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Benefits from a new transit line: Exploring the impact of rare users and spatially heterogeneous variations in intensity of use

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ABSTRACT

What are the city-wide benefits of introducing a new transit mode? Justification of a new transit mode is often based on claims of transformational change regarding mode share, ridership, or passenger-kilometers travelled (PKT). Detractors argue that these dramatic benefits are not experienced uniformly across populations or places. This paper quantifies the extent and intensity of the change in travel behaviour caused by the addition of a new mode and builds on measures of increased ridership and PKT to explore who is travelling on the new mode and in what ways. Recent advances in smartcard data analysis provide detailed insights into transit ridership but are often temporally limited, restricting the ability to analyse long-term behavioural trends. While research on transit ridership patterns exists, few studies compare users of the old and new modes in terms of spatial distribution and intensity of use. This study relies on a long baseline of data to estimate the home locations of travellers and their intensity of use. Our findings challenge assumptions about infrequent users and reveal that rare users significantly influence ridership patterns. Increased reach of ridership is substantiated based on the appearance of new cards 48 % higher than usual after the light rail introduction. However, only about 4 % of new card IDs make trips at a rate equivalent to a daily commute. The results show strong spatial patterns, with 50 % of frequent light rail riders having inferred home locations at the new stations and 63 % of daily riders not using the bus to access the light rail. This approach suggests that (1) rare users, though they ride less often, have a notable impact on ridership trends; (2) transit-access distances are shorter than conventional assumptions of approximately half-a-mile; and (3) ridership benefits show strong spatial patterns.

1. Introduction

1.1. Background

Public transport helps to reshape urban regions and drives real estate development, particularly towards more compact and higher-density residential developments, due to the connections that public transit forges between higher residential densities and increased accessibility to jobs and labour (Wu et al., 2019). User-friendly public transport is crucial for any comprehensive transport planning strategy in large cities, as it significantly influences the long-term development of urban structure and land use (Wardman, 2004). Public transit travel behaviour has a crucial role in urban planning and development (Knowles et al., 2020). There is significant evidence and potential for transformational impact from public transport investment towards more sustainable urban forms. However, to develop effective policy recommendations and optimise the delivery of investments in public transport, the behavioural response to changes in transit infrastructure and service must be considered. It is generally intuitive that there is diversity in travel habits within a city (Zhang, 2004) and behavioural responses to new investments in public transport might be expected to vary across places and populations.

To encourage a behavioural switch towards public transit, many localities worldwide have invested in light rail transit systems. Light rail transit (LRT) is the modern incarnation of trams, utilising newer vehicles, advanced technology, and reduced road allocation compared to its predecessor. In some cases, it can accommodate six times as many passengers as a bus with a lower travel time and better safety (Cervero, 1984). These benefits aim to attract riders who might otherwise drive cars, which in turn drives the preference for light rail over more or less expensive bus systems. Light rail has a huge impact on reshaping the built environment as transit investment frequently goes hand in hand

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with transit-oriented and accessibility-oriented land use development. The success of light rail as measured through ridership is affected by many factors including land use and accessibility, as noted by Cervero (1984) and Kuby et al. (2004). Given that light rail is typically more expensive than bus, previous studies have questioned whether the investment in the light rail can be justified through traditional cost-benefit assessment (Langston and Crowley, 2021; Nicolaisen et al., 2017; Ryan, 2005; Shefer and Aviram, 2005).

Understanding how individuals adapt to a new transit mode is pivotal for informed and holistic decision-making about investments (Hiremath et al., 2013). To make a sensible investment in light rail, it's crucial to comprehend behavioural reactions, such as the transition from car or bus usage to light rail. Instead of solely considering all ridership on the light rail transit as an advantage, the cost-benefit analysis should factor in baseline ridership dynamics, attrition from buses or other established transit modes, the continuity of old behaviours, the adoption of new ones, and the spatial distribution of these behaviours. This includes keeping track of travellers who shifted from existing modes to new transit modes and monitoring changes in trip frequency around the addition of a new transit mode.

To evaluate the success of a light rail system, the baseline performance assessment is the number of boardings both before and after its introduction, as well as the extent to which it attracts new users. However, for informed city planning, it is essential to understand the origins of these riders. This includes determining whether the light rail is bringing in new users or simply offering an alternative to existing riders on other public transit modes, like buses or trains. The intensity of use and the spatial distribution of changes in travel behaviour reveal the areas where travel behaviour is most impacted by the new mode and the regions that contribute most to new mode ridership.

The article tests this approach by evaluating the performance of a new light rail line in Canberra, Australia concerning the spatial variation in intensity of use of the new mode offering a more nuanced assessment than ridership alone.

The remaining sections of the paper are structured as follows: **Section 2** discusses the literature context; **Section 3** outlines the study approach, incorporating a demonstration of the study area and data used in this study; **Section 4** presents the findings regarding ridership changes attributed to light rail and spatial trends in light rail utilisation; Finally, **Section 5** concludes the paper by discussing the policy implications of adopting a spatial intensity of use approach.

2. Literature context

Numerous empirical studies have examined the benefits of investing in light rail transit. The work presented here builds most directly on a set of recent papers using smartcard data to evaluate new transit modes as summarised in Table 1. The remainder of this section presents a broader literature context around the topic and positions the key studies within that literature to motivate research questions.

Previous studies have mainly focused on ridership increases due to the new mode often using traditional survey data (Barry, 1991; Cao and Ermagun, 2017; Engebretsen et al., 2017; Hensher, 1999; Park et al., 2018; Senior, 2009) and cost-benefit analysis of the newly built light rail (Bonotti et al., 2015; Hensher, 1993; Pan, 2013).

Tramway systems in Nantes (1985) and Grenoble, France (1987), swiftly attained an operating cost recovery surpassing 50 % within two years of their beginning (Barry, 1991). Fixed-track transit, exemplified by tramways, often attracts real estate development over more adaptable alternatives such as buses, perceived as less stable and dependable (Hensher, 1999). This inclination toward fixed-track transit assists in justifying the added expense of light rail. Moreover, light rail systems afford transit enthusiasts the chance to live close to light rail routes, thereby fulfilling their transportation preferences (Hensher, 1999).

Some work has increasingly leveraged advanced datasets and methodologies. For example, Ng (2011) used automatically collected smartcard data to preliminarily assess the impacts of the East London Line extension, providing valuable insights into ridership impacts but focusing primarily on short-term changes. Similarly, Van Oort et al. (2016) highlight how transit smartcard data can accurately capture detailed passenger information, such as boarding, alighting, and transfer points, enabling more precise assessments of travel demand. Additionally, Berrebi et al. (2022) investigated ridership impacts of new light rail transit and arterial bus rapid transit lines in the Twin Cities, finding nuanced effects on ridership depending on service characteristics and surrounding land use.

Even as data collection improved over time, the advantages of light rail investment are not uniform. Some authors contend that the

Table 1
Summary of previous studies examining light rail transit impacts, detailing the datasets used, methodologies adopted, and key findings. This table highlights the diversity of approaches in existing relevant research, emphasising the need for further comprehensive, longitudinal, and spatial analyses to understand better transit system impacts.

Study	Year	Dataset	Methodology	Key Findings
Berrebi et al.	2022	Automated Passenger Count (APC) data for total weekday ridership and frequency on the transit corridors. Longitudinal Employer-Household Dynamics (LEHD) dataset for population and job data within catchments from 2012 to 2017	Panel regression models, Fixed-effects models, Elasticity analysis, Comparative analysis	Light rail increased ridership by 86 % compared to the replaced bus service despite a 22 % frequency reduction. BRT boosted ridership by 12 % with a 36 % frequency increase.
Burger et al.	2023	Transit smartcard data and Qualtrics survey from UK rail commuters from December 2020 (Pilot study), February 2021 (Pre-screening phase), March 2021 (Main study)	Online behavioural experiment, Crowding sensitivity measurement, Regression analysis	In-carriage crowding causes behaviour change, but motivation and persistent are not yet understood.
Pinho et al.	2024	Metro station ridership data from Porto Light Rail Transit (LRT) system	Direct Ridership Model (DRM), OLS regression model, GIS-based spatial analysis	Strong spatial dependencies when modeling ridership in a multimodal transit network.
Weng et al.	2024	Taxi Order Data for one week for morning peak, evening peak and off-peak hours, Smartcard data for one week (November 25 to December 1, 2019) from bus and metro transactions from light rail and Built environment data from Beijing, China	Door-to-Door travel time calculation, Public transport competitiveness evaluation, Spatial Durbin Model (SDM), Moran's I Analysis	High spatial and time of day variation in PT competitiveness due to transit schedules, infrastructure provision and congestion.

introduction of light rail undermines the market share of buses (Engebretsen et al., 2017; Senior, 2009), contradicting the aim of promoting alternative modes of transportation. Moreover, light rail appears to have minimal impact on car ownership (Cao and Ermagun, 2017; Park et al., 2018), implying that commuters continue to rely on personal vehicles or at least maintain them as an option. This suggests that more research is needed on how intensely riders use the new mode.

The uncertainty surrounding the benefits of the light rail systems partly arises from the timeframes of the studies. While property value benefits may materialise over decades (Hensher, 1993), some behavioural shifts become apparent immediately upon implementation (Dos Santos et al., 2024; Engebretsen et al., 2017; Senior, 2009). Even studies focusing on immediate changes in ridership often overlook the modes of transportation before the introduction of light rail (Senior, 2009). Surveys, used to gauge travel behaviours associated with light rail will typically concentrate on light rail users rather than the broader populace (Cao, 2013; Luan et al., 2020; Yeboah et al., 2019). Recent advances in transit smartcard data analysis have facilitated a more comprehensive examination of transit ridership (Bonotti et al., 2015; Pan, 2013). However, these datasets often have limited temporal coverage, hindering the assessment of longer-term trends and enduring behaviours. Past literature shows that passenger travel behaviour changes during a disruption (Drabicki et al., 2021; Marsden et al., 2016) and justifies the need for adjusting transport policies around disruptive events (Marsden et al., 2016). Some disruptions, such as home relocation, impact individuals whereas some, such as a natural disaster or pandemic, might impact the entire region. The introduction of a new transit system triggers the formation of new travel habits for a subset of the population (Aranda, 2006; Heilmann, 2018; Hong et al., 2016; Kuhlman et al., 2014; Nakanishi and Black, 2016; Sener et al., 2020).

The effect of the light rail stations on land development varies spatially (Wang et al., 2019). The interrelationship between the built environment and mode choices is a major area of research (Cervero, 2002; Chen et al., 2008; Ewing and Cervero, 2001; Munshi, 2016; Pinjari et al., 2007; Sun et al., 2017). Research on spatial land use interaction with public transit systems (Isard, 2017; Liu et al., 2021) encompasses job-housing relationships (Long and Thill, 2015; O'Sullivan et al., 2000; Ren et al., 2020; Sarkar et al., 2019), accessibility to public transport (Baker et al., 2021; García-Palomares et al., 2013; Saif et al., 2019; Wu et al., 2019), transit-focused housing choices (Cervero, 2006; Ewing and Cervero, 2010; Li, 2018) and the formation of new habits (Ewing and Cervero, 2010). Analysing the spatial distribution of the travellers using light rail can help policymakers better prepare for the disruption and new habit formation associated with a new transit mode (Tamakloe et al., 2021).

Summarising the literature, past studies have focused on the changes in ridership, cost-effectiveness, and impacts of major transit investments after the introduction of a new mode. We identify three gaps in understanding the ridership of new transit modes.

Firstly, while recent advances in smartcard data analysis have provided more detailed insights into transit ridership, these datasets are often temporally limited. This restricts the ability to analyse long-term behavioural trends (Ge et al., 2021; Liu et al., 2023a; Lu et al., 2020; Nelson et al., 2019; Xiao and Wei, 2023). Burger et al. (2023) highlighted the necessity for understanding long-term behaviour changes in transit users. Ramos-Santiago (2022) pointed out that the cross-sectional nature of existing studies creates a gap in tracking ongoing ridership trends. Furthermore, Liu et al. (2023b) noted in their review that while many aspects of transit ridership are discussed, researchers rarely focus on long-term monitoring, fluctuation tracking, and data-driven decision-making for future disruptions. Our study addresses these gaps, contributing to the ongoing dialogue.

Secondly, Although a lot of research has been done on transit ridership patterns, not many studies directly compare light rail and bus users in terms of where they live and how close they are to transit infrastructure (Chan et al., 2023; Pinho et al., 2024; Weng et al., 2024).

Finally, existing research often assumes a widespread impact of new transit modes like light rail across an urban area (Kuo et al., 2023; Yang et al., 2023). Although there are studies that discuss the changes in travel behaviour, only a few talk about the spatial distribution of changes in travel intensity (Cao and Ermagun, 2017; Engebretsen et al., 2017; Sanjust et al., 2015; Spears et al., 2017). There is little evidence of research on the spatial threshold of the impact of a new transit mode, and studies that considered spatial interaction with new transit mode development are based on small-sample surveys (Kuhlman et al., 2014; Nakanishi and Black, 2016).

To fill these gaps in the literature, this paper uses a spatiotemporal approach to investigate how travel behaviour changes after the introduction of a new transit system. Requiring a long baseline of data, the methodology improves on ridership counts to understand the spatial variation in intensity of use in the system. The contribution of this research comprises two specific research questions. These are:

Research Question 1. : How intensely do travellers use the new system compared to their previous transit use?

Research Question 2. : Which areas experience a strong impact on travel behaviour from the new mode and which areas contribute the most riders to the new mode?

3. Approach

This study explores the impact of a new transit system on ridership levels, analysing changes in the frequency of transit use following the introduction of this new mode of transportation. The primary research inquiry seeks to uncover evidence of alterations in transit usage, analysing changes in the number of smartcard IDs surrounding the launch of light rail, fluctuations in total trip volumes at an aggregate level, and variations in individual usage intensity.

At a first pass, the impact of the new mode can be measured by the number of trips or card IDs associated with the light rail. These simplistic measures can mask several effects related to baseline fluctuations in transit use. Many transportation systems experience seasonal variations in ridership, and in Australia especially, public transport use is less frequent during the holiday periods than in other months. Analysing ridership patterns after the opening month shows the long-term effects of the light rail. Comparing card turnover around the light rail opening to other months (pre-light rail introduction), we can identify how much change in ridership is expected from the distribution of card churn. If the number of new transit users at the time of the light rail opening is outside the normal distribution, it may be attributable to the introduction of the light rail. Churn rates over an extended period determine if the increase in ridership during the opening month is sustained or if it gradually tapers off. This information is crucial for assessing the overall impact of the light rail on ridership.

To measure changes in the intensity of use, we define four non-comprehensive use categories after examining our data using exploratory methods. These are:

(1) **Novelty users:** Smartcard IDs who use a mode less than 3 times in the post light rail period (May 2019- January 2020) (approximately equivalent to a one-way or one round trip)
(2) **Rare users:** Smartcard IDs who use a mode 1–8 times a month (approximately equivalent up-to 2 days a week)
(3) **Frequent users:** Smartcard IDs who use a mode 8–20 times a month (approximately equivalent up-to 5 days a week)
(4) **Super users:** Smartcard IDs who use a mode 20 + times a month, approximately equivalent to more than 5 days a week, i.e., every workday.

These categories are non-comprehensive because none of the categories capture the user with at least three trips but fewer than one per month.

Each card can be classified in these categories before and after the light rail opening and for each of the two modes (light rail and bus). The introduction of light rail may increase ridership because more people ride and/or because the existing riders make more trips. We address the influence of the new mode on intensity of use by quantifying the flows between these four intensity categories before and after the light rail opening. These flows allow us to attribute any ridership growth to the intensive or extensive margin. In this study, our second objective is to comprehend the spatial patterns among various categories of light rail and bus users. In order to spatially locate the riders associated with each card ID, the first boarding and last alighting of each day are labelled as the terminal stops, and each card ID is associated with their most frequently used terminal stop. In this work, we identify this stop as a location of significance, but its role as a repeated terminal stop suggests that it is likely to be near the home location (Kundu et al., 2022b). Matching the card IDs to their location of significance allows us to measure spatial effects in behaviour changes.

We hypothesise that riders who live near the light rail are more likely to experience changes in their transit use intensity than those who live far away. To discover spatial patterns, we analyse the distance from home locations to the nearest light rail stations for each mode and intensity classification. Within the intensity categories, visualising cumulative histograms of home-to-station distance, the distribution of distances lends some insight into the spatial extent of the benefits of the light rail investment. These distributions are used to identify characteristics of spatial boundaries for each level of light rail use.

3.1. Study Area

Canberra, with an approximate population of 478,000 according to (Australian Bureau of Statistics, 2024), serves as the capital city of Australia. Traditionally reliant solely on bus transportation, Canberra introduced its light rail network, known as the Canberra Metro, in 2019. This network initially covers a 12 km route linking the northern town center of Gungahlin (the fastest-growing region in Canberra) to the city center (Civic) through 14 stops. Operations commenced on April 20, 2019. Canberra's transit system is well integrated with active travel compared to other Australian cities— in addition to a network of separated cycle paths, most buses have racks for 2 bicycles on the front of the vehicle, cycle racks are available inside the light rail carriages and travellers can access bike lockers throughout the network using their transit smartcard. This study describes the effects on travel behaviour after the implementation of the light rail transit system in Canberra. It leverages trip data collected from MyWay card users over a 5.5-year period, spanning from January 2016 to July 2021.

MyWay serves as an electronic ticketing system utilised across public transport services in the Australian Capital Territory. It is the exclusive payment method for transit since magnetic stripe tickets were phased out in 2011. Unlike survey data, the MyWay dataset offers a comprehensive overview of almost all trips undertaken across various public transport modes during this timeframe. Each transaction accurately records details such as the stop name and ID, tap-on and tap-off timestamps, trip cost, and passenger card type (Adult, Concession, Student,

Fig. 1. The map illustrates the distribution of all (existing and removed) bus stops that ever existed and light rail stations across Canberra overlaid on the population density of the city as of 2021. Canberra's urban planning features bushland reserves depicted in pale green, which serve as buffers between 5 town centers highlighted by red circles. A newly announced town center, Molonglo Valley, is highlighted with a blue circle. The bus network follows a multi-hub-and-spoke design centered around these town centers.

etc). This dataset comprises 86 million trips from 563,509 unique card IDs showing overarching travel demand patterns and individualised shifts in transit utilisation.

Fig. 1 illustrates the distribution of all (existing and removed) bus stops that ever existed and light rail stations juxtaposed against residential density in Canberra, underscoring its reputation as a planned city with bushland reserves interspersed among 5 town centers (Belconnen, Gungahlin, Tuggeranong, Woden, Weston Creek). Molonglo Valley town center is under development. Activity centres tend to have paid or time-limited parking and the journey to work mode share is slightly higher than the Australian average (6.0 % vs 4.5 %) (Australian Bureau of Statistics, 2024).

4. Results

4.1. Changes in ridership

Fig. 2 illustrates the percentage change in population, active MyWay users, and trip numbers, all indexed to the average of 2016. Strong seasonal variations are evident in both the number of active card users and trip counts. After accounting for these seasonal patterns, consistent year-to-year growth was observed in 2016, 2017, and 2018, with the introduction of the light rail becoming apparent in 2019. Fig. 3 provides a breakdown of bus and light rail trips over 5 years. While a decline in bus ridership may account for growth from some of the ridership generated from the new light rail corridor, the period following the light rail's inauguration (May 2019) up to the onset of COVID-19 reveals an overall increase in boardings compared to the corresponding period in preceding years.

Anticipated ridership expansion coincided with the inauguration of the light rail due to Canberra's consistent population growth from 2016 to 2021. However, a decline in ridership occurred around 2020 attributed to the impact of COVID-19, as evidenced by Table 2. Notably, Fig. 2 illustrates that the escalation in active MyWay users and trip numbers outpaced Canberra's population growth pre-COVID-19. The data also reveals pronounced seasonal fluctuations in both active card users and trip counts. After adjusting for these seasonal variations, consistent year-on-year growth is evident in 2016, 2017, and 2018, with the introduction of the light rail becoming discernible in 2019. However, the confluence of the light rail's debut and the onset of COVID-19-induced ridership declines renders the total trip growth insufficient for gauging the sustained benefits of the new mode (Kundu et al., 2022a).

The evolution of unique users reflects alterations at the extensive margin, exhibiting similar growth patterns until 2019 followed by declines during the COVID-19 period. While the overall increase in active card IDs obscures churn, it encompasses individuals losing or replacing their cards, relocating in or out of the area, or adjusting their travel behaviours. The last four columns of Table 2 delineate the count of unique smartcard IDs, persistent card IDs, deactivated smartcard IDs, and newly added card IDs for each year. For instance, in 2016, there were 166,929 active MyWay users recorded. The rise of 15,788 active card IDs in 2017 comprises 81,145 card IDs not previously documented and 71,721 card IDs that became inactive. This churn in the card population encompasses alterations unrelated to user changes (such as lost or stolen cards and transitions in card type, such as from youth to adult) and changes in card IDs associated with user transitions (new users, intercity migration). Only the attraction of new users directly correlates with measuring the benefits of new transit investment.

Temporal nuances in the attraction of new users are illustrated in Fig. 4. The spike in cards in light rail boarding in May 2019 is the expected novelty effect. Most of the drop in cards between May and June is due to the loss of previously observed cards— these could be bus riders who tried light rail for the novelty effect and then returned to bus riding. From June 2019 onwards, the previously observed cards (pink) show the expected level of de-activations. Likewise, the growing thickness of the purple region that results in a flat total size indicates that normal churn is roughly replacing the deactivations. This suggests that the initial month represents an atypical novelty effect, but the light rail induced ridership increases from June 2019 are stable.

In the 3.5 years preceding the introduction of the light rail, the dataset recorded a total of 328,721 unique MyWay card IDs. Following the introduction of the light rail in mid-2019, there was a notable surge, with an additional 125,546 MyWay cards entering the dataset in 2019, marking a substantial increase compared to previous years. Accounting for the loss and gain of unique card IDs in each calendar year, consistent year-to-year growth was observed between 2016 and 2018 (9.5 % and 7.3 %, respectively), with the introduction of the light rail becoming apparent in 2019 at 27.8 % year-to-year growth. Among the total 563,509 MyWay card users in the dataset, approximately 35 % (199,754 individuals) made at least one light rail journey, while approximately 65 % (363,755 individuals) exclusively utilised the bus.

Some of these light rail users are trying the new mode for novelty

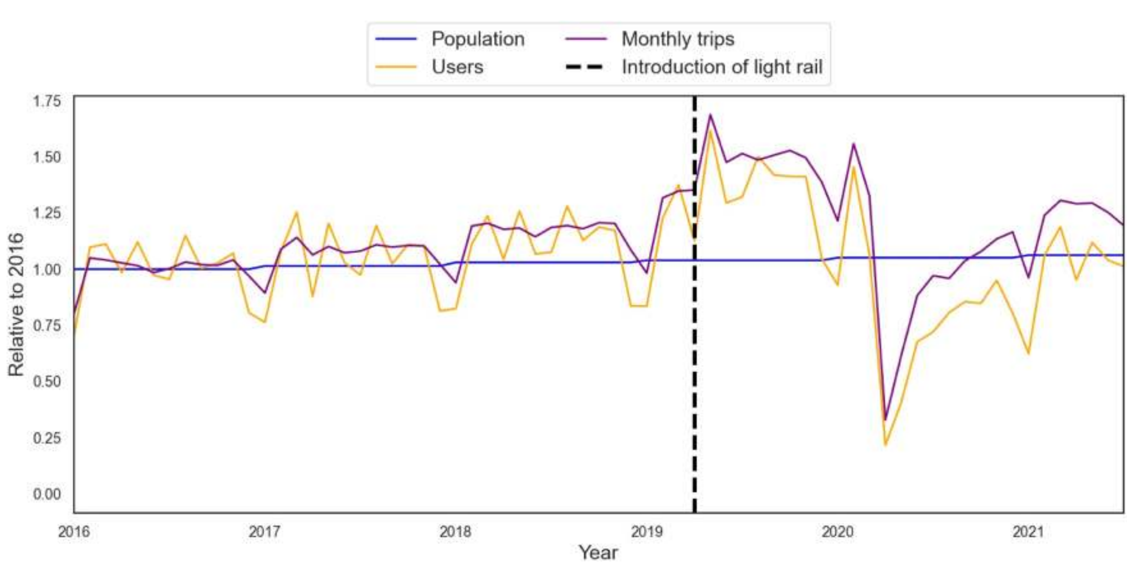

Fig. 2. The population, MyWay card users, and trip numbers are indexed to 2016. Over 5 years, the population has demonstrated a consistently upward trajectory. Conversely, the number of MyWay cards experienced a sharp surge upon the introduction of light rail, with subsequent patterns obscured by changes resulting from the COVID- 19 pandemic.

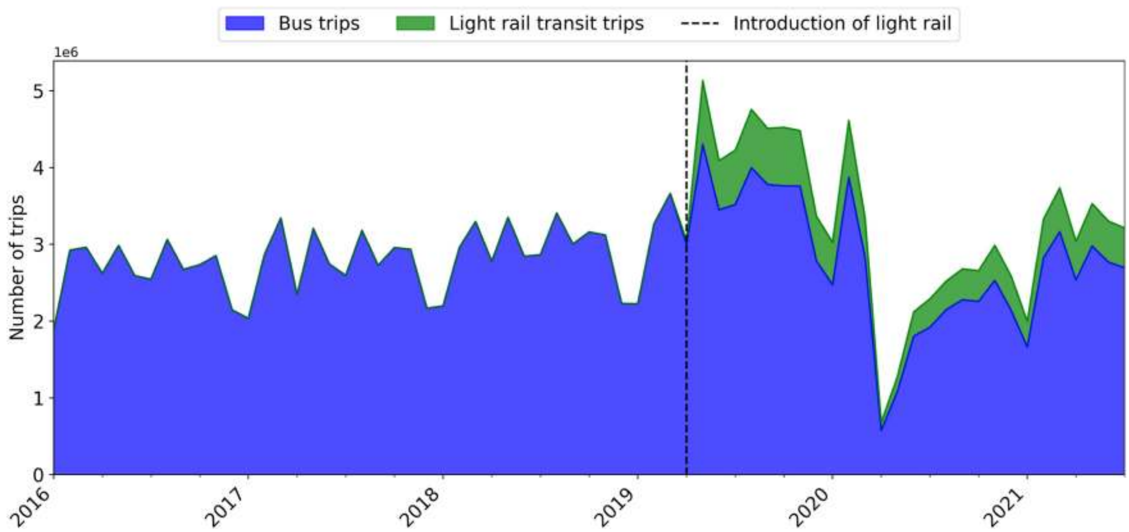

Fig. 3. Analysis of bus trips and light rail boardings reveals noteworthy trends. During the period spanning from the commencement of light rail operations to the onset of the COVID-19 pandemic, the total monthly boardings surged by approximately 50 %. Notably, even as bus ridership surpassed pre-light rail levels during this timeframe, indicating that the rise in ridership was not at the expense of bus patronage.

Table 2
Year-by-year growth (January 2016 to July 2021) in MyWay travel measured through number of trips, population, unique card IDs, persisting card IDs, deactivated card IDs and new cards. In the pre-COVID period, growth in travel outpaces population growth, and the light rail represents a notable increase in both trips and new users.

Year	Number of trips	% change in trips from previous year	Population	% change in population from previous year	MyWay Users	% change in MyWay users from previous year	Persists from previous year	Deactivated since previous year	New since previous year
2016	15,983,733		435,036		166,929				
2017	16,549,315	3.54	441,318	1.44	182,717	9.46	101,572	65,357	81,145
2018	17,605,348	6.38	447,692	1.44	195,969	7.25	110,996	71,721	84,973
2019	20,753,876	17.88	452,497	1.07	250,495	27.82	124,949	71,020	125,546
2020	12,963,750	−37.54	457,330	1.07	205,689	−17.89	136,735	113,760	68,954
2021	9314,899	−28.15	462,213	1.07	175,939	−14.46	116,055	89,634	59,884

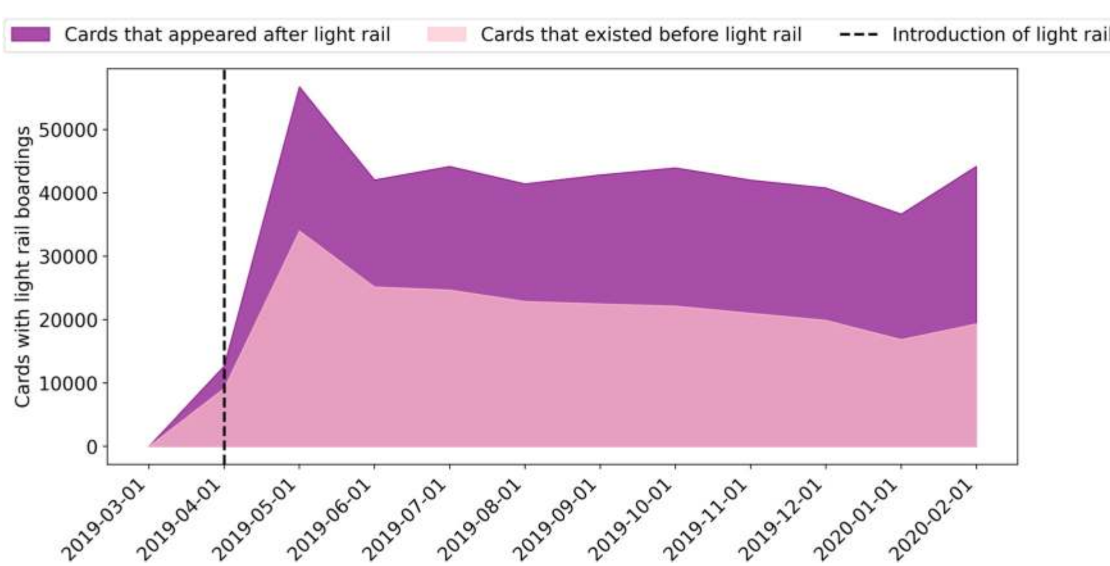

Fig. 4. The count of smartcards associated with light rail usage during the period between the opening of the light rail and the onset of COVID-19 is depicted. The pink region represents cards existing before the light rail's introduction, while the purple region signifies cards added after its introduction. The peak immediately following the opening indicates heightened demand for the new system, while June 2019 onwards illustrates the typical turnover of cards.

reasons and do not represent stable growth in the system. About one-quarter of cards that made any light rail trips (47,400 users) used light rail less than 3 times in total. Fig. 5 shows that these novelty users are more common with light rail than the bus, as expected for a new public transit investment. During the initial period after the introduction of a light rail system, there tends to be heightened interest and

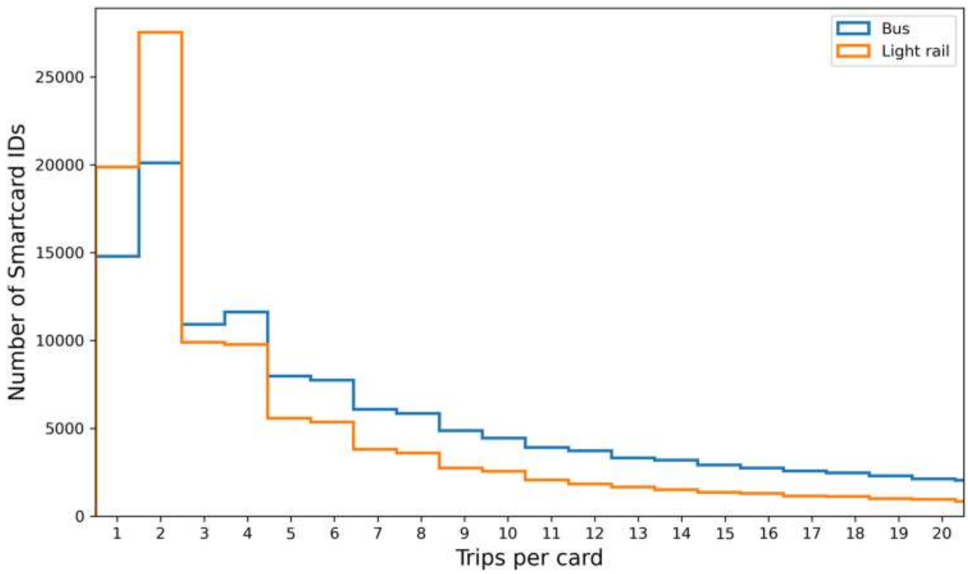

Fig. 5. The comparison between bus and light rail usage among novelty users. Specifically, it highlights that out of 47,400 novelty users, a significant portion used the light rail less than three times, primarily as a joy ride. A significant number of novelty users view the light rail as a leisurely mode of transportation, using it for joy rides rather than as a primary means of travel.

enthusiasm. People may be eager to try out the new mode of transportation, even if it is not their regular means of getting around. The introduction of light rail triggers the initial excitement and interest of people sometimes leading to a joy ride. The most common number of light rail trips per card is 2 trips, which corresponds to a round-trip joy ride on the new system. Fig. 5 underscores the novelty effect where many individuals get a card and rarely use it. This is corroborated by a 32 % increase in rare users in the next nine months after the introduction of light rail which is shown in Table 3.

The findings from our study show the impact of ridership changes on public transportation usage. The results indicate a notable increase in the total number of boardings, surpassing the rate of population growth. Specifically, a 28 % rise in the number of card IDs is observed, even after accounting for churn. This suggests a significant surge in public transportation utilisation.

Table 3 tabulates the users' intensity before (rows) and after (columns, broken by mode) the introduction of the light rail. 125,241 new cards appeared in the 9 months following the introduction of the light rail (May 2019 to Jan 2020). Out of 125,241 new card IDs, 37,721 IDs used the bus rarely after the introduction of light rail— rare users are the most common category both before and after and for both modes. Out of 40,603 bus super users before the light rail transit, only 3647 became super users of light rail whereas nearly 40 % (15,818) remained bus super users.

Fig. 6 shows the transition between the intensity of bus use categories before and after the introduction of the light rail. Data from nine months before (May 2018 - January 2019) and nine months after (May 2019 - January 2020) the commencement of light rail is considered. Despite high churn with more than 100,000 new cards, the sizes of the bus use categories stay fairly stable over this period. The most substantial growth is in rare users, which grew from 66,796 to 73.717. The maintenance of these sizes is achieved through large portions of each

Table 3
Number of users with different transit categories before (rows) and after (columns broken by mode) the introduction of light rail 9 months before light rail (May 2018-January 2019) and 9 months after light rail (May 2019-January 2020). The diagonals show the users who maintained their intensity regardless of mode. Most users are rare users and bus users are more common than light rail users.

	Total number of users before light rail	Did not use Bus	Number of IDs with bus trips in a month after the introduction of Light rail				Did not use light rail	Number of IDs with light rail trips in a month after the introduction of Light rail				Cards deactivated	Total number of users after light rail
			Other User	Rare User (1–8 times)	Frequent User (8–20 times)	Super User (20 +times)		Other User	Rare User (1–8 times)	Frequent User (8–20 times)	Super User (20 +times)		
Cards did not exist	125,241	**28,306**	30,179	37,721	14,346	14,689	**50,651**	39,941	26,106	4903	3640	0	67,456
Other	39,267	22,005	**7393**	6732	1583	1554	28,702	**6147**	3523	554	341	19,024	57,430
Rare User (1–8 times)	66,796	30,704	9387	**17,477**	5031	4197	46,016	10,355	**7845**	1594	986	27,504	90,097
Frequent User (8–20 times)	28,193	11,411	2444	6052	**4345**	3941	18,478	4130	3601	**1140**	844	10,422	35,587
Super User (20 + times)	40,603	11,498	2460	5735	5092	**15,818**	22,768	6469	5540	2179	**3647**	10,506	49,530
Total	300,100	103,924	51,863	73,717	30,397	40,199	166,615	67,042	46,615	10,370	9458	67,456	300,100

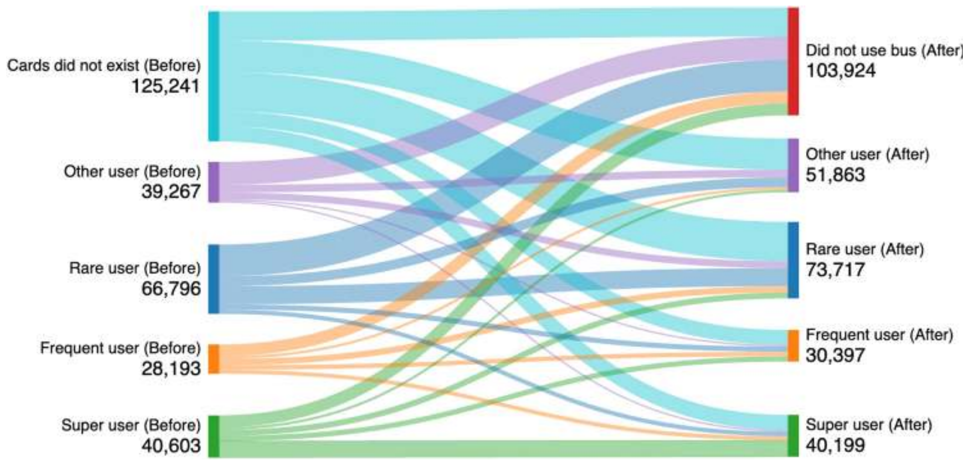

Fig. 6. Intensity of bus use in the nine months before (left) and after (right) the introduction of light rail. The category sizes stay stable across the two periods despite significant churn without rare users (dark blue) dominating. Rare users are the most common category and about half enter/exist the system on a nine-month time scale.

category shifting to other categories— none of the categories retained more than half of their users after the opening of light rail. However, each of these users is also categorised by their light rail behaviour, so a bus super user from the before period might become only a frequent bus user because a portion of their trips are now made on light rail.

Fig. 7 shows the flow between the intensity of use categories for the bus before and light rail after the introduction of light rail service using the same period as Fig. 6. The majority of card IDs do not have any light rail use in the post-opening period. This alone indicates that the transformative benefits of the light rail are not felt universally across the population. Of the 9458 cards in the light rail super user category, about 40 % of them were bus super users before the light rail, so the new transit system cannot be credited for creating their demand for intensive transit use. However, 4866 card IDs did not exist (3640 users) or used the bus less frequently (1327 users) and then became super users. This small population exemplifies the imagined transformative benefit of a new light rail mode.

The results presented in Table 3 reveal notable trends. Following the introduction of the light rail, 125,241 new card users emerged, while 67,456 previous bus users were no longer observed. Only 123,458 unique users (22 % of the total 563,509 unique users) exhibited trip evidence both before and after the light rail's introduction. Within this cohort, nearly a quarter increased their usage intensity post-light rail introduction, preceding the onset of COVID-19. Conversely, approximately a third experienced a decrease in usage intensity after the light rail's introduction. The remaining ~45 % maintained a relatively stable usage pattern, with a change of less than one trip per month. With three-quarters of the persistent system users either maintaining or reducing their usage intensity, it suggests that the majority of riders remain unaffected by the opening of the light rail. This outcome aligns with expectations, considering the light rail's limited service coverage, which may not cater to the travel needs of most Canberra residents across various origin-destination pairs.

In addition to the intensity of use, light rail may attract different types of people. Fig. 8 indicates that cards that appear after the introduction of the light rail system follow roughly the same distribution of passenger types as total, with Adults and Students remaining the predominant groups in both all riders and new riders categories. As the light rail corridor terminates near Civic employment centre as well as Australian National University, Adult and Tertiary Student cards were slightly over represented in the new card group, whereas Students are underrepresented compared to the set of all card holders in the same period.

The findings from this study provide valuable information about the

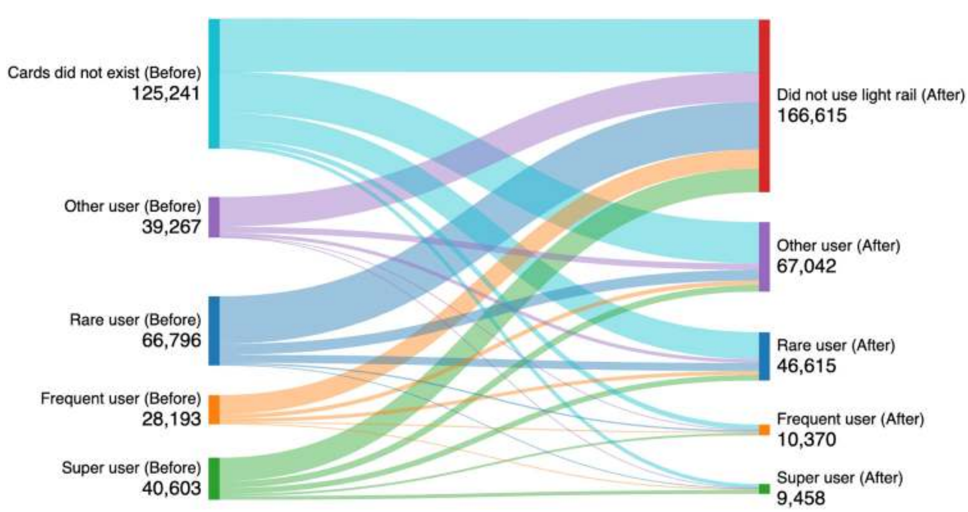

Fig. 7. Flows from intensity of bus user category in the nine months before to intensity of light rail use category in the nine months after introduction of light rail. More than 50 % of all cards did not use light rail after the introduction of light rail which indicates the benefits are highly concentrated. Around 50 % of light rail super users were also bus super users before light rail.

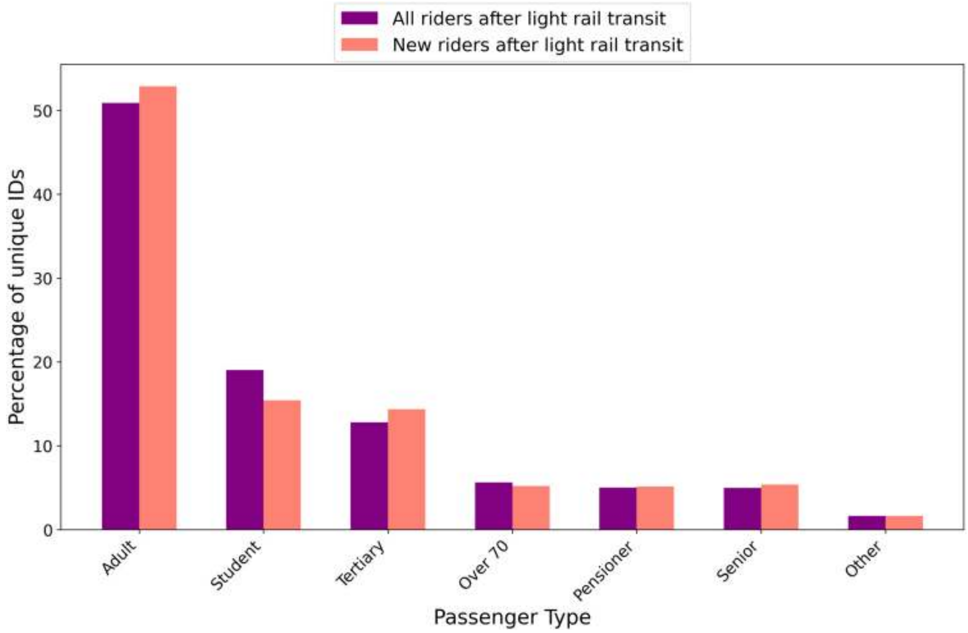

Fig. 8. Comparison of new and all card holders in the after light rail period across five passenger types: Adult, Over 70, Pensioner, Student, Tertiary and Other. The proportions are similar with small differences relevant to the destinations served by the corridor. This suggests that new riders attracted to the system are from roughly the same demographic as all card holders but biased towards workers and tertiary students.

intensity of transit usage, addressing a key aspect of the first research question. The rare users constitute the largest intensity category, showing a substantial influence on ridership patterns. This suggests that even though they don't use transit often, the group behaviour makes a significant difference in how much transit is used overall. These findings further led to the second research question of how travel intensity varies.

4.2. *Spatial trends in light rail use*

The previous section demonstrated that the opening of light rail is associated with an increase in the number of trips, but this change cannot be attributed to a widespread increase in transit use intensity. Rather, the trends in intensity of use indicate that most card IDs use transit, and especially light rail, rarely. This section further explores the spatial distribution of transit users by intensity of use.

4.2.1. *Intense light rail users tend to live near light rail stations*

All card IDs with sufficient trips are associated with an inferred home location (their most frequently used terminal stop) and the distance between their inferred home and the nearest light rail. Fig. 9 shows the reverse cumulative distribution of trips of these home to light rail stations for each bus vs light rail use category for the 9 months after (May 2019 - Jan 2020) the introduction of light rail. As the intensity of light rail use increases, the distribution of distances becomes more sharply peaked around zero. This shows that transformative behavioural change associated with light rail is primarily experienced within a narrow corridor. In contrast, the spatial distribution of novelty light rail users is broader– in fact, these home-to-light rail distances closely resemble those of the bus riders shown in the top part of Fig. 9.

Since bus stops are spread much more evenly around Canberra than light rail stations, the super, frequent and rare bus user curves provide a benchmark roughly matching the general population's spatial separation from the light rail corridor. The interception of the dashed 80th percentile line in Fig. 9 shows how similar the 80th percentile distances are for bus users compared to light rail users. Novelty bus users are a notable exception— because home locations can only be inferred for cards with multiple trips and novelty bus users have less than 3 bus trips over the 9 months post-opening, many of the card IDs in this category are predominately light rail users. So the bus novelty user cumulative distribution resembles the rare or frequent light rail user distribution.

Table 4 suggests more than 50 % of the light rail super and frequent users have inferred home location at the light rail stations. Half of the rare users live within 420 m of the light rail stations. Half of the novelty users, those who use the light rail as a joy ride or on a special occasion, display a broader range living within 5.46 m of the stations. This illustrates that frequent light rail use is generally associated with excellent accessibility to the stations and that proximity is correlated with more intensive use. The transformative behavioural change promoted with a new transit mode is demonstrated to be highly spatially concentrated.

Table 4 shows how many card IDs in each category have their inferred home location at a light rail station. This helps explain how many people live near the light rail stops but also how much they contribute to the number of journeys. 63 % of the light rail super users have inferred home location at a light rail station, 56 % of frequent users, 38 % of rare users and less than 4 % of novelty users. The dominance of light rail stations as the terminal stops explains why the distance from light rail is so small— intense light rail users usually do not access it by bus. This may be partially supported by Canberra's network of walking and cycling paths and support for integrating transit and cycling— both of which expand station catchments without impacting the inferred home locations of the travellers.

In contrast, higher-intensity bus use is associated with a decreasing fraction who live near a light rail station. Since home locations are the most common terminal stop, a bus super user can only be matched with a light rail home location if he or she is also a light rail super user *or* if the first and last trips of the day are light rail-based but more trips are made on the bus in the middle. The high fraction (24 %) of novelty bus users whose home location is at a light rail station suggests that many bus novelty users (less than 3 bus trips in nine months) have more trips on light rail.

Transit investments are promoted with a stereotype of local residents practising daily commutes to work on the new service. This analysis captures this behaviour with the super user category— more than 20 trips per month equivalent to every weekday. Table 4 depicts the distribution of the inferred home locations of different categories of light rail users. Assuming that people tend to live near their most frequent

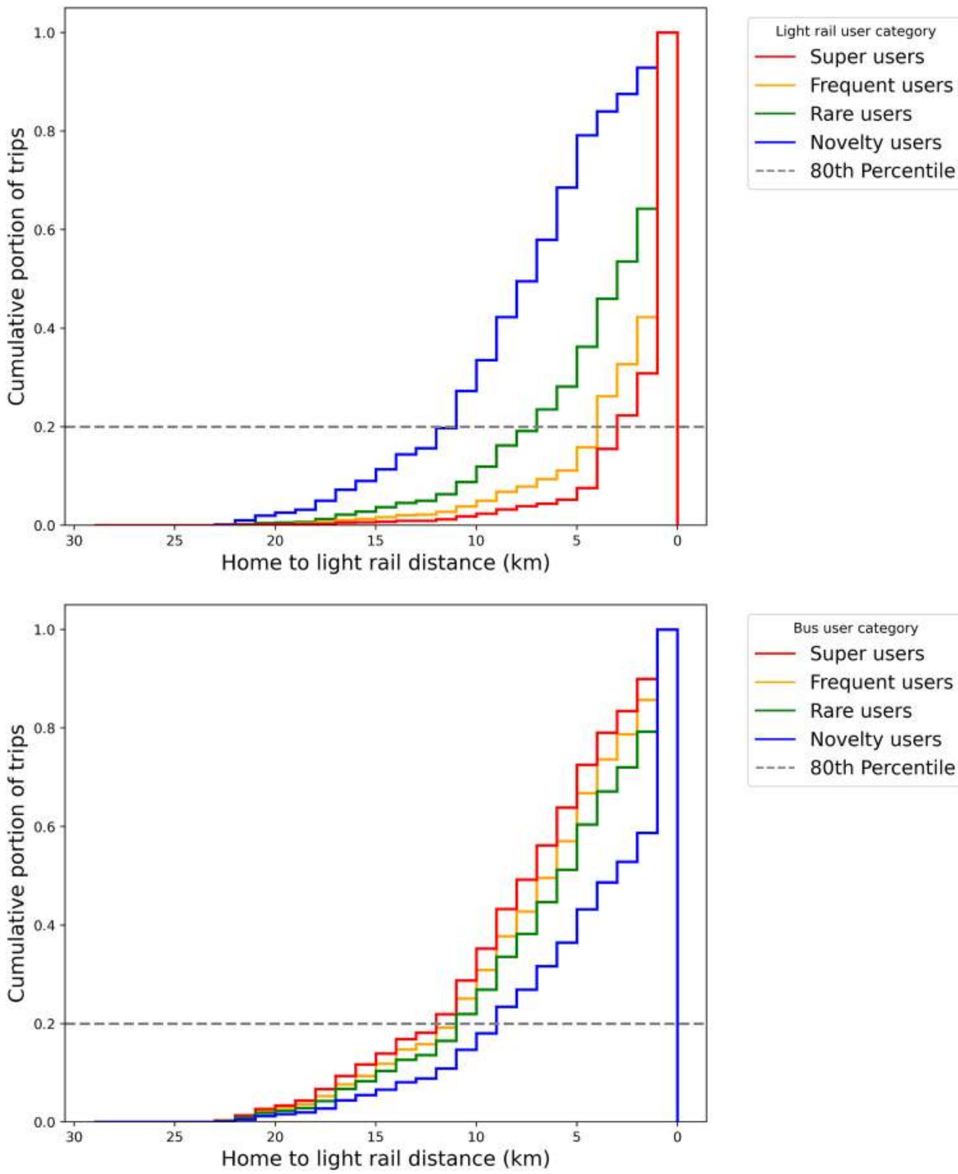

Fig. 9. Cumulative distribution of home to light rail station distances separated by trips of bus (bottom) and light rail (top) use category. The bus-use categories show similar patterns whereas the intensity of light rail users is correlated with proximity to the station. The strong peak in the light rail super user distribution shows that the home location of the most frequent riders is usually inferred to be at the light rail station.

terminal stop (Kundu et al., 2022b), the results support the picture that transit benefits are spatially concentrated and riders living near the transit corridor are more likely to use light rail and to use it intensely. Conversely, the opening of the new mode is largely irrelevant to transit users living outside the corridor. These findings are consistent with a few other past studies (Cooper et al., 2002; Dueker and Bianco, 1999; Kim and Li, 2021; Olesen, 2014). This emphasises the importance of integrating new light rail with the existing public transport network, including bus and subway routes, to broaden the benefits outside the corridor.

4.2.2. Spatial distribution of inferred home location of different categories of bus users vs light rail users

Fig. 10 shows the light rail corridor with highlighted 0.8 km (0.5 mi) catchments. There are currently 2438 bus stops in Canberra serving 65 bus routes. The light rail was introduced on one of the busiest bus corridors of the city and replaced existing bus stops. The catchments around the light rail stations show how little of Canberra's area falls within an easy walk of light rail. This reinforces the intuitive result shown above that the ongoing benefits of light rail are experienced by a small portion of the population.

Fig. 11 shows super, rare and novelty users of bus and light rail users 9 months after the opening of light rail. This map shows the inferred home location of bus and light rail users and the influence of light rail on them. Light rail super users are dense along the light rail route, especially in the southern part of Gungahlin showing that the transit investment enabled behavioural change for a set of origin-destination pairs (shown in (a) and (d) of Fig. 11).

On the other hand, light rail novelty users are much more widely spread. However, the users who take a joy ride or a one-off occasion trip on the light rail, are more concentrated in the northern suburbs than the south. For comparison, the bus super users are the most evenly distributed across Canberra; their locations demonstrate by contrast that even the novelty users of light rail are still somewhat spatially concentrated (shown in (c) and (f) of Fig. 11).

As discussed above, due to the process for inferring home locations, bus novelty users are likely to be intense light rail users. Therefore, their

Table 4
Median home-to-light rail distances for each bus and light rail user category. Despite the extreme differences in the number of cards in each light rail user category, the number of trips made by members of those categories is more balanced. There are no strong trends between the bus use categories, which is expected.

Light rail users					
Category	Number of card IDs	Median distance (km)	Number of cards within the median distance	Number of total trips made by those users	People with most frequent stop at light rail stations
Super users	3900	0	2446	1522,667	2446
Frequent users	7832	0	4372	1596,491	4372
Rare users	29,306	0.42	14,657	2733,987	11,056
Novelty users	10,857	5.46	13,609	1735,046	770
Bus users					
	Number of card IDs	Median distance (km)	Number of cards within the median distance	Number of total trips made by those users	People with most frequent stop at light rail stations
Super users	18,911	6.90	9734	5719,709	631
Frequent users	28,017	5.94	14,120	3264,974	1452
Rare users	57,285	5.40	29,456	1872,800	5965
Novelty users	11,492	2.60	5801	17,287	2792

distribution shows a concentration along the light rail corridor as expected, although the degree of concentration is less than for light rail super users.

Both maps that show novelty users include notable clusters considerably south of the light rail corridor (along Athlon Drive in Phillips). Examining Fig. 12, it becomes evident that the proportion of residents along Athlon Drive who are light rail users is not exceptional. This feature occurs because there are so many transit riders at these stops.

Fig. 5(b) and (e) show the number of users who have inferred home location at the bus stops for light rail rare users and bus rare users. The illustration presented in Fig. 5(b) and (e) sheds light on the number of users whose inferred home locations are associated with bus stops, particularly distinguishing between light rail rare users and bus rare users. Notably, the depiction reveals a noticeable difference in the spatial distribution of these two user groups. Bus rare users appear to exhibit a more scattered pattern, implying that their home locations are dispersed across various locations with less concentration. In contrast, the light rail rare users have a distinct spatial characteristic, with a dense crowd clustered around the light rail. The tendency of light rail rare users to cluster around the light rail stations may be indicative of a preference for this mode of transportation, while the more dispersed nature of bus rare users' residential locations suggests bus rare users are not influenced by the presence of the light rail and are generally non-transit users.

The tendency of light rail rare users to cluster around the light rail stations may be indicative of a preference for this mode of transportation, while the more dispersed nature of bus rare users' residential locations suggests bus rare users are not influenced by the presence of the light rail and they are non-transit users in general.

4.2.3. Relationship between home to light rail distance and the number of light rail transit trips

Fig. 13 shows that there is a strong correlation between the intensity of light rail usage and the proximity of individuals' inferred home location to light rail stations. Specifically, it was observed that approximately fifty percent of super users (individuals who use light rail more than 20 times per month) have their most frequent terminal stop situated at light rail stations. This suggests a significant trend where individuals who heavily rely on light rail services tend to reside in close proximity to these transportation hubs.

Based on the plot, we can interpret that there is a clear downward trend in the distribution of the dots from super users (red) to novelty users (blue) as the median values of the number of trips in 9 months decrease as the distance from home to light rail increases. This trend is evident because super users have the highest median count of trips (244 trips in 9 months) because they are closest to the light rail stations. Following super users, frequent users (orange) exhibit a slightly lower median count (108 trips in 9 months). Rare users (green), further from the hub (420 m), have a lower median count (23 trips in 9 months) compared to frequent users. Lastly, novelty users (blue), residing farthest from the light rail stations (5.46 km), exhibit the lowest median count (2 trips in 9 months) of trips among all categories. This trend suggests a correlation between proximity to light rail stations and the frequency of light rail usage, with closer proximity to the stations associated with higher usage frequency.

The findings from our study challenge the traditional theory that people typically walk about 800 m to reach their most frequently used transit stop. Contrary to this notion, our research indicates that the actual distance people usually walk to access transit is significantly shorter than 800 m (half a mile). This suggests that the conventional assumption about walking distances to transit stops may not accurately reflect real-world behaviours. In support of this, our analysis, as presented in Table 4, demonstrates that fifty percent of frequent users reside at the light rail transit (LRT) corridor. Recognising the actual distances people are willing to walk to access transit can help develop more effective transit-orientated development strategies.

5. Discussion

Our study presents three significant findings regarding public transportation usage and its dynamics surrounding the introduction of a new mode. *Firstly*, we observe a substantial increase in total boardings, surpassing population growth rates, signifying a notable surge in public transportation utilisation.

To substantiate the first finding, this study investigates changes in ridership after the implementation of a new light rail system in April 2019. At the most basic level, the transit smartcard data show that the opening of Can- berra's light rail was a success, with 5341,710 boardings occurring within the first 9 months. A deeper examination of the bus boardings on the same interval shows that these trips were not made at the expense of existing bus trips, so the new transit mode's additional service capacity likely addressed latent demand in the system. The smartcard data further indicates that over 125,000 new cards entered the system in the year that the light rail opened, which contributed to net growth of 28 % in unique cards when typical growth is less than 10 %. This illustrates the impor- tance of long baseline data to provide context for growth in boardings, PKT or card IDs.

Secondly, our findings shed light on the relationship between transit usage intensity and overall transit use, with rare users exerting a significant influence on ridership patterns despite their infrequent usage. The dataset supports consideration of the new mode's benefits across different user categories of bus and light rail services. The combination of increased users and increased trips might naively imply that the light rail has welcomed a fresh set of regular commuters, but analysis of the intensity of use does not support that picture. Key insights include distinct patterns in the spatial distribution of different categories of bus and light rail users, indicating a strong relationship between the intensity of use and proximity to the stations.

Closer inspection shows that 47,400 card IDs were those riding light rail for the novelty effect, which may rep- resent the co-benefit of

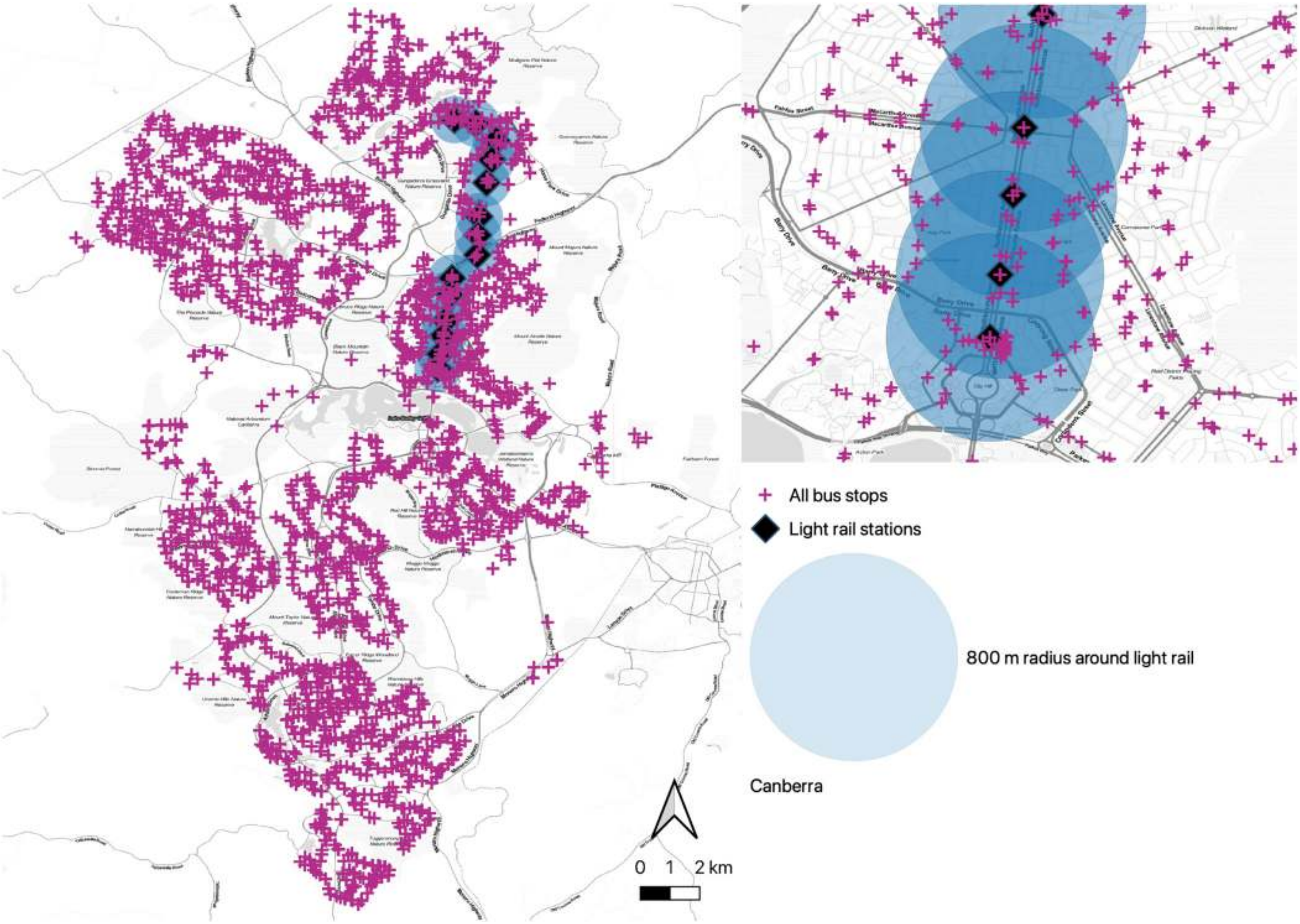

Fig. 10. Map highlighting transit stops with 0.8 km catchments around light rail stations. The areas covered by the 0.8 km catchments indicate typical walking access distances from light rail stations. The map reveals how little of Canberra falls inside the typical walking access distance to light rail.

familiarising non-riders with the system and opening up possibilities for future travel. This effect is notable for cards that appeared after the light rail— 39 % (42,156 of the 109,186 new cards) were bus-only whereas 53 % (98,635 of the 185,505 existing card IDs) were bus-only. The 109,186 new cards included about as many light rail frequent and super users as there were bus super users before the light rail (41,019).

This research also highlights the need to study how the introduction of a new mode affects the travel habits or routines of individual users. We presented a substantial increase in the number of new cards which is evidence that the new mode attracts new card IDs. Although 16 % of these customers only use the light rail for novelty (1 or 2 trips), an additional 13 % go on to use the transit system more frequently (1–8 trips per month). This underscores that new modes have the potential to capture new markets for transit. Additionally, changes in the intensity of transit use are another quantification of the benefit of the new mode. Comprehensive smartcard data can be used to anticipate which geographic areas are vulnerable to increases in intensity with the right investment.

Finally, our research challenges traditional assumptions about walking distances to transit stops, revealing that inferred home locations are not predictably distributed across typically-assumed catchments. These results combine both temporal trends in ridership and the spatial dynamics of transit users in relation to the introduction of a new light rail system. It examines the distribution of inferred home locations of transit users with respect to the light rail stations. The maps make it clear why this concentration is natural— most residents of Canberra don't live near the light rail. These results are consistent with past studies (Cervero, 1984; Kuby et al., 2004), including findings that public transport use increases when access distance to public transport reduces (Jiang et al., 2012). These findings can be used to revisit traditional assumptions about 0.8 km or 0.5-mile walking access catchments— we see that many trips are made by super users with inferred home locations much closer to the stations than 800 m. They may live close to the light rail corridor or they may access the light rail by car, walk or bicycle. But even more trips are made by rare users, and half of them live more than 2.4 km away from a station.

In summary, the benefits of increased ridership are largely influenced by a small group of occasional users who are spread out across a wide area. However, significant changes in commuting habits and transportation preferences are often limited to specific routes or corridors, indicating a more localised impact of transformative behaviour. These findings are only possible because of the availability of long-baseline smartcard data.

The interpretation of these findings supports policy and planning implications. Previous research on the catch- ment area mostly focused on the influence of station and walking accessibility and changes in land use. However, in this study, the large smartcard data gives a broader sense of how the catchment depends on the intensity of use. The results from this study, therefore, can help policymakers to extend the existing rail corridors based on the population density of a region (Higgins et al., 2014). This suggests that benefits from new modes will be max- imised if, instead of their introduction as an alternative mode into the already high-access, high-density corridors in the city, they are introduced in high-population-density areas with low or no public transit accessibility

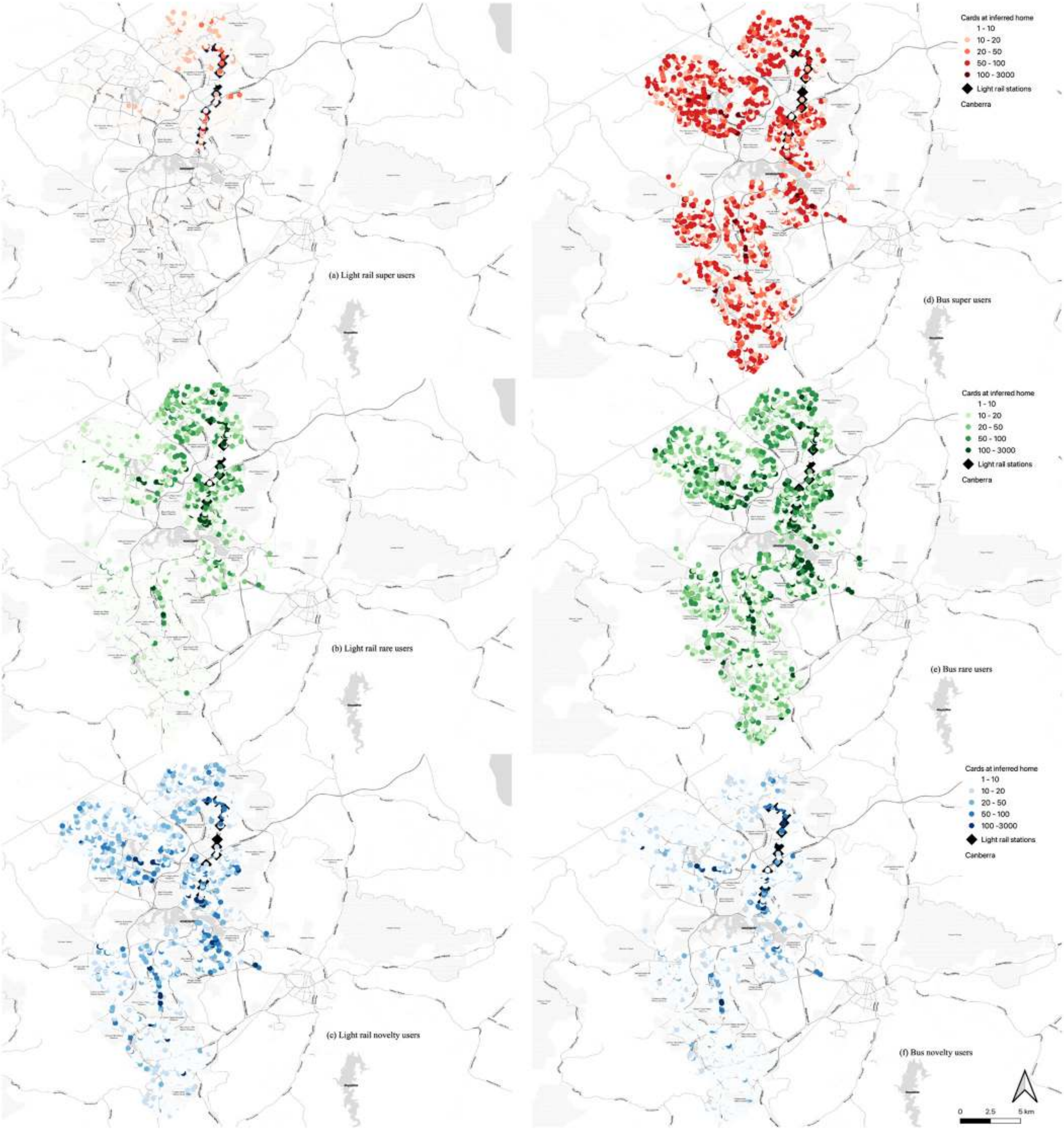

Fig. 11. This Map compares the distribution of light rail and bus super users (a, d), rare users (b, e) and novelty users (c, f), nine months post the opening of the light rail. As anticipated, bus super users exhibit a more scattered spatial pattern, and their locations appear unaffected by the presence of the light rail. This shows the distinct geographical behaviours of bus and light rail super users over the specified time frame.

to the rest of the city-region. In such cases, the localised effects could translate into city-wide benefits. An example of such transit planning is seen in the ACT government's plan to extend the light rail corridor in the south direction from the city center to the Woden town center, contributing to the spinal-cord design of the transit system. In this context, the present findings can help to quantify the potential ridership impact due to increases at both the intensive and extensive margins, as well as the spatial scale of the catchment (Knowles, 2007). Furthermore, the benefits of public transport investment, as measured through ridership gains and intensity of use, of the new mode are highly concentrated in the corridor, which may be appropriate for alleviating congestion (Choi et al., 2023; van der Waerden, et al., 2024; Wardman, 2004; Woldeamanuel et al., 2022).

This research presents opportunities for future extension. Creating more convoluted journeys, especially those in- volving transfers, is a risk associated with converting a branching bus corridor into a light rail corridor. Further investigation is needed to understand whether the changes in ridership and intensity of use are associated with improved accessibility.

Card churn shows that many riders discarded their previous cards

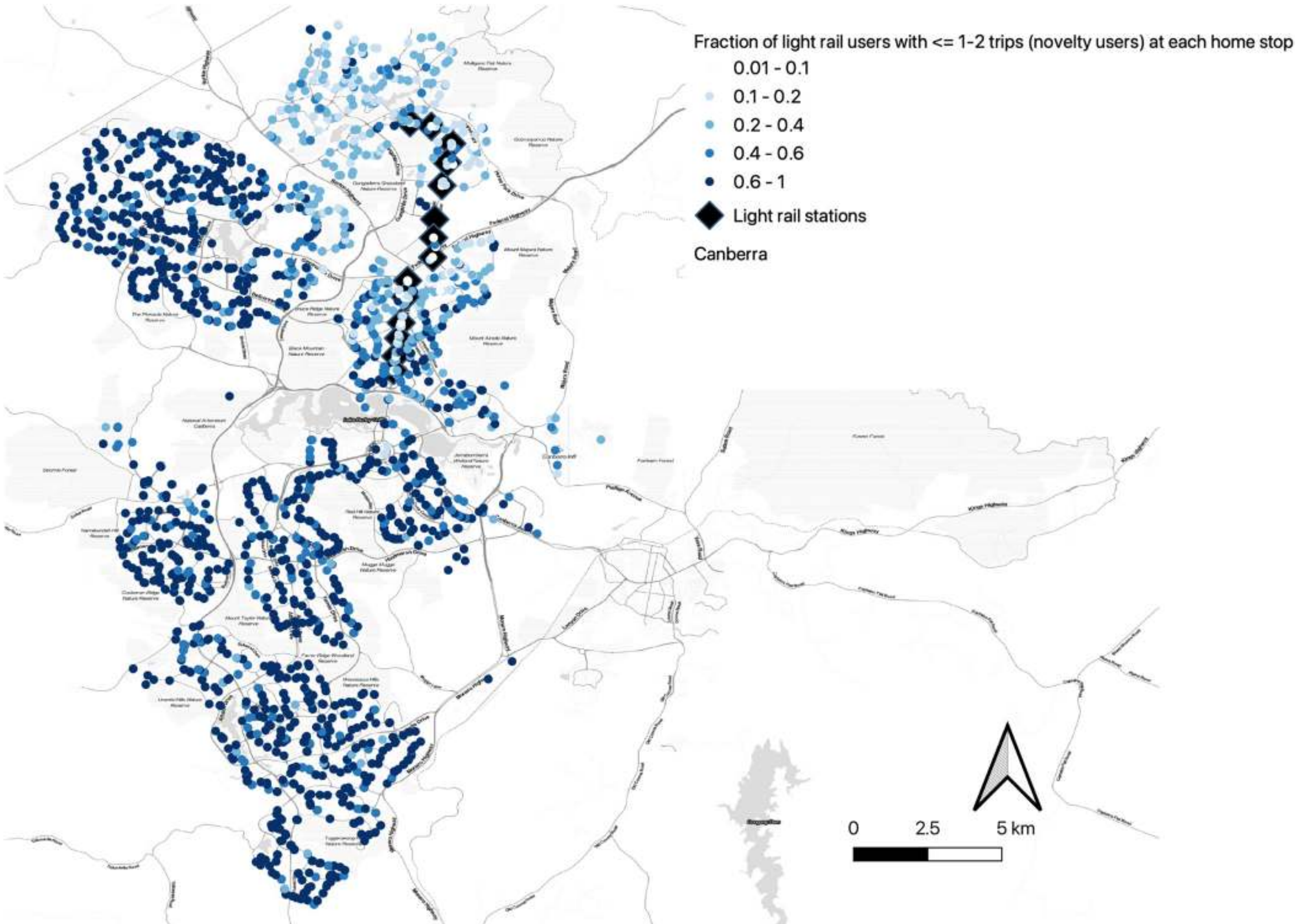

Fig. 12. The figure illustrates the fraction of residents at each bus stop who are light rail novelty users.

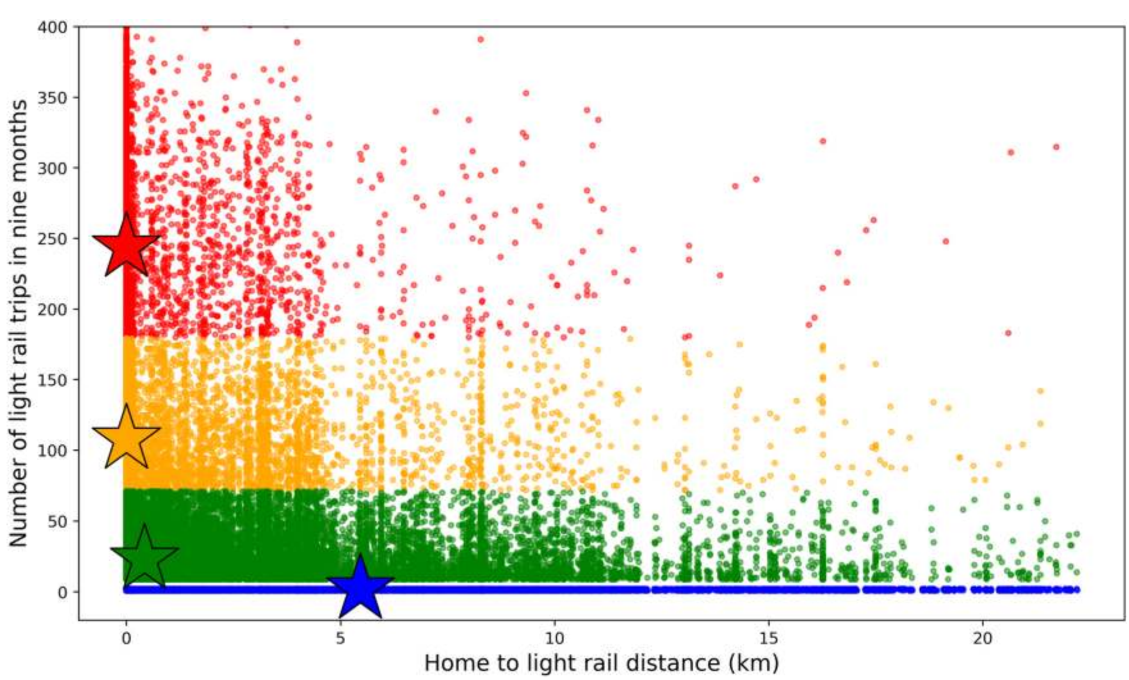

Fig. 13. This figure illustrates the relationship between home to light rail distance and the number of light rail trips over 9 months. It highlights that proximity to light rail stations strongly influences transit usage, with a significant concentration of trips observed among users living closer to stations. The trends show that the median of light rail super users live near the light rail, followed by frequent users, rare users and novelty users.

and got new card IDs; however, the persistence of the users independent of their card IDs is not addressed in the study. This is particularly relevant in cases where a user might use two different cards (e.g., work versus personal trips) or where a change in card status (student to adult) partially explains a change in travel behaviour, or where a lost/stolen card creates a discontinuity in an otherwise persistent travel behaviour.

It is also important to note that this study only considers changes in travel habits after the introduction of the light rail. However, it does not incorporate any other environmental factors like weather conditions, personal-level disruptions (e.g., work or home relocation), or other behavioural changes like shifts in destination, purpose, journey

duration, number of transfers, or the boarding time for the first trip of the day. A better understanding of socio- economic factors could provide deeper insights, such as how ridership changes for different income levels within a city. By merging smartcard data with surveys, future work can include trip purposes and trip chains to better understand shifts in behaviour.

CRediT authorship contribution statement

Kundu Durba: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sarkar Somwrita:** Writing – review & editing, Validation, Supervision. **Moylan Emily:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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