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Evaluation of an incentive program to stimulate the shift from car commuting to e-cycling in the Netherlands☆

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ABSTRACT

This paper reports on the effects of an e-cycling incentive program in the province of North-Brabant, The Netherlands, in which commuters could earn monetary incentives when using their e-bike. The study used a longitudinal design allowing to observe behaviour change and mode shifts. The program appeared to be highly effective in stimulating e-bike use, as one month after the start of the program, the share of commute trips made by e-bike increased from 0% to 68%, with an increase up to 73% after half a year of participating. The environmental, congestion and health benefits of this shift are however mixed. Half of the e-bike trips substitute car trips, with positive effects on environment, congestion and health. The other half substitutes conventional cycling trips, implying fever health benefits. Our analyses further suggest that distance is an important factor for adopting e-cycling, where e-bike has a larger acceptable distance than a conventional bike. Nevertheless, we observed that the likelihood to use the e-bike decreased as commuting distance increased. Multivariate analyses suggest that a shift to e-cycling is affected by age, gender, physical condition, car ownership and household composition. Our study did find support for the hypothesis that having a strong car-commuting habit decreases the probability of mode shift to a new mode alternative. In contrast, multimodality may increase the likelihood of e-bike use as a result of openness to other travel options and a more deliberate mode choice. Lastly, dissatisfaction with the current travel mode positively influences mode shift towards the e-bike. Our results imply that stimulating e-cycling may be a promising way of stimulating physical activity, but that it will be most effective if targeted at specific groups who are not currently engaging in active travel.

1. Introduction

In recent years, there has been growing interest in the role of the bicycle in Western urban transport systems as an alternative to cars (Fishman and Cherry, 2015; Pucher and Buehler, 2012). Cycling has positive impacts on not only the environment, but also health through increased physical activity (Akar and Clifton, 2009; Badland and Schofield, 2008; Sugiyama et al., 2008). In areas with a high dependence on cars (e.g., the US), utilitarian cycling is often considered a fringe activity (Pucher et al., 1999; Moudon et al., 2005). Across European cities, however, non-motorized trips account for 10 to 48% of the total number of trips travelled (Rietveld and Daniel, 2004). In the Netherlands, cycling is a very popular mode of travel, accounting for 26% of all national trips (KiM, 2015). Of all trips shorter that 7.5km, which is 70% of all trips, 35% are made by bicycle. Despite this high share of cycling trips, there is still considerable potential for an increase in cycling.

Extensive research has identified determinants of cycling to work (e.g., Heinen et al., 2010, 2012; Vandenbulcke, 2011;

☆ Transition to E-Cycling in daily commuting.

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Gatersleben and Appleton, 2007). These studies indicate that apart from cultural and societal factors, important factors that influence cycling behavior include personal and household characteristics, topography, distance, and time limitations. Various studies have shown that people who live close to their workplaces (< 5 km) are significantly more likely to use bicycles to commute than those with longer commutes (Kingham et al., 2001; Dickinson et al., 2003; Krizek 2010). The unattractiveness of utilitarian cycling for longer distances is related to physical effort (sweating) and the limited speed and range.

Bicycle-style e-bikes (i.e., bicycles assisted by electric motors) could potentially mitigate these factors given the lower physical effort required, higher speed, and greater range compared to regular bicycles (MacArthur, 2014, Dill and Rose 2014). Thus, e-bikes offer new modal shift opportunities in daily commuting. A shift from car commuting to using e-bikes has positive effects in terms of both sustainability and health. E-bikes are 18 times more energy efficient than car travel (Shreya, 2010). Physical activity levels during e-bike use are lower than in conventional cycling but markedly higher than in car use (Sundfør, 2017; Simons et al., 2009).

E-bikes have attracted a considerable amount of research attention (Fishman and Cherry, 2015; Rose, 2012; Dill and Rose 2014; MacArthur et al., 2014; Popovich et al., 2014; Jones et al., 2016). To date, only a few studies have investigated the factors influencing e-bike use. Various studies show that demographic characteristics like age, education, and income influence e-bike use (Popovich et al., 2014; MacArthur et al., 2014). Compared to traditional bike users, e-bike users are older, have a higher income, and have a higher educational level. Given the higher speed and lower effort associated with e-bike use compared to conventional cycling, e-bike trips are longer and tend to be made for a greater variety of purposes (Langford et al., 2013).

Replacing car travel with e-bike use is a key motivation for e-bike purchase in North America and Australia (Johnson and Rose, 2013; MacArthur et al., 2014; Popovich et al., 2014). The studies suggest that e-bike ownership indeed reduces the number of car trips. In the context of the first e-bike sharing program in North America, Langford et al. (2013) found that 11% of all e-bike trips would have previously been made using cars. A survey conducted among Northern-American e-bike users shows an increase of cycling at least once per week from 55% among those owning a conventional bike to 93% among those owning an e-bike (MacArthur et al., 2014). In addition, 45% use the e-bike for commuting as the primary reason. Reported reasons for e-cycling include greater range, easier acceleration, higher speed, and easier ascent of hills. Norwegian research shows that the percentage of cycling trips increased from 28% to 48% when people were provided with an e-bike (Fyhri and Fearnley, 2015).

Although the studies provide insights into the adoption rate of e-cycling and its impact on the reduction in trips by other travel modes, there is limited information on the factors that influence the use of e-bikes and their substitution for other travel modes. Only recently, a rather methodological study has been done on the substitution of travel modes related to e-bike ownership using data from a general mobility study (Kroesen, 2017). This is partly due to the fact that interventions in which travelers were encouraged to switch to or use e-bikes typically result in small samples or limited periods of time (Plazier et al., 2017) that do not allow extensive testing of influential variables using multivariate techniques. One recent study used qualitative methods that do allow the disentanglement of the effects of influential factors on e-bike use, but they do not allow for generalization of the results (Jones et al., 2016).

This study contributes insights into the actual behavioral responses to introducing e-bikes based on a unique large-scale (n = 547) and longitudinal dataset. The adoption of e-cycling in daily commuting was recorded in a reward-based e-cycling incentive program involving car commuters in the Netherlands. The data allow for exploring the actual effects of a wide array of factors that influence the extent of modal shift toward e-bikes. According to the literature on cycling and e-bike use, these variables include personal and household characteristics, work-related circumstances, and spatial characteristics (Fishman and Cherry, 2015, Heinen et al., 2010, 2012, Plazier et al. 2017).

However, given the longitudinal nature of our data, we add two factors that represent path dependency to our analysis. First, we assume that one's travel behavior prior to the incentive program influences the extent of using e-bikes in the program. Past behavior or habits have frequently been demonstrated to predict future behavior better than measures of intention and attitude (e.g., Bentler and Speckart, 1979; Ouellette and Wood, 1996). Verplanken et al., (1997, 1998) found that participants with a strong habit towards a particular travel mode acquire less information and use less elaborate choice strategies compared to participants with a weak habit. Likewise, it can be expected that those with a weaker habit who already combined commuting by car occasionally with other modes would be more open to using alternative travel modes and willing to try new travel options.

A study on mobility behavior among free-floating car-sharers compared to non-car sharers confirms this (Kopp et al., 2015). People with multimodal travel behavior (i.e., not always choosing the same mode for each trips) in the baseline situation were more willing to consider and use new transport options such as car sharing. Likewise, we expect that participants with multimodal commuting behavior prior to the program world be more willing to adopt e-cycling and use it more frequently. A related consideration is that e-cycling bears resemblance to conventional cycling in terms of propelling and maneuvering the vehicle as well as exposure to and experiencing the weather, landscape, and traffic conditions. Thus, those who occasionally cycle to work prior to the program may be expected to use e-bikes more frequently in the program.

Second, we predicted that participants' evaluations of their commute prior to the program would impact the extent of shifting toward e-bike use. In particular, if the car commute is experienced as less pleasant, it is predicted to lead to a higher frequency of using a new alternative mode. Various scholars outside the transportation area suggest that affect may drive behavioral change. Russell (2003) describes how individuals' affective states and a core driver of action in the sense that they seek to move away from negative affective states (avoidance) and seek positive affective states (approach). In a similar way, negative affective states associated with a certain current travel mode may trigger individuals to explore and use alternative methods of travel, leading to better affective outcomes. Another indication of the relevance of affect related to current behavior is obtained from the Extended Model of Goal-directed Behavior (EMGB) (Perugini and Conner 2000). EMGB extends existing attitudinal behavioral models by adding the element of volition originating from individuals' specific goals.

Along with cognitive factors such as attitude and perceived norms, EMGB poses that anticipated emotion is a driver of decisions, such as those related to environmental behavior. This mechanism also suggests that negative affect associated with one choice outcome based on previous experiences may lead to an increased likelihood of changing one's behavior. Based on these notions, this study tests the extent to which satisfaction with the current car commute impacts frequency of e-bike use as an alternative mode.

The contribution of this study is that it provides insight into the factors that determine the frequency of e-bike use based on a large longitudinal dataset. It tests typical factors related to socio-demographic characteristics, spatial setting, and work organization, as well as the extent that travel behavior and travel satisfaction prior to the behavior change influence the frequency of e-bike use. Finally, the study investigates e-bike use and its determinants within one month and six months after the intervention to test whether e-bike use and its determinants change over time.

2. Materials and methods

2.1. Data collection

To stimulate switching from cars to e-bikes, the province of North-Brabant in the Netherlands implemented an e-cycling incentive program ("B-Riders") aimed at car commuters in 2013. Participants were recruited individually to take part in the program in an open call by several media channels (newspapers, social media, newsletters of companies). To stimulate the use of e-bikes instead of cars, participants receive monetary compensation depending on their e-bike use while commuting. To reduce car congestion, the monetary incentive was set at €0.15 per kilometer during the peak hours and €0.08 per kilometer in the off-peak hours. Participants could earn a maximum of €1.000 (one thousand euros) per person overall based on the amount of kilometers cycled multiplied by the incentive.

E-bike use was monitored through a smartphone app that tracks e-cycling behavior. Given the average e-cycling commute distance, it would take up to a year to reach the maximum reward, implying that the incentive is effective for a long period. Participants in the program had to meet three conditions: (i) conducting at least 50% of their total weekly work trips by car before entering the program, (ii) having a commute distance of at least 3km, and (iii) being between 18 and 65 years old and working in the province of North-Brabant.

Three questionnaires were used to measure behavioral change, which all participants were obliged to complete. The baseline questionnaire (T0) recorded the travel modes used for commuting during one week before entering the program. Participants reported the frequency of days of choosing a specific main mode of transport for commuting on an average week before purchasing their e-bike. The options for the main mode of transport were car, carpool, motor, bus, tram, metro, moped/scooter, bike, and walking. In addition, respondents reported their satisfaction with current car travel to work and a set of personal and household characteristics.

Satisfaction with the car commute trip was measured using the Satisfaction with Travel Scale (STS) (Ettema et al., 2011). Consistent with theories on subjective well-being, this scale uses both cognitive and affective items. To measure affective wellbeing, the endpoints of each scale are defined as combinations of the valence/activation dimensions of the affect circumplex (Västfjäll and Gärling, 2007). Six scales were designed, of which three distinguish between positive deactivation (-3) (e.g., relaxed) and negative activation (3) (e.g., time pressed), and three which distinguish between positive activation (3) (e.g., alert) and negative deactivation (-3) (e.g., tired). Another three items measure the quality of travel and tap cognitive appraisal of the commute trip. The order between the ratings scales was counterbalanced. The items included in the STS are summarized in Table 1. Scores for satisfaction with travel were constructed for each respondent by averaging the ratings for each of three subscales.

Finally, in addition to personal and household characteristics like age, gender, education, income, and composition, participants reported their physical condition on a range of "very bad" to "very good" on a seven-point Likert scale. Based on the zip code of the home location, the degree of urbanization and the actual cycle distance using the available cycle network were derived. A follow-up questionnaire was administered one month after the start of participation in the program (T1). It included the same questions about frequency of travel modes used for commuting (including the e-bike) and satisfaction with the e-bike commute. The third and final questionnaire was held six months after the start of participation in the program (T2). It was similar to the questionnaire at T1 and included questions about the frequency of travel modes used for commuting (including the e-bike) and satisfaction with the e-bike

Table 1
End points of the Satisfaction with Travel scale.

Positive deactivation-negative activation (items 1–3)	
… I feel stressed	… I feel calm
… I feel hurried	… I feel relaxed
… I feel worried arriving too late	… I feel confident arriving on time
Positive activation-negative deactivation (items 4–6)	
… I'm bored	… I'm *enthusiastic*
… I'm tired	… I'm alert
… I'm fed up	… I'm e*ngaged*
Cognitive evaluation (items 7–9)	
… *Travel was laborious*	… *Travel was prosperous*
… *Travel was uncomfortable*	… *Travel was comfortable*
… *I experience my trip as bad*	… *I experience my trip as optimal*

Table 2
sample composition.

Variable	Category	All participants	Unimodal car commuters	Multimodal car commuters
Age	25–39 years	12%	15%	11%
	40–49 years	37%	34%	38%
	50–64 years	51%	51%	51%
Gender	Male	48%	45%	50%
	Female	52%	55%	50%
Education	Low	13%	17%	17%
	Medium	28%	26%	28%
	High	58%	58%	55%
Physical condition	Physical condition bad	14%	17%	12%
	Physical condition neutral	18%	17%	19%
	Physical condition good	33%	33%	33%
	Physical condition excellent	35%	33%	36%
Car ownership	1 car	50%	45%	52%
	2+ cars	50%	55%	48%
Household income (in € per month)	< 3.000	43%	35%	46%
	3.000 - < 4.000	37%	42%	35%
	> 4.000	20%	23%	18%
Household composition	Single	7%	6%	7%
	Single parent	2%	2%	2%
	Couple without children	35%	40%	33%
	Couple with children	56%	52%	58%
Residence urbanization	(very) strong Urbanized	15%	11%	17%
	moderate urbanized	23%	26%	21%
	Less urbanized	32%	33%	31%
	Not urbanized	30%	30%	30%
Cycle Distance (per commute trip)_	0–5 km	4%	1%	5%
	5 < 10 km	19%	13%	22%
	10 < 15 km	31%	30%	31%
	15 < 20 km	29%	30%	28%
	20+ km	18%	26%	14%
Commuting days a week	1–3 days	14%	26%	9%
	4 days	33%	31%	33%
	5+ days	53%	43%	58%
Flexibility working hours	Yes	60%	62%	59%
	No	40%	38%	41%

commute.The study is based on responses from 547 participants, who fully completed all three questionnaires. The participants were split into two groups of varying commute behavior prior to the program: those who only commuted by car during the baseline measurement (n = 172) and those who used multiple modes for commuting (n = 375).

2.2. Sample descriptives

The baseline survey included questions about personal and household characteristics like gender, age, educational level, income, car ownership, household composition, and subjective physical condition. Based on reported home and work locations, the levels of urbanization of both the work and home locations and cycling distance were derived from land use statistics and Open Street Map. Table 2 shows the sample characteristics of all participants (both unimodal car commuters and multimodal car commuters).

Table 2 shows that more than half of the sample is between 50–64 years old and highly educated. The age is in line with literature reporting that e-bikes are especially popular among older age cohorts. Almost 70% of the sample reported good or excellent physical condition. More than 50% of the sample belongs to the category of "couples with children." Half of the sample owns two or more cars,

Table 3
Satisfaction with car-commuting (T0).

Variable	Category	All participants	Unimodal car commuters	Multimodal car commuters
Positive deactivation - negative activation	x < - 1.0	8%	8%	9%
	-1.0 < = < 1.0	40%	35%	42%
	x > = 1.0	52%	58%	49%
Positive activation - negative deactivation	x < - 1.0	10%	9%	11%
	-1.0 < = < 1.0	59%	59%	60%
	x > = 1.0	30%	33%	29%
Cognitive evaluation	x < - 1.0	6%	6%	6%
	-1.0 < = < 1.0	56%	47%	60%
	x > = 1.0	38%	47%	34%

and the majority (57%) falls in the higher income categories (> 3000 EURO/month). 78% of them had commutes longer than 10km, suggesting that e-bikes may be an important alternative travel mode that offers acceptable travel times and is useful for longer distances. About 60% had flexible working hours.

The unimodal car commuters and multimodal car commuters do not differ substantially in most characteristics. However, the car-only commuters have longer commutes and more often have two or more cars in the household. They also tend to have higher incomes. Finally, the number of travel days to work is less for car commuters compared to the other group, with 74% of car users travelling 4 days or more to work and 91% doing so among multimodal car commuters.

2.2.1. Satisfaction with car travel

Table 3 shows the distribution of satisfaction scores with car commuting. For each participant, the scores for all three subscales were calculated by averaging the scores (ranging from -3 to 3) on the three items related to each subscale.

As might be expected, car-only commuters are more positive about the affective evaluation of car travel than multimodal car commuters. This is shown by the higher percentages of scores above 1.0 on both the positive activation and positive de-activation sub-scales. Regarding cognitive evaluation of the car commute, more car-only commuters are positive (47%) compared to multi-modal-commuters (34%) with a score above 1.0. Multimodal users might be less positive about their car commuting because of their experience with alternative modes like cycling, or they might have already partly switched to alternatives in an earlier stage because of a negative evaluation. Overall, however, multimodal car commuters appear to be mostly positive or neutral about their car commute, and only a small number have negative scores on the affective or cognitive scales. Notably, a small number of car commuters also have negative scores on the various dimensions of travel satisfaction, suggesting that introducing a new travel mode may help them to improve their travel satisfaction.

2.3. Analyses

To explore the responses to the e-bike incentive program and the factors influencing the responses, we carried out descriptive analyses of the modal split across all trips made over one week by participants before (T0) and one month after the start of the program (T1). To investigate the effect of commute distance and the difference between unimodal and multimodal car commuters, analyses were split between both dimensions. Next, we carried out multivariate regression analyses of e-bike usage frequency at T1 and T2 with personal characteristics, household characteristics, commute characteristics, and satisfaction with the car commute as explanatory variables. This allows us to draw conclusions about the factors that lead to a positive response to the e-bike incentive program.

3. Results

3.1. Descriptive analyses

Table 4 shows the modal split as percentages of weekly commuting trips per mode compared to the total number of weekly commuting trips for T0 and T1. Before the program (T0), 61% of all commuting trips were made by car, 33% were made by regular

Table 4
Modal split (commuting) per distance class at T0 and T1.

		T0				T1				T2			
All participants	n	Car	Bike	e-bike	Other	Car	Bike	e-bike	Other	Car	Bike	e-bike	Other
0–5 km	20	42%	47%	0%	11%	18%	0%	80%	2%	12%	0%	87%	1%
5 < 10 km	105	55%	42%	0%	3%	24%	0%	74%	2%	18%	0%	80%	2%
10 < 15 km	167	61%	34%	0%	4%	27%	1%	70%	2%	23%	1%	74%	3%
15 < 20 km	156	63%	31%	0%	6%	32%	0%	65%	3%	26%	1%	71%	3%
20+ km	99	72%	21%	0%	7%	31%	1%	63%	5%	30%	1%	64%	5%
Total	547	62%	33%	0%	5%	28%	1%	68%	3%	24%	1%	73%	3%
Unimodal car commuters	n	car	bike	e-bike	other	car	bike	e-bike	other	car	bike	e-bike	other
0–5 km	2	100%	0%	0%	0%	30%	0%	70%	0%	10%	0%	90%	0%
5 < 10 km	22	100%	0%	0%	0%	31%	1%	65%	3%	22%	0%	78%	0%
10 < 15 km	52	100%	0%	0%	0%	27%	1%	70%	1%	23%	0%	73%	4%
15 < 20 km	51	100%	0%	0%	0%	38%	0%	61%	1%	36%	0%	62%	1%
20+ km	45	100%	0%	0%	0%	40%	0%	60%	0%	34%	1%	62%	3%
Total	172	100%	0%	0%	0%	34%	0%	64%	1%	29%	0%	68%	2%
Multimodal car commuters	n	car	bike	e-bike	other	car	bike	e-bike	other	car	bike	e-bike	other
0–5 km	18	35%	52%	0%	12%	16%	0%	81%	2%	13%	0%	86%	1%
5 < 10 km	83	43%	53%	0%	4%	22%	0%	76%	2%	17%	1%	80%	2%
10 < 15 km	115	45%	48%	0%	6%	27%	1%	69%	3%	24%	1%	74%	2%
15 < 20 km	105	47%	45%	0%	8%	29%	0%	67%	4%	21%	1%	75%	3%
20+ km	54	51%	38%	0%	12%	24%	1%	65%	9%	27%	2%	66%	6%
Total	375	46%	47%	0%	7%	25%	1%	70%	4%	21%	1%	75%	3%

bicycle, and 6% were made by other modes. Thus, a reasonable percentage of participants had already experienced alternative travel modes. For all categories, as distance increases, the percentage of car use also increases from 51% (distance 5–10 km) to 71% (distance > 20km). Logically, the effect is also seen for the multimodal car commuters, where car use increases from 31% to 51% from the shortest to the longest distances.

Table 4 also shows that participation in the program leads to a strong modal shift. Overall, car use drops from 62% to 28%, conventional bicycle use drops from 33% to 1%, and e-bike accounts for 68% of all commute trips at T1. Hence, e-bikes substitute for cars and conventional cycling to about the same extent. E-bike use is highest for the shortest distances (0–5 km: 80%) and decreases with distance, but it still accounts for 63% of trips longer than 20 km. At T2, the use of e-bikes increased further, with car use dropping further to 24% and e-bikes accounting for 73% of all commute trips. The further increase in e-cycling is particularly shown in the distance range of 0–20km.

In the group of unimodal car commuters, the percentage of e-cycling at T1 is lower (64%) than in the other group (70%) but still very substantial. This difference remains at T2, where the shares of e-cycling have further increased to 68% and 75%, respectively. The reduction in car use is much higher for unimodal car commuters (-66%) than for multimodal car commuters (-21%) at T1 and T2 (-71% and -25%, respectively).

For both groups, there were significant decreases in car use and the adoption of e-cycling for all distance ranges, but the effect tends to diminish with distance, implying that e-bikes provide the best alternative to car travel for distances less than 15 km. For the car-only commuters, this implies a reduction in the substitution of car use with increasing distance. For the multimodal car commuters, the reduction of car use is more or less independent of distance because e-bikes also substitute for conventional bicycle use.

3.2. Regression models of e-bike frequency

To explore the effects of a wide array of factors on the transition to e-bikes, multivariate regression models were used with the number of e-bike commuting trips at T1 and T2 as dependent variables. Commute distance, satisfaction with car commuting before entering the program, and the percentage of conventional cycling at T0 were also investigated as independent variables in addition to personal and household characteristics (gender, age, physical condition, income, education, household composition, and car occupancy), as well as work-related circumstances (urbanization level, flexibility, and travel days to work). Furthermore, we included commute frequency in order to scale the e-bike frequency to the total number of commutes per week. Table 5 shows the estimation results of the regression analyses for the total group of participants, car-only commuters, and multimodal commuters.

All models are highly significant with acceptable goodness-of-fit measures. Overall, the factors that influence e-bike use at T1 and T2 are similar, although some subtle differences emerge. The estimations indicate that at T1 and T2, men use e-bikes more often than women. However, this effect is only observed for the multimodal commuters. A potential explanation is that women are more bound to their cars as they combine their commute trip with household-related stops such as dropping off or picking up children and grocery shopping.

Participants with bad physical condition e-cycle significantly less than all other participants, but there is no effect of having a neutral or good level of physical condition (relative to excellent condition). Apparently, physical condition is not an obstacle for riding an e-bike unless one's physical condition is very bad. Remarkably, this effect is weaker in effect size and significance at T2. This may be due to the fact that the health of participants improves as a result of the shift to e-cycling, as shown in an accompanying paper describing the project (De Kruijf et al., 2018).

As expected, having only one car in the household correlates with a higher frequency of e-cycling relative to those who have two or more. However, this effect is observed for only multimodal car commuters at T1 and T2. This makes sense as car-only commuters have access to a car every day by definition, and as a consequence, the number of cars in the household has no effect. For T2, we find an income effect for the car-only commuters. Lower-income participants have a higher e-cycling frequency. This may be explained by the higher value they place on the financial incentive, but it is not clear why this effect is not observed for multimodal commuters and at T1.

Single individuals e-cycle less compared to couples with children, while couples without children e-cycle more. According to other studies (Popovich et al., 2014; MacArthur et al., 2014), older couples without children at home are generally known as frequent e-cyclists. In addition, having to take care of children may involve more complex trip patterns, which are more easily made by car and less easy to do by e-bike. However, these effects disappear at T2. It is possible that during several months of participation, participants find ways to organize their household obligations and activities such that the e-bike commute is no longer hampered.

Although descriptive statistics showed a decreasing trend of e-cycling with distance, only the shorter distances (0–10km) show a significant impact on e-cycling frequency in the estimation results of T1 and T2. Logically, e-cycling frequency is higher when there are shorter distances. However, this effect is not significant for the car-only commuters. This outcome reflects the descriptive results in Table 4, which show lower variation of the modal share of e-bikes between different distances. For multimodal car commuters, the pattern of e-bike use could possibly follow their conventional cycling behavior (through substitution), which is highly dependent on distance. As expected, the number of commute days to work positively influences e-cycling, basically indicating that the number of e-bike trips increases with the number of trips in general. This variable serves as a control variable in order to obtain unbiased effects of the other variables.

The frequency of conventional cycling at T0 has a positive effect on the number of e-bike trips in both the total model and in the model of multimodal car commuters and at T1 and T2. There are multiple possible explanations for this effect. First, since e-cycling is similar to conventional cycling in terms of the type of activity (although less intensive), exposure to the environment and weather, and parking, it is likely that those with a preference for cycling who cycle more at T0 will also be more likely to use e-bikes at T1.

Table 5
Regression analysis of e-cycling for total sample, car-only commuters, and multimodal car-commuters.

		T1						T2					
		All participants		Unimodal car-commuters		Multimodal car-commuters		All Participants		Unimodal car-commuters		Multimodal car-commuters	
		B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.
	Constant	2.969	**0.000**	2.728	**0.000**	2.980	**0.000**	3.112	**0.000**	3.542	**0.000**	2.807	**0.000**
Age	25–39 years	-0.265	0.084	-0.295	0.303	-0.274	0.145	-0.169	0.296	-0.475	0.112	0.000	0.998
	40–49 years	-0.120	0.284	0.005	0.984	-0.133	0.292	-0.039	0.740	-0.105	0.685	0.048	0.716
	50–65 years												
Gender	Male	0.348	**0.001**	0.387	0.091	0.279	**0.025**	0.279	**0.015**	0.217	0.362	0.271	**0.038**
	Female												
Physical condition	Phys. cond. bad	-0.463	**0.002**	-0.689	**0.025**	-0.438	**0.018**	-0.366	**0.023**	-0.427	0.181	-0.377	0.051
	Phys. cond. neutral	-0.044	0.744	0.087	0.763	-0.114	0.459	-0.201	0.157	-0.425	0.160	-0.124	0.441
	Phys. cond. good	-0.015	0.894	-0.273	0.274	0.056	0.666	-0.097	0.412	-0.576	**0.028**	0.023	0.868
	Phys. cond. excellent												
Car ownership	1 car per household	0.262	**0.008**	0.104	0.611	0.319	**0.005**	0.153	0.140	-0.235	0.271	0.282	**0.018**
	2+ cars per household												
Household Income (€)	< 3.000	-0.060	0.607	0.327	0.207	-0.161	0.233	0.034	0.782	0.580	**0.032**	-0.122	0.388
	3.000 - < 4.000	0.021	0.858	0.072	0.753	-0.018	0.895	-0.097	0.430	-0.089	0.711	-0.142	0.324
	> 4.000												
Household composition	Single	-0.698	**0.002**	-0.636	0.181	-0.830	**0.002**	-0.368	0.124	-0.418	0.399	-0.460	0.095
	Single parents	-0.679	**0.040**	-0.033	0.980	-0.807	**0.027**	-0.093	0.789	-0.634	0.639	-0.111	0.770
	Couples without children	0.615	**0.007**	0.507	0.272	0.725	**0.007**	0.214	0.374	0.080	0.868	0.306	0.274
	Couples with children												
Urbanization	(very) Strong urbanized	-0.033	0.821	0.298	0.391	-0.107	0.518	-0.142	0.362	0.079	0.828	-0.164	0.343
	Moderate urbanized	-0.048	0.715	0.153	0.555	-0.120	0.442	-0.211	0.126	-0.313	0.247	-0.134	0.412
	Less urbanized	-0.107	0.363	0.266	0.280	-0.216	0.113	-0.096	0.437	-0.088	0.732	-0.055	0.701
	Not urbanized												
Cycle distance	0–5 km	0.732	**0.008**	0.530	0.728	0.646	**0.027**	0.899	**0.002**	1.482	0.351	0.853	**0.005**
	5 < 10 km	0.431	**0.007**	0.234	0.489	0.477	**0.013**	0.644	**0.000**	0.732	**0.039**	0.653	**0.001**
	10 < 15 km	0.162	0.251	0.458	0.085	0.056	0.752	0.324	**0.029**	0.536	0.054	0.273	0.138
	15 < 20 km	0.049	0.728	0.146	0.568	-0.014	0.935	0.213	0.151	0.024	0.927	0.346	0.061
	20+ km												
Commuting days	1–3 days a week	-0.785	**0.000**	-0.575	**0.038**	-1.076	**0.000**	-0.837	**0.000**	-0.680	**0.019**	-1.079	**0.000**
	4 days a week	-0.421	**0.000**	-0.417	0.085	-0.405	**0.001**	-0.382	**0.001**	-0.420	0.095	-0.346	**0.009**
	5 days a week												
Habitual cycling	Cycle share	0.565	**0.000**			0.847	**0.000**	0.534	**0.001**			0.833	**0.000**
Satisfaction with (car) travel	Positive deactivation - negative activation	-0.005	0.922	-0.009	0.943	-0.006	0.919	0.021	0.708	0.082	0.521	0.005	0.938
	Positive activation - negative deactivation	-0.038	0.523	-0.053	0.673	-0.048	0.497	-0.066	0.301	-0.144	0.272	-0.055	0.461
	Cognitive evaluation	-0.106	0.068	-0.130	0.305	-0.088	0.191	-0.096	0.116	-0.136	0.304	-0.078	0.269
Goodness-of-fit (R2)		0.265		0.227		0.305		0.217		0.247		0.238	

Second, using multiple modes at T0 (including cycling and cars) may be an indicator of openness to alternative travel options and a more deliberate mode choice process from day to day. Such an attitude may also lead to a more frequent choice of the e-bike if this is an attractive option. Third, having no organizational constraints for cycling to work, such as having to drop off family members, carrying equipment, or wearing cycling-unfriendly clothes, implies that e-cycling to work will also be easier to do. These factors also persist after six months.

Finally, satisfaction with the commute at T0 has a close to significant impact on using the e-bike at T1. No significant effects of the affective dimensions were found (positive activation and positive de-activation), suggesting that positive or negative emotions do not translate into a greater willingness to shift modes in this case. However, those with a more positive cognitive assessment of the car commute are marginally less likely to use the e-bike in the total model and the model of multimodal car commuters. Nevertheless, the effect is weak and is not found for car-only commuters and multimodal commuters separately or at T2.

4. Discussion

This paper reports on the effects of an e-cycling incentive program in the province of North-Brabant, the Netherlands, in which commuters could earn monetary incentives when using their e-bikes. The study uses a longitudinal design that can be used to observe behavior changes and mode shifts. The e-bike incentive program from which data was taken in this study provides a unique dataset that covers the recording of behavior over a year-long period. This allows us to test behavioral changes for not only the one-month period reported in this paper but also longer periods. Future research is planned to investigate longer-term behavioral processes, which will provide much needed insight into adherence to the mode shift and the extent to which personal and commute characteristics influence adherence.

The program was found to be highly effective in stimulating e-bike use, as 66% of the commute trips were made by e-bike at one month after the start of the program. However, the environmental, congestion, and health benefits of this shift are mixed. Half of the e-bike trips substitute for car trips and thus have positive effects on the environment, congestion, and health. The rest of the trips substitute for conventional cycling trips, implying less health benefits because e-cycling is less strenuous than regular cycling. However, Simons et al., (2009) showed that all three power settings on an e-bike provided a useful contribution in meeting minimum physical activity requirements. E-cyclists achieve the necessary physical activity to enhance health and reduce the chance of sedentary lifestyle diseases, despite the electrical assistance (De Geus et al., 2013). However, given the higher speed, e-cycling reduces the duration of physical activity in daily commuting. Nevertheless, it should be noted that this difference is context specific, and there may be less difference in speed between conventional cycling and e-bikes in more congested urban environments and without dedicated cycling lanes.

Some research suggests that cyclists spend more time on their e-bikes than if the e-bike was unavailable (MacArthur et al., 2014). This holds in particular for those using only cars for commuting before the incentive program. The substitution of conventional cycling with e-bike use might suggest that e-cycling is more attractive than conventional cycling. Sperlich et al. (2012) established that sedentary women in a small-scale experiment found e-cycling more enjoyable than conventional cycling, which alluded to the less cardiorespiratory effort involved. On the other hand, Ekkekakis et al. (2008) state that physical activity can have a positive effect on enjoyment, suggesting that there is an optimal level of intensity of physical activity in terms of affect. However, this optimum may be different for car users than for regular cyclists, who are better trained and enjoy the exercise. In interpreting the findings, it should also be kept in mind that behavior was recorded when the financial incentive for each kilometer e-biked was still in place. It is possible that e-bike use will diminish after the incentive period, which may also imply that commuters partly return to conventional cycling.

Our analyses also suggest that distance is an important factor for adopting e-cycling. While e-bikes increase the range of acceptable distance, we still see a decreasing effect of e-bike use according to distance as cars are still significantly faster and lead to savings in travel time with longer distances. We also found that the effect of distance differs between multimodal car commuters and those solely relying on cars to commute. The latter group appears to be less sensitive to distance in our study. The reduction of car use for the multimodal car commuters is more or less independent of distance because e-bikes also substitute for conventional bicycle use.

Multivariate analyses suggest that a shift to e-cycling is affected by gender, physical condition, car ownership, and household composition. No effect was found for the degree of urbanization, which was somewhat unexpected, as e-bikes might be more competitive in urban settings between cities and suburbs. However, the degree of urbanization referred only to the residential location and did not take into account the location of the workplace and the route between home and work.

Our study found that commuting behavior prior to the intervention influenced e-cycling frequency in that a higher cycling frequency is associated with a higher e-cycling frequency. As mentioned, this may be due to similarities between cycling and e-cycling, so that those with a preference for cycling also have a greater preference for e-cycling, greater openness to other travel options, or a lack of constraints for both cycling and e-cycling. In the current setup, we could not disentangle these factors. However, future research should address the various ways in which such path dependencies in travel behavior occur.

We found no clear impact of the experience of the car commute on e-cycling frequency. The marginally significant effect at T1 is an indication that the mode change is affected by the evaluation of the current mode and that avoidance (Russell, 2003) takes place to some extent. However, more research is needed to identify whether more substantial effects are at play for specific segments or based on specific aspects of the travel experience.

Altogether, the study suggests that incentive programs for e-cycling can be effective tools to relieve congestion and stimulate physical activity, but that care should be taken in regard to which groups are targeted. The greatest potential gain is among car-only commuters, as every e-bike trip substitutes for a car trip and not a conventional cycling trip. However, excluding multimodal car commuters may be practically difficult and lead to problems of fairness and acceptance. In terms of distance, the reduction of the share of car commuters is less for longer distances, but the effect on congestion, environmental impact, and physical activity is still very worthwhile. Hence, e-bike incentive programs can be targeted at both shorter and longer distance commuters.

From a policy point of view, our results imply that promoting e-cycling may be an effective way of stimulating physical activity with associated health effects. However, as the effects on physical activity and health strongly depend on mode use before the intervention, incentive programs should target groups that are currently not engaged in active travel (or are engaged to a limited extent). Among those not engaging in active travel before the program, physical condition appeared to be the only relevant predictor of e-cycling adoption. While those with a bad condition were least likely to adopt e-cycling, they will likely have the largest health benefit of doing so. This suggests that interventions should specifically focus on groups with bad physical condition by providing tailored information and support programs. In line with our hypotheses, we found that distance has a negative effect on the adoption of e-cycling, but this effect is only slight, and the mode share of e-bikes is still very substantial (57%) for the longest distance category. As longer e-bike commute trips imply more physical activity, policy efforts should be directed at improving conditions for longer distance cycling—for instance, by creating dedicated infrastructure (such as cycling highways).

This study is a first step in investigating the potential of e-cycling in commute travel. More effort is needed to come to more general conclusions and further increase our knowledge about influential factors. First, the mode shift observed in this study was induced by an incentive as part of a program. It cannot be concluded that mode shifts in other contexts (e.g., without providing incentives or in different geographical contexts) will be comparable in size or be subject to the same influential factors. More longitudinal studies of e-bike adoption in a variety of contexts will be needed to answer these questions.

Second, the current study paid limited attention to route characteristics, which were only represented by distance. Obviously, aspects such as quality and safety of the cycling infrastructure, landscape, and aesthetics may be important factors in e-bike use, which can be targeted in policies. For instance, these characteristics may differ strongly between the Netherlands, which has an extensive cycling infrastructure, and North-American and the United Kingdom, where such infrastructure is often lacking. Route characteristics could be investigated based on GPS tracking of commute trips, which is available for our sample, and augmented with detailed information about land use, buildings, and vegetation.

Third, while our study provides valuable additional insights as compared to cross-sectional studies, it makes sense to study mode choice behavior over longer periods. Adherence to healthy behaviors (e-cycling in this case) is a crucial aspect for sustained positive health effects, and studies in other domains (Ettema et al., 2010) have shown that behaviors triggered by incentives are not necessarily sustained when the incentive ends. Finally, as noted, conventional cycling is also substituted by e-bike use. More research is needed to investigate what motivates cyclists to switch to e-bikes, how the experiences of cycling and e-cycling differ, and how these aspects differ between cyclists according to gender, age, fitness, and motivation.

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Conflict of interest

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