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The ramifications of emerging mobility modes on active travel

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ABSTRACT

The current study reports how the adoption of emerging travel modes might change the prevalence of active travel (i.e., walking and biking) in the future. Results from a national survey in Norway indicate that, overall, increased use of emerging modes such as electric vehicles (EVs), autonomous vehicles (AVs), mobility services, and e-scooters does not significantly relate to the share of active travel. Neither ridesharing nor the use of AVs or e-scooters show any significant association with either a decrease or increase in active travel. Nevertheless, the role of e-bikes (shared/private) is noteworthy, as they are statistically less likely to replace traditional active travel modes. However, e-bikes do not show a positive correlation with increased rates of walking and biking (shared/private). Individuals who anticipate maintaining the same level of EV and carsharing use in the future as they do presently are less likely to reduce their walking frequency. In summary, while the promotion of emerging mobility modes may not pose a substantial threat to active travel, they do not appear to present a significant opportunity for increasing active travel participation.

1. Introduction

Transitioning away from fossil-fuel cars is one of the goals of promoting emerging mobility options. However, the ramifications of emerging mobility modes on active travel present a critical area of inquiry in understanding the evolving landscape of "transport and health". As societies worldwide embrace novel technologies and transport paradigms, such as Electric Vehicles (EVs), Autonomous Vehicles (AVs), mobility services (e.g., carsharing, ridesharing), micro-mobility (e.g., e-scooter, e-bikes), and others, it becomes imperative to assess their associations with the share of active travel modes (De Vos et al., 2020), particularly walking and biking as the well-known source of mobility-related physical activities. Revealed daily travel behavior alongside future anticipated behavior could offer insights into potential shifts in individuals' mobility patterns and the consequent effects on physical activity levels.

Understanding the implications of adopting emerging mobility modes on active travel is crucial. This provides policymakers, urban planners, and public health officials with valuable information to inform decision-making processes regarding policy development. By anticipating potential shifts to many alternative (sustainable) emerging modes (e.g., ridesharing (Khattak et al., 2021); e-scooters (Wang et al., 2023); carsharing (Kent, 2014); e-bikes (Bourne et al., 2020), and AVs (Booth et al., 2019; Singleton et al., 2020; Pettigrew, 2022; Shatu and Kamruzzaman, 2022)), stakeholders could proactively design interventions to mitigate adverse effects on the share of walking and biking. While the adoption of EVs, AVs, carsharing, ridesharing, e-scooters, and e-bikes may offer energy efficiency, convenience, and safety benefits, it is essential to recognize the potential unintended consequences on physical activity levels via daily mobilities. Neglecting the impact of emerging mobility modes on active travel could exacerbate existing public health challenges related to sedentary lifestyles and insufficient physical activity.

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How might emerging modes change active travel share? Who might decrease their active travel? Who will maintain the same active travel rate and who will increase it? To address these research questions, a national travel survey was conducted in Norway in 2023. Revealed daily travel behavior (the frequency of mode use for 10 modes encompassing conventional and emerging alternatives) and anticipated daily travel behavior (the frequency of mode use for 11 modes) in the future (the year 2030) were asked from a population-based sample. This could give insights into changes in active travel mode shares considering the role of emerging modes. It can be hypothesized that with the accessibility and adoption of various emerging modes for different trip purposes, the rate of mobility (trip-making) might increase (Heineke et al., 2023). Furthermore, widespread and sustained adoption of alternative emerging modes may be anticipated to have a negative association with the frequency of use of active travel modes (e.g., Booth et al., 2019; Khattak et al., 2021). This study, therefore, presents findings on anticipated shifts in active travel mode use in the future compared to the present, while considering the role of various emerging mobility alternatives.

2. Method

A nationwide survey was conducted in December 2023, involving 1002 Norwegians aged 18 and over who self-administered an online questionnaire. In this survey, random selection was implemented from a survey panel facilitated by "infact",[1] ensuring an adequate representation of various geographical regions, age brackets, and genders in Norway. Throughout the country, all 11 counties were surveyed.

The survey was about mobility innovations and transport policies in Norway. The data used in this study are drawn from this extensive survey. The survey shows 49% of respondents were female. Age-wise, 10.9% were 18–22, 37.1% were 25–44, 34.6% were 45–64, and the rest were over 64. A comparison with official population stats from Norway revealed the sample closely matched the general population's demographics.

During the sampling process, ethical considerations such as confidentiality and anonymity were rigorously upheld. In the survey, "revealed travel behavior" (mode use) for the following modes, car, EV, ridesharing, carsharing, taxi, public transport (PT), bike, e-scooter, e-bike, and walking, was recorded on a 6-point scale from (1) almost never; (2) 1–5 days per year; (3) 6–11 days per year; (4) 1–3 days per month; (5) 1–3 days per week; to (6) 4 or more days per week. The "anticipated travel behavior in the future[2]" for the same modes plus AVs was also asked through the same answer scale. This scale has been validated in the Netherlands Mobility Panel surveys (Hoogendoorn-Lanser et al., 2015).

3. Analysis

Descriptive cross-tabulation is employed to profile socio-demographic characteristics of emerging mobility users, including both current and anticipated future users. The paired-sample *t*-test is a statistical method used to determine whether there is a significant difference between the means of two related groups (i.e., the difference between anticipated mode use in the future and current mode use). Mean differences were calculated, along with standard deviations to measure variability. Significance was determined by comparing the calculated t-value to the critical value from the t-distribution at a 5% significance level.

Next, two new nominal dependent variables, walking changes, and biking changes, were created using available data. These variables aim to capture variations in walking and biking rates, categorizing them into increases, no changes, or decreases. Both variables have three categories: increased, unchanged, and decreased.

Moreover, independent variables showing changes in the share of other modes (including conventional and emerging modes) were made. For each mode, three dummy variables were created to capture these behaviors. For example, for EV, the following dummy variables were made: increased EV use (1 = those who increase EV use, otherwise = 0), unchanged EV use (1 = unchanged, otherwise = 0), and decreased EV use (1 = those who decrease EV use, otherwise = 0). The same methodology was applied to other modes. For AV, a single dummy variable was formed, with 1 indicating individuals intending to use AVs 1–3 days per week or more, and 0 otherwise. The descriptive statistics for these variables are available in the supplementary material file.

Two multinomial logit (MNL) models were employed to test whether different changes among independent variables can explain changes in walking and biking rates. In addition, age, gender, income, and education level were also considered other covariates in the models. The basics regarding MNL model formulations and fits can be found in several books such as those reported in Train (2009).

4. Results

Socio-demographic profile of emerging mobility users, encompassing both current and anticipated future users, is outlined in Table 1. Examining Table 1, it becomes evident that across several emerging modes, men are more inclined to use them compared to women. However, comparatively, women express a greater likelihood of increasing their trips in the future across many modes when compared to their current use, in contrast to men. In terms of age, the overall trend indicates that younger individuals are more prone to using emerging modes compared to their older counterparts, both presently and in the foreseeable future. Moreover, highly educated individuals show a propensity to use emerging modes more frequently than those with lower levels of education. Similarly,

[1] (https://www.infact.no/).

[2] The following explanation was also provided for this question: "Imagine yourself six years ahead in time (year 2030) - given that you have access to the transportation means on the list, how often would you anticipate traveling with each mode in 2030?"

Table 1

Socio-demographic profile of emerging mobility users (current and anticipated future users).

Variable		Current and future mode use (on a scale from 1 to 6[a])										
		EV_current	EV_future	Ridesharing_current	Ridesharing_future	Carsharing_current	Carsharing_future	E-scooter_current	E-scooter_future	E-bike_current	E-bike_future	AV_future
Sex	Man	2.54	3.54	2.03	2.12	1.66	1.85	1.67	1.95	1.73	2.23	2.27
	Woman	2.17	3.28	1.97	2.19	1.46	1.74	1.36	1.73	1.49	2.01	2.10
Age	18–24	2.67	3.47	2.81	3.04	2.23	2.76	2.06	2.48	1.97	2.54	2.89
	25–34	2.40	3.64	2.31	2.49	1.98	2.11	1.91	2.23	1.84	2.46	2.72
	35–44	2.87	3.81	2.31	2.48	1.81	2.10	1.81	2.17	1.93	2.54	2.49
	45–54	2.38	3.49	1.71	1.88	1.31	1.53	1.27	1.70	1.33	1.82	2.15
	55–64	1.83	2.96	1.60	1.67	1.09	1.36	1.13	1.38	1.31	1.83	1.70
	65+	1.92	2.92	1.49	1.58	1.13	1.19	1.09	1.24	1.38	1.63	1.32
Education	College/university	2.56	3.58	2.05	2.20	1.66	1.88	1.63	1.90	1.69	2.23	2.35
	Otherwise	2.10	3.18	1.92	2.08	1.44	1.69	1.39	1.77	1.52	1.99	1.98
Income	Middle to high income[b]	3.07	4.20	2.14	2.30	1.60	1.87	1.69	2.03	1.80	2.36	2.48
	Otherwise	2.02	3.03	1.93	2.08	1.54	1.75	1.44	1.75	1.52	2.01	2.04

[a] (1) almost never; (2) 1–5 days per year; (3) 6–11 days per year; (4) 1–3 days per month; (5) 1–3 days per week; to (6) 4 or more days per week.

[b] Household earning more than 900,000 NOK/year.

individuals from higher income brackets tend to report a higher frequency of trips using emerging modes in comparison to those from lower-income households.

As reported in Table 2, the paired-sample *t*-test was assessed to see statistical changes between future mode use and current use per mode. The results show that participants anticipate changing their use of every single mode to the current situation except for taxis and walking. Except for cars, people will be more likely to increase their mode use.

To reveal how changes in other modes can relate to changes in walking and biking, two MNL models were tested. Table 3 shows the results of predictors of walking change. 19.3% of participants increase their walking, 14.9% decrease, and the remaining 65.9% maintain the same amount of walking. In the calibration process, unchanged walking behavior serves as the reference category. Thus, coefficients were estimated for two utility functions, one for a decrease in walking and the other for an increase in walking. Since the aim of this model was to test the relative roles of many explanatory variables on the dependent variable, all variables even insignificant ones were also retained in the model. The results indicate that higher use of PT, e-bikes, and bikes is negatively correlated with a decrease in walking rates. However, there is no statistically significant link between increased e-bike and bike use and higher walking rates. This might suggest that while e-bikes and bikes may not directly compete with walking, they also might not serve as clear complements. Contrastingly, the relationship between PT and walking shows a different picture. On one hand, there is a negative association between higher PT use and decreased walking rates. On the other hand, there is a positive association between higher PT use and increased walking rates. This might suggest that PT has a complementary relationship with walking rather than a competitive one.

Individuals planning to maintain their current levels of EV and carsharing use show a negative association with future decreases in walking rates. This finding may suggest that stability in the use of these specific modes could serve as a predictor for maintaining walking patterns over time. One plausible explanation could be rooted in the concept of habit formation and behavioral consistency. Individuals who show a commitment to maintaining their current levels of EV and carsharing use may inherently possess a preference for incorporating walking into their lifestyle. This commitment might reflect a broader preference for sustainable and health-conscious travel behaviors. Moreover, increased PT use and being female are positively associated with an increase in walking rates.

As described in Table 4, the same modeling approach was employed to see how changes in other modes can relate to changes in biking. 33.8% of participants increase their biking, 10.2% decrease, and the remaining 56.0% maintain the same amount of biking. It appears that people who maintain their level of e-bike use as they do at present are negatively associated with a decrease in biking. This suggests that while e-bike use may not directly compete with biking, it also may not strongly complement it, as there is no statistically significant relationship between e-bike use and increased biking rates. Those intending to maintain their current levels of car and taxi use show a negative association with an increase in biking. Conversely, higher use of PT is positively associated with an increase in biking. Also, older individuals are less likely to be associated with an increase in biking.

5. Conclusion

One may argue that the adoption of several emerging mobility alternatives might reduce the likelihood that we will engage in mobility-related physical activities on a daily basis, such as walking and biking. The current study examines how the adoption of emerging travel modes might change the prevalence of active travel (i.e., walking and biking) in the future.

Using a population-based sample, this study finds that, overall, increased use of emerging modes such as EVs, AVs, mobility services, and e-scooters does not significantly relate to the share of active travel. Neither ridesharing nor the use of AVs or e-scooters is associated with a decrease or increase in active travel. Nevertheless, e-bikes (shared or private) play an important role, as they statistically show less tendency to substitute traditional active travel modes. However, e-bikes do not exhibit a positive correlation with increased rates of walking and biking (shared/private). Those who anticipate maintaining their level of EV and carsharing use in the future as they currently do are less likely to reduce their walking frequency. Except for cars (and taxis), people anticipate increased use of every mode compared to now, but walking does not show a statistically significant increase. It can therefore be concluded that embracing and promoting various emerging alternative mobility options is unlikely to threaten active travel share. However, it does not guarantee an increase in active travel rates following the adoption of these options.

The overall increase in the use of various modes observed in this study may be linked to an anticipated surge in mobility in the future. As diverse travel alternatives expand over time, they can contribute, to some extent, to this rise in multimodal use. Emerging

Table 2
The paired-samples *t*-test (N = 1002).

Modes	Mean_now	*SD_now*	Mean_future	*SD_future*	*t*-test	p-values	Change
Car (as a driver or passenger)	3.78	*2.07*	3.09	*2.05*	−11.54	<0.001	–
EV (as a driver or passenger)	2.35	*1.99*	3.40	*2.14*	16.16	<0.001	+
Ridesharing	2.00	*1.40*	2.15	*1.54*	4.07	<0.001	+
Carsharing	1.56	*1.31*	1.79	*1.42*	6.08	<0.001	+
Taxi	1.95	*1.19*	1.99	*1.29*	1.25	0.104	+
Public transport	2.96	*1.46*	3.10	*1.51*	4.69	<0.001	+
Bike (private or shared)	2.34	*1.57*	2.83	*1.81*	11.61	<0.001	+
E-scooter (private or shared)	1.51	*1.07*	1.84	*1.33*	10.57	<0.001	+
E-bike (private or shared)	1.61	*1.17*	2.12	*1.43*	13.42	<0.001	+
Walk	4.61	*1.70*	4.65	*1.66*	1.03	0.150	+

Table 3
MNL results predicting changes in anticipated future walking.

Walk change[a]		B	Std. Error	Wald	Sig.	Exp(B)
Decrease in walking	Intercept	3.299	0.746	19.565	<0.001	
	Increased_Car	0.514	0.305	2.826	0.093	1.671
	Unchanged_Car	−0.277	0.241	1.317	0.251	0.758
	Decreased_Car	0[b]	.	.	.	.
	Increased _EV	−0.327	0.323	1.027	0.311	0.721
	Unchanged_EV	−0.727	0.328	4.916	**0.027**	0.483
	Increased_ridesharing	−0.289	0.321	0.814	0.367	0.749
	Unchanged_ridesharing	−0.288	0.285	1.019	0.313	0.750
	Increased_carsharing	−0.428	0.372	1.327	0.249	0.652
	Unchanged_carsharing	−0.676	0.343	3.889	**0.049**	0.509
	Increased_taxi	0.705	0.328	4.619	**0.032**	2.023
	Unchanged_taxi	0.003	0.295	0.000	0.991	1.003
	Increased_PT	−0.743	0.260	8.150	**0.004**	0.476
	Unchanged_PT	−0.753	0.251	9.013	**0.003**	0.471
	Increased_e-scooter	−0.058	0.348	0.028	0.867	0.943
	Unchanged_e-scooter	−0.464	0.346	1.805	0.179	0.629
	Increased_e-bike	−0.950	0.332	8.198	**0.004**	0.387
	Unchanged_e-bike	−0.777	0.329	5.576	**0.018**	0.460
	Increased_bike	−0.660	0.313	4.458	**0.035**	0.517
	Unchanged_bike	−0.487	0.300	2.641	0.104	0.614
	High_AV	−0.473	0.276	2.943	0.086	0.623
	Age	−0.004	0.007	0.422	0.516	0.996
	Sex (Man = 1, Women = 2)	−0.434	0.203	4.563	**0.033**	0.648
	Education	−0.146	0.117	1.548	0.213	0.864
	Income	−0.042	0.037	1.300	0.254	0.959
Increase in walking	Intercept	−0.850	0.736	1.333	0.248	
	Increased_Car	0.226	0.284	0.631	0.427	1.253
	Unchanged_Car	−0.139	0.205	0.463	0.496	0.870
	Increased_EV	0.015	0.326	0.002	0.964	1.015
	Unchanged_EV	−0.186	0.323	0.330	0.566	0.830
	Increased_ridesharing	−0.212	0.290	0.533	0.466	0.809
	Unchanged_ridesharing	−0.168	0.255	0.433	0.510	0.846
	Increased_carsharing	0.144	0.378	0.146	0.702	1.155
	Unchanged_carsharing	−0.112	0.355	0.100	0.752	0.894
	Increased_taxi	0.266	0.294	0.815	0.367	1.304
	Unchanged_taxi	−0.001	0.247	0.000	0.997	0.999
	Increased_PT	0.521	0.248	4.411	**0.036**	1.683
	Unchanged_PT	−0.103	0.255	0.162	0.687	0.902
	Increased_e-scooter	0.031	0.335	0.009	0.926	1.031
	Unchanged_e-scooter	−0.302	0.325	0.863	0.353	0.739
	Increased_e-bike	−0.127	0.351	0.132	0.717	0.881
	Unchanged_e-bike	−0.276	0.352	0.613	0.433	0.759
	Increased_bike	0.116	0.324	0.128	0.720	1.123
	Unchanged_bike	0.007	0.321	0.000	0.983	1.007
	High_AV	−0.418	0.231	3.283	0.070	0.658
	Age	−0.010	0.006	2.669	0.102	0.991
	Sex (Man = 1, Women = 2)	0.418	0.168	6.161	**0.013**	1.519
	Education	−0.009	0.096	0.010	0.921	0.991
	Income	0.000	0.010	0.000	0.986	1.000
	Model Fitting Information					
	Model	Model Fitting Criteria		Likelihood Ratio Tests		
		−2 Log Likelihood		Chi-Square	df	Sig.
	Intercept Only	1752.042				
	Final	1575.134		176.908	46	<0.001
	McFadden Pseudo R-Square = 0.101					

[a] The reference category is: unchanged (same rate).
[b] This parameter is set to zero because it is redundant. The same is true for other modes as well. Consequently, for other modes, this category (Decreased) is removed to keep the table as short as possible.

modes, by providing improved accessibility, first/last-mile connectivity, flexibility, and support for multimodal travel, empower individuals to make informed choices and navigate journeys more efficiently, thus enhancing overall mobility (Heineke et al., 2023). A 2022 consumer preferences survey by The McKinsey Center for Future Mobility, revealed a significant willingness among respondents to change their travel habits and explore new trips (Heineke et al., 2023). Additionally, this increase in mode use may also be influenced by demographic shifts, technological advancements, and changes in lifestyle/work preferences.

Comparing the methodology (e.g., data, measurement techniques) of this study with past research reveals a notable trend. Previous empirical studies, such as those by Millard-Ball (2018), Booth et al. (2019), Gehrke et al. (2019), Khattak et al. (2021), and Pettigrew

Table 4
MNL results predicting changes in anticipated future biking.

Bike change[a]		B	Std. Error	Wald	Sig.	Exp(B)
Decrease in biking	Intercept	1.007	0.800	1.582	0.208	
	Increased_Car	−0.059	0.386	0.023	0.879	0.943
	Unchanged_Car	−0.085	0.277	0.094	0.759	0.918
	Decreased_Car	0[b]	.	.	.	.
	Increased_EV	0.264	0.388	0.462	0.497	1.302
	Unchanged_EV	0.006	0.391	0.000	0.988	1.006
	Increased_ridesharing	0.102	0.372	0.076	0.783	1.108
	Unchanged_ridesharing	−0.101	0.335	0.091	0.762	0.904
	Increased_carsharing	0.466	0.423	1.212	0.271	1.594
	Unchanged_carsharing	−0.705	0.408	2.983	0.084	0.494
	Increased_taxi	0.288	0.386	0.556	0.456	1.334
	Unchanged_taxi	−0.315	0.345	0.832	0.362	0.730
	Increased_PT	−0.310	0.311	0.997	0.318	0.733
	Unchanged_PT	−0.462	0.297	2.421	0.120	0.630
	Increased_e-scooter	−0.383	0.404	0.895	0.344	0.682
	Unchanged_e-scooter	−0.629	0.396	2.526	0.112	0.533
	Increased_e-bike	−0.594	0.370	2.582	0.108	0.552
	Unchanged_e-bike	−1.139	0.369	9.523	**0.002**	0.320
	Increased_walk	−0.519	0.376	1.906	0.167	0.595
	Unchanged_walk	−0.533	0.302	3.119	0.077	0.587
	High_AV	−0.411	0.325	1.596	0.206	0.663
	Age	0.000	0.008	0.001	0.981	1.000
	Sex (Man = 1, Women = 2)	−0.175	0.236	0.548	0.459	0.840
	Education	0.060	0.131	0.214	0.644	1.062
	Income	0.005	0.012	0.151	0.698	1.005
Increase in biking	Intercept	−0.149	0.624	0.057	0.811	
	Increased_Car	0.309	0.261	1.400	0.237	1.362
	Unchanged_Car	−0.449	0.183	6.034	**0.014**	0.638
	Increased_EV	0.475	0.292	2.643	0.104	1.608
	Unchanged_EV	0.062	0.291	0.046	0.831	1.064
	Increased_ridesharing	0.364	0.265	1.883	0.170	1.440
	Unchanged_ridesharing	−0.024	0.234	0.010	0.918	0.976
	Increased_carsharing	0.160	0.346	0.214	0.644	1.174
	Unchanged_carsharing	−0.055	0.317	0.030	0.863	0.947
	Increased_taxi	−0.381	0.272	1.966	0.161	0.683
	Unchanged_taxi	−0.657	0.221	8.800	**0.003**	0.518
	Increased_PT	0.657	0.222	8.773	**0.003**	1.929
	Unchanged_PT	−0.025	0.222	0.012	0.911	0.976
	Increased_e-scooter	0.201	0.305	0.434	0.510	1.222
	Unchanged_e-scooter	−0.331	0.295	1.259	0.262	0.718
	Increased_e-bike	0.409	0.316	1.673	0.196	1.505
	Unchanged_e-bike	−0.324	0.315	1.062	0.303	0.723
	Increased_walk	0.218	0.279	0.607	0.436	1.243
	Unchanged_walk	0.110	0.244	0.204	0.652	1.116
	High_AV	0.142	0.202	0.497	0.481	1.153
	Age	−0.012	0.005	5.470	**0.019**	0.988
	Sex (Man = 1, Women = 2)	0.277	0.155	3.211	0.073	1.319
	Education	0.031	0.088	0.121	0.728	1.031
	Income	−0.008	0.011	0.537	0.464	0.992
	Model Fitting Information					
	Model	Model Fitting Criteria		Likelihood Ratio Tests		
		−2 Log Likelihood		Chi-Square	df	Sig.
	Intercept Only	1850.290				
	Final	1570.900		279.390	46	<0.001
	McFadden Pseudo R-Square = 0.151					

[a] The reference category is: unchanged (same rate).
[b] This parameter is set to zero because it is redundant. The same is true for other modes as well. Consequently, for other modes, this decrease category (Decreased) is removed to keep the table as short as possible.

(2022), have predominantly focused on a limited set of travel modes. They aimed to explore how a select few emerging modes might substitute for walking or biking. In contrast, the present study diverges from this trend by adopting a broader perspective. It evaluates mobility rates across a diverse spectrum of both emerging and traditional modes. This approach provides a more nuanced understanding of modal patterns and substitution dynamics, taking into account the potential role of various other travel modes.

Recognizing the methodological differences between this study and prior research, my findings indicate that several emerging travel modes do not necessarily compete with active travel. However, they may not always serve as clear complements either. On the other hand, previous studies on AVs revealed both substitution and complementary dynamics. For example, an Australian study found that a significant portion of respondents were willing to replace walking (18%) and cycling (32%) with AV use (Booth et al., 2019). Additionally, a qualitative inquiry presented two scenarios for the AV era: one envisions a shift towards walking, public transit, and on-demand transport, while the other predicts increased private AV ownership leading to traffic congestion and discouraging walking (Pettigrew, 2022). Another study suggests that AVs have the potential to disrupt active travel while offering opportunities for its uptake (Shatu and Kamruzzaman, 2022). Insights from game theory indicate increased pedestrian freedom in urban areas with prevalent AVs, potentially fostering pedestrian-oriented neighborhoods (Millard-Ball, 2018). Other studies have also explored the impact of ride-sharing services and e-scooters, emphasizing primarily substitutionary effects. Wang et al. (2023) conducted a comprehensive review revealing that shared e-scooter users often substitute walking. Conversely, bicycling is rarely reported as a substitution mode among shared e-scooter users (Wang et al., 2023). Khattak et al. (2021) utilized data from the 2017 U.S. National Household Travel Survey and showed that ridesharing and taxi modes can compete with walking. Additionally, an intercept survey in the Greater Boston region showed that inclement weather significantly influenced the substitution of active travel modes with ride-sharing services (Gehrke et al., 2019).

Recognizing the diverse competing and complementary effects of different emerging mobility modes across different studies, countries and methodological approaches highlights the need for systematic future research in this area. I suggest a need for additional empirical studies employing advanced methodological approaches to investigate how various emerging modes may impact future rates of active travel. Regarding data and measurement, future research should broaden its scope beyond a single or few emerging options. Instead, it should encompass all potential mobility alternatives, including both emerging and traditional modes along with their trip-making rates. This approach would provide a more comprehensive understanding of how different modes interact within travel patterns across various trip purposes.

All in all, based on this study, one key policy avenue is the promotion of e-bikes, which do not substitute for traditional active travel modes. By incentivizing the use of e-bikes, policymakers can encourage individuals to adopt active travel habits. Furthermore, in line with another finding that shows the positive role of public transport, efforts should be made to integrate e-bikes/bikes with public transport systems (Musselwhite, 2022), facilitating seamless first and last-mile connectivity for commuters. However, additional research is needed to determine how other emerging modes can be effectively adopted to promote physical activity related to mobility.

I acknowledge that this work is based on a cross-sectional survey design, where participants self-reported both their "revealed travel behavior" and their "stated (anticipated) future travel behavior". Panel (longitudinal) studies could potentially provide a better understanding of the ("causal") "effects" over time, a dimension this study cannot address. Nevertheless, despite its cross-sectional nature, this study still offers valuable insights into the potential "associations" between different travel modes.

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CRediT authorship contribution statement

Milad Mehdizadeh: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, 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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jth.2024.101839.

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