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Requiem for transit ridership? An examination of who abandoned, who will return, and who will ride more with mobility as a service

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ABSTRACT

To adhere to health regulations and reduce the risks associated with the COVID-19 pandemic, employers, mobility operators, and travelers alike adopted new strategies such as teleworking, rigorous sanitation, and social distancing. In this research, we examine the individual-level factors contributing to transit ridership abandonment and return decisions. We utilize comprehensive survey-based data of transit users in the Chicago metropolitan area (N = 5648) collected prior to reopening. We investigate three ridership behaviors, namely (1) discontinued public transit ridership, (2) the intent to return to pre-pandemic transit ridership levels once health concerns are alleviated, and (3) the likelihood of using public transit more often if its fare systems are integrated with other mobility services such as ridehailing and micromobility. Examining the role of sociodemographics, employment characteristics, transit investment priorities, and travel behavior before and during the pandemic, this research reveals fine-grained details about transit usage decline, as well as future intentions. The results indicate that teleworking, unemployment, and vehicle access are the major factors behind discontinued transit ridership. Analysis of race, ethnicity, and gender effects reveals that vulnerable users often have a higher risk of abandonment coupled with a lower likelihood of returning. These results point to the need for transit agencies to consider the specific concerns of ethnic/racial minorities and women. Encouragingly, there is an opportunity for agencies to attract more ridership with fare integration. Several respondent segments would use transit more if fare systems are integrated with ridehailing and micromobility, highlighting the importance of lowering the barriers to accessing these mobility services. This research informs several policies that can be adopted by transit agencies and other mobility providers. We discuss the importance of an equitable return to transit, possibilities for Mobility-as-a-Service with fare integration as a starting point and stress the significance of teleworking in future transit policies.

1. Introduction

Public transit plays an important role in urban transportation systems with many relying on it to provide access to employment and a plethora of other services. However, the shifting ridership in response to health concerns arising from the COVID-19 pandemic threatens future transit ridership and introduces many new challenges for planning and operating transit in the future. Notably, The National Transit Database (2022) showed that national transit ridership (unlinked trips) in the United States fell to 20% in April 2020 (compared to April 2019) and is only slowly growing towards pre-pandemic levels. The slow post-pandemic public transit ridership return is problematic for a variety of reasons. For example, historically marginalized groups and essential workers are particularly reliant on public transportation, especially during the pandemic. Declining transit fare revenue during the COVID-19 years can disproportionately affect these population segments should agencies cut their services (Pucher and Renne, 2003; Wilbur et al., 2020; Liu et al., 2020). Additionally, challenges carrying over from pre-pandemic times will likely persist. In the years leading up to the pandemic, transit ridership in the United States was steadily declining due to ridehailing, teleworking, and growing car ownership (Erhardt et al., 2022). Consequently, transit agencies and other stakeholders face several challenges when planning for the future.

The goal of this research is to investigate the factors that shape public transit pandemic behavior, specifically focusing on explaining individual-level choices to discontinue ridership, as well as intentions to

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return to transit when COVID-19 no longer poses a significant health risk. Research early in the pandemic relied on revealed and trace/app data with limited socio-demographic details (Dean and Zuniga-Garcia, 2022; Hara and Yamaguchi, 2021; Molloy et al., 2021; Hu et al., 2021), so it remains largely underexplored what individual factors shape not just the abandonment, but also, importantly, the future return to transit. Specifically, it is important to identify both sociodemographic and behavioral factors that led to pandemic-era ridership abandonment, along with those affecting future ridership intentions. To understand transit usage decisions at the individual level, we analyze data from a comprehensive survey conducted by the Regional Transit Authority (RTA) in the greater Chicago, IL metropolitan region (N = 5648).

This research examines transit ridership decisions. The specific objectives are to (1) shed light on the role played by sociodemographics, remote work arrangements, employment status, user-informed transit investment priorities, and travel behavior variables in ridership changes. As a second objective (2) we study three main decisions, namely; a) abandonment of transit used during the acute stage of the pandemic, b) intentions to return to riding under the scenario of alleviated health concerns, and c) the likelihood of increasing ridership with transit fare integration. Together these objectives enable us to identify detailed and varied explanations for both abandonment and return intentions. Third (3) we discuss the practical implications, with a particular focus on transit-user-reported investment priorities and vulnerable user groups.

In summary, the results reveal that employment characteristics and vehicle ownership had the highest impact on COVID-19 ridership discontinuation, followed by race, user priority for sanitation of transit facilities and vehicles, and type of transit service utilized. We also find that racial and ethnic minorities (Asian, Black, and Hispanic) are less likely to lapse in ridership but looking forward, are less likely to return to transit, which emphasizes the need for careful recovery strategies targeting these communities. Gender effects are also present. Women are more likely to lapse in ridership but are also less likely to use transit in the future. Lastly, racial minorities, those who used on-demand modes to substitute transit or to access it, and those who travel during off-peak times are willing to increase their transit usage should fare integration be implemented. These results can be used to inform policies that spur growth in transit ridership and a smooth transition into the post-pandemic era.

The rest of this research article is structured in the following way. After this introduction, we analyze the literature on pandemic-era travel behavior. Beyond the salient issues during the pandemic, we examine research on the return to transit. In section three we describe the dataset used in this analysis along with exploratory data analysis of survey respondents from the three major public transit agencies, access modes, mode substitution during the pandemic, and transit investment priorities. The next section is the methodology followed by the results of the modeling. To complete the article, we then provide policy implications and conclusions.

2. Literature review

In March of 2020, the World Health Organization declared that the rapid escalation of COVID-19 cases had resulted in a global pandemic (Xu and Li, 2020). The novel coronavirus had spread to 203 countries by this point, and as a result, numerous governments implemented mitigation strategies such as social distancing, mask mandates, and sanitation requirements in a variety of sectors, including public transit (Lewnard and Lo, 2020). A review of 134 articles by Peralvo et al. (2022) on global pandemic transport mitigation strategies found that public transit was the predominant mode of focus, most strategies were developed at the city level, and that ventilation, mask-wearing and crowding were some of the top transit-strategies analyzed.

Because of the health risks of COVID-19 and subsequent interventions, travel demand plummeted globally, and many transit services struggled to maintain their normal operations due to decreased revenue (UITP, 2020). At their lowest, transit trips in the United States fell by 80% in April 2020 compared to April 2019 (National Transit Database, 2022). As a result, many public transport agencies made service cuts that disproportionately impacted low-income and otherwise vulnerable groups (Parker et al., 2021; Harris and Branion-Calles, 2021). A study of 40 major cities in the United States and Canada found that while local responses varied, almost all transit agencies made major service adjustments; however, Chicago is an outlier in this regard (DeWeese et al., 2020)

The Chicago Transit Authority (Chicago Transit Authority, 2022) avoided making significant cuts, as they maintained that public transit is an essential service, particularly for healthcare workers and vulnerable groups (Chicago Transit Authority, 2020). Nonetheless, there were significant reductions in ridership. This decline was steeper in areas with a greater proportion of white, educated, and high-income residents, whereas ridership declined less in areas with more essential workers and a greater number of COVID-19 cases or deaths (Hu and Chen, 2021). In the following subsections, we further explore the factors contributing to lapsed ridership and the plans for returning. We focus on survey-based studies, though we would like to acknowledge that there are several valuable studies utilizing aggregated ridership or mobile trace data that will not be reviewed in detail (DeWeese et al., 2020; Hu and Chen, 2021; Xin et al., 2021; Diaz et al., 2021; Molloy et al., 2021; Zheng et al., 2021; Dean and Zuniga-Garcia, 2022; Hu et al., 2021; Hara and Yamaguchi, 2021)

2.1. Demand changes during the pandemic

Safety perceptions of transit changed as the pandemic caused users to re-evaluate the tradeoffs and risks associated with riding with strangers (Soria et al., 2022). Several social distancing protocols were enacted by transit agencies. During the beginning of the pandemic, agencies added train cars to increase opportunities for distancing, taped off seats on buses and trains, added more physical barriers between riders, and reduced the capacity of vehicles (Kamga and Eickemeyer, 2021; Gkiotsalitis and Cats, 2021).

Even with a plethora of strategies to mitigate health risks, perceptions of transit were affected. Shamshiripour et al. (2020) found that users perceived transit to have the highest risk followed by ridesplitting and ridehailing. These perceived risks also affected mode choice (Rahimi et al., 2021). During a particularly restrictive period of COVID lockdowns in Germany, risk perceptions were strong enough that some carless households reportedly considered purchasing a vehicle (Eisenmann et al., 2021). Apprehension towards transit hygiene has since calmed after the initial acute stages of the pandemic, though passengers are still reluctant compared to pre-COVID times (Beck and Hensher, 2020). Because of this reluctance, there is a modal shift from transit to modes that better facilitate physical distancing such as using a private vehicle, especially for those with household vehicle access, and active modes which also include shared bikes and scooters (Abdullah et al., 2020; Dai et al., 2021; Das et al., 2021; He et al., 2022). What is unclear is how these perceptions will shape future ridership intentions. For that reason, this study focuses on the factors contributing to the return to transit as this can highlight the determinants behind this intent.

2.2. Activity restrictions during the pandemic

The pandemic caused restrictions on non-essential activities including eating at restaurants, nightlife, sporting events, and other large social gatherings (Centers For Disease Control, 2022). Activity restriction effects are seen across modes (Parr et al., 2020; Beck and Hensher, 2020). There are important links to household characteristics. Fatmi et al. (2021) found that out-of-home activities were reduced by 50% with higher-income groups less likely to reduce activity participation. Wang et al. (2022) found that individuals living in low- and medium income areas decreased their visits to retail stores. Indeed, the closure of non-essential activities also affected the ability to access essential activities. For example, the pivot from in-person schooling to remote at-home schooling caused difficulties for women in particular because of the change in domestic responsibilities (He et al., 2022). In areas where transit agencies reduced service in response to lower demand, captive riders would lose nearly all accessibility to essential activities (He et al., 2022). For those who could, a major shift in activities outside of the home includes adopting work-from-home via advanced ICT. We further explore the impact of teleworking in the next subsection.

2.3. Hybrid work and teleworking

Teleworking is not new with this subject appearing several decades prior to the pandemic (Mokhtarian, 1991). The pandemic pushed several companies to allow their employees to work remotely. Studies show that 30%–50% of survey respondents indicated they moved towards teleworking and other remote activities such as shopping, learning, and accessing healthcare (Mouratidis and Papagiannakis, 2021; Abdullah et al., 2020; Beck and Hensher, 2020). Before the pandemic, researchers found that the choice and frequency of telecommuting were positively correlated with higher incomes, being well-educated, having children at home, and being white (Plaut, 2005; Popuri and Bhat, 2003). During the pandemic, these factors remain similar with the opportunity to work from home predominately seen in high-income, well-educated, and non-minority households (Barbour et al., 2021; Yasenov, 2020; Matson et al., 2021). Research on the connection between remote work and travel pattern changes is growing. A national study found that individuals who telework spend less time on out-of-home non-work activities, travel more during the off-peak mid-day hours, and travel shorter distances overall (Tahlyan et al., 2022a). Similarly, Rafiq et al. (2022) and Shamshiripour et al. (2020) find that remote working is associated with making fewer discretionary trips.

Research is ongoing on the connections between future work policies and post-pandemic travel patterns. One important aspect is the experience of workers, which is diverse (Tahlyan et al., 2022b; Martin et al., 2022). What is clear is that having experienced remote work during the pandemic is associated with an increased preference for hybrid work arrangements among employees (Venkataramani, 2021). The growing role of telework and hybrid work carries several implications for long-term travel behavior which will be discussed in the next section on the return to transit (Nayak and Pandit, 2021; Olde Kalter et al., 2021; Beck et al., 2020).

2.4. Literature on the return to transit

As COVID-19 restrictions loosen, the need to understand the immediate to long-term effects of the pandemic on transit ridership is clear. Gkiotsalitis and Cats (2021) review transit and COVID measures and find strong evidence of the transition from ad-hoc (e.g. initial social distancing measures) to evidence-based transit planning which adapts to the current state-of-the-art in transit and COVID research. With a multitude of data to draw on, researchers look to a future where COVID-19 is endemic and not directly at the center of transit planning.

The hesitation among lapsed riders due to risk perceptions and ongoing working-from-home policies will make it difficult for public transit to return to pre-pandemic ridership levels (Vickerman, 2021; Rothengatter et al., 2021; Wang et al., 2021). These studies suggest that even a return to 100% capacity of transit services will not lead to a full return of riders due to behavioral inertia. Thombre and Agarwal (2021) recommend policies for short, medium, and long-term recovery and a shift toward a more sustainable and resilient transport system. In the short term, they suggest that transit agencies ought to re-establish trust with their constituents and expand services. In the medium term, they propose incentivizing non-auto travel as the increased usage of private vehicles is likely to cause increased congestion. Shamshiripour et al. (2020) call for research to promote sustainable and safe non-auto travel to prevent car dependency. In the long term, Thombre and Agarwal (2021) suggest infrastructure improvements to continue enhancing access by non-auto means (e.g. improve pedestrian and bicycle facilities and expand public transit infrastructure to areas where it did not exist). Beck and Hensher (2020) warn that decision-makers should think carefully about policies that would promote auto travel over transit. Other long-term strategies involve monitoring the effects of teleworking as residential location choices are likely to change and there may be more work schedule, and thereby housing location, flexibility (Shamshiripour et al., 2020; Beck and Hensher, 2020). Beck and Hensher (2020) also point to a "two speed economy" where some employees are successfully transitioning to working from home while other groups are left behind. Transit agencies will need to evaluate their priorities carefully, considering equity and the tradeoffs between attracting choice riders who reduced their transit usage, and improving services for captive riders who fill essential roles during the pandemic and post-pandemic eras.

The silver lining to the pandemic is that it has opened opportunities for public transit both assisting in the post-pandemic recovery *and* strengthening its role in the urban transport system. Dai et al. (2021) explain the case for aggressive public transit fare policies that drastically reduce the cost to ride. Three Chinese cities implemented policies to bring riders back. One city attempted fare-free transit during peak hours and did not significantly impact ridership; however, ridership significantly increased when fare-free transit was offered during off-peak times. Hensher (2020) sees an opportunity for MaaS to further reduce car dependency. One possibility the author discusses is the growing expectations for working from home flexibility as a result of pandemic-era experiences and policies. In that scenario, private auto usage is reduced since there is a lower demand for commuting. With mobility investments for walking and cycling and overall greater support for multi-modality, MaaS can integrate several services that better suit non-work travel.

3. Data

The survey data used for the analysis were obtained from the Chicago Regional Transportation Authority (RTA) which is charged with overseeing finance and planning for the public transportation agencies in the Chicago Region. The study is part of the strategic plan policy priority area of 'COVID Recovery' (Regional Transit Authority, 2022). The survey was distributed in two waves. The first wave lasted from November 9, 2020, to December 4, 2020. The second wave lasted from January 19, 2021, to February 5, 2021. The spatial coverage of survey respondents is expansive. Fig. 1 illustrates the timing of the two survey waves against general Chicago region agencies and national ridership statistics. Transit ridership statistics for Fig. 1 were obtained from the National Transit Database (National Transit Database, 2022).

Sending emails to transit users listed in customer databases maintained by the transit agencies was the primary method of recruitment. The secondary dissemination strategy was through social media and the transit agencies' websites. Survey screening was used to only include respondents who had used CTA, Metra, or Pace services before March 2020 and who live in the Chicagoland region or near the distant Metra stations in Wisconsin or Indiana. Fig. 2 illustrates the zip codes represented in the data along with the extent of the three agencies, namely CTA, Metra, and Pace route coverage. Zip codes with more respondents appear in darker gray. In the map, we use observations that are weighted to be representative with regard to official demographics. More details about the study are available in Regional Transit Authority (2021).

Before proceeding to the analysis, it is valuable to point out the different service missions of the regional agencies. The CTA provides local bus and heavy rail transit in the City of Chicago. Because it serves the relatively dense areas of Chicago with a wide range of accessibility to

Fig. 1. Transit ridership (unlinked trips) from March 2020 until March 2022 comparing national versus Chicago Region (survey timing of waves 1 and 2 shaded).

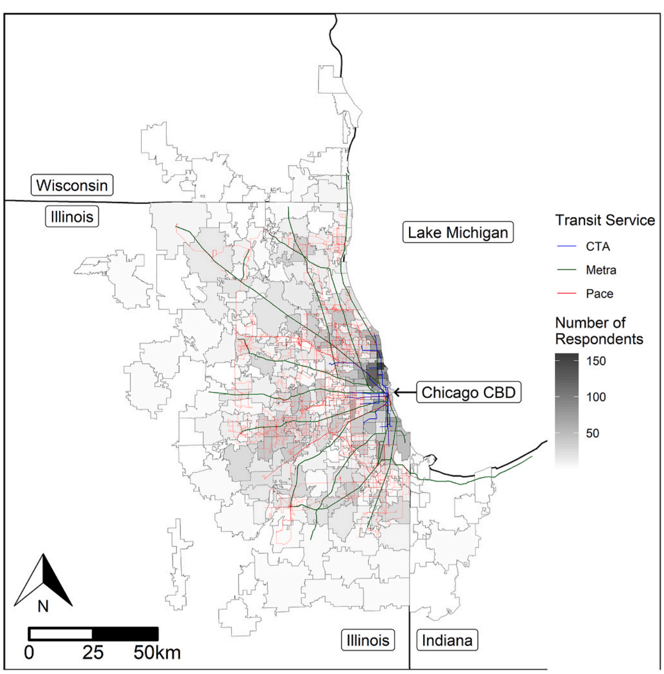

Fig. 2. Heat map of zip codes represented in the data with Chicago Region transit service coverage for CTA, Metra and Pace.

employment centers, this agency serves multiple trip purposes (commuting, maintenance trips, recreational and leisure). Metra is a commuter rail service whose lines run well into the periphery of the metro area and into bordering states to the Central Business District (CBD) of Chicago. Its main purpose is to transport employees, who typically have higher incomes, from the suburbs to the CBD. Lastly, Pace is the suburban bus service which operates primarily outside of the City of Chicago. Its purpose is to provide transit services to those without vehicle access in suburban areas outside the core city. These riders are typically lower-income and are often dependent on transit, also known as captive riders.

The data were cleaned prior to being shared with the researchers and the process is outlined in Regional Transit Authority (2021). In summary, the data were cleaned of inconsistent responses and responses that were completed too quickly to be answered genuinely. In total, 5648 observations are utilized in this research which represents 98% of all responses. All observations are used in the lapsed ridership model. Some respondents did not respond to the attitudinal items that constitute the dependent variables in the remaining two models. Therefore, 5518 observations are used in the ordered logit "Return to Transit" model and 4965 observations in the ordered logit "MaaS-fare" model. The dependent variables obtained from the survey and their definitions are provided below (see Fig. 3 for a statistical breakdown).

- **LAPSED:** Lapsed ridership status – Coded one for respondents who use a transit service less than one day per week during the pandemic but used it one day per week or more leading up to the pandemic
- **RETURN:** Return to Transit intention – "Health Concerns Alleviated: I would return fully to transit as I used it before COVID-19" (Responses collected on a 5-point Likert Scale response)
- **MaaS-fare**: "Health Concerns Alleviated: I would consider riding transit more frequently if fare payments were seamless across transit, shared bikes, and ride services (e.g., Uber/Lyft)" (Responses collected on a 5-point Likert Scale response)

The survey collected sociodemographic information such as age, income, ethnicity and race, and gender. It also collected data on

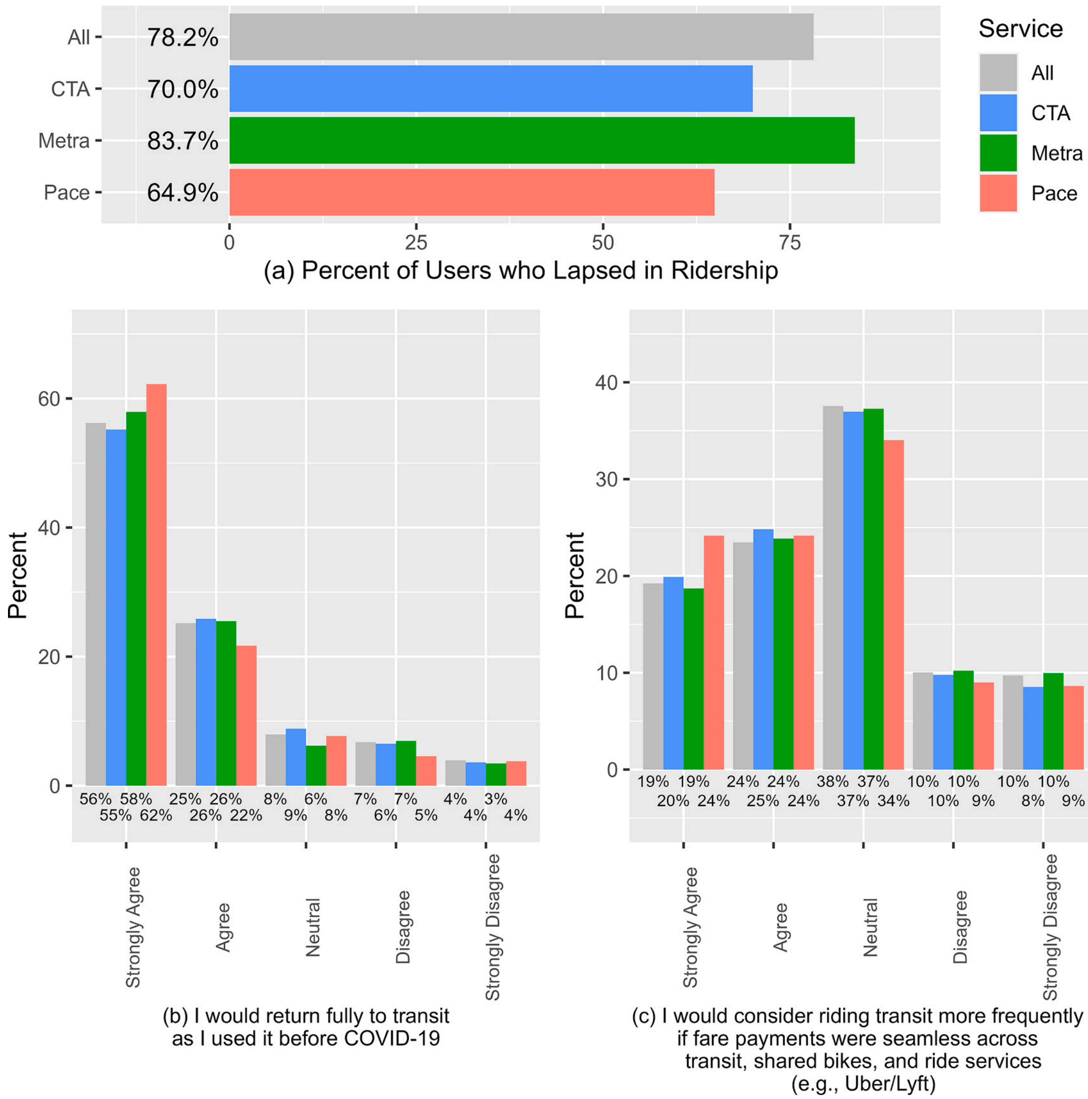

Fig. 3. Dependent variable response frequencies by transit agency; (a) Respondents who reduced their transit ridership levels during the pandemic; (b) Respondent who would return to transit once health concerns are alleviated; (c) Respondent who would use transit more with fare integration.

employment characteristics such as sector, unemployment status, and teleworking frequency. In terms of travel behavior, respondents were asked about past travel behavior, which transit agency services they used, their access modes, and which modes substituted transit during the pandemic. An innovative section of the survey presents a hypothetical budgeting question to respondents to reveal their transit investment allocation preferences. This serves as a basis for modeling the interest in added-value transit services that may favor a future return to transit. In the next subsection, we explore the data pertinent to this study. We expand on the analysis completed in Regional Transit Authority (2021) to gain more insights into nuances of ridership decline and return intentions, relevant to post-pandemic transport policies and planning.

3.1. Exploring the ridership data

We begin this analysis by providing context for the survey timing. As shown in Fig. 1, ridership for each of the transit agencies plummeted following the early stage of the pandemic and the start of the local shelter-in-place order in March 2020 (City of Chicago, 2020). Each data point represents the percent ridership of that month compared to the same month in 2019. At their low points in April 2020, the CTA, Metra, and Pace saw a precipitous decline to 22%, 14%, and 4%, respectively, of ridership when compared to April 2019. Transit ridership then rose and stabilized for several months. It is during this period of relative stabilization that both waves of the survey occurred. After the winter of 2020/2021 ridership grew towards pre-pandemic levels slowly, though remained below the national trend based on data from the National Transit Database (2022). Following the start of the reopening phase in June 2021(Cook County Department Of Public Health, 2021) ridership has continued to be unsteady. In 2023 Chicago transit ridership is still averaging around 60% (for urban buses) and hovers around 30% for Metra commuter rail (UITP 2023) underscoring the critical importance to understand return intentions.

The difference in ridership levels across the different agencies could be explained by the types of trips they cater towards. Given the switch to teleworking by many of the higher-income workers in the Chicago CBD, we expect that Metra, the suburban commuter rail service, has the lowest ridership compared to pre-pandemic levels. They, and likely other transit agencies providing suburban commuter rail services, will need to contend with the impact of teleworking more than other mobility providers. Indeed, as the urban bus and rail service for the City of Chicago, the CTA serves a wider range of trip purposes in less auto-dependent areas. Accordingly, this agency saw, comparatively, the smallest reduction in ridership. Pace, which serves mainly suburban users without car access, is in the middle. With the modeling results, in future sections, we further discuss the factors that contribute to the return to transit.

Continuing with this exploratory data analysis, we find that the respondents have high levels of multi-modality, clear investment priorities, low trip replacement, and a shift towards the automobile during the pandemic for the trips that are replaced. Fig. 4 shows that 50.7% of respondents use more than one transit service with regularity. 16% of respondents use all three agencies. This multimodality underscores the importance of joint planning among agencies. This is further evidenced when considering the budgeting allocation experiment results in Fig. 5 showing that transfers between services constitute the highest investment priority.

3.1.1. *Rider investment priorities*

In our effort to understand the willingness to return to transit, a natural area to investigate is which service improvements users value the most. Each respondent was presented with two investment allocation exercises, one for general transit investments and one specific to COVID-19. Each time, they were assigned a hypothetical $10 to allocate in any way they wished across nine investment categories so long as the sum of their investment choices did not exceed their budget. All respondents allocated the entirety of their budget to at least one general investment category. In Fig. 5 the average budget allocation to each category is shown with standard error bars calculated using **Equation (1)**. The metrics are distinguished by the transit agency that is used. For example, if a rider uses both CTA and Pace, this rider's investment allocations are used in both sets of aggregate calculations. On average, the highest priority for CTA and Metra users is a seamless travel experience across modes. For Pace users, increased access to micromobility and improved suburb-to-suburb services were the highest priorities. Though the third most prioritized investment for Pace users is train speed and reliability, a large portion of these users also utilize the rail services which could explain this oddity.

Respondents were given an additional hypothetical $10 to allocate in any way they wished across COVID-19-related transit investment categories. These investment categories along with the average budget allocation shown with error bars (standard errors) are shown in Fig. 6. There is a trend among the three agencies to prefer investments that are related to reducing the risk of contracting COVID-19 on transit vehicles. Ventilation, sanitation, and mask/social distancing enforcement are the clear top investment priorities. After these categories, the safety on vehicles is the next prioritized investment.

$$Std.\ Error = \frac{\sigma_{Agency}}{\sqrt{n_{Agency}}} \qquad \text{Equation 1}$$

To provide further insight into different preferences among respondent groups, Table 1 and Table 2 show the percent of the total budget allocation for each investment category across several dimensions including gender, race, lapsed ridership status, and by transit service. We alos include the rank of each investment with the higher priority having a higher rank. Tables 1 and 2 will be further discussed in later sections. The investment allocation preference data, along with several other explanatory variables that were tested in the final ridership models.

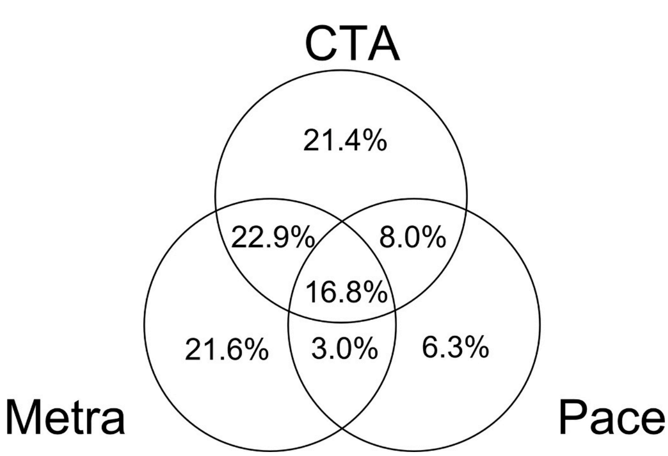

Fig. 4. Chicago transit agencies utilized by survey respondents (N = 5648).

3.1.1.1. *Travel behavior factors.*

Fig. 7 shows which modes are used to access transit. The CTA which operates within the core metropolitan city of Chicago is accessed primarily by active modes (79%) which is in stark contrast to the commuter rail service Metra where only 37% of respondents use personal active modes to access it. Again, Pace is between these two extremes with 68% of users using active modes to access the bus. When combining the share of users who use personal active modes or the private auto, these two modes constitute a majority share of access modes. The next largest shares are followed by ridehailing, shared active modes known as micromobility, taxi, or shuttle, then other modes such as a moped, though the highest mode share (ridehailing) that is not "Other" does not exceed 3%.

Next, we turn to explore travel modes used for nine different trip purposes, shown in Fig. 8 (typically used) and Fig. 9 (during the pandemic). Respondents were able to choose multiple modes to complete a single trip purpose because of the possibility of trip-chaining or transferring between modes. Based on comparing these two figures, the clearest shift in travel behavior from pre-pandemic to during the pandemic is a shift away from transit to an auto-based mode (e.g. household auto, carpool, carshare). Usage of ridehailing also decreased during the pandemic across multiple purposes.

It has been established that ridership was significantly reduced during the pandemic waves of 2020/2021. Here we address the question of where these trips shifted to. Fig. 10(a) shows that the majority of respondents did not replace their transit trips. CTA trips had the lowest replacement share at nearly 60%, while for Metra and Pace over 70% of trips did not get replaced by other modes, suggesting they were suppressed. After considering only the minority of trips that were replaced (30%–40%), the modes that replaced transit are shown in Fig. 10(b). In approximately 80%–90% of cases, former transit trips were replaced by private auto, followed by active modes, ridehailing or taxis, then other transit services. Note that the percentages across modes within a service can be greater than 100%. Because the respondents were able to select multiple options in the survey, this suggests that multiple modes are used to replace a trip formerly made by transit. For example, a trip to the grocery store that was previously made by transit could be made by car in one instance and then by an active mode the next.

Finally, the definitions and descriptive statistics for all variables included in the models presented in section 6 are provided in Table 3.

4. Methodology

Three models are estimated. The first model is a binary logit model using lapsed ridership status as the dependent variable. The second and third models are ordered logit models which analyze attitudes towards the return to transit and fare integration, defined as a 5-level ordered variable from "Strongly Disagree" to "Strongly Agree." (See Fig. 3). Each model was estimated using PandasBiogeme (Bierlaire, 2018). For more specific information about the methods described here, please refer to Train (2009).

4.1. *Binary logit*

The first model investigates the main determinants of the changed ridership status (lapsed versus non-lapsed) via thorough testing of variables relating to personal characteristics such as sociodemographics, employment, remote work status, transportation behavior, and transit investment priorities. Once candidate final models were identified, we

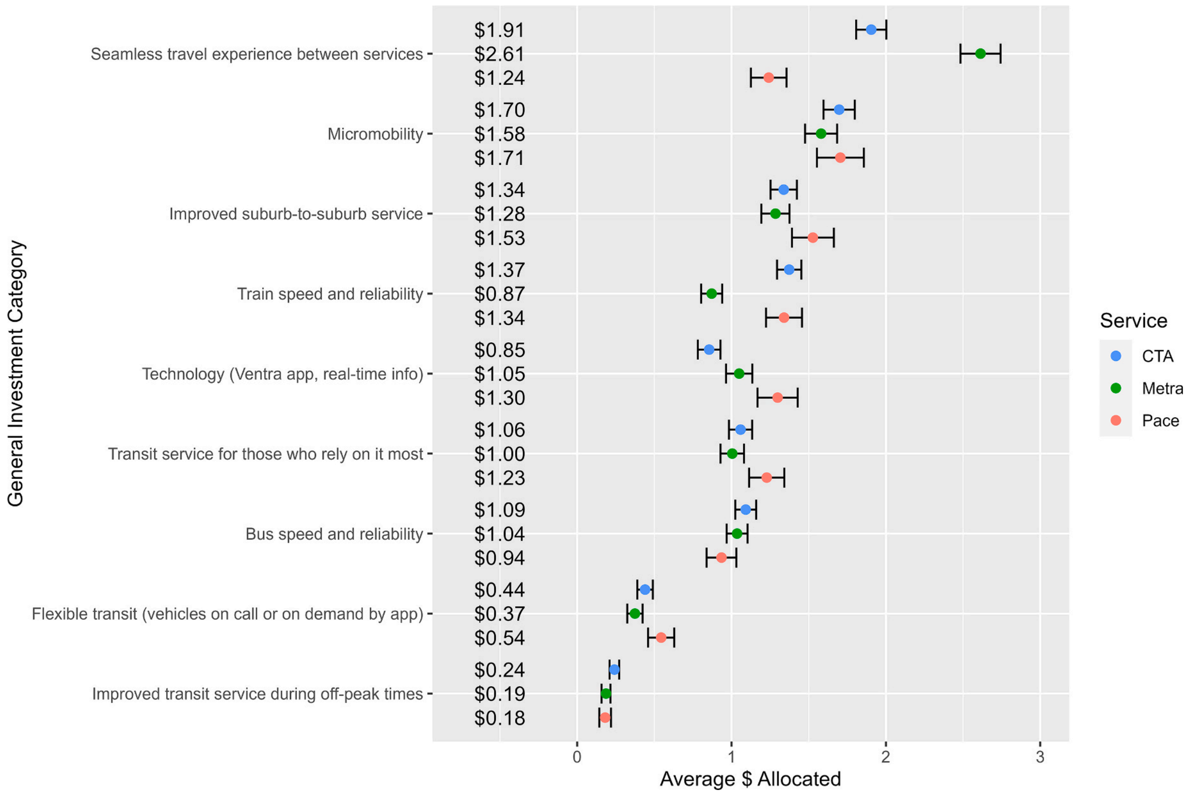

Fig. 5. Average allocation of general investment categories with standard error bars (out of 10 $).

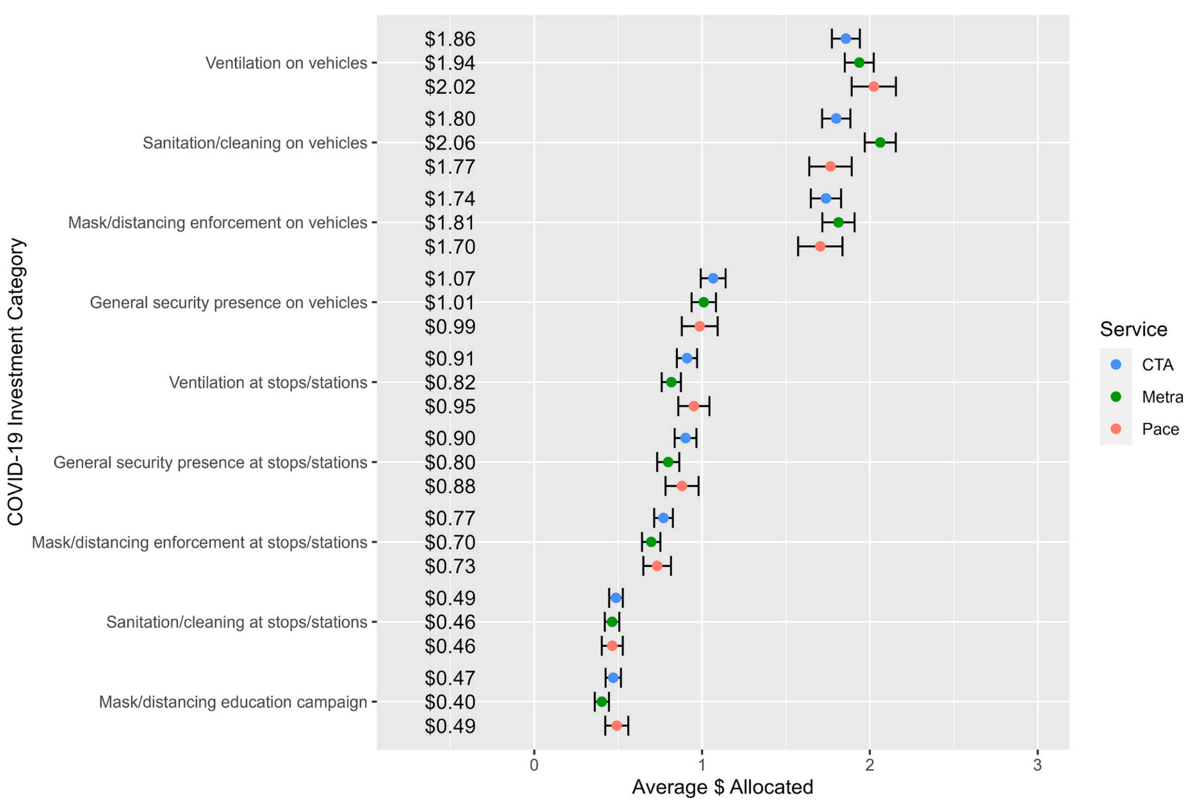

Fig. 6. Average allocation of COVID-19 investment priorities with standard error bars (out of 10 $).

conduct likelihood ratio tests to test the significance of model improvements by comparing nested model specifications. To choose between models we use the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The final model contains variables that are all statistically significant at the $\alpha = 0.05$ level, are behaviorally meaningful, and has the lowest AIC and BIC. Based on the categories of

Table 1
General transit investment priority share of investment and rankings by different user segments.

Investment priority	Everyone (rank)	Female (rank)	Non-female (rank)	Non-minority (rank)	Minority (rank)	Current Rider (rank)	Lapsed Rider (rank)	CTA Rider (rank)	Metra Rider (rank)	Pace Rider (rank)
Seamless travel experience between CTA, Metra, and Pace	22% (1)	21% (1)	24% (1)	25% (1)	16% (2)	18% (1)	23% (1)	19% (1)	26% (1)	12% (5)
Other shared mobility options (Divvy, scooters, etc.)	17% (2)	19% (2)	14% (2)	17% (2)	17% (1)	17% (2)	17% (2)	17% (2)	16% (2)	17% (1)
Improved suburb-to-suburb transit service	13% (3)	14% (3)	13% (3)	13% (3)	15% (3)	17% (3)	12% (3)	13% (4)	13% (3)	15% (2)
Bus speed and reliability	11% (4)	11% (4)	11% (4)	11% (4)	11% (5)	10% (5)	11% (5)	11% (5)	10% (4)	9% (7)
Transit service for those who rely on it most	11% (5)	11% (5)	11% (5)	10% (6)	14% (4)	13% (4)	11% (4)	14% (3)	9% (7)	13% (4)
Train speed and reliability	10% (6)	10% (6)	10% (6)	10% (5)	9% (7)	10% (6)	10% (6)	9% (7)	10% (6)	13% (3)
Technology (Ventra app, real-time info)	9% (7)	9% (7)	10% (7)	9% (7)	10% (6)	9% (7)	10% (7)	11% (6)	10% (5)	12% (6)
Flexible transit (vehicles on call or on demand by app)	4% (8)	5% (8)	4% (8)	4% (8)	6% (8)	4% (8)	4% (8)	4% (8)	4% (8)	5% (8)
Improved transit service during off-peak times	3% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)	2% (9)
Sum	100	100	100	100	100	100	100	100	100	100

Table 2
COVID-19 transit investment priority share of investment and rankings by different user segments.

Investment priority	Everyone (rank)	Female (rank)	Non-female (rank)	Non-minority (rank)	Minority (rank)	Current Rider (rank)	Lapsed Rider (rank)	CTA Rider (rank)	Metra Rider (rank)	Pace Rider (rank)
Ventilation on vehicles	20% (1)	21% (1)	19% (1)	19% (2)	22% (1)	23% (1)	19% (2)	19% (1)	19% (2)	20% (1)
Sanitation/cleaning on vehicles	19% (2)	19% (2)	19% (2)	20% (1)	16% (2)	15% (3)	20% (1)	18% (2)	21% (1)	18% (2)
Mask/distancing enforcement on vehicles	18% (3)	18% (3)	17% (3)	19% (3)	15% (3)	16% (2)	18% (3)	17% (3)	18% (3)	17% (3)
General security presence on vehicles	10% (4)	10% (4)	10% (4)	11% (4)	9% (5)	11% (4)	10% (4)	11% (4)	10% (4)	10% (4)
Ventilation at stops/stations	9% (5)	9% (5)	9% (5)	7% (6)	11% (4)	10% (5)	8% (5)	9% (5)	8% (5)	10% (5)
General security presence at stops/stations	8% (6)	8% (6)	8% (6)	8% (5)	9% (6)	10% (6)	8% (6)	9% (6)	8% (6)	9% (6)
Mask/distancing enforcement at stops/stations	7% (7)	7% (7)	7% (7)	7% (7)	8% (7)	7% (7)	7% (7)	8% (7)	7% (7)	7% (7)
Sanitation/cleaning at stops/stations	5% (8)	5% (8)	5% (9)	5% (8)	5% (9)	4% (9)	5% (8)	5% (8)	5% (8)	5% (9)
Mask/distancing education campaign	4% (9)	4% (9)	5% (8)	4% (9)	5% (8)	5% (8)	4% (9)	5% (9)	4% (9)	5% (8)
Sum	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

explanatory variables listed previously, a latent measure of utility is estimated for each alternative, and the probability of each respondent being either lapsed or non-lapsed is assigned. Because the probability of being lapsed or non-lapsed depends on differences in utility, the utility specification for the two alternatives can be simplified according to Equation (2) where the utility for being non-lapsed, $U_{nonlapsed}$, is fixed to 0. The utility for lapsed ridership status, U_{lapsed}, includes all explanatory variables as shown in Equation (3) where **X** is a matrix of explanatory variables, **β** is a matrix of estimated coefficients, and **ε** is an independent and identically distributed Gumbel(0,1) error term. The general form of the logit probability is described by Equation (4) with the probability of being a lapsed rider described by Equation (5). The coefficients, **β**, are estimated by maximizing the log-likelihood which is defined by Equation (6).

$$U_{nonlapsed} = \mathbf{0} \qquad \text{Equation 2}$$

$$U_{lapsed} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \qquad \text{Equation 3}$$

$$P(y_i) = \frac{\exp(U_i)}{\sum \exp\,(U_n)} \qquad \text{Equation 4}$$

$$P(lapse) = \frac{1}{1+\exp\left(-U_{lapsed}\right)} \qquad \text{Equation 5}$$

$$LL(\beta) = \sum\sum(y_{ni}\ \ln(P(lapse)\,)\,) \qquad \text{Equation 6}$$

4.2. Ordered logit model of returning to transit and fare integration

The ordered responses from attitudinal statements on transit ridership after health concerns are alleviated range from "Strongly Disagree" to "Strongly Agree." Given the ordered nature of the question, modeling is based on the Ordered Logit, also known as the proportional odds model (Train, 2009). An interpretation of the Ordered Logit is to generalize the decision problem into several binary logits where the latent utility score in Equation (7), U_{OL}, is also a function of the matrix of explanatory variables **X**, the estimated coefficients **β**, and the error

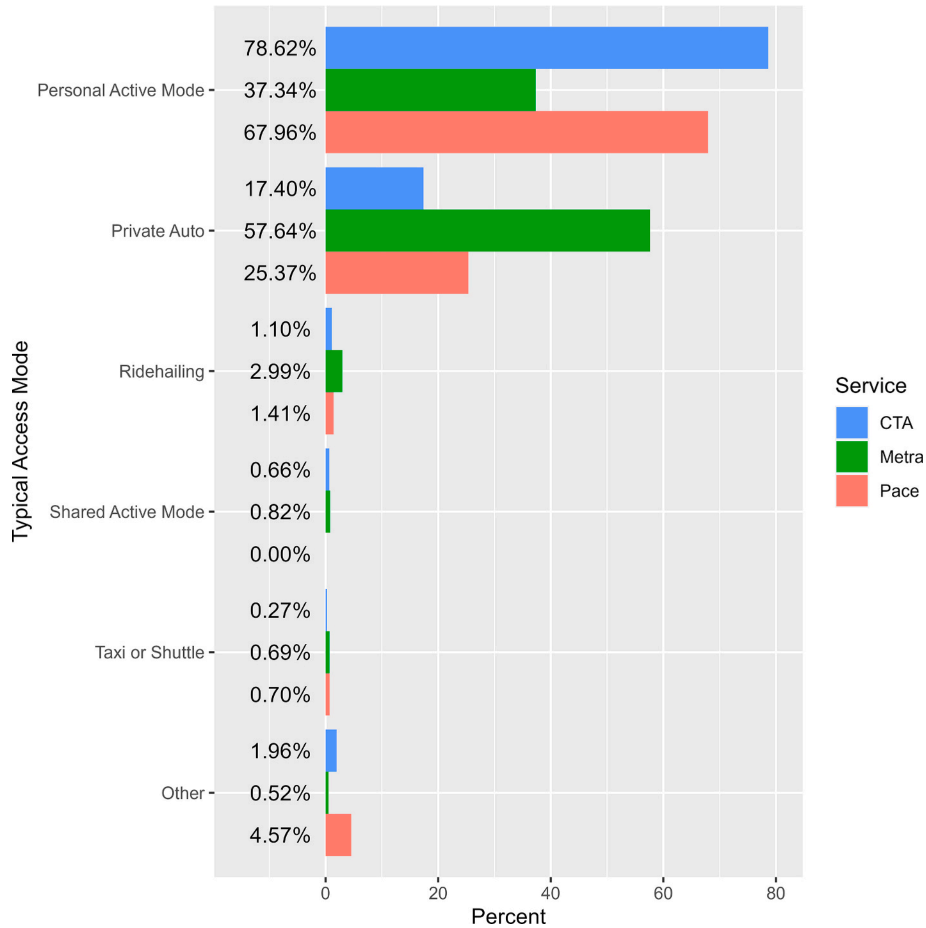

Fig. 7. Modes typically used to access public transit stations or stops.

term ε which is independently and identically distributed Logistic(0,1) Equation (8). shows which ordered response is associated with the latent utility score where k_1 to k_4 are the estimated threshold parameters.

$$U_{OL} = X\beta + \varepsilon \qquad \text{Equation 7}$$

$$y_i = \begin{cases} \text{Strongly Disagree}, U_{OL} \leq k_1 \\ \text{Disagree}, \quad k_1 < U_{OL} \leq k_2 \\ \text{Neutral}, \quad k_2 < U_{OL} \leq k_3 \\ \text{Agree}, \quad k_3 < U_{OL} \leq k_4 \\ \text{Strongly Agree}, k_4 < U_{OL} \end{cases} \qquad \text{Equation 8}$$

proportional odds assumption inherent in the model implies that in Equation (10), the coefficients **β** are equal across the ordered response scale. In other words, the effect of explanatory variables **X** has an equal effect in each of the categorical responses in Equation (8). To test this assumption the Brant test is employed (Brant, 1990). Final model selection is completed using the same process as for the binary logit. Model improvements were evaluated using the likelihood ratio test and the final model is chosen based on behavioral validity, AIC and BIC.

$$P(\text{Strongly Disagree}) = P(U_{OL} \leq k_1) = P(XB + \varepsilon \leq k_1) = P(\varepsilon \leq k_1 - X\beta) = \frac{\exp\,(k_1 - X\beta)}{1 + \exp\,(k_1 - X\beta)} = \frac{1}{1 + \exp(X\beta - k_1)} \qquad \text{Equation 9}$$

$$P(\text{Disagree}) = P(k_1 < U_{OL} \leq k_2) = P(k_1 < X\beta + \varepsilon \leq k_2) = P(k_1 - X\beta < \varepsilon \leq k_2 - X\beta) = P(\varepsilon \leq k_2 - X\beta) - P(\varepsilon < k_1 - X\beta) = \frac{\exp\,(k_2 - X\beta)}{1 + \exp\,(k_2 - X\beta)} - \frac{\exp\,(k_1 - X\beta)}{1 + \exp\,(k_1 - X\beta)} \qquad \text{Equation 10}$$

The probability of the respondent indicating that they "Strongly Disagree" with a statement is shown in Equation (9). Continuing from Equation (9), the probability of the respondent indicating that they "Disagree" can be described with Equation (10). The probabilities of other responses being chosen can be obtained similarly. The

5. Model results

On the whole, nearly 80% of respondents lapsed in ridership at the

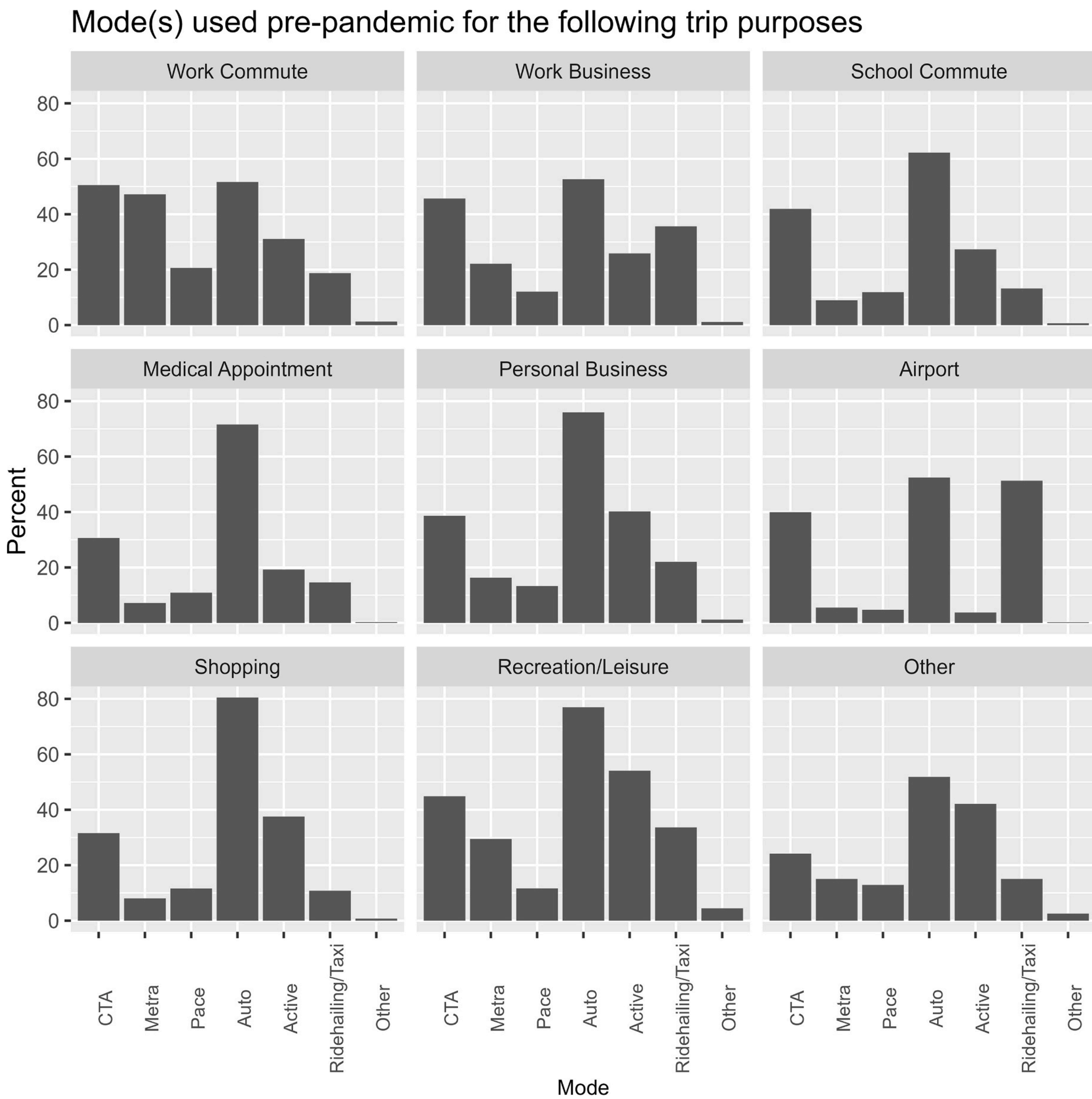

Fig. 8. Mode(s) typically used to complete the following trip purposes before the pandemic.

time of the study. This level of reduction matches empirical data as shown in Fig. 1. There is no available reference data for the return intention exactly, but we note that 80% stated they would return to transit, and 38% agree that they would use transit more with MaaS-fare integration. We note that the return intention in the survey roughly matches the 50–60% ridership observed in 2022 by CTA (Chicago Transit Authority, 2022).

The results for the binary logit model and the two ordered logit models are shown in Table 4 (Variable summary statistics are shown in Table 3). Using the Brant test, we confirm that both ordered logit models satisfy the proportional odds assumption (Brant, 1990) indicating that uniform variable effects can be assumed. After extensive variable testing, each model is estimated using as many common variables as possible to facilitate comparisons among the three models. The models fit the data fairly well. The McFadden Pseudo-ρ^2 of the lapsed rider, return, and MaaS-fare models are 0.406, 0.696, and 0.416, respectively, which indicates excellent model fit (McFadden, 1977). Comparing the model fit between the two ordinal future ridership models, the return model shows a better fit likely because it does not involve speculation of future transit usage with new technology. Because the coefficients across models cannot be directly compared due to sample differences, we calculate the odds ratios shown in Table 5.

Sociodemographic and **employment** variables are highly significant in each model. Gender, race/ethnicity, and age appear in all models. Interesting observations can be made by comparing sociodemographic effects across models. For example, female respondents are more likely to lapse in ridership, consistent with prior findings (Palm et al., 2021; He et al., 2022). Here we also find that women are less likely to return to transit in the future, even with pandemic concerns alleviated and in combination with a MaaS upgrade to encompass fare integration. Non-white respondents are less likely to lapse to begin with, which mirrors findings that they are disproportionally represented among essential workers (Wilder, 2021). Yet, looking at the future ridership model, this segment is less likely to return to transit than white respondents. Future research should further analyze the attitudes towards transit in these communities as minority choice riders run a higher risk of not returning to transit. An interesting nuance is that Asian and Hispanic respondents were more likely to increase their use of transit in the future with fare integration compared to Black and White respondents. This is consistent with findings suggesting that Hispanic identifying respondents are more likely to engage with technology (Rahimi et al., 2020; Asgari and Jin, 2020).

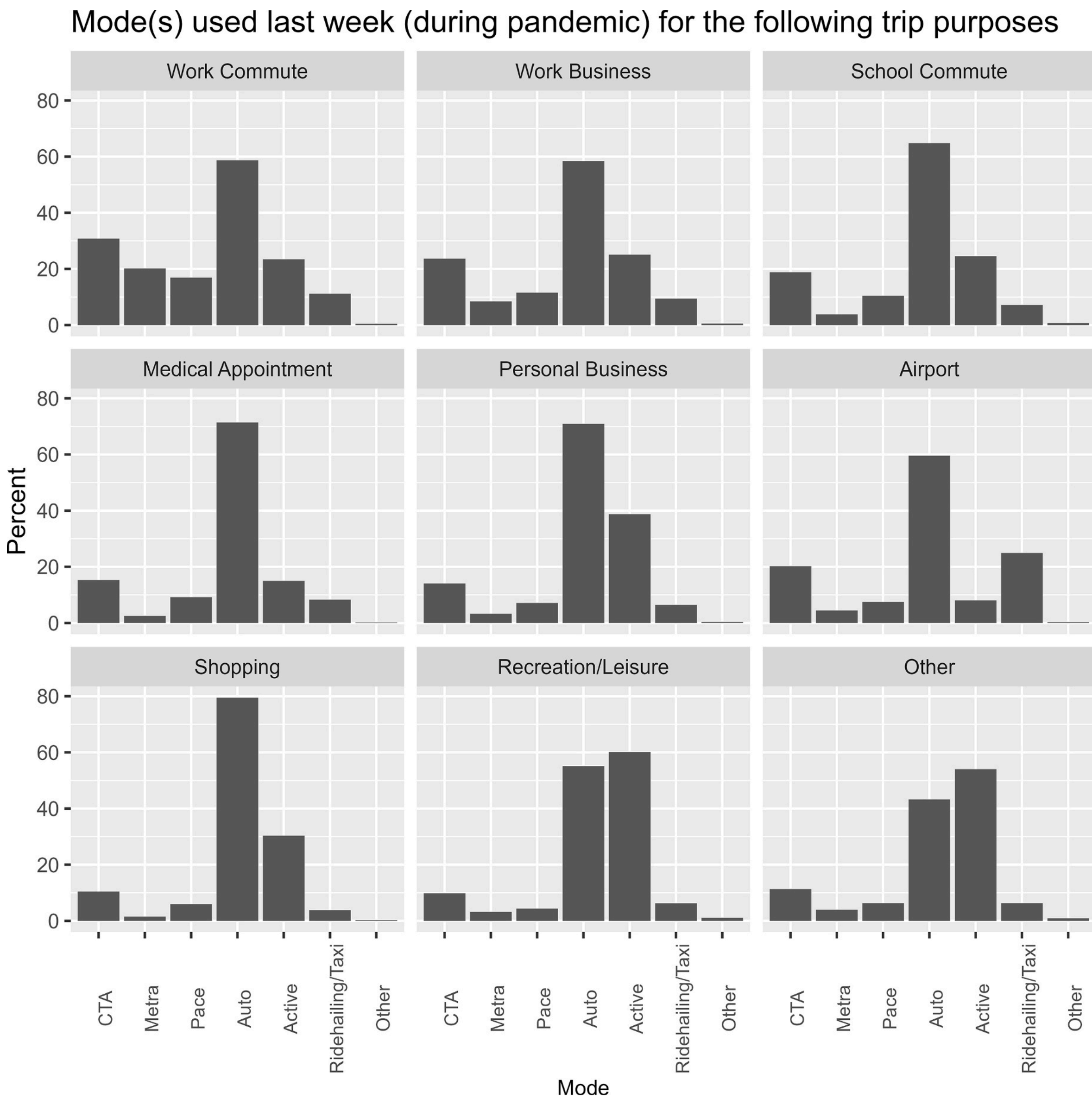

Fig. 9. Mode(s) used for trips taken the week prior to completing the survey for the following trip purposes.

Income appears in the lapsed ridership and MaaS-fare model where higher incomes are associated with an increased probability of abandoning transit during the pandemic, but also a lower likelihood to use transit more with fare integration. This is likely because of the higher propensity for higher-income workers to telework, work in industries with flexible work opportunities, and to have access to other mobility alternatives, like a household vehicle (Barbour et al., 2021; Yasenov, 2020; Matson et al., 2021). Therefore, higher-income earners would appear to not receive many benefits from fare integration. Employment characteristics only appear in the lapsed ridership model. In line with expectations, unemployment status and teleworking at least 4 days per week increase the probability of lapsing. The decision to model teleworking as a dummy variable using at least 4 days per week as the threshold was not arbitrary. During the model-building process, using any threshold below 4 days per week was statistically insignificant. Additionally, Model 1 outperforms an alternative model where telework is included as a count variable (AIC = 4698, BIC = 4791). This suggests that there is a strong threshold effect observed for workers that telework 4 or more days per week.

Several **transportation-related** variables are also included in each model. Access to a household vehicle affects ridership abandonment status, following the findings of other studies (Abdullah et al., 2021; Das et al., 2021). However, vehicle ownership does not appear to affect intentions to return or not. Some instructive differences are observed for different transit services: Bus users were less likely to lapse in ridership overall, are more likely to return to transit as they used it before, and specifically, Pace bus users are more likely to state they would use transit more with MaaS-fare availability. Riders who substituted transit with MoD or used it to access transit are also more likely to indicate they would ride transit more with fare integration. Interestingly, a trip purpose variable that appears significant in all models is a dummy variable representing users who only use transit for non-commute purposes. This user segment is more likely to lapse, but also more likely to return and use transit more with MaaS-fare, suggesting a more elastic behavior for non-mandatory travel.

The **investment allocation** preference variables show the impact of different service priorities on rider behavior and intentions. While most of the budget allocation measures were not significant in the modeling, three reveal valuable insights. Prioritizing sanitation correlates with a higher probability of lapsing, likely related to heightened concerns during the pandemic. Parker et al. (2021) find that survey respondents are more likely to return to transit if transit agencies improved

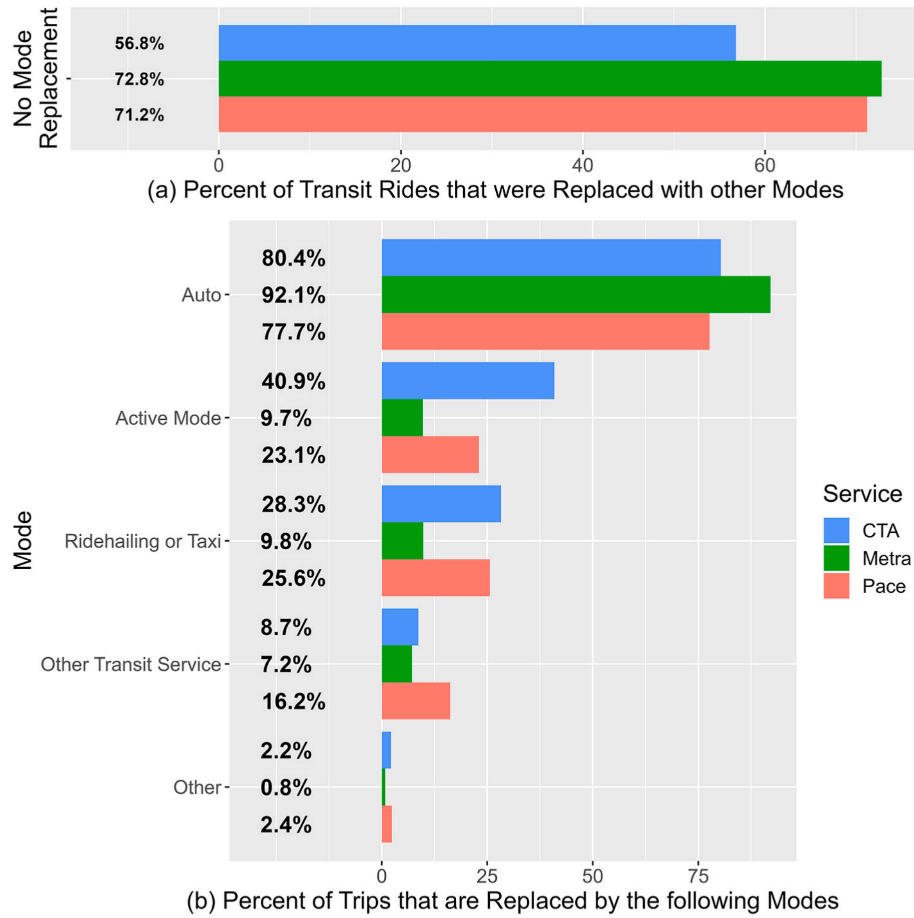

Fig. 10. (a) Percent of pre-pandemic rides that were no longer taken during the pandemic; (b) Out of the subset of public transit rides that were replaced, the percent breakdown of the modes used for substitution.

Table 3
Descriptive statistics of modeling variables.

Variable	Percent of Respondents	Notes
Women	56.3%	
Asian	5.6%	Considered racial/ethnic minority
Black	15.1%	Considered racial/ethnic minority
Hispanic	10.0%	Considered racial/ethnic minority
Younger than 35 years	22.1%	
At or older than 65 years	16.0%	
Unemployed	21.7%	Unemployed at the time of taking the survey: unemployed but looking; unemployed not looking (retired, disabled, student)
Teleworking at least 4 days per week	46.7%	
Has HH Vehicle	80.6%	
CTA Bus User	24.0%	Before or during the pandemic
Pace (Bus) User	14.4%	Before or during the pandemic
Substituted Transit with TNC	10.1%	During the pandemic, trips that were once completed with public transit were substituted with on-demand ride services
Access Mode TNC	2.7%	Before or during the pandemic
Non-commute travel purposes only	28.2%	

sanitation. Prioritizing improvements to shared mobility (e.g. e-scooters and bikeshare) correlated with increased intent to return to transit. More altruistic and equity-oriented concerns, namely prioritizing transit improvements for those who need it most and during off-peak hours were associated with being more likely to increase the use of transit if combined with MaaS-fare, providing evidence towards MaaS as a tool for pandemic recovery similar to findings by Hensher (2020). We tested several interactions between investment categories and sociodemographic variables. However, these were not statistically significant. We attribute their insignificance to the lack of heterogeneity in investment allocation as can be observed in both Tables 1 and 2.

While it is clear to see which variables affect each dependent variable, the coefficients themselves do not speak to the likelihood of each respondent lapsing in ridership, returning to transit, or utilizing transit more with MaaS-fare availability. Therefore, the odds ratios of explanatory variables are reported in Table 5 along with each variable's impact ranked.

Though the models are informative, the results are not without their caveats. The modeling was done without segmenting the data by transit users (e.g. CTA vs. Pace vs. Metra). There is the possibility that the coefficients and subsequent odds ratios are different across user groups. We chose not to pursue this user segmentation to keep the number of models low, instead of segmenting to 9 models. Rather, we tested the statistical significance of variables such as CTA bus, CTA train, Pace, and Metra user dummy variables. Additionally, the timing of the surveys was during a period with stagnated growth of transit ridership returns to pre-

Table 4
Logit modeling coefficients.

Coefficient Names	LAPSED RIDER (Binary Logit)	RETURN (Ordered Logit)	MaaS-fare (Ordered Logit)
	Model 1	Model 2	Model 3
Sociodemographic and Employment	Beta Value (t-stat)	Beta Value (t-stat)	Beta Value (t-stat)
Constant (Lapsed)	−1.070 (7.11)	–	–
Female	0.202 (2.67)	−0.157 (2.93)	−0.201 (3.82)
Asian	−0.504 (3.37)	−0.381 (3.42)	0.414 (3.64)
Black	−0.584 (6.00)	−0.547 (7.24)	–
Hispanic	−0.631 (5.63)	−0.395 (4.50)	0.397 (4.55)
Younger than 35 (base 35 < Age <64)	–	−0.241 (3.62)	0.181 (2.78)
At or older than 65 (base 35 < Age <64)	0.396 (3.62)	0.267 (3.48)	–
Income ($10,000s)	0.0317 (4.81)	–	−0.150 (4.05)
Unemployed	1.030 (10.6)	–	–
Teleworking at least 4 days per week	1.980 (20.8)	–	–
Transportation			
Has HH Vehicle	0.959 (10.3)	–	–
CTA Bus User	−0.267 (3.16)	0.209 (3.23)	–
Pace (Bus) User	−0.432 (4.62)	0.401 (5.02)	0.217 (2.84)
Substituted Transit with TNC	–	–	0.33 (3.85)
Access Mode TNC	–	–	0.51 (3.29)
Non-commute travel purposes only	0.602 (7.00)	0.148 (2.48)	0.199 (3.36)
Investment Priorities			
Sanitation	0.0839 (4.5)	–	–
Shared Mobility	–	0.118 (2.21)	–
Transit for those who rely on it most	–	–	0.19 (10.6)
Improve off-peak service	–	–	0.211 (4.75)
THRESHOLDS			
Tau_1	–	−3.21 (34.3)	−2.02 (22.2)
Delta2	–	1.080 (19.1)	0.842 (23.0)
Delta3	–	0.659 (21.5)	1.77 (48.5)
Delta4	–	1.26 (40.5)	1.20 (37.0)
FIT STATISTICS			
Sample size (n)	5648	5518	4965
Initial Loglikelihood	−3914.895	−21207.14	−12338.51
Final Loglikelihood	−2324.28	−6438.101	−7204.744
ρ^2	0.406	0.696	0.416
AIC	4676.561	12904.20	14439.49
BIC	4769.508	12996.82	14537.14

The odds ratios represent the likelihood of being a lapsed rider in the lapsed rider model, and it represents the likelihood of agreeing with the attitudinal statements in the other two models. These results are discussed in more depth in the *Policy Implications* section below. For interpretation purposes, the farther away the odds ratio is from 1 the greater the effect. For example, an odds ratio greater than 1 suggests an increased probability of being a lapsed rider or agreeing with the intent statements. For more information on odds ratio interpretations, see Davies et al. (1998).

pandemic levels as indicated in Fig. 1. Vaccinations for COVID-19 were not widely available at the time. Therefore, intentions about future transit use need to be taken with caution and we recommend further work with longitudinal data to capture ridership intentions evolving in response to transforming circumstances.

6. Policy implications

6.1. Top community-informed transit investments

Before discussing the implications of the model results, our earlier data exploration informs us about users' priorities for transit investments. From Tables 1 and 2, we note that the percentage of money allocated to the different investment priorities along with their rankings across the user segments is fairly consistent. The top pandemic investment priorities for all user segments are to directly reduce the health risks in vehicles. Ventilation, sanitation, and mask/distancing enforcement on vehicles are the top priorities by a large margin. These categories garnered between 15% and 23% of the total budget allocation while the remaining 6 categories ranged between 4% and 11% across all user segments. Though investments at stations and stops garnered some support, investing in and advertising clean vehicles can be an important tool to attract ridership. For nearly all user segments, general security presence on vehicles is the next priority. This further emphasizes the need to have a safe riding environment inside transit vehicles.

The top priority among general investments is seamless travel across the different transit services and agencies. With transfer penalties having a high value, it is expected that this is one of the top priorities (Lee and Vuchic Vukan, 2005). While faster buses and trains have some support, reducing the penalties associated with inefficient transfers could increase the attractiveness of transit more than the equivalent time savings from improving vehicle speeds. This debate is reflective of current concerns about unpredictability of wait times and unreliable tracking of buses (Dudek 2023). The next two investment priorities have a common theme of network accessibility. Transit users prioritized investments into micromobility. These mobility options could be used to access transit or to replace a trip. The third-highest priority is improved suburb-to-suburb services. These connectivity improvements should coincide with necessary support policies to increase the likelihood of success. Examples of support for micromobility is the installation of protected bike lanes, which is shown to increase bike lane ridership (Karpinski, 2021). Micromobility can also aid with improving suburb-to-suburb services by being strategically placed in areas for customers to access public transit. Though, a better strategy may be to focus on bicycle infrastructure and build protected bikeways between suburbs. Fig. 7 shows that micromobility is hardly used as an access mode to transit. If not to access transit, micromobility can be used as an alternative to it. Although this may not increase transit ridership, micromobility and supporting investments still contribute to reducing auto-dependency.

6.2. Key contextual factors to consider

Employment variables had the highest impact on lapsed ridership status with teleworking at least 4 days per week and unemployment status having odds ratios of 7.24 and 2.80, respectively. This suggests that those who teleworked a majority of the week are highly likely to be lapsed riders compared those who do not. Similarly, unemployment status has a strong association with lapsed rider status. These results were expected as transit ridership during the pandemic depended on employers' teleworking policies and whether there was even a need for a commute trip given that jobs relating to non-essential activities were heavily impacted by pandemic restrictions.

Outside of employment status, trip purpose appeared significant in all three models. Respondents who used transit for only non-commuting purposes likely lapsed in ridership due to the lack of recreational activities. The two return-to-transit models suggest that these users, though, are likely to return and use transit more with MaaS focused on fare integration. The loosening of restrictions on recreational activities will likely cause more trip-making and should be closely monitored.

While employment characteristics and restrictions on recreational activities are not within the control of transit agencies, the importance of agencies being prepared for growing demand is clear. DeWeese et al. (2020) find that several agencies chose to reduce their services which leaves them vulnerable to missing out on ridership when demand increases. One strategy that could prepare agencies is to increase their employment. The return to transit and maintaining ridership likely depend on the level of service that an agency can provide. This is a motivation for agencies to consider increasing their labor pool. Mack et al. (2021) found that 30% of urban transit employees could not work because of the pandemic. In Chicago, worker shortages caused service disruptions that led to significant delays for users (Freishtat, 2021,

Table 5
Logit modeling odds ratios.

Coefficient Names	LAPSED RIDER (BINARY)		RETURN (ORDERED)		MaaS-fare (ORDERED)	
	Model 1		Model 2		Model 3	
Sociodemographic and Employment	Odds Ratio (Inverse)	Rank[a]	Odds Ratio (Inverse)	Rank[a]	Odds Ratio (Inverse)	Rank[a]
Female	1.22	11	0.854 (1.17)	8	0.818 (1.22)	7
Asian (base White)	0.604 (1.66)	7	0.683 (1.46)	4	1.51	2
Black (base White)	0.558 (1.79)	6	0.579 (1.72)	1	–	–
Hispanic (base White)	0.532 (1.88)	4	0.674 (1.48)	3	1.49	3
Younger than 35 (base 35 < Age <64)	–	–	0.786 (1.27)	6	1.20	10
At or older than 65 (base 35 < Age <64)	1.49	9	1.31	5	–	
Income ($10,000s)	1.03	13	–	–	0.985 (1.02)	11
Unemployed	2.80	2	–	–	–	–
Teleworking at least 4 days per week	7.24	1	–	–	–	–
Transportation						
Has HH Vehicle	2.61	3	–		–	–
CTA Bus User	0.766 (1.31)	10	1.23	7	–	–
Pace (Bus) User	0.650 (1.54)	8	1.49	2	1.24	5
Substituted Transit with TNC	–	–	–	–	1.39	4
Access Mode TNC	–	–	–	–	1.67	1
Non-commute travel purposes only	1.83	5	1.16	9	1.22	8
Investment Priorities						
Sanitation	1.08	12	–	–	–	–
Shared Mobility	–	–	1.13	10	–	–
Transit for those who rely on it most	–	–	–	–	1.21	9
Improve off-peak service	–	–	–	–	1.23	6

[a] Ranking is based on absolute impact, therefore the inverse of an odds ratio which is less than 1 is used to facilitate cross-comparison.

National Transit Database, 2022).

In addition to the contextual factors and their own labor pool, transit agencies can consider other avenues to increase ridership. The next subsections discuss the model results for race and ethnicity, the potential for fare integration to attract more ridership, and strategies transit agencies may consider preparing for in a future when COVID-19 no longer poses a significant health concern.

6.3. On an equitable return

The model results on lapsed ridership and the intent to return to transit show a concerning result for gender. Women are more likely to lapse in ridership and less likely to return to pre-pandemic ridership levels. They are also more likely to have limited access to a household vehicle because of gendered household car use dynamics where women are less likely to use the household vehicle to complete tasks (Palm et al., 2021). Therefore, women are particularly vulnerable to reduced access to public transportation.

Also of importance are the race and ethnicity results. Significant effects appear in all models and are all highly impactful as well. As a group, race and ethnicity constitute the second most impactful factor after employment characteristics, with minority riders being less likely to lapse in ridership. This result reflects the high representation of minorities holding essential jobs and in-person job positions (Wilder, 2021). However, race and ethnicity are the most impactful variable in the return model which indicates that even if abandonment is lower, racial/ethnic minorities are less likely to return to past ridership levels of transit. We hypothesize that the disproportionate impact of COVID on minority communities within Chicago plays a major role in the decision not to return (Pierce et al., 2021). With higher rates of infection in these communities, minority transit users may consider the risk of infection too high to be willing to share a bus or train with others. Indeed, Table 2 further shows that the top three priorities among minority riders are ventilation, sanitation, and mask/distancing enforcement on vehicles. In addition to health risk perceptions, another issue that compounds the finding that Asian, Black, and Hispanic users are less likely to return to transit are safety perceptions about crime.

With the substitution of transit for other modes being correlated with higher crime rates at or near transit stops that are less frequented during the pandemic (Meredith-Karam et al., 2021), an increased general security presence around transit infrastructure can create a safer environment that attracts lapsed riders, especially in minority communities where crime rates are higher. Increased security may also help transit become an attractive mode for women as perceptions of safety are important (Lubitow et al., 2017). Though, security measures must be taken carefully so that policing does not become discriminatory (Carter and Johnson, 2021). Beyond increasing security, transit agencies can also improve the level of service in these communities, though equity is the focal point of any strategy's implementation.

Improving access to jobs for minority and low-income communities by responding to the spatial mismatch of people and employment centers could spur ridership, especially for low-income workers who live outside of the inner city (Liu and Kwan, 2020). For women in particular, investigating the relationship between household responsibilities and travel could lead to opportunities to reduce their transportation vulnerability (Scheiner and Holz-Rau, 2017). This further emphasizes the need to understand the ongoing dynamics surrounding teleworking, labor, and household dynamics as cities transition out of restrictive measures. Strategies that emphasize transit-oriented development ought to consider strong community engagement to ensure equitable outcomes (Lubitow et al., 2017; Lung-Amam et al., 2019). Increased security presence and continued development of transit service access are ongoing efforts by many agencies. One further effort that transit agencies may consider is to accelerate fare integration with private services such as micromobility, ridehailing, and carsharing.

7. Conclusion

In this research, we examine the individual-level factors contributing to transit ridership abandonment and return intentions using data from the Chicago metropolitan area (N = 5648). Three models are estimated to understand how individual, employment, transit investment priorities, and transportation variables contribute to the pandemic and post-pandemic transit ridership decisions. The **lapsed rider** model focuses on understanding the factors leading to reduced transit ridership during the pandemic. The strongest factors which lead to ridership cessation are teleworking a majority of the work week, being unemployed, and household car ownership levels. The **return to transit** model considers the potential return to pre-pandemic transit ridership levels. It showed the concerning impact of race and ethnicity on the reduced likelihood of returning. Though being a minority is not in itself a reason to shift away from transit, this highlights a need to understand how transit is perceived in these communities and how to best serve different racial and ethnic groups via an attractive alternative to private auto ownership and use. This model also highlights that bus users are more likely to return than train riders and that age does play a role with younger commuters being less likely to return. The return with **fare integration** model analyzes the factors leading to increased transit ridership should the fare system across several shared modes be integrated. This model shows that transit riders who also use ridehailing are likely to increase their usage, pointing to an opportunity for ridehailing and public transit to complement each other in well-designed multimodal systems. Interestingly, race and ethnicity play a role here and show the reverse outcome seen in the previous model, namely that Asian and Hispanic transit riders are *more* likely to increase their ridership. The fare integration model also reveals how transit investment priorities point to a relationship between MaaS and accessibility, where those who prioritize off-peak services are likely to use transit more with fare integration.

Drawing on the model results, we also provide avenues for future research and policy recommendations. For future research, an equitable public transit system depends on understanding the unique needs of minority communities. It behooves researchers and service providers to understand how transit can attract vulnerable customer segments during the pandemic recovery phase. Additionally, the importance of telecommuting is evident here and confirmed in other studies. The pandemic-induced shift towards remote and hybrid work highlights the need to investigate long-term residential choices in response to work-flexibility, employer-worker scheduling preferences, future office design/location, evolving mobility/activity patterns, and the varying opportunities for accessing shifting livelihood opportunities among diverse residents. Specifically, more research is needed to understand the evolving challenges pressures, and opportunities for transit to meet demand in a new era of work, mobility and service preferences. On the policy side, the transit investment priorities shed light on what service dimensions riders would like to prioritize. Among several population segments, improved coordination between CTA, Metra, and Pace services was the consensus top priority. The next top priority is more shared mobility options, specifically bikeshare, scooters, and carsharing. The third top priority is improved suburb-to-suburb services. These last two priorities focus on transit accessibility where shared mobility can be used to fill gaps for fixed-route transit and suburb-to-suburb services to increase accessibility. On the whole, these models illuminate both agreement and differences in how different rider-groups navigate transit abandonment and return plans.

CRediT authorship contribution statement

Soria: Writing - Original draft preparation, **Soria, Stathopoulos, Edward:** Writing - Reviewing and Editing, **Soria:** Visualization. **Stathopoulos:** Conceptualization, **Stathopoulos**, **Soria:** Methodology, **Soria:** Data curation, **Stathopoulos:** Supervision, **Stathopoulos**: Funding acquisition.

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Declaration of competing interest

None.

Data availability

The authors do not have permission to share data.

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