.74%**

CHAPTER 5: CONCLUSIONS

We are in an era where permanent travel behavior changes could be ongoing as the pandemic-driven shocks are being selectively resolved and new technologies rapidly emerge. In any scenario, it is not too much to emphasize the importance of connecting people, especially those who depend on transit. The mobility-as-a-service platform deployed in Southern Minnesota was expected to enhance people's connectivity and the convenience of planning, reserving, and riding rural transit services.

Following a thorough review of existing literature, our initial focus was on examining the operational dynamics and user behaviors within the study area's transit system before the implementation of the MaaS platform. Macroscopic analyses using NTD monthly ridership data revealed disruptions in ridership attributable to the COVID-19 pandemic. The disruptions persisted until the period just prior to MaaS deployment, along with observed seasonal fluctuations. On a granular level, our microscopic analyses uncovered disparities between use patterns of reservation-based DRT services and fixed-route bus services. These analyses highlighted various inconveniences stemming from the current reservation system configuration and the supply-demand dynamics of DRT. It became evident that MaaS has the potential to address these issues effectively. Furthermore, the study identified opportunities to optimize current DRT operations by integrating certain trips with existing bus routes using MaaS, thereby maximizing societal benefits. This synergy underscores the potential for MaaS to enhance overall transit efficiency and accessibility in the study area.

Our comprehensive analysis of the MaaS deployment impact has yielded valuable insights into ridership patterns, behavioral changes, and equity considerations within the transit ecosystem. By applying the seasonal ARIMA statistical framework to pre- and post-deployment NTD ridership data, we were able to estimate the net impact, highlighting the effectiveness of MaaS in driving ridership gains. Specifically, the analysis revealed a substantial monthly ridership increase averaging 4.2% for DRT and paratransit over nine months following the MaaS platform deployment, compared to the control group's 0.2% increase.

Furthermore, the comparative analysis of pre-and post-deployment ODR datasets shed light on shifts in reservation behaviors, with the MaaS deployment flattening hourly call-in time distributions and influencing same-day trip requests. The examination of equity considerations through the Equity Lens Framework and the computation of Equity Scores demonstrated a positive overall impact of MaaS on equitable access, with increases observed across various equity measures. Notably, language barriers exhibited the most significant rise in Equity Score, indicating the potential of MaaS to address communication challenges in transit services.

These post-deployment phase findings underscore the multifaceted impact of MaaS adoption, encompassing ridership dynamics, behavioral shifts, and advancements in equity. As the transit landscape continues to evolve, these insights are valuable for policymakers, transit agencies, and urban planners seeking to enhance the efficiency, accessibility, and inclusivity of public transportation systems through innovative technologies like MaaS.

Being in the early deployment stage without fully stabilized functionality (as of late 2023), MaaS still has the potential to achieve more social goals. Based on the literature reviewed, pre-deployment travel pattern analyses, and the estimations of how the MaaS deployment changed transit use in the region, further implications or opportunities can be drawn regarding the future direction of the MaaS updates that can improve connections for people, reduce the workload for transit agencies, and expand the benefit of the region's transit system:

- Convenience and efficiency: MaaS could make booking and canceling trips more convenient and efficient by fully automating the processes to eliminate the need for passengers to make phone calls and communicate with agency staff.
- Notifications and real-time information: MaaS could provide real-time notifications and vehicle location updates, enabling passengers to respond promptly to schedule changes or delays. This can improve the overall passenger experience and satisfaction.
- Intermodal Connection: MaaS could enable intermodal connections that make transit services more efficient. For example, a trip to Rochester that originates from a rural area can use fixed bus routes once in the city rather than continuing the demand response ride.

While the platform's features and the above expectation focus on DRT services, it does not mean that rural transit agencies have to switch all their services to demand response transit with an enhanced MaaS. Fixed-route buses, defined by many studies as a backbone of a MaaS platform, have the advantage of always being available without the need for booking, and their higher vehicle capacity and passenger occupancy can reduce road congestion and carbon emissions by addressing multiple travel demands at once. MaaS can facilitate intermodal connections by enhancing the experience of searching, planning, booking, paying, and accessing real-time information. In other words, if MaaS is designed to facilitate such intermodal connections, the systemwide vehicle-miles-traveled numbers can be decreased, and the agency can offer more services to decrease the users' schedule displacements.

As pointed out by Hensher et al. [6], such a future direction to elevate the integration level of MaaS is imperative for the platform to achieve broader social goals, especially in rural areas. They reviewed the impacts of many MaaS platforms currently deployed worldwide, mostly in integration levels 0–3 (see Figure 2-1), and stated: "*MaaS faces a very uncertain future… without evidence of MaaS contributing to sustainability goals, the future may be one of the apps with no provision for bundling mobility… a proactive approach, led by government, seems essential for any future positive outcomes.*"

A promising trajectory for MaaS in the study area or rural region involves advancing its established convenience while striving for integration across modes to promote social equity. One strategy entails gathering eligible passengers at fixed route stops using demand response vehicles, then enhancing route flexibility to accommodate more destinations and easier deviation requests. This seamless integration should mirror the convenience of private car rides, fostering expanded service areas and improved accessibility alongside increased reliability, efficiency, and emissions reduction. Moreover, future developments could prioritize features benefiting marginalized communities, such as applying selective fare discounts for them. This can be facilitated through another emerging technology, such as the concept of a mobility wallet that further streamlines intermodal fare payments and can incentivize users who generate less carbon footprint.

However, achieving successful integration necessitates numerous optimizations, including demand response vehicle routing and identifying optimal transfer points while also managing conflicting deviation requests. This requires consensus among multiple agencies and further research, both in-field and in-lab, to address these complexities effectively.

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