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Revealing latent trajectories of (intended) train travel during and after COVID-19

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A R T I C L E I N F O

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A B S T R A C T

This study investigates whether the decline in public transit ridership is a temporary phenomenon or indicative of a structural shift in travel patterns and attitudes. We estimate a latent class trajectory model using data from a comprehensive and large-scale survey administered by the Dutch national train operator conducted at eight different points in time after the onset of the pandemic. Six latent trajectories in train use and stated future intentions to use the train are revealed, showing different 'recovery' pathways. Whereas low-educated frequent commuters travel almost as much as before, highly educated frequent commuters and mixed-purpose travellers still travel much less, even in the last wave when all restrictions are lifted. The results indicate that travellers belonging to these classes have structurally changed their behaviour. The shift to working from home is more pronounced than the shift to private car use.

1. Introduction

The COVID-19 pandemic and related restrictions imposed by governments had a profound and far-reaching impact on travel behaviour, particularly in the realm of public transport (PT) ridership. While most countries have eased restrictions and societies have returned to normalcy, the PT sector continues to face significant challenges, grappling with a persistent and seemingly structural loss in ridership (Beck et al., 2021; Javadinasr et al., 2022).

For PT service providers, it is not only crucial to know which population groups have reduced their train use, but also imperative to delve deeper into the underlying factors contributing to this decline. Numerous studies have already investigated this pertinent question, offering valuable insights that we will thoroughly review in the next section. These studies consistently reveal a decline in ridership among individuals with higher incomes and levels of education, likely because they have greater flexibility in working from home (WFH) or switching to alternative modes of transportation, such as private cars. This understanding enables PT service providers to tailor their strategies to address the specific needs and preferences of these user segments, devising targeted initiatives that can help regain their trust and patronage.

In addition to comprehending the demographics of people riding less frequently or not at all anymore, it is crucial to determine whether the decline in ridership is a temporary phenomenon or indicative of a structural shift. While travel demand data provides some

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insights, it is insufficient to fully address this complex question. One way to assess whether the changes are structural or not is to reveal the trajectories of specific user groups. In this way, it can be assessed whether some groups are still increasing their usage (after the initial decline), or whether they have reached a new steady-state situation.

In this study, we aim to address these critical questions by leveraging a comprehensive and large-scale survey administered by the Dutch national train operator (NS). This survey was conducted at eight different points in time after the onset of the pandemic, enabling us to capture the evolving intentions and behaviours of train travellers over an extended period. Our specific objective is twofold. Firstly, we aim to assess whether the observed decline is structural in nature (or not) by revealing the various latent trajectories in the train use and stated intentions to use the train. By looking at train use and stated intentions simultaneously specific user groups can be identified. For example, some groups may exhibit a decline in train usage compared to pre-COVID levels, but express their commitment to using the train as frequently as before. For other groups this may not be the case, which would be indicative that the observed decline is structural in nature. Still other segments may have already converted to pre-pandemic travel patterns and intend to travel as much as before or even intend to travel more than pre-COVID.

Secondly, we aim to profile the identified user groups not only on relevant demographic variables but also other relevant attitudes and behaviours, e.g. related to WFH and the use of alternative transport modes. The revealed trajectories as well as the extended profiles of the various user groups can provide a basis to assess (for each segment) whether the observed change in train travel is indeed durable or not. In the end, by exploring these dynamics, we intend to provide PT service providers with valuable insights that go beyond a mere understanding of the present circumstances but also offer a glimpse into the future trajectory of train travel as well as how to handle similar shocks in future disruptions.

The remainder of the manuscript is organised as follows: in section 2 we review the state-of-the-art literature on the impacts of COVID-19 on travel behaviour and PT ridership. Section 3 describes the methodology for this paper, after which section 4 discusses the results. In section 5 the results are discussed in the light of the state-of-the-art and practice. Finally, section 6 concludes the study.

2. Travel behaviour impacts of COVID-19 and PT ridership loss

The COVID-19 pandemic had strong impacts on people's travel behaviour. Due to recommended or mandatory WFH, and in-person activities being cancelled or organised online, people's trip frequencies dropped significantly (e.g., Abdullah et al., 2020; Mouratidis & Papagiannakis, 2021; Parady et al., 2020). However, not all travel modes suffered from the pandemic to the same degree. Car use and active travel have recovered quite well after the pandemic. Partly due to new (temporary) walking/cycling infrastructure, active travel rates often even increased during the pandemic in many cities (Buehler & Pucher, 2021), possibly because trips on foot or by bicycle were often performed for recreational reasons (e.g., Hook et al., 2022). PT has suffered the most during and after the pandemic due to concerns about COVID infection, the decline in transit supply, and shifts to active modes, car use, or even ridehailing services (e.g., Bhaduri et al., 2020; Eisenmann et al., 2021; Monahan & Lamb, 2022). According to Parker et al. (2021), PT riders reduced their travel more than non-riders. In many regions, while traffic volumes have recovered near the pre-COVID levels, PT levels are still significantly below the levels before the pandemic (e.g., Beck et al., 2021; Javadinasr et al., 2022).

The drop in PT use is not surprising, as crowdedness and close distances from other passengers result in a significant risk of infection. In the early days of the pandemic, typical government orders (e.g. in the Netherlands) only allowed essential workers without access to a car and living too far to walk or cycle to use PT. PT service providers often responded to these reduced ridership levels by making service cuts, thereby making it less appealing for people to return (e.g., Gkiotsalitis & Cats, 2021). Furthermore, studies have shown that the pandemic resulted in less favourable attitudes towards PT, while attitudes towards other modes remained stable (de Haas et al., 2020). However, not all population groups stopped using PT to the same extent. Especially, people with higher incomes reduced their ridership, as they often had the chance to work from home or switch to car use, while low-income individuals often have no other choice than to use PT (Kim et al., 2021; Parker et al., 2021). Hu and Chen (2021) found that ridership especially declined in areas with higher percentages of white, educated, and high-income individuals, while Palm et al. (2022) found that young adults (ages 18–29) and recent immigrants shifted to car use and often even purchased a car.

WFH also had a strong impact on PT ridership. Many people reducing their ridership did not shift to other travel modes but travelled less frequently due to WFH (e.g., Huang et al., 2023). This is especially the case for highly-educated people with specialised and well-paid jobs that allow remote working. As this group of people often commute long distances either by train or car, their WFH had strong negative impacts on train use. Additionally, due to the longer commute distances, these people may have a stronger desire to work from home (e.g., De Abreu e Silva & Melo, 2018). Ton et al. (2022a) also indicated that positive attitudes towards WFH negatively impact train ridership. Studies analysing intended travel behaviour after the pandemic have suggested that PT use after the pandemic will be substantially lower than pre-pandemic. Downey et al. (2022), for instance, found that a third of their Scottish respondents expected to use PT less frequently post-COVID-19 compared to before the pandemic, while Javadinasr et al. (2022) found that only 6 % of the respondents intended to use PT as main commute mode post-pandemic, as compared to 12 % pre-COVID. Currie et al. (2021), additionally, estimate that future PT ridership will remain 20 % below pre-COVID levels.

The drop in both actual and intended ridership levels worry many PT service providers and policy makers as lower revenues make it difficult to offer good services, which in turn may have negative sustainability impacts, such as high levels of car use and congestion. Despite some studies already looking into the reasons for leaving PT, evidence is lacking for the demographics of those who have left PT and people's future ridership intentions.

In this study, we will create PT users' profiles based on their train use during the pandemic and intended train use post-pandemic and analyse how these profiles are influenced by socio-demographics, travel behaviour, and WFH (attitudes). This will be done by using an eight-wave panel data set, not only looking at the evolution in actual train use, but also enabling us to analyse the evolution in intended train use. In this way, it will be possible to identify groups that have structurally changed their behavioural patterns.

3. Method

3.1. Context and data collection

The COVID-19 pandemic had a profound impact on people's travel behaviour, primarily due to government-imposed restrictions and concerns regarding infection risks. To understand and capture these changes for train travel in particular, NS (Dutch Railways) and Delft University of Technology collaborated on a longitudinal survey. In the Netherlands, the trains provide (mostly) commuter transport between (large) cities. The average distance travelled by train is 50 km (CBS statline, 2023), which means that the car is the most likely alternative if one would not travel by train. Given the long-distance nature of train travel in the Netherlands, attempts to recover the demand are thus important for sustainability reasons.

The survey that was set up aimed to delve into current travel behaviour, attitudes, and intended changes in travel behaviour across various modes of transport. Participants were recruited through NS's internet panel, which consists of approximately 80,000 members representing the Dutch train-traveling population. These panel members are invited to participate voluntarily in a wide range of research initiatives, including this survey. Given the uncertain nature of the pandemic and the expected behavioural shifts, the survey was designed as a longitudinal panel data study, with the number of survey waves contingent upon the duration of the pandemic and significant changes in the situation, such as new measures or increases in COVID-19 cases.

The first wave of this longitudinal data collection was conducted in April 2020 and achieved a response rate of approximately 57 % (46,000 completed responses, with 96 % agreeing to participate in follow-up surveys). This initial wave aimed to capture respondents'

Table 1
Sample distributions of socio-demographic and travel-related variables (N = 45,937).

Variable	Category	Sample (%)
Gender	Male	45
	Female	51
	Other or missing	4
Age (mean = 54.7)	18–34	9
	35–44	7
	45–54	12
	55–64	23
	65–74	32
	75+	14
	Missing	3
Level of education	Intermediate secondary education	9
	Higher secondary education	10
	Intermediate vocational education	12
	Higher vocational education (college)	32
	University	32
	Missing	5
Occupation	Paid employment	41
	Freelancer or self-employed	5
	Attends school or is studying	5
	Takes care of the housekeeping	2
	Pensioner	36
	Other	7
	Missing	4
Employment sector	Industry, production	2
	Transport and logistics	2
	Healthcare	8
	Education	7
	Government	8
	ICT and information services	4
	Other services (business, financial, personal)	8
	Culture, sport and recreation	2
	No paid employment, other or missing	60
Main travel purpose by train	Work or school	38
	Visiting friends/family	23
	Recreation	24
	Other	15
Train subscription	No subscription	2
	Discount card	39
	Business card (paid by employer)	6
	Student card	2
	Action card (one-time offer)	3
	Senior card	4
	Other or missing	44

behaviour during the “intelligent lockdown” implemented in April 2020, which restricted train travel to individuals with essential jobs, such as hospital staff. Additionally, to establish a baseline for comparison, this survey included questions about the pre-COVID situation in February 2020, indicated as wave 0 in this study. Subsequently, seven more survey waves were distributed in June 2020 (end of lockdown with remaining limitations), September 2020 (increased in-person education and office work), December 2020 (delta COVID- wave and initial vaccinations), April 2021 (relaxation of restrictions), September 2021 (further relaxation of measures), March 2022 (no restrictions), and November 2022 (potential new normal situation). Each wave of the survey, in addition to examining travel behaviour, attitudes, and future intentions, featured in-depth questions on specific topics such as vehicle purchases, home or work relocation, vaccinations, flexibility in changing travel days and times, and experiences with remote work. A minimum of 18,000 respondents completed each wave of the survey, with over 5,000 participants completing all waves.

To assess any potential bias or self-selection among the NS panel, the first wave of the survey was also distributed among an external panel comprising a representative sample of the Dutch train-traveling population based on trip motives, trip frequency, and age. This external panel, consisting of 1,500 respondents, provided a benchmark to verify the behaviour, attitudes, and intentions of the NS panel members. Additionally, the data from each survey wave were weighted against the Dutch train-traveling population. The findings indicated that the NS panel and the external panel exhibited similar current travel behaviour, attitudes, and future intentions. Therefore, the internal NS panel can be considered representative of the Dutch train-traveling population (Ton et al., 2022b).

These comprehensive surveys, conducted longitudinally and across various waves, provide valuable insights into the dynamic nature of travel behaviour during the COVID pandemic. The data collected from a diverse range of respondents contribute to a deeper understanding of the impacts and potential long-term changes in travel behaviour and preferences.

3.2. Data description

For this study data from all eight waves are used (April, June, September, and December 2020, April and September 2021, March and November 2022). Table 1 shows the socio-demographic and travel-related characteristics of the sample in the first wave. In total 45,937 respondents participated in this wave.

For subsequent waves, all members of the initial response group were invited to participate. Table 2 shows the sample sizes and response rates compared to the initial sample. In total, 5,052 respondents participated in all waves. While such a pure stayer sample would result in no missing values, the resulting group would become quite biased due to selective attrition. To be able to include the entire sample and deal with the missing values, we applied a Full Information Maximum Likelihood estimator, which is available in the software package we used to estimate the models (Latent Gold). This means that the parameters are estimated using all available information for each respondent across the waves (Vermunt and Magidson, 2013).

3.3. Measures

To measure train use, the following question was asked: *How often did you travel by train during the previous week?* 1= ‘not’, 2 = ‘1 day’, 3= ‘2 or 3 days’ and 4 = ‘4 days or more’. In each wave, the question was formulated in exactly the same way. A retrospective question for train use was also included in the first wave, which measured the use of the train pre-COVID. This item is also included in the latent class trajectory model and serves as a reference to assess whether — for each class — train use is similar to pre-COVID levels or is still structurally lower (or higher) than before. To measure train use intention the following statement was used: *‘I expect to travel [answer] by train after COVID when compared to pre-COVID.’* with the following answer categories 1 = ‘a lot less’, 2 = ‘less’, 3 = ‘just as much’, 4 = ‘more’, 5 = ‘a lot more’. In November 2022, when all government restrictions were relaxed and the pandemic is over, this statement was reformulated as follows: ‘*In the coming months I expect to travel [answer] by train*’ with the same answer categories.

In addition to train use and stated intentions, the classes were additionally profiled on the socio-demographic and travel-related variables presented in Table 1. In addition, the clusters were profiled in terms of the frequency of WFH and the intention to WFH (after COVID). The question formulations and scales were exactly the same as for train use and the train use intention. In the last wave, the intention to WFH was not measured. In addition to WFH, the use of other modes was also included. In line with the conceptual model, we consider the use of the car, the use of BTM, and the use of the bicycle. These behavioural variables were measured in each wave and retrospectively (pre-COVID) in the first wave. Again, the question formulations and the used scales were the same as for train use. Finally, from wave 4 onwards respondents were asked to indicate the reasons for expecting to travel less or more when compared to pre-COVID (in waves 4–7) and compared to current levels (in wave 8). Respondents could select multiple reasons from a list. During

Table 2
Sample sizes of the waves.

Wave	Sample size	% of initial sample
1	45,937	
2	30,632	67
3	24,427	53
4	23,202	51
5	23,031	50
6	18,185	40
7	17,769	39
8	16,146	35

wave 8 there was a reduced train frequency due to a shortage of staff, and as a result of that more crowded trains. Reduced frequency and crowded trains were therefore added as reasons to travel less by train. We profiled the latent trajectories on the stated reasons in the second last and last wave (7 and 8).

3.4. The longitudinal latent class model

There are various methods to reveal trajectories based on repeated observations from the same individuals (i.e., panel data). A common method is the mixed-effects model, whereby the population-average trajectory is captured by fixed effects (e.g. a fixed intercept and slope), and variation across individuals around this average is captured by random effects (with a particular variance–covariance structure). A more recent popular generalisation of the mixed-effects model is the growth mixture model (Jung and Wickrama, 2008). This model assumes the existence of latent classes that have similar distributional shapes for the intercepts and slopes, allowing the researcher to uncover subgroups of people that have specific growth trajectories, i.e., with a particular mean intercept and slope.

The mixed-effects and growth mixture model represent flexible ways to model development in certain outcomes and the heterogeneity in trajectories. However, a main drawback of these models is that they force the data to fit certain parametric relationships between considered outcomes and time (i.e. they assume the existence of certain intercepts and slopes). Arguably, these models are less suited when dealing with outcomes that are not driven by growth or developmental processes. In addition, they are not well-equipped to handle ordinal/nominal outcomes. This is the case in the present context, where we try to reveal trajectories in train use and stated intentions to use the train (measured using ordinal scales, Section 3.4) during a turbulent time period, with varying levels of government restrictions and infection rates (hence with no clear development pathways). In this case, a more suitable and also more straightforward model is the longitudinal latent class model (Eggleston et al., 2004; Herle et al., 2020). In this model, it is assumed that the (repeated) outcomes are directly informed by an underlying latent class variable. At each point in time the relationship between this latent class variable and the outcome can be different. The trajectories thus revealed are entirely flexible and do not have to fit certain parametric relationships.

The classification in a latent class model is driven by similarities between the response patterns on the variables that are specified as indicators. Essentially, the indicators are assumed to be caused by the underlying latent class variable. Depending on the measurement scale of the indicators involved, different link functions can be specified between the latent class variable and the indicators. Subjects are classified into clusters using model-based posterior membership probabilities estimated by maximum likelihood (ML) estimation. Hence, clustering in latent class analysis is probabilistic, which means that each individual has a certain probability of belonging to each of the classes. Probabilistic classification has certain benefits over deterministic classification (like K-means), namely that the cluster centres become less biased (Magidson & Vermunt, 2002). Given that latent class analysis is a model-based technique, covariates to explain class membership can directly be added to the model (Magidson & Vermunt, 2002).

Fig. 1 presents the specification of our longitudinal latent class model. The model consists of two sets of indicators: train use and train use intentions. Train use is measured at each point in time (including the pre-COVID wave) using retrospective measurement, while the stated future intentions to use the train are measured only during the pandemic (i.e., eight waves). In addition to the indicators, various covariates are included in the model, namely socio-demographic characteristics (e.g., gender, age, level of education, occupation, and work sector), the main travel purpose and type of train ridership subscription, three variables related to WFH (i.e.,

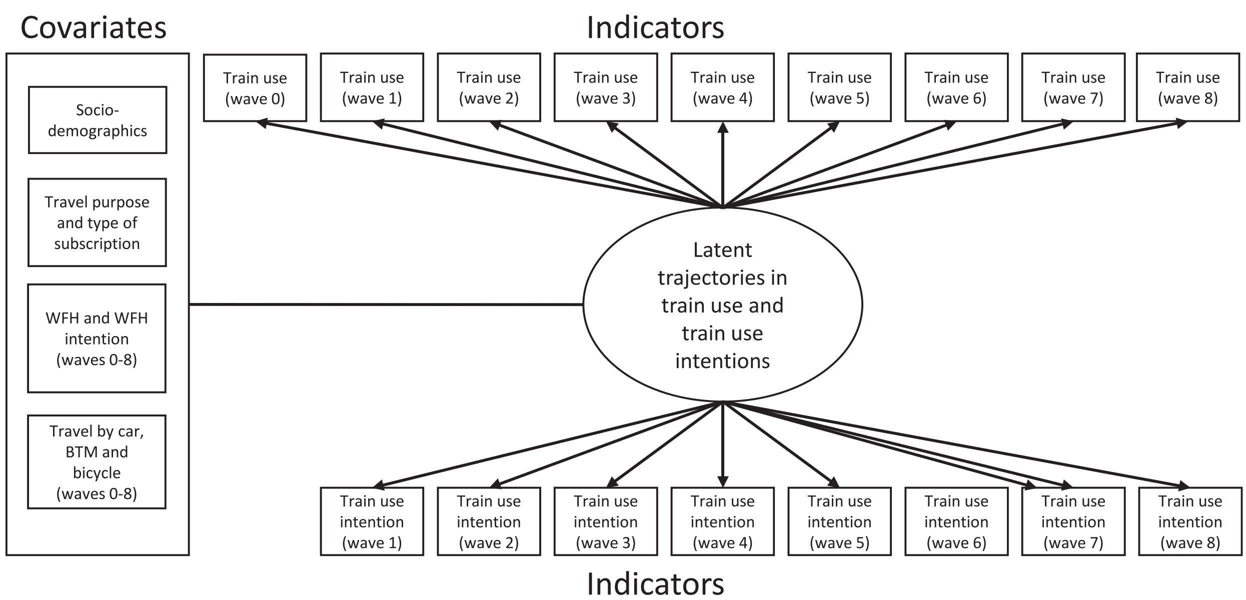

Fig. 1. The longitudinal latent class model.

frequency, future intentions to WFH and attitude towards WFH), three travel behaviour variables (i.e., car use, the use of bus, tram and metro (BTM) and bicycle use) and finally, various stated reasons for using the train less or more. By profiling the latent trajectories on these variables it can be assessed to what extent each segment is relying on substitutes for travelling by train (WFH and the use of other modes).

3.5. Model estimation and selection

In line with the conceptual model (Fig. 1), both train use and train use intentions – measured at eight time points – are included as indicators of the model. They are specified as ordinal variables, which means that the relationships between the latent class variable and the indicators are modelled using a series of ordered logit regressions. In addition, for train use the pre-COVID level (retrospectively measured in wave 1) was included. All (time-constant and time-varying) covariates described in the previous section were included as inactive covariates to ensure that the clustering was entirely driven by the considered indicators. To find the optimal number of latent classes, models were estimated with 1 through 10 classes. Table 3 shows the fit of the resulting models. The BIC value, which in the context of latent class modelling has been shown to perform well to determine the optimal number of classes (Nylund et al., 2007), keeps declining with increasing number of latent classes. This indicates that the optimal model (based on this criterion) is one with at least 10 classes.

Since such a solution would be difficult to interpret, we relied on a less formal approach to determine the optimal number, related to the relative size of the smallest class. In this regard, it has been suggested to only consider solutions where classes represent at least 5 % of the sample (Weller et al., 2020). The results indicate that solutions with 5–7 classes fall in the range of this threshold. The profiles of these solutions indicated that when moving from 5 to 6 classes, the additional class that is revealed is one that consistently intends to travel more by train than pre-COVID. Since this is a substantive interesting pattern in light of our research aim, we preferred the 6-class over the 5-class model. Moving from the 6 to the 7-class model did not reveal a qualitatively distinctive pattern while adding more complication in interpreting the results. Based on these considerations we decided to select and present the 6-class model.

4. Results

Table 4 presents the latent class trajectories with respect to the two indicator variables, train use behaviour, and train use intentions. Figs. 2 and 3 display these trajectories graphically. Table 5 shows the profiles of the 6 classes in terms of the socio-demographic variables and the two travel-related indicators. Overall, all trajectories are strongly affected by the initial lockdown and travel restrictions, yet each pattern shows a different 'recovery' pathway. In addition, three classes (1,2 and 6) expect to travel as much as before, two classes expect to travel less (3 and 4) and one expects to travel more than before (5). Note again that this question in the final wave (8) was formulated differently, namely whether the respondent expected to travel more in the coming months compared to current levels (in wave 8).

In the following, we interpret the classes based on these covariates/indicators, after which we also characterise the classes in terms of the trajectories associated with the time-varying covariates.

The first class (43 % of the sample) can be identified as **infrequent recreational travellers who expect to travel as much as before**. Before the pandemic, most travellers (80 %) in this cluster did not use the train at all. During the pandemic, almost the entire group stopped travelling by train, but then recovered to their previous level (or even higher) in the last wave (wave 8). Regarding future intention, this group also consistently expects to use the train as much as before. The main travel purpose of this group is recreation (36 %) followed by visiting friends/family (30 %). A substantial share has a discount card (39 %) (allowing users to travel with a discount in off-peak hours and/or during the weekend) and — compared to the other clusters — relatively often have a senior card (7 %). The average age of this group is highest across all clusters (59.5) and many people in this cluster are retired (51 %).

The second class (19 % of the sample) can be identified as **frequent work and recreational travellers who expect to travel as much as before**. Pre-COVID, most people in this cluster travelled around 2 to 3 days a week (32 %). During the pandemic, their train

Table 3
Model fit of latent class models.

No. of classes	Npar	LL	BIC(LL)	Size of the smallest class (%)
1	59	−424499	849,631	100
2	77	−402582	805,990	24
3	95	−384345	769,710	19
4	113	−380325	761,863	9
5	131	−377073	755,552	6
6	149	−374837	751,273	5
7	167	−373733	749,259	5
8	185	−372576	747,138	3
9	203	−371798	745,775	3
10	221	−371080	744,533	2

NPar Number of parameters.
LL Log-Likelihood.
BIC(LL) Bayesian Information Criterion (based on LL).

Table 4
Trajectories in train use and train use intention of the 6 classes.

	Class							Class					
	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	6 (%)		1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	6 (%)
Category	**Train use – pre-COVID**												
None	80	24	32	1	64	0							
1 day	14	21	23	4	21	1							
2 or 3 days	4	32	29	24	12	15							
4 or more days	1	23	17	72	3	83							
Category	**Train use – wave 1**						**Category**	**Intention to use the train – wave 1**					
None	99	84	99	89	96	36	Much less	1	1	16	8	0	1
1 day	1	10	1	8	3	16	Less	16	11	40	32	3	9
2 or 3 days	0	4	0	2	0	23	As much as before	72	72	43	57	55	70
4 or more days	0	1	0	1	0	25	More	10	14	1	3	27	16
							Much more	1	3	0	0	15	4
Train use – wave 2							**Intention to use the train – wave 2**						
None	95	52	97	65	87	4	Much less	0	0	20	11	0	0
1 day	5	28	2	24	11	12	Less	14	9	56	52	2	9
2 or 3 days	0	18	0	10	2	42	As much as before	76	75	24	36	50	75
4 or more days	0	3	0	1	0	42	More	9	15	0	1	32	15
							Much more	1	2	0	0	15	2
Train use – wave 3							**Intention to use the train – wave 3**						
None	85	28	94	42	71	1	Much less	0	0	24	13	0	0
1 day	13	33	6	33	22	5	Less	10	5	53	50	1	6
2 or 3 days	2	33	0	22	6	39	As much as before	74	68	22	36	38	70
4 or more days	0	6	0	3	0	55	More	15	24	0	1	45	22
							Much more	1	2	0	0	16	2
Train use – wave 4							**Intention to use the train – wave 4**						
None	93	44	98	66	85	1	Much less	0	0	21	12	0	0
1 day	7	32	2	25	13	7	Less	8	4	58	55	1	5
2 or 3 days	0	21	0	9	2	40	As much as before	76	70	21	33	35	72
4 or more days	0	3	0	1	0	51	More	14	22	0	0	40	20
							Much more	1	4	0	0	25	3
Train use – wave 5							**Intention to use the train – wave 5**						
None	94	45	98	66	86	2	Much less	0	0	25	15	0	0
1 day	6	32	2	25	12	9	Less	9	6	64	65	1	8
2 or 3 days	0	21	0	8	2	43	As much as before	72	69	12	20	32	72
4 or more days	0	3	0	1	0	46	More	18	22	0	0	45	19
							Much more	1	2	0	0	22	2
Train use – wave 6							**Intention to use the train – wave 6**						
None	77	25	87	34	60	1	Much less	0	0	29	16	0	0
1 day	19	34	12	35	29	8	Less	11	8	59	61	1	11
2 or 3 days	4	33	1	26	10	40	As much as before	73	71	12	23	35	73
4 or more days	0	8	0	5	1	50	More	16	19	0	0	52	16
							Much more	1	1	0	0	12	1
Train use – wave 7							**Intention to use the train – wave 7**						
None	75	24	80	20	58	0	Much less	0	0	31	14	0	0
1 day	20	33	17	32	30	5	Less	13	9	52	50	1	12
2 or 3 days	4	36	3	39	12	38	As much as before	71	69	17	35	39	71
4 or more days	0	7	0	9	1	57	More	14	21	0	1	49	16
							Much more	0	1	0	0	10	1
Train use – wave 8							**Intention to use the train – wave 8**						
None	74	23	66	13	60	1	Much less	6	5	16	5	1	6
1 day	20	30	24	25	27	5	Less	6	6	10	6	2	6
2 or 3 days	5	38	9	46	12	37	As much as before	68	68	64	68	58	68
4 or more days	0	9	1	16	1	57	More	19	21	11	21	35	19
							Much more	1	1	0	1	4	1

Note: the intensity of the green colour varies with the size of the share.

use frequency fluctuates along with the severity of the pandemic and related government restrictions. Consistent with this pattern, train use in the last wave (when almost all restrictions were lifted) is almost as high as pre-COVID. Similar to travellers in class 1, travellers in this cluster consistently expect to use the train as much as before. The main travel purpose of this group is work (43 %), yet substantial shares also use the train mainly for visiting friends/family (25 %) and recreation (16 %). Many have discount cards (32 %). People in this class are 52 years of age (on average) and most are paid employees (41 %), even though the share of retirees is also relatively high (30 %).

The third class (14 % of the sample) is labeled as **frequent work and recreational travellers who expect to travel less than before**. The pre-COVID train use of this group is more or less the same as in cluster 2 (most travelling 2–3 days per week), but in this cluster, train use dropped most strongly in the first wave (during the first lockdown in the Netherlands) and never recovered. Travellers

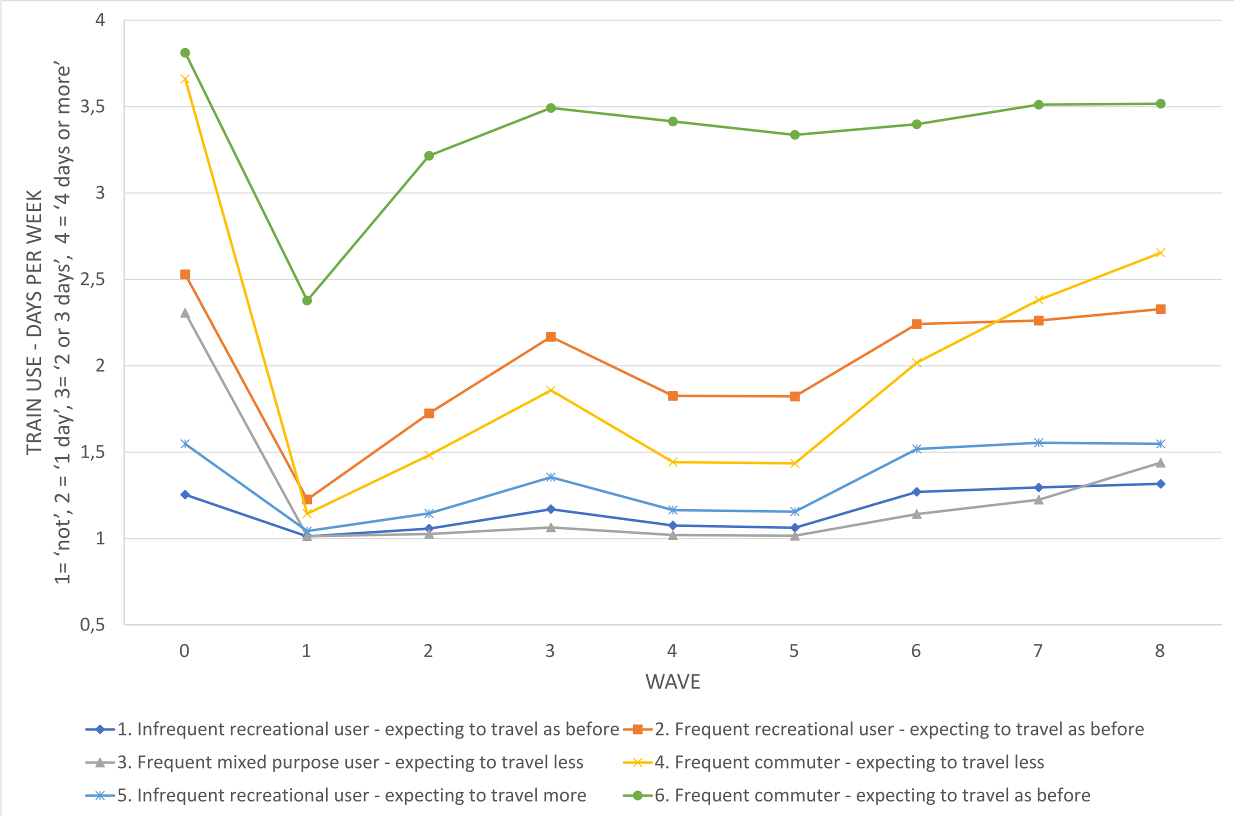

Fig. 2. Trajectories in train use.

in this class most strongly (across the 6 classes) and consistently (across the 8 waves) indicate that they expect to use the train less than before. Even in the last wave they still expect to travel less compared to current use (in wave 8). Similar to class 2, travellers in this cluster use the train mainly for work (56 %) but also for visiting friends/family (15 %) and recreation (16 %). Yet, the share of work is higher, which is also reflected in the higher share of paid workers (55 %). The average age (52.4) is again similar to class 2.

The fourth class (10 % of the sample) is identified as **frequent train commuters who expect to use the train less than before**. Before the pandemic, their train use was second highest across all classes, with a majority (72 %) travelling 4 or more days per week. During the pandemic, this class follows a similar trajectory as the second class (along with the government restrictions). In the final wave, their train use is still substantially lower than pre-COVID, most (46 %) now travel 2 to 3 days per week. Similar to class 3, this group also (consistently) expects to use the train less than before. In the last wave, the members of this class indicate to travel as much as they are currently doing, indicating that they expect that the current (lower) use of the train will persist over time. The main travel purpose is work (86 %) and most are paid employees (79 %). The travellers in this class are relatively young compared to the sample (average age = 44.6) and highly educated (47 % have a university degree). Many work in government, education and the service industry (e.g. IT). Finally, relatively many (12 %) have a business card to travel by train.

The fifth class (9 % of the sample) is identified as **infrequent recreational travellers**, **expecting to use the train more than before**. In terms of train use, travellers in this class follow a similar trajectory as those in class one, with a slightly higher frequency. Yet, unlike travellers in class 1, travellers in this class consistently expect to use the train more than before. In line with this expectation, train use in wave 8 is also slightly higher than the pre-COVID level. The profile of this class is overall similar to the first class. Most travel to visit friends/family (32 %) or for recreational purposes (35 %). The average age is 59.1 and a small majority is retired (52 %).

Finally, the sixth class (5 % of the sample) represents **train commuters who expect to travel as much as before**. Travellers following this trajectory experienced a dip in train travel in waves 1 and 2, but from wave 3 onwards the level of train use is consistently high, although not entirely at the level of the pre-COVID train use. The main travel purpose is work (83 %) and the majority is in paid employment (74 %). The level of education is, however, lower compared with the other group of workers (class 4) and people more often work in low-skilled jobs like production, transport, and health with very limited ability to telework.

Figs. 4 and 5 respectively show the trends in WFH and the future intention to WFH across 6 classes. All classes increased the level of WFH in wave 1 (during the first lockdown), but there are large differences in the uptake. Especially, classes 3 and 4 received a strong boost in WFH, which is consistent with the reduced train use in these classes. The members of these classes also predicted that they would increase WFH compared to pre-COVID (and increasingly so over the study period) and had the most favourable attitudes

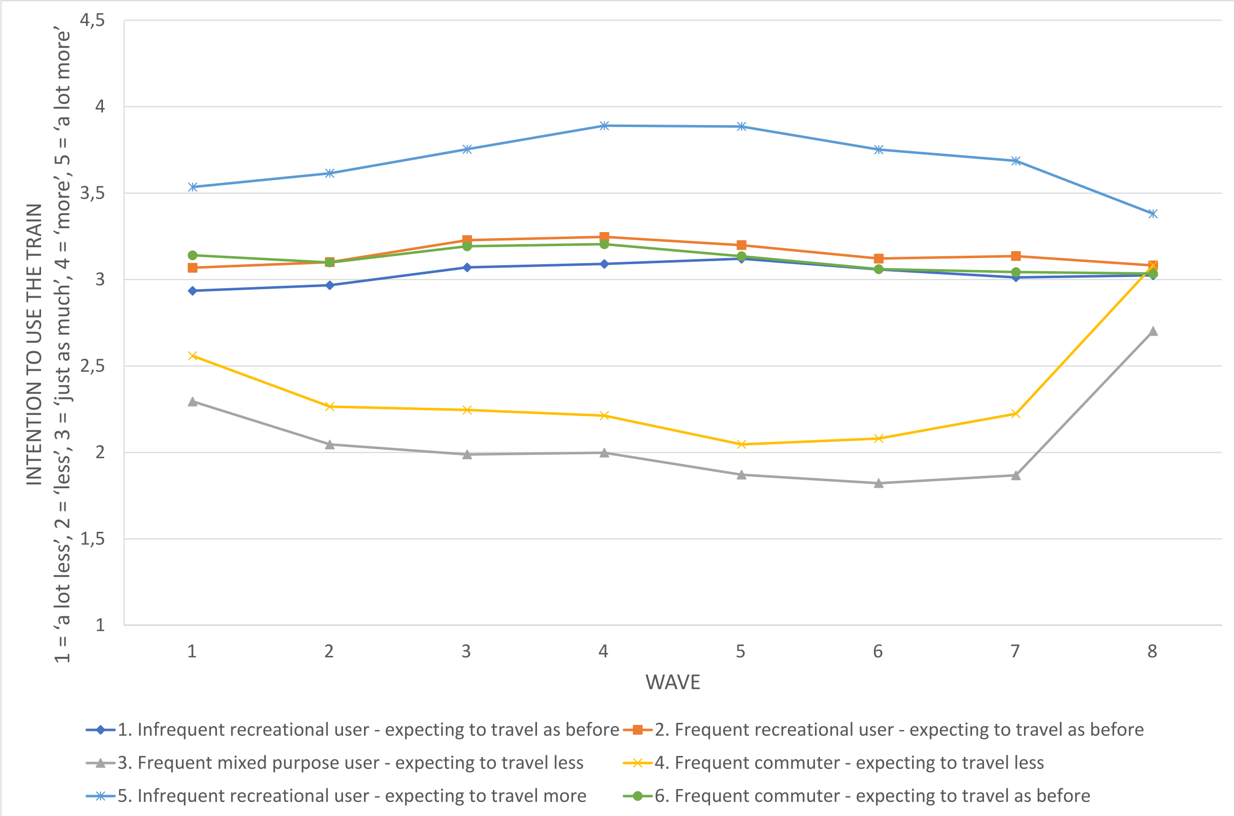

Fig. 3. Trajectories in train use intention.

towards WFH. Interestingly, class 6 initially also took up WFH in wave 1, but in wave 2 again strongly reduced WFH, which is consistent with their increased train use. Members of this class do not expect to increase WFH after COVID (mean around 3) and they have the least favourable attitude towards WFH, although the mean remains above the neutral point (3). The low uptake of WFH in this class is consistent with the large portions working in low-skilled jobs (health, transport, and production), for whom WFH is often not feasible.

Fig. 6 shows the class trajectories with respect to car, BTM and bicycle use. Regarding car use, an interesting pattern is visible in the first wave. Classes that have relatively high car use pre-COVID (classes 1, 3 and 5) generally reduce their car use, while classes that have relatively low car use pre-COVID (classes 2, 4 and 6) increase their car use. For classes 4 and 6, the frequent train commuters, it seems likely that the increase comes from people switching to the car for their commute. The reduction in car use in classes 1, 3 and 5 is likely simply due to the lockdown. Structural increases in car use seem to be present for classes 3 and 4, which is consistent with the structural decline in train use in these classes. The other four classes have all returned to pre-COVID levels of car use. Regarding BTM use, the patterns generally follow those of train use, which is plausible given that BTM use often functions as an access and egress mode for the train. Furthermore, the restrictions imposed by the government held for all PT modes. Finally, with respect to cycling, all classes show a strong reduction in the first wave, and at the end of the study period (wave 8) the cycling levels are structurally lower than pre-COVID (wave 0).

Table 6 presents the distributions of the stated reasons to travel more or less in the penultimate and last wave (waves 7 and 8). As discussed in section 3.4, the formulation of the stated intention to travel less or more was slightly different across these waves. In wave 7, respondents were asked to indicate whether they expected to travel less or more compared to pre-COVID levels, while in wave 8 respondents were asked to indicate whether they expected to travel less or more in the coming months. In wave 8 several additional reasons were also listed which respondents could indicate. Overall, the results are consistent with the earlier findings in this section. Train users in classes 3 and 4 expect to travel less. For class 4 the main reason is WFH, while for class 3 it is a combination of WFH and the use of other modes. Members of class 5 expect to travel more and mainly for recreational activities and visiting friends/family. In wave 8 most people (across all classes) expect to travel the same amount in the coming months. Among those who expect to travel less, the reduced frequency and the crowdedness are among the top reasons for travelling less.

5. Discussion

We found three classes of train users who stated to travel as much as before, namely class 1 (43 % population, infrequent train users

Table 5
Socio-demographic and travel profiles of the 6 classes.

		1	2	3	4	5	6
Class size		43	19	14	10	9	5
Gender	Male (%)	43	44	49	49	44	50
	Female (%)	53	51	46	45	52	44
	Other or missing (%)	4	4	4	5	4	5
Age	18–34 (%)	4	13	8	17	5	20
	35–44 (%)	4	8	9	14	4	13
	45–54 (%)	8	12	17	22	7	20
	55–64 (%)	19	23	28	33	16	32
	65–74 (%)	42	32	24	9	45	9
	75+ (%)	20	9	10	1	20	1
	Missing (%)	3	3	4	4	3	4
	Mean	59.6	52.0	52.4	44.6	59.1	43.3
Level of education	Intermediate secondary education (%)	12	7	7	3	13	7
	Higher secondary education (%)	10	10	9	8	10	10
	Intermediate vocational education (%)	14	11	10	7	14	18
	Higher vocational education (college) (%)	34	31	33	30	32	29
	University (%)	27	35	35	47	26	30
	Other or missing (%)	4	5	5	6	4	6
Occupation	Paid employment (%)	26	41	55	79	23	74
	Freelancer or self-employed (%)	4	7	5	4	4	3
	Attends school or is studying (%)	3	8	4	6	3	9
	Takes care of the housekeeping (%)	3	1	2	0	2	0
	Pensioner (%)	52	30	25	3	52	5
	Other (%)	9	9	6	2	11	3
	Other or missing (%)	4	4	5	5	4	5
Employment sector	Industry, production (%)	2	2	2	3	2	5
	Transport and logistics (%)	1	2	2	4	1	5
	Healthcare (%)	7	8	6	7	6	20
	Education (%)	5	8	6	11	5	11
	Government (%)	4	7	15	22	3	8
	ICT and information services (%)	2	4	7	9	2	3
	Other services (business, financial, personal) (%)	5	7	13	17	3	8
	Culture, sport and recreation (%)	1	3	2	3	1	3
	No paid employment, other or missing (%)	73	59	45	25	77	37
Main travel purpose	Work or school (%)	17	43	56	86	16	83
	Visiting friends/family (%)	30	25	15	4	32	5
	Recreation (%)	36	16	16	2	35	2
	Other or missing (%)	17	16	13	7	17	9
Train subscription	No subscription (%)	3	1	3	1	2	1
	Discount or free travel card (%)	39	44	32	34	40	40
	Business card (employer pays) (%)	2	5	12	16	2	8
	Student card (%)	1	3	1	2	1	3
	Action card (one-time offer) (%)	4	1	2	0	3	0
	Senior card (%)	7	1	4	0	6	0
	Other (%)	2	2	4	4	2	2
	Missing (%)	42	42	42	42	44	45

for recreation), class 2 (19 %, frequent train users for work and recreation), and class 6 (5 %, frequent train commuters). While these classes account for a large share of the population (68 %), the majority of them use the train infrequently (i.e., class 1). Their actual train use mostly aligns with the stated intention, where the train use level is almost the same as the pre-COVID level. For these classes, the commonly cited reasons for their current level of train use include changes in the frequency of social and recreational trips and positive attitudes toward sustainability (see Table 5). Mode shift was also cited as a reason for future reduction in train use.

Only one class of users stated that they will travel more often by train in the future, namely class 5, consisting of infrequent recreational train users who account for 9 % population. Their actual train use level is similar to that before the pandemic. Common reasons for their increase in train use intention include more trips, especially for social and recreational purposes, and sustainability.

Two classes of train users intended to travel less by train, namely class 3 (14 % population) and class 4 (10 %), which consist of frequent train commuters (who also travel for other purposes). Their behaviour indeed aligns with intention: their train use level in the last wave (8) is lower than the pre-COVID level although these two classes see a sharp increase in train use between waves 7 and 8. Members of these classes also have the highest levels of WFH and intention to WFH, and cited WFH as the main reason for using the train less often. Additionally, they reported driving more compared to pre-COVID. Importantly, although these two classes account for only 24 % of the population, their reduction in train travel would have a large impact on the PT system due to their high train frequency pre-COVID.

Overall, our results reveal that train ridership may suffer from the pandemic for various reasons, including WFH and shifting to driving. More importantly, the results suggest that PT operators (e.g., NS) may lose many frequent users and many trips due to the larger share of frequent riders intending to travel less by train in the future. Since intention overall has a strong effect on actual

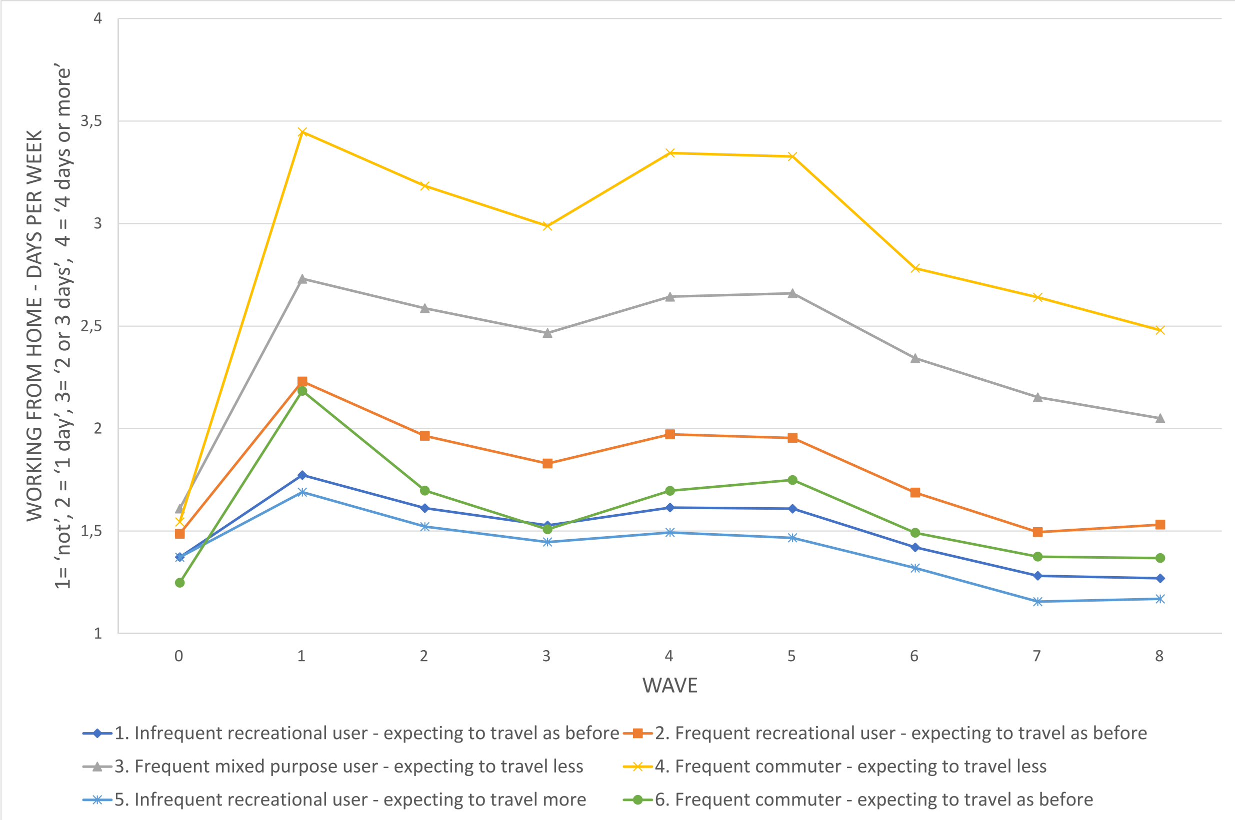

Fig. 4. Trajectories in working from home.

behaviour (e.g., Ajzen, 1991), we may expect lower train use from a large group of frequent users. Meanwhile, only a very small share of users (6 %), who are infrequent riders, intend to travel more, meaning that their travel may not offset the loss in ridership from frequent users.

The main strength of the present study is that the analysis is based on a large panel of train travellers who participated 8 times in a survey across a time span of over 1.5 years. Consequently, it can provide more nuanced behavioural insights compared to studies that focus on trends in aggregate demand over time (e.g. Currie et al., 2021) or studies that have only survey respondents at one or two time points (e.g. Beck et al., 2020). Our present analysis thus reveals the entire behavioural pathways of various latent groups, and to some extent, compares people's intended vs. actual train travel behaviour over time to help understand the train travel landscape beyond COVID. Here, we discuss some additional insights and novelty of the present study.

Firstly, we observe a structural change in train travel in some classes (e.g., classes 3 and 4) that may persist over time beyond COVID. From our results, it is interesting to see that the two classes with the highest pre-COVID train use, namely classes 4 and 6, show very different recovery pathways. Travellers in class 6 already returned to their old behaviour in wave 3 (September 2020) when the pandemic was still ongoing, whereas travellers in class 4 travelled much less by train, even in the last wave (November 2022) when all government restrictions were lifted. Their stated intention in the last wave is also to travel as much as they do presently (i.e. in the last wave). Hence, it seems likely that their behaviour has indeed structurally changed. This also aligns with the observation that in the Netherlands train use is still lower compared to the pre-COVID level; presently the average daily number of travellers is 1.1 million, compared to 1.3 million pre-COVID (NS half-yearly report, 2023). In addition, a recent survey among Dutch employers revealed that 'hybrid working', i.e. working two days a week from home, is still very popular (I&O Research, 2023).

Secondly and relatedly, by segmenting the populations by their behaviours and intentions over time, we find that the ridership decline is not driven by the fact that everyone travels a little bit less by train, but mainly because the two groups of frequent pre-COVID train users (classes 3 and 4, 24 % of the population) travel substantially less. This finding sets up apart from previous studies looking at the aggregate, population-wide demand rather than looking at distinctive population segments. In addition, the socio-demographic profiles of these groups can be assessed in detail. Specifically, government employees are strongly represented in the classes that have shifted to WFH (15 % and 22 % of classes 3 and 4 respectively work in government). A practical implication is that governments can also indirectly steer train travel demand by adjusting their commute / WFH policies, although this is a complicated matter given that flexible work hours and WFH may be essential to attract and retain employees.

Thirdly, whereas previous studies have also concluded that travellers shifted to WFH as well as private car use, the present analysis sheds more light on the specific degrees of substitution. Looking again at classes 3 and 4 who both have shifted to WFH and increased

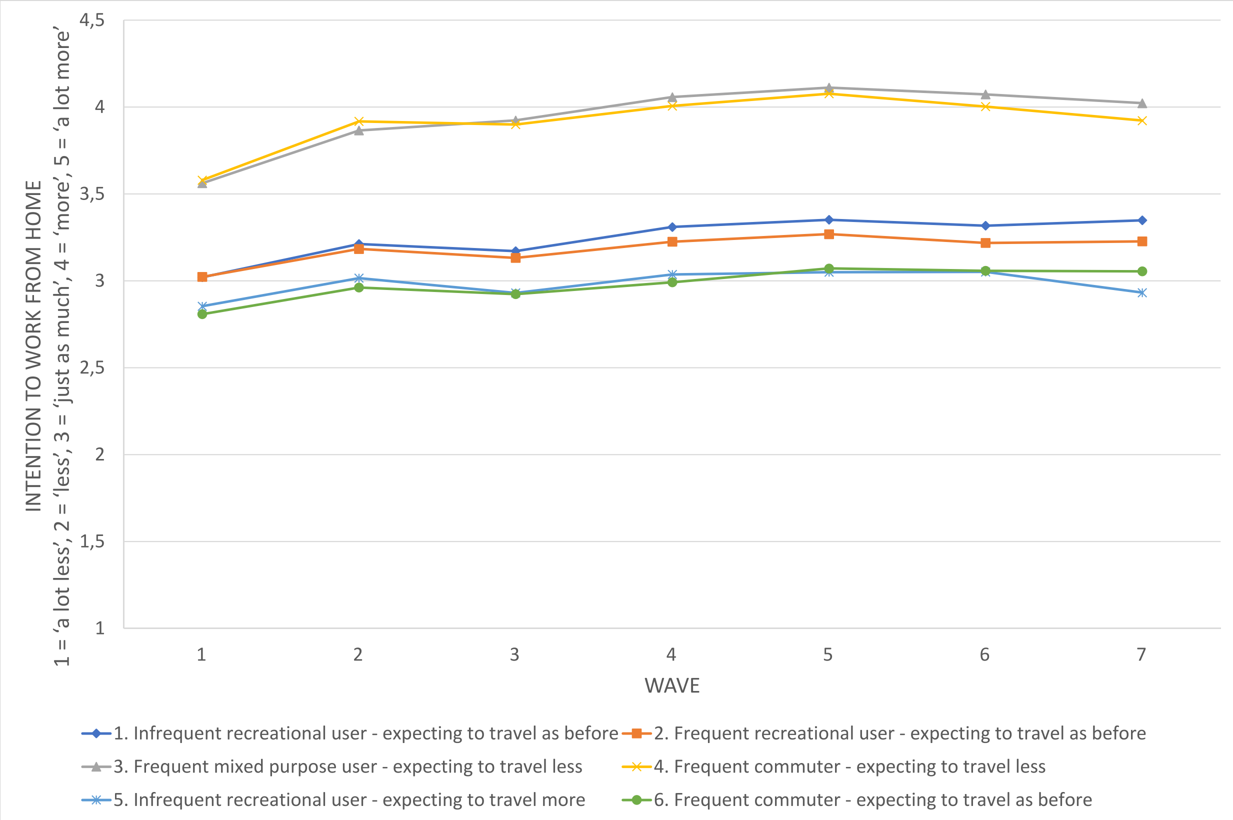

Fig. 5. Trajectories in intention to WFH.

their car use, it is interesting to note that the shift to WFH is much more pronounced than the shift to private car use. For example, pre-COVID, 59 % of the members of class 4 did not WFH (at all), whereas in the last wave (November 2022, when all restrictions were lifted), 49 % of this class worked from home 2 or 3 days per week. The increase in car travel is less strong, rising from 38 % using the car at least once a week pre-COVID to 55 % in the last wave. It may even be speculated that the car is not used to substitute travel by train, but that the increase in use is an indirect effect from WFH, i.e. because people may use the time gained from not commuting to make more recreational trips by car. It is also interesting to note that no class strongly shifted to driving. In addition, the two classes that have almost fully recovered (classes 2 and 6) also did not increase the use of the car. Hence, the loss in ridership in these groups is not due to an increase in the use of the car. Overall, it can be concluded that among train travellers in the Netherlands, the car is not generally considered a substitute. This is a somewhat surprising result given that the car is often the only viable alternative given the long distances typically travelled by train in the Netherlands (on average 50 km).

While this study was conducted in the Netherlands, it seems plausible that the results are to some extent generalisable to other European countries such as Belgium, Germany and Denmark, where the railway system provides commuter transport between cities as it is in the Netherlands. Of course, whether the results are indeed generalisable also depends on how WFH norms and policies have evolved in these respective countries. Yet, similar trends can be observed, for example, in Belgium where 34 % of the employees regularly worked from home in 2022 as compared to 18 % in 2019 (pre-COVID) (Statbel, 2023). Working 2–3 days per week from home has become a new norm in Belgium as in the Netherlands. As such, train operators should consider restructuring their services and pricing to cater to the needs of recreational travellers so that their farebox revenue is not solely dependent on commuters.

6. Conclusion and implications

In this study, we investigated the train use trajectories of train riders during the COVID-19 pandemic using eight waves of data collected by the Dutch Railways (NS) from April 2020 to November 2022. Based on travellers' current and predicted future train use, we classified train riders into six classes that exhibit different patterns of train use and future intention of riding the train. The results indicate that travellers belonging to these classes have structurally changed their behaviour. In addition, the shift to working from home is much more pronounced than the shift to private car use.

Based on the results, some implications can be formulated for transport practitioners in recovering from the COVID pandemic and future responses to similar shocks and disruptions. First, our findings imply that PT service providers may lose a significant number of riders whose frequent train trips to work are now replaced by WFH and, to a lesser extent, private vehicles. This trend leads to potential

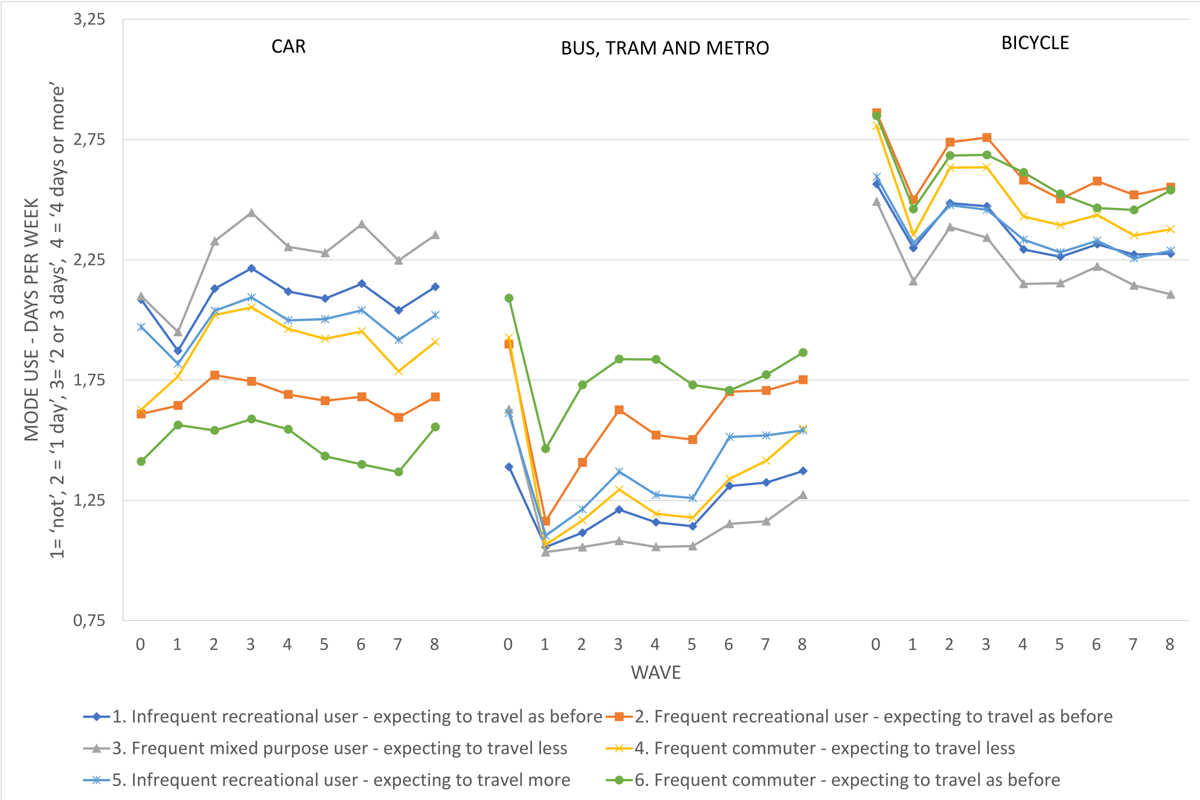

Fig. 6. Trajectories in car use (left), BTM use (middle), and bicycle use (right).

losses in farebox revenue and challenges in delivering the same level of service. While the shift to driving is obviously less sustainable, the environmental effects of the shift to WFH are less clear. In this regard, Anand (2023) shows that WFH may increase home-based energy use, which is often less efficient than office energy use. WFH also induces other types of non-work travel due to the former commute time that is now available to spend on discretionary activities (Faber et al., 2023; Huang et al., 2023).

To respond to PT ridership, transport practitioners may target groups of users, such as those who intend to ride the train less, and offer incentives such as off-peak hours discounts (suitable for teleworkers who want to ride the train for non-work purposes), offer on-board working-friendly environments to increase productivity during travel, and employer-subsidising PT passes. One suggestion, following up on the findings in this study, is to offer new forms of subscriptions in line with the new ways of working. For example, instead of offering a general discount card (to travel in off-peak hours), discount card mays be offered for the off-peak working days (in the Netherlands on Monday, Wednesday and Friday). Or subscriptions may be offered that allow free travel for 3 days a week (instead of all days). Indeed, the Dutch Railway operator is presently considering offering such discount subscriptions.

Specific offers could be made available for older adults who wants to increase train travel (i.e., class 5) for recreation and visitation purpose, such as train pass for unlimited rides on weekends. Overall, monetary incentives are useful to attract people of all classes who have reduced their train commute but may ride the train for other purposes.

Additionally, maintaining and/or improving service levels is perhaps even more important than monetary incentives (e.g. discounts). As shown in the last wave, the recovery of ridership has slowed down due to decreased service levels, which lead to overcrowding onboard and reduced train frequency, as reported by all classes, not only those that have strongly reduced train use (classes 3 and 4). These are mainly the result of a lack of personnel. In this regard, the Dutch Railways has hired a lot of new staff to operate the trains. In addition, there is even an experiment that invites Dutch Railways office personnel to be trained in operating trains. The results of the present analysis strongly support these efforts.

Finally, train travel, and in a broader context, travel behaviour, is dependent on various other non-transport factors, such as WFH policies, location choice, activity scheduling and opening hours of services (e.g., schools, daycares, shops) – which in turns depend on WFH policies. The world after COVID has changed in many of these aspects as WFH has become the new norm. As such, PT operators may need to rethink their approach to enhancing ridership by moving beyond commuting and increasing their attractiveness to other trip purposes and non-commuting travellers. Employers may also consider incentives to promote sustainable transport among workers such as train subscription, so that employees will not switch to driving when they come back to the office.

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.

Data availability

The authors do not have permission to share data.

References

Abdullah, M., Dias, C., Muley, D., Shahin, M., 2020. Exploring the impacts of COVID-19 on travel behavior and mode preferences. Transport. Res. Interdisciplinary Perspect. 8, 100255.
Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179–211.
Beck, M.J., Hensher, D.A., Wei, E., 2020. Slowly coming out of COVID-19 restrictions in Australia: Implications for working from home and commuting trips by car and public transport. J. Transp. Geogr. 88, 102846.
Beck, M.J., Hensher, D.A., Nelson, J.D., 2021. Public transport trends in Australia during the COVID-19 pandemic: An investigation of the influence of bio-security concerns on trip behaviour. J. Transp. Geogr. 96, 103167.
Bhaduri, E., Manoj, B.S., Wadud, Z., Goswami, A.K., Choudhury, C.F., 2020. Modelling the effects of COVID-19 on travel mode choice behaviour in India. Transport. Res. Interdisciplinary Perspect. 8, 100273.
Buehler, R., Pucher, J., 2021. COVID-19 impacts on cycling, 2019–2020. Transp. Rev. 41 (4), 393–400.
CBS statline, 2023. Onderweg in Nederland (ODiN) 2022. Available at: https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84711NED/table?ts=16075235920920.
Currie, G., Jain, T., Aston, L., 2021. Evidence of a post-COVID change in travel behaviour – Self-reported expectations of commuting in Melbourne. Transp. Res. A 153, 218–234.
De Abreu e Silva, J., Melo, P.C., 2018. Home telework, travel behavior, and land-use patterns. J. Transport Land Use 11 (1), 419-441.
De Haas, M., Faber, R., Hamersma, M., 2020. How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. Transportation Research Interdisicplinary Perspectives 6, 100150.
Downey, L., Fonzone, A., Fountas, G., Semple, T., 2022. The impact of COVID-19 on future public transport use in Scotland. Transp. Res. A 163, 338–352.
Eggleston, E.P., Laub, J.H., Sampson, R.J., 2004. Methodological sensitivities to latent class analysis of long-term criminal trajectories. J. Quant. Criminol. 20, 1–26.
Eisenmann, C., Nobis, C., Kolarova, V., Lenz, B., Winkler, C., 2021. Transport mode use during the COVID-19 lockdown period in Germany: The car became more important, public transport lost ground. Transp. Policy 103, 60–67.
Gkiotsalitis, K., Cats, O., 2021. Public transport planning adaption under the COVID-19 pandemic crisis: literature review of research needs and directions. Transp. Rev. 41 (3), 374–392.
Herle, M., Micali, N., Abdulkadir, M., Loos, R., Bryant-Waugh, R., Hübel, C., De Stavola, B.L., 2020. Identifying typical trajectories in longitudinal data: modelling strategies and interpretations. Eur. J. Epidemiol. 35 (3), 205–222.
Hook, H., De Vos, J., Van Acker, V., Witlox, F., 2022. 'On a road to nowhere…'. analyzing motivations for undirected travel. Transp. Res. A 163, 148–164.
Hu, S., Chen, P., 2021. Who left riding transit? Examining socioeconomic disparities in the impact of COVID-19 on ridership. Transp. Res. Part D: Transp. Environ. 90, 102654.
Huang, Z., Loo, B.P.Y., Axhausen, K.W., 2023. Travel behaviour changes under Work-from-home (WFH) arrangements during COVID-19. Travel Behav. Soc. 30, 202–211.
I&O Research, 2023. Werkgeversenquête 2023 Onderzoek onder werkgevers over stimuleren duurzaam reisgedrag werknemers. Amsterdam.
Javadinasr, M., Maggasy, T., Mohammadi, M., Mohammadain, K., Rahimi, E., Salon, D., Conway, M.W., Pendyala, R., Derrible, S., 2022. The Long-Term effects of COVID-19 on travel behavior in the United States: A panel study on work from home, mode choice, online shopping, and air travel. Transp. Res. F 90, 466–484.
Jung, T., Wickrama, K.A., 2008. An introduction to latent class growth analysis and growth mixture modeling. Soc. Pers. Psychol. Compass 2 (1), 302–317.
Kim, S., Lee, S., Ko, E., Jang, K., Yeo, J., 2021. Changes in car and bus usage amid the COVID-19 pandemic: Relationship with land use and land price. J. Transp. Geogr. 96, 103168.
Magidson, J., Vermunt, J., 2002. Latent class models for clustering: A comparison with K-means. Canadian J. Market. Res. 20 (1), 36–43.
Monahan, T., Lamb, C.G., 2022. Transit's downward spiral: Assessing the social-justice implications of ride-hailing platforms and COVID-19 for public transportation in the US. Cities 120, 103438.
Mouratidis, K., Papagiannakis, A., 2021. COVID-19, internet, and mobility: The rise of telework, telehealth, e-learning, and e-shopping. Sustainable Cities Soc. 74, 103182.
Nylund, K.L., Asparouhov, T., Muthén, B.O., 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. Struct. Equ. Model. Multidiscip. J. 14 (4), 535–569.
Palm, M., Allen, J., Zhang, Y., Tiznado-Aitken, I., Batomen, B., Farber, S., Widener, M., 2022. Facing the future of transit ridership: shifting attitudes towards public transit and auto ownership among transit riders during COVID-19. Transportation. https://doi.org/10.1007/s11116-022-10344-2.
Parady, G., Taniguchi, A., Takami, K., 2020. Travel behavior changes during the COVID-19 pandemic in Japan: Analyzing the effects of risk perception and social influence on going-out self-restriction. Transport. Res. Interdisciplinary Perspect. 7, 100181.
Parker, M.E., Li, M., Bouzaghrane, M.A., Obeid, H., Hayes, D., Frick, K.T., Chatman, D.G., 2021. Public transit use in the United States in the of COVID-19: Transit riders' travel behavior in the COVID-19 impact and recovery period. Transp. Policy 111, 53–62.
Statbel, 2023. Thuiswerk is een blijver. AVaiable at: https://statbel.fgov.be/nl/themas/werk-opleiding/arbeidsmarkt/thuiswerken (accessed September 2023).
Ton, D., Arendsen, K., De Bruyn, M., Severens, V., Van Hagen, M., Van Oort, N., Duives, D., 2022a. Teleworking during COVID-19 in the Netherlands: Understanding behaviour, attitudes, and future intentions of train travellers. Transport. Res. Part A 159-55-73.
Ton, D. De Bruyn, M., Van Hagen, M., Van Oort, N., & Duives, D., 2022b. Monitoring the impact of COVID-19 on the travel behavior of train travelers in the Netherlands. Proceedings of the 12th International Conference on Transport Survey Methods.
Vermunt, J.K., Magidson, J., 2013. Technical guide for Latent GOLD 5.0: Basic, advanced, and syntax. Statistical Innovations Inc., Belmont, MA.
Weller, B.E., Bowen, N.K., Faubert, S.J., 2020. Latent class analysis: a guide to best practice. J. Black Psychol. 46 (4), 287–311.