Highlights of Sustainability

Article

The Substitution Effect of E-bikes and Psychological Processes Influencing Its Use: Results from Two Randomised Controlled Trials in Sweden

Alfred Söderberg

Trivector Traffic AB, 222 36 Lund, Sweden; E-Mail: alfred.soderberg@trivector.se

Abstract The market share of e-bikes has increased extensively in Europe over the last decade. How this trend will affect the transport system depends to a large extent on the substitution effect which needs to be determined in detail to allow projections on the potential of e-cycling as a means to promote sustainable transport systems. Further, little is known about what psychological determinants influence e-bike use, an important topic for policy makers that wish to promote e-cycling. This study aggregates GPS data from two randomised controlled trials in Sweden to determine the effect of e-bike use on travel behaviour. Motives behind e-bike use are investigated within a path-analytic structural model, based on an expanded theory of planned behaviour. The results reveal that, on average, total cycling increased by 4.5 kilometres per person and day during the trials and its modal share measured in distance increased by 19%. E-bike use was predicted by the intention to bike to work, which in turn mediated the effects of attitudes and self-efficacy on e-cycling. Attitude mediated the indirect effect of personal norm on intention and collective efficacy amplified the effect of self-efficacy on intention. The results show that e-cycling has a large potential to contribute to a sustainable transport system. Policy makers could increase the use of e-bikes by strengthening individuals' attitudes toward cycling and perceived self-efficacy to e-cycle, by making environmental personal norms more salient and by highlighting collective action in the effort to limit environmental degradation.

Keywords cycling; e-bikes; substitution effect; path-analysis; TDM

1. Introduction

The popularity of the pedal-assisted electric bicycle (e-bike) is growing rapidly and has great potential to replace heavy, fossil fuel-powered vehicles and thus contribute to a more sustainable transport system [1]. The European bicycle market is currently driven by an increasing interest in e-bikes, which grew by 23% from 2018 to 2019, marking three million units sold which represents 17% of the total bicycle sales, a figure expected to double in 2025 [2]. In Germany, e-bike sales have exceeded expectations and accounted for almost 40% of total bicycle sales in 2020 [3], and in Sweden, now every fifth bicycle sold is an e-bike [4].

The individual benefits of e-cycling are more or less the same as for conventional cycling, with the added bonus of reduced effort due to the electric motor, which enables more people to use the bicycle for everyday activities, and for longer distances [5,6]. Even though the level of physical activity is less for e-bikers compared to cyclists, it is sufficient for achieving the daily physical activity recommendations. However, substantial health benefits are primarily achieved when e-bikers switch from motorised transport modes such as cars and public transport [7,8]. Likewise, environmental gains from more e-bike use could be substantial [9,10] but are dependent on the substitution effect. Recent studies have found promising results where about half of the e-bike trips replace car trips [11–14] and the remaining half substituting bicycling, public transport and walking (see [4] for a review of the e-bike substitution effect). The substitution effect is highest for the most prominent mode within a given context [15], and targeting frequent drivers offer the highest net benefit potential [16].

One major limitation of previous studies that investigate substitution effects of the e-bike is their reliance on cross-sectional data which does not allow an assessment of within-person travel mode changes [17]. Further, there is a lack of evaluations, of both e-bike trials and travel interventions in general, that employ rigorous research designs with participants randomly assigned

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to treatment and control groups and where the collection of travel behaviour data is made with objective measurement tools. This carries the risk of bias from confounding factors and lack of internal validity [16], as well as social desirability bias [18], and several authors in the field call for more intervention evaluations based on randomised controlled trials (RCTs) [5,16,19–21], and to utilise apps for collecting travel data [12,22]. To the best of the author's knowledge, the study by Söderberg f.k.a. Andersson et al. [4] is as of yet the only RCT study on the substitution effect of e-bikes, which also used app-based data collection. In this study, the data used in that study will be combined with an additional RCT trial conducted in Sweden, which increases the validity of the results. Since few studies have investigated the substitution effect of e-bikes in Sweden, this study contributes crucial evidence. This is especially needed now because e-bikes are increasingly used to promote active transport, in Sweden and elsewhere.

A further aim of this study is to increase the understanding of what psychological determinants affect e-bike use. Previous research has emphasised the need for addressing motivational reasons for the use of e-bikes [12], by investigating the role of psychological variables, e.g., related to cycling attitudes, environmental attitudes, and social norms for cycling [15]. From a broader perspective, there is a need for studies to use behavioural theory to evaluate interventions aimed at changing behaviours, for the reason of understanding the process behind the observed change that followed an intervention. This could help us understand how behaviour change interventions have their effects, advancing the knowledge of when and why behaviour change is likely to occur [23]. Hence, in this study, the effect of two e-bike trials will be evaluated, as well as the influence of intention, attitudes, social and personal norm, efficacy, perceived behavioural control, and habit, on e-bike use within a path-analytic model. Additionally, to assess more complex indirect relationships, mediation and moderation analysis will be conducted as part of the path analysis. This study thus contributes to the need for understanding the reason behind e-bike substitution which has been lacking in previous studies.

The paper structures as follows. First, an introduction of the behavioural theoretical framework is presented from which the hypothesised path-analytic model is built. Next, the sample, trial procedure, data collection, and analysis strategy, are explained in the method section. The results from the trial period are then presented in Section 4.1, and the path analysis in 4.2. A discussion of the results and conclusions are then presented in Sections 5 and 6, respectively.

2. Theoretical Framework and Hypotheses

The idea of promoting sustainable travel behaviours with behavioural interventions stems from behavioural theory, which has identified specific psychological determinants assumed to mediate the impact of an intervention on travel behaviour [24]. The theory of planned behaviour (TPB) [25] has been particularly influential in this research field for the last two decades, often teamed up with the moral construct of personal norm [26]. Another concept that has been highly influential in behavioural research is efficacy [27,28]. These theoretical models and concepts, and how they have been applied in this study, are explained next. The proposed path-analytic model is illustrated in Figure 1.

TPB is referred to as a rational decision-making theory in that it stipulates that individuals form intentions to perform or not perform behaviours based on attitudes towards the behaviour, subjective norms, and perceived behavioural control (PBC), which respectively, originate from behavioural beliefs, normative beliefs, and control beliefs [25]. As such, TPB can be classified as an expectancy-value theory, in that motivation is regulated by the expectation that a given behaviour will produce certain outcomes and the value of those outcomes. Generally, the more favourable the attitude and subjective norm, and the greater the perceived control, the stronger should be the person's intention to perform the behaviour in question [29]. One meta-study found the TPB to account for 21% of the variance in objective or observed behaviour (31% for self-reported behaviour) and 39% in intention[30]. Many studies have found support for TPB in explaining transport-related behaviours [31].

TPB neglects to incorporate the influence that habit has on repetitive behaviours, for example, using the car because it is comfortable, fast, and private may result in a car-use habit that is facilitated by the frequent use in a stable context [32]. It has been found that habit indeed is an important antecedent of behaviour that regulates the predictive power of attitudes; when a habit is strong the attitude-behaviour relation is weak, whereas when a habit is weak, the attitude-behaviour link is strong [33]. A recent study that extended TPB to include a measure of habit to predict change in cycling in three UK municipalities found that attitudes, PBC, and habit had a positive effect on cycling [34].

It was expected that the use of e-bikes in this intervention study to be affected by attitudes, subjective norms, and perceived behavioural control, through intentions. Since mobility behaviours are quite complex, and because the sample consisted of habitual car users, it was further expected that perceived behavioural control and habit would exert a direct positive and negative influence on behaviour, respectively. Consequently, it was hypothesised that:

a) Intention and perceived behavioural control will have a positive effect on e-bike use.
b) Habit will negatively affect intention and e-bike use.
c) Attitude, social norm, and perceived behavioural control will positively affect intention.
d) Intention mediates the effect of attitude, social norm, and perceived behavioural control on e-bike use.

There are two types of efficacy, namely self-efficacy, and collective efficacy [27,28]. Self-efficacy, defined as "a belief in one's ability to effectively perform and to exercise influence over a specific event", is the most widely used construct of the two, and an important determinant for behavioural achievement. People do not only act on their beliefs about the likely outcomes of a behaviour, but also on their beliefs about what they can do. The motivating influence of behavioural outcomes is thus partly governed by self-beliefs of efficacy, and Bandura notes that the predictiveness of expectancy-value theories such as TPB is enhanced by including the influence of perceived self-efficacy [35]. In general, individuals are more inclined to perform behaviours they believe to be achievable, and people with high self-efficacy set higher goals for themselves, put more effort into changing behaviour, and persevere when facing obstacles [35]. Klöckner found self-efficacy to be at least as important as attitudes when promoting environmental behaviour, including travel behaviour [36].

Self-efficacy is similar to perceived behavioural control, but several authors have argued that they differ in the sense that self-efficacy is more concerned with cognitive control factors, while PBC also reflects external control factors. The PBC construct often combines "perceived difficulty" with "perceived control", and the former has been shown to better predict intentions [37]. Armitage and Connor concluded that self-efficacy should be the preferred measure of perceived control [30] and other authors have recommended the inclusion of both [38]. In this study it was decided to include both constructs, expecting self-efficacy to capture internal ability more fully, and PBC to better comprehend external control, thereby hypothesising that:

a) Self-efficacy affects attitude positively.
b) Self-efficacy will have a positive effect on intention.
c) Attitude mediates the positive effect from self-efficacy to intention.
d) The effect of self-efficacy on e-bike use is mediated through intention.

Strong perceived collective efficacy, that is, the belief that the members of a group can together achieve desired outcomes [28], has recently been shown to be predictive of pro-environmental behaviours [39–41]. Moreover, messages promoting sustainable transport induced more motivation to reduce private car use if framed around collective efficacy than if they emphasised self-efficacy [42]. When people feel that their group is efficacious, collective action is fostered [28]. Interestingly, Jugert et al. demonstrated that collective efficacy increased pro-environmental intentions through increased self-efficacy, suggesting that believing in the group strengthens the belief in oneself which increase the intention to act [43]. Against this background, it was expected that collective efficacy not only predicts self-efficacy but also that collective efficacy moderates the effect from self-efficacy to intention to e-cycle. Consequently, it was hypothesised that:

a) Collective efficacy will positively influence self-efficacy.
b) Collective efficacy moderates the effect of self-efficacy on intention.

As earlier mentioned, rational utility theories such as TPB have a proven ability to predict modal choice behaviours. However, when it comes to modal shift behaviours it has been argued that moral constructs such as personal norm, a feeling of moral obligation to act [26], gain in importance because reducing car use is often affected by individuals' moral concern for the environment, and should therefore be incorporated alongside utility theories [44]. Previous studies have demonstrated personal norms as an important predictor of sustainable transport mode choices, such as buying an electric car and switching to public transport [32,44–48], as well as adopting e-bikes [49]. Similarly, climate morality has been found to positively affect motivation to decrease private car use [50]. However, personal norms are believed to only exert an indirect effect on pro-environmental travel behaviours through, for example, attitudes [36]. Further, since the habit construct has more to do with the level of automaticity in executing a behaviour than merely acting as a description of past behaviour [51], personal norm was expected to influence habit strength. Consequently, it was anticipated that:

a) Personal norms affect attitude positively.
b) Attitudes mediate the relationship between personal norm and intention.
c) Personal norm has a negative effect on habit.

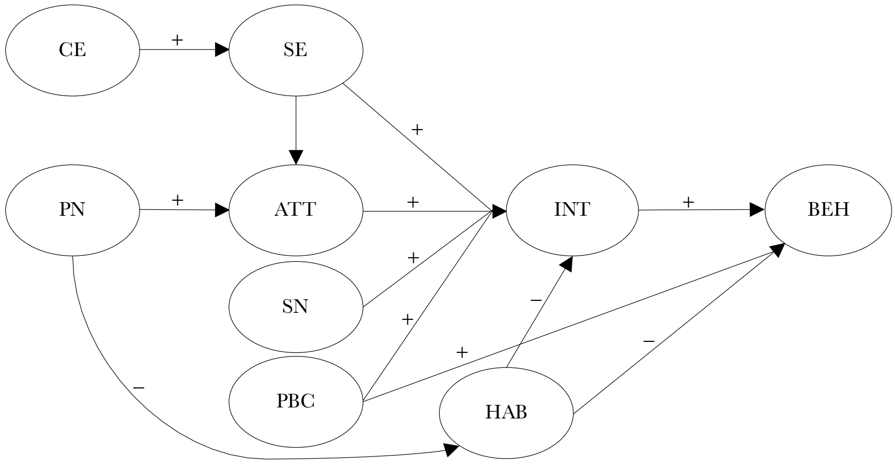

Figure 1. Proposed path-analytic model: Influence of self- and collective efficacy (SE, CE), personal norm (PN), attitude (ATT), subjective norm (SN), perceived behavioural control (PBC), habit (HAB), and intention (INT) on behaviour/e-bike use (BEH).

3. Method

Two e-bike trials were carried out with participants from two major companies, one in Skövde and one in Trollhättan, two medium-sized cities in Sweden with just over 50,000 inhabitants each. These cities are characterized by relatively low levels of cycling compared to the national average and have several large companies which would be suitable targets for an e-bike intervention. The procedures for recruiting participants and collecting data have already been comprehensively described in the study by Söderberg f.k.a. Andersson et al. [4] and will therefore be presented here in brief. Figure 2 provides an overview of the methodological steps for collecting and analysing the data of the study.

3.1. Recruitment and Sample Characteristics

Employees at the two companies were contacted with an offer to participate in a research project (written consent to share data was mandatory) in which they would borrow an e-bike for five weeks and use it for as much as they liked. In return, they were asked to log their travel behaviour data and fill in a couple of surveys. Approximately 5000 employees were contacted, of which 736 stated that they would like to be part of the trial. Since only 50 e-bikes were at the project's disposal, the aim was to recruit 100 participants each in Skövde (trial carried out in the spring of 2020) and Trollhättan (autumn 2020), where half of the samples would constitute control groups. Those interested were asked to give information about age, gender, usual travel mode and distance to work. Frequent drivers with 5–12 km to the workplace were prioritised, as this group was being considered to have the largest substitution potential and benefit of the e-bikes. At the start of the trials, the sample consisted of a total of 182 persons. In the end, 118 participants logged their travel activities during all measurement periods, of which 67 belonged to the treatment group and 51 to the control group. This sample formed the basis for the substitution effect analyses (SE sample).

To conduct the path analysis with the psychological variables, we needed to combine the travel data with the survey data. Amos 25, the software we used for running the path analyses, requires no missing data, which resulted in a smaller sample due to missing responses. For respondents with five percent or fewer missing values, we used the Expectation-Maximization (EM) procedure in SPSS to make imputations. It is an iterative procedure that uses other variables to impute a value (Expectation) and then checks whether that is the value most likely (Maximization). If not, it re-imputes a more likely value. This goes on until it reaches the most likely value. EM imputations are better than mean imputations because they preserve the relationship with other variables, which is essential for this study since the path analysis we will conduct is all about examining relationships between variables. In the end, our path analysis sample (PA sample) consisted of 60 participants.

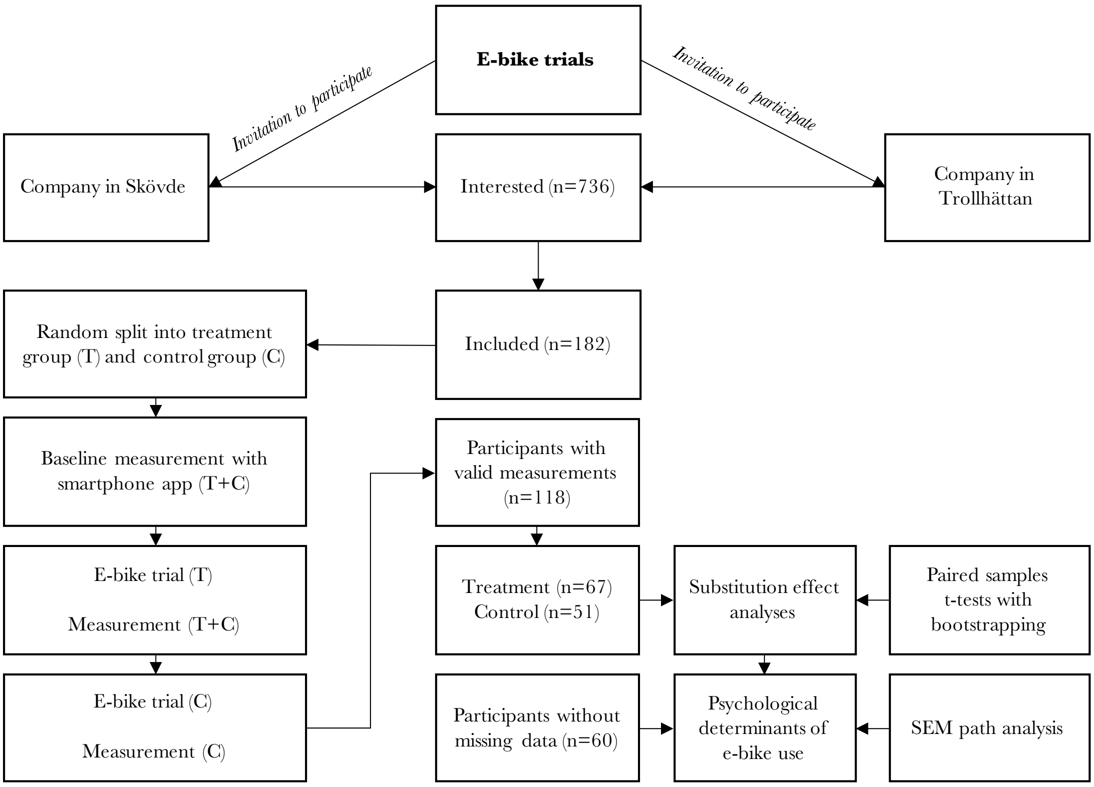

Figure 2. Data flow chart with the methodological steps for collecting and analysing the data of the study.

The samples were not intended to represent the municipal average but instead aimed to be suitable target groups for the e-bike interventions. As can be seen in Table 1, the gender balance for the samples was biased, probably due to an overrepresentation of male employees at the companies. Further, car use was quite high; around 80% of the participants usually drove to work and most of them had two or more cars within the household. In the SE sample, the treatment group had 13% more females and 10% more with higher education compared to the control group. Otherwise, the composition of the groups was quite similar.

Table 1. Demographic characteristics of the samples.

	SE Sample (*N* = 118)		**PA Sample**
	Treatment group (*N* = 67)	Control group (*N* = 51)	(*N* = 60)
Mean age	47	47	45
Female	21%	8%	5%
Education	Elementary: 2% Upper second: 49% Uni. < 3 years: 11% Uni. ≥ 3 years: 38%	Elementary: 6% Upper second: 55% Uni. < 3 years: 22% Uni. ≥ 3 years: 17%	Elementary: 4% Upper second: 50% Uni. < 3 years: 15% Uni. ≥ 3 years: 31
Have a driving license	98%	98%	97%
Nr of cars in the household	None: 4% One: 34% Two: 53% > two: 9%	None: 5% One: 31% Two: 56% > two: 8%	None: 6% One: 24% Two: 60% > two: 10%
Owns a regular bike	88%	83%	82%
The most common means of transport for work	Car: 81% PT: 2% Bicycle: 15% Walk: 2%	Car: 81% PT: 0% Bicycle: 14% Walk: 5%	Car: 84% PT: 2% Bicycle: 10% Walk: 4%

3.2. Data Collection and Trial Procedure

Data was collected with the semi-automated GPS-tracker app TravelVu, which was also used for distributing the survey. It identifies 10 modes of transport automatically and logs distance, route, location, and start and stop time. The user must confirm trips that have been made and were encouraged to do so after each day. Since logging is automatic, few if any trips are missed altogether (except for those where the participants do not carry their phones with them), and the distances travelled are measured with a relatively high degree of accuracy [52]. The data was imported and analysed in IBM SPSS Statistics 25 and Amos 25. For a more detailed description of the TravelVu app as a travel logging method, see for instance [53] and [54].

In total there were three measurement periods of one week each. In the first two, both the treatment and the control group participated (baseline measurement and trial measurement). The third measurement period was only for the control group's trial period, which was conducted to keep the interest high and prevent dropouts since earlier intervention studies have had such issues [55]. It is also a way of acquiring validation results, although without a control group since no second control group was participating.

3.3. SEM and Path Analysis

Structural equation modelling (SEM) is a comprehensive statistical approach to testing hypotheses about relations among observed and latent variables. It is mostly used to test hypothesized patterns of directional and non-directional relationships among a set of observed (measured) and unobserved (latent) variables. One can think of SEM as a series of regressions applied sequentially to data. Further, in a regression model, the direct effects of each independent variable on the dependent variable are tested. In SEM, indirect effects are accounted for in addition to direct effects. Path analysis is a special case of SEM in that it only contains observed variables and no latent variables as is the case in SEM. Path analysis assumes that all variables are measured without error while SEM uses latent variables to account for measurement error. Overall, path analysis has a more restrictive set of assumptions than SEM.

3.4. Variables Used in the Path Analysis

Index variables were computed from the survey items, a common method when conducting path analyses [48,56]. Internal consistency was assessed by Cronbach alpha, and an alpha of at least 0.7 is considered an acceptable level of reliability [57]. All items were assessed on a scale from 1 (strongly disagree) to 7 (strongly agree), except for self-efficacy and collective efficacy which were measured from 0 (no confidence) to 100 (complete confidence), and behaviour/e-bike use which consisted of the raw scores of kilometres e-cycled per day during one week. An overview of the variables is presented in Appendix A.

Intention was measured with two items, *I will try to use the bike more to get to work from now on*, and *I intend to cycle more to work from now on* (α = 0.90). Ajzen stressed that there often are two types of attitude components, instrumental and experiential, which form a person's overall evaluation of the behaviour in question [58]. The statements used were: *You think that taking the bike to work would… be inconvenient, take a long time* (reversely coded), *be good for the environment*, *save me money*, *be good for my health*, and *be risky* (reversely coded) as instrumental items and *be relaxing*, *give me a sense of freedom*, and *be boring* (reversely coded) as experiential items. The *be risky* item was omitted due to a low corrected item-total correlation (0.227). The rest of the items contributed to an acceptable internal consistency (α = 0.77). Subjective norm was measured with four items in total, two describing descriptive social norms, *It is common for people I know to cycle to work*, *The people whose opinions I value highly cycle to work*, and two items for injunctive social norms, *I am expected to cycle to work by my peers*, *The people whose opinions I value highly think that I should cycle to work*. The correlations of these coefficients were not ideal and indicated poor internal consistency (α = 0.54). Omitting one or two items did not increase the alpha, and so the decision was made to include all four items. It is not unusual for measurements of the subjective norm to hold low reliability, which might be the cause of low predictive power [30]. Perceived behavioural control was measured with two items, *Cycling to work would be easy for me*, and *It is entirely up to me to decide whether I cycle to work or not*. These items had also a poor internal consistency (α = 0.40) and this is something we should consider when interpreting the path model later on.

Due to limited space in the survey, habits could not be measured with the twelve-item Self-Report Habit Index [51]. Fewer items have been shown to be adequate [59] and, in line with

[60], two items were used, *I take the car to work without thinking much about it*, and *Taking the car to work is done automatically for me* (α = 0.73).

Four items of personal norm were adapted from [45,61], *I personally feel that it is important to think about the environment in my everyday behaviour*, *Personally, I feel that it is important to travel as little as possible with vehicles that run on fossil fuels*, *I feel a moral responsibility to reduce my greenhouse gas emissions by driving less*, and *I get a bad conscience when I take the car to work* (α = 0.89).

Self-efficacy and collective efficacy were measured with six items each, adapted from [62]. For self-efficacy, the statement, *Assuming I have access to a bicycle, I can*… was followed by, … *start a new habit where I cycle to work more often than I take the car*, … *keep that habit for an extended period of up to six months*, … *cycle to work on a rainy day*, *cycle to work a stressful morning*, *contribute to a better environment by cycling more instead of driving*, and *reduce the climate impact by cycling more instead of driving*. For collective efficacy, the respondents were informed that their peers at work also would participate in the trial, and then asked to provide answers to the statement, *In general, we as a group can*…, followed by the same items used for self-efficacy. The constructs had good internal validity (α = 0.88 for self-efficacy and α = 0.86 for collective efficacy).

Variable inflation factors were examined (VIF) by regressing all dependent variables in the path model against the relevant predictors and no value greater than 2.269 was observed. This indicated that there are no serious multicollinearity problems. Influential cases were checked for by studying Cook's distances where no value greater than 0.258 was found, indicating no particularly influential cases. The correlations between variables are presented in Table 2.

Table 2. Mean, standard deviation, and Pearson correlation coefficients for the variables in the path model.

	Mean	S.D	PN	CE	SE	HAB	PBC	SN	ATT	INT
PN	3.73	1.42								
CE	59.48	15.61	0.408 **							
SE	64.84	19.89	0.396 **	0.698 **						
HAB	3.91	1.49	−0.366 **	−0.23	−0.193					
PBC	3.99	1.03	0.035	0.383 **	0.338 **	−0.134				
SN	2.58	0.86	0.178	0.067	−0.012	−0.144	−0.057			
ATT	4.54	0.69	0.528 **	0.314 *	0.539 **	−0.280 *	0.113	0.002		
INT	4.25	1.19	0.278 *	0.434 **	0.507 **	−0.185	0.137	0.071	0.518 **	
BEH	3.69	3.03	0.189	0.131	0.218	−0.185	0.027	0.115	0.284 *	0.440 **

** $p < 0.01$; * $p < 0.05$

3.5. Effects of COVID-19 on the Study

Because the baseline measurement in Skövde (M1) started at the same time as the outbreak of COVID-19 was gaining momentum in Sweden, questions were asked to the participants via the questionnaire sent out in period M2 about how the virus had affected their travel habits during the test period. The purpose was to capture how the results of the study may have been affected by the pandemic. When asked how COVID-19 has affected participants' commuting to work, 73% responded that it was affected. The number of days the participants commuted to work during the test period averaged 2.3 days per week, which differs from the average of four days per week, in which participants on average stated that they usually commute to work. Respondents were also asked about their modal choice during the pandemic. 95% stated that the pandemic did not affect their driving, cycling, walking, or transit use. About 30% of the respondents stated that they used the e-bike less because of the pandemic, another 30% that it was not affected, 20% said they used it more and 20% that they did not know. In summary, it is difficult to establish how the pandemic affected the trial except that the participants in general travelled less to work. Given this situation, it was fortunate that control groups were added to the study, which made the influence of COVID-19 less of an issue.

4. Results

In this section, the aggregated results from the e-bike trials in Skövde and Trollhättan are presented.

4.1. Effect of the Trial on the Number of Trips, Distance, and Modal Share

The effect of the trial on the number of trips and modal shares is presented in Table 3. On average, the participants conducted 4.4 trips per day during the test periods (M1–M3). Between M1 and M2, the treatment group decreased their number of car trips by 0.8 and increased their e-bike trips by 0.4. The use of regular cycling, public transport, and walking stayed at approximately the same levels. For the control group, there were no significant changes from M1 to M2. Between M1 and M3, however, the control group decreased their number of car trips by 0.7 and increased their e-bike trips by 0.8. Walking decreased somewhat, however; this change was non-significant.

On average, the number of car trips expressed as the share of total trips went from 63% at M1 to 52% at M2 for the treatment group and from 59% to 64% for the control group. The share of e-bike trips increased by 12% for the treatment group and the sum of cycling (both bicycle and e-bike trips) increased on average by 25%. No significant changes occurred for the control group between M1 and M2. From M1 to M3, however, the control group increased the share of e-bike trips by 18%, aggregating to a 28% cycling share, while decreasing the share of car trips down to 43%, compared to 59% in M1.

Table 3. Paired-samples t-tests on modal shares in relation to the average number of trips travelled per day on each mode of transport for treatment and control group at M1 and M2 as well as M1 and M3 for the control group. Based on 2000 bootstrap samples. Means, standard deviations, and Cohen's d effect sizes (significant differences).

	Treatment Group					**Control Group**						
	M1		**M2**			**M1**		**M2**		**M3**		
	Trips	**SD**	**Trips**	**SD**	***d***	**Trips**	**SD**	**Trips**	**SD**	**Trips**	**SD**	***d***
Car	2.73	1.51	1.97 **	1.19	0.50	2.73	1.46	2.86	1.79	2.08 **	1.28	0.44
PT	0.06	0.19	0.01	0.05		0.07	0.18	0.04	0.11	0.03	0.09	
Bicycle	0.43	0.55	0.49	0.68		0.40	0.68	0.27	0.44	0.51	0.54	
E-bike	0.02	0.09	0.45 **	0.61	4.66	0.00	0.02	0.03	0.20	0.78 **	0.92	31.63
Walk	1.09	1.21	0.72	0.90		1.90	2.26	1.30	1.22	1.64	1.50	
Total	4.49	1.72	3.84 **	1.70	0.38	5.23	2.87	4.61	1.95	5.17	1.75	
B & e-b	*0.45*	*0.56*	*0.94* **	*0.76*	*0.88*	*0.40*	*0.68*	*0.31*	*0.47*	*1.29* ***	*0.85*	*1.30*
						Modal Share						
Car	0.63	0.27	0.52 **	0.25	0.42	0.59	0.23	0.64	0.29	0.43 **	0.25	0.69
PT	0.02	0.04	0.00	0.01		0.02	0.05	0.01	0.02	0.01	0.02	
Bicycle	0.12	0.17	0.13	0.18		0.08	0.12	0.07	0.11	0.10	0.12	
E-bike	0.01	0.03	0.13 **	0.19	4.84	0.00	0.00	0.01	0.05	0.18 **	0.21	49.91
Walk	0.23	0.18	0.21	0.23		0.31	0.20	0.27	0.25	0.29	0.22	
B & e-b	*0.12*	*0.19*	*0.27* ***	*0.21*	*0.78*	*0.08*	*0.12*	*0.08*	*0.11*	*0.28* ***	*0.19*	*1.60*

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

The effects of the trial on the distance covered by different modes, and modal splits, are presented in Table 4. On average, the treatment group decreased the distance made by car by 17.3 km per person and day between M1 and M2, while increasing the distance made by bicycle and e-bike by 1.1 km (non-significant) and 3.4 km, respectively. Consequently, the total cycling (the sum of regular cycling and e-cycling) increased on average from 1.8 km at M1 to 6.4 km at M2. During the same period, the control group decreased the distance made by car by 2.9 km and the distance made by bicycle by 0.7 km, (both changes non-significant). Between M1 and M3, the control group decreased the distance made by car by 10 km on average (non-significant), while increasing the distance made by bicycle and e-bike by 0.5 km (non-significant) and 5.4 km, respectively. The total cycling increased on average from 1.7 km from M1 to 7.6 km at M3.

The treatment group decreased their car use as the share of total distance travelled by 18% and increased the share of e-cycling by 12% and the share of conventional bicycling by 5%. For the control group, there were no significant changes from M1 to M2. At M3, however, the control group had decreased their car use as the share of total distance travelled compared to M1 by 14% and increased their share of e-cycling by 14%.

The results reported in Tables 3 and 4 are aggregated for the participants in Skövde and Trollhättan. To get an external validation of the results in Skövde [4] it is also interesting to evaluate Trollhättan in isolation. The outcomes from the two case studies were similar, with a sharp and significant reduction in car travel during the test period, expressed both as the number of trips and distance. In both places, the increase in e-cycling was significant, but the effect was smaller in Trollhättan. This affected the total share of cycling before and during the test period, where the increase was greater in Skövde (from 5% to 26%) than in Trollhättan (from 4% to 18%). However, the general trend from the e-bike trials was similar, most notably that the entire increase in e-cycling was at the expense of car use.

An interesting observation that we did not attach much importance in the previous study in Skövde, but which was also repeated for the sample in Trollhättan is that the total travel measured in distance decreased when the participants gained access to the e-bike. In total, the decrease was about 20% in Skövde and 30% in Trollhättan, for the treatment groups. This could be due to the participants switching to more nearby destinations for the same type of errands, thereby shortening the distance during the trial period compared to before. However, we have not been able to fully explore this possibility, and the conclusion is therefore only preliminary.

The effect sizes were medium for the decrease in car trips (d = 0.5–0.6), medium to large for the decrease in car distances (d = 0.6–1.1) and high for the effect on e-bike trips and distance covered by e-cycling (d = 2.8–49.9) as referred to by previous research [63].

Table 4. Paired-samples t-tests on modal shares in relation to the average distance travelled per day at M1 and M2 for the treatment and control group as well as M1 and M3 for the control group. Based on 2000 bootstrap samples. Means, standard deviations, and Cohen's d effect sizes (significant differences).

	Treatment Group					**Control Group**						
	M1		**M2**			**M1**		**M2**		**M3**		
	Km	**SD**	**Km**	**SD**	***d***	**Km**	**SD**	**Km**	**SD**	**Km**	**SD**	***d***
Car	38.52	29.87	21.18 **	19.38	0.58	40.21	26.61	37.31	32.14	30.20	32.26	
PT	0.31	0.84	0.01	0.04		0.36	1.80	0.75	4.19	0.10	0.33	
Bicycle	1.53	2.27	2.63	4.58		1.68	3.17	1.03	1.90	2.21	3.13	
E-bike	0.27	1.24	3.72 *	6.99	2.78	0.00	0.01	0.10	0.61	5.43 **	3.93	n/a
Walk	0.55	0.77	0.40	0.70		0.72	0.77	0.69	1.11	0.70	0.82	
Total	41.18	45.78	27.94 *	16.06	0.29	42.97	24.35	39.88	32.67	38.64	22.94	
B & e-b	*1.80*	*2.62*	*6.35* **	*5.64*	*1.74*	*1.68*	*3.17*	*1.13*	*1.94*	*7.64* ***	*7.01*	*1.88*
						Modal Share						
Car	0.94	0.23	0.76 ***	0.27	0.82	0.94	0.18	0.94	0.28	0.78 ***	0.22	1.05
PT	0.01	0.14	0.00	0.00		0.01	0.08	0.02	0.07	0.00	0.02	
Bicycle	0.04	0.15	0.09 *	0.22	0.45	0.04	0.15	0.03	0.18	0.06	0.10	
E-bike	0.01	0.04	0.13 **	0.21	2.59	0.00	0.00	0.00	0.07	0.14 **	0.24	n/a
Walk	0.01	0.05	0.01	0.18		0.02	0.02	0.02	0.19	0.02	0.06	
B & e-b	0.04	*0.17*	0.23 ***	*0.25*	*1.10*	0.04	*0.15*	0.03	*0.19*	0.20 ***	*0.22*	*1.26*

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

4.2. Path Analysis

The proposed model was put to the test with data from the 60 participants in the PA sample and was set up following the hypotheses as described in Section 2. Firstly, we turn to the model fit parameters. Previous research suggest good model fit in general to have a CFI value larger than 0.95 and RMSEA value smaller than 0.06 [64], and for models with sample sizes smaller than 250 it is recommended to have an insignificant Chi-square value, a CFI of 0.97 or better (i.e., higher) together with an RMSEA value smaller than 0.08 [65]. The fit of the current model was not ideal, with a Chi-square value of 36,281 with 24 degrees of freedom (p = 0.052), a CFI value of 0.896 and an RMSEA value of 0.093. The modification indices suggested correlating personal norm and collective efficacy to gain model fit. Including correlations between exogenous factors often makes the estimates for the dependent relationships more reliable [65], and such a path was added. Re-running the model returned good model fit measures (Chi-square = 25,550, df = 23 (p = 0.323), CFI = 0.978, RMSEA = 0.043).

The result of the estimated path model, with unstandardised path coefficients for direct and indirect effects, is presented in Table 5, and standardized path coefficients and proportions of explained variance for the endogenous factors are presented in the path diagram (see Figure 3). The expected effects were all significant except for the paths from habit, social norm and PBC to intention, and the paths from PBC and habit to behaviour. The low internal consistency of social norm and PBC could be the reason for their non-existent effects. To check for their influence, the model was estimated without social norm and PBC, which did not change the estimates or explained variance of the full model, although the model fit was slightly enhanced. Thus, based on the principle of parsimony, SN and PBC would be omitted from the model. However, this would transcend the analysis from confirmatory to explanatory and the model was therefore kept in accordance with the a priori theory.

Intention had a positive effect on e-bike use, and attitude and self-efficacy, in turn, influenced intention. Self-efficacy also had a direct positive effect on attitude, and self-efficacy, in turn, was predicted by collective efficacy. Personal norm had a positive influence on attitude and a negative effect on habit. Collective efficacy had an indirect effect on attitude and intention. There was also an indirect effect from personal norm to intention. Further, attitude and self-efficacy predicted behaviour indirectly.

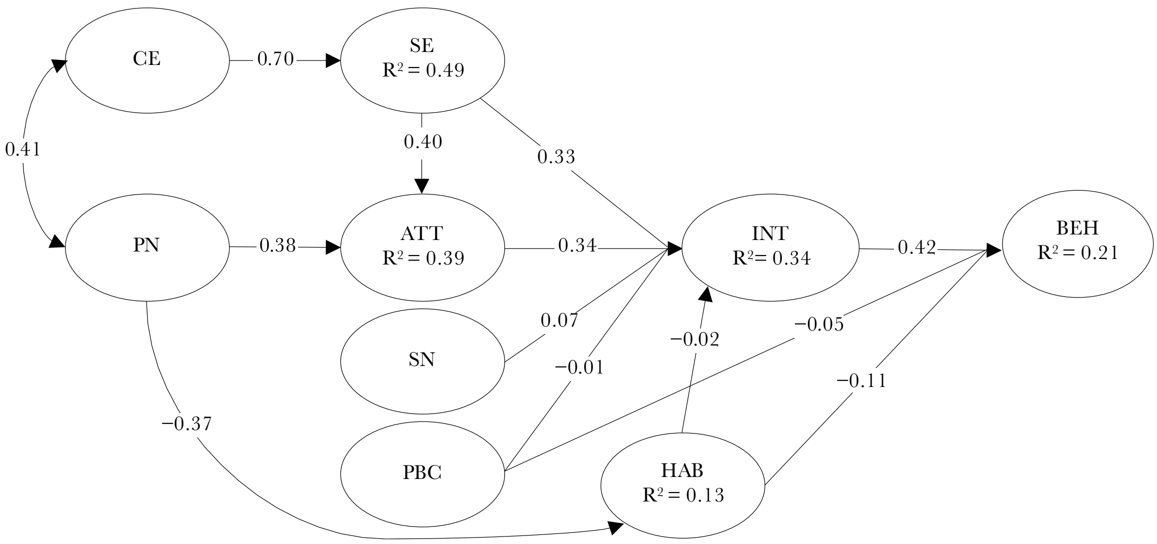

Figure 3. Summary of path analysis with standardized path coefficients indicating strength of predicted relations. Exogenous factors: collective efficacy (CE), personal norm (PN), subjective norm (SN), and perceived behavioural control (PBC). Endogenous factors: self-efficacy (SE), attitude (ATT), habit (HAB), intention (INT), and behaviour/e-bike use (BEH).

Table 5. Direct and indirect effects.

Unstandardised Direct Effects			***β***	**Unstandardised Indirect Effects**					***β***
CE	→	SE	0.890 ***	CE	→	SE	→	ATT	0.012 **
SE	→	ATT	0.014 ***	CE	→	SE	→	INT	0.017 *
PN	→	ATT	0.181 ***	SE	→	ATT	→	INT	0.008 *
PN	→	HAB	−0.385 **	PN	→	ATT	→	INT	0.106 *
SE	→	INT	0.019 **	PN	→	HAB	→	INT	0.006
SN	→	INT	0.097	PN	→	HAB	→	BEH	0.088
ATT	→	INT	0.583 **	SE	→	INT	→	BEH	0.021 *
PBC	→	INT	−0.012	PBC	→	INT	→	BEH	−0.013
HAB	→	INT	−0.015	SN	→	INT	→	BEH	0.106
INT	→	BEH	1.085 ***	ATT	→	INT	→	BEH	0.632 *
HAB	→	BEH	−0.228	HAB	→	INT	→	BEH	−0.016
PBC	→	BEH	−0.136						

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

To conduct the mediation analyses within the path model, specific indirect effect analyses were conducted, requesting 5000 bootstraps resamples with 95% bias-corrected confidence intervals, which is preferred to the conventional Sobel's test approach [66] that carries the assumption that the sampling distribution of the indirect effect is normal when in reality it tends to be asymmetric [67]. Mediation can be established if zero lies outside the 95% confidence interval of the unstandardized indirect effect [68], and according to [69], full mediation (or indirect-only mediation) occurs when the direct effect between the independent variable (IV) and dependent variable (DV) is non-significant, while partial (complementary) mediation exist when this relationship is significant and the Beta score for IV→M × M→DV × IV→DV is positive.

The results from the mediation analyses are presented in Table 6. Regarding the indirect effect of personal norm on intention, and consistent with the hypothesis, attitude was mediating the effect. However, the mediation was only partial, meaning that personal norm could exert influence on intention through an additional mediator not included in our model. Attitude was also partially mediating the effect from self-efficacy to intention. A full mediation between self-efficacy and e-bike use through intention was observed. Likewise, intention fully mediated the effect of attitude on e-bike use.

Table 6. Results from mediation analysis. Based on 5000 bootstrap samples with 95% bias-corrected confidence intervals.

				95% CI		**Direct *β***			
IV	**M**	**DV**	**Indirect *β***	**Lower**	**Upper**	**IV→M**	**M→DV**	**IV→DV**	**Mediation**
PN	ATT	INT	0.115 *	0.016	0.307	0.181 **	0.633 *	0.232 *	Partial
SE	ATT	INT	0.008 *	0.002	0.020	0.014 **	0.583 *	0.030 ***	Partial
SE	INT	BEH	0.021 *	0.001	0.052	0.019	1.085	0.032	Full
ATT	INT	BEH	0.637 *	0.070	1.647	0.583 *	1.093 *	0.883	Full

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

To test the hypothesised moderating effect of collective efficacy on the relationship between self-efficacy and intention, the CE and SE variables were z-standardised (i.e., mean-centred) [70]. The interaction term was then computed by multiplying SE with CE. The full path analysis was then re-estimated with the new z-standardised SE and CE variables and the interaction term predicting intention.

The model fit measures were acceptable (Chi-square value of 32.519 with 29 degrees of freedom (p = 0.298), a CFI value of 0.972 and an RMSEA value of 0.045). The interaction term was significantly predicting intention (Beta = 0.263, p = 0.017) while SE and CE were non-significant (Beta = 0.242, p = 0.347 and Beta = 0.264, p = 0.137, respectively). This suggests that collective efficacy indeed is acting as a moderator on the relationship between self-efficacy and intention. To better understand how moderation influences the positive relationship between self-efficacy and intention, and to ease interpretation, the effect from a two-way interaction was plotted with values that are one standard deviation above and below the mean [70].

The result of the two-way interaction shown in Figure 4 demonstrates that the relationship between self-efficacy and intention is always positive, but greater for participants with high collective efficacy (the dotted line) than for those with low collective efficacy (the solid line). Thus, collective efficacy strengthens the effect from self-efficacy to intention. The effect size was small but significant (d = 0.35). The results of the hypotheses are presented in Table 7.

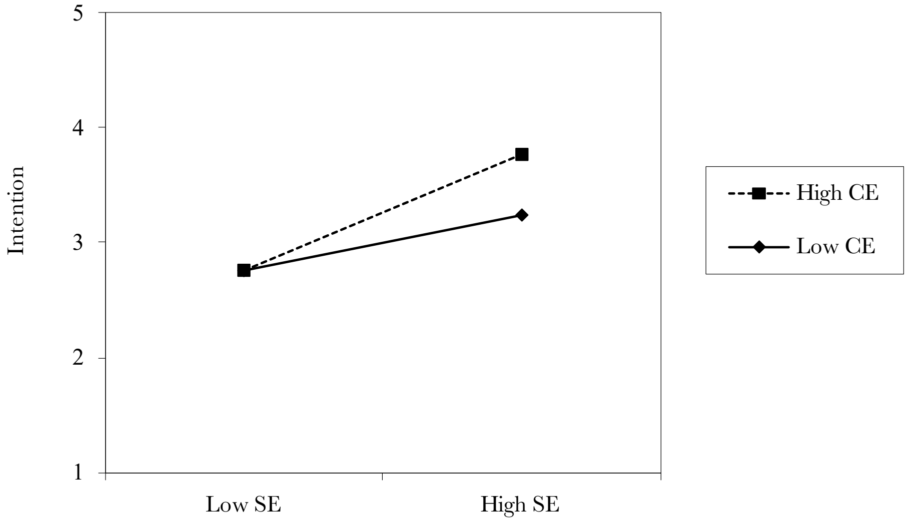

Figure 4. Moderating effect (two-way interaction) of collective efficacy on the positive relationship between self-efficacy and intention.

Table 7. Results for the hypotheses.

Hypotheses		**Results**
a	Intention and PBC will have a positive effect on e-bike use.	Supported for attitude
b	Habit will negatively affect intention and e-bike use.	Rejected
c	Attitude, social norm, and PBC will positively affect intention.	Supported for attitude
d	Intention mediates the effect of attitude, social norm, and PBC on e-bike use.	Supported for attitude
e	Self-efficacy affect attitude positively.	Supported
f	Self-efficacy will have a positive effect on intention.	Supported
g	Attitude mediates the positive effect from self-efficacy to intention.	Supported
h	The effect of self-efficacy on e-bike use is mediated through intention.	Supported
i	Collective efficacy will positively influence self-efficacy.	Supported
j	Collective efficacy moderates the effect of self-efficacy on intention.	Supported
k	Personal norms affect attitude positively.	Supported
l	Attitudes mediate the relationship between personal norm and intention.	Supported
m	Personal norm has a negative effect on habit.	Supported

5. Discussion

This study reports the substitution effect of e-bikes as well as the underlying psychological processes behind e-cycling, based on two randomised controlled e-bike trials conducted in Sweden.

5.1. The Effect of the E-bike Trials on Travel Behaviour

For the treatment group, both conventional cycling and e-cycling increased due to the e-bike trial, averaging an increase in bike distance of 4.5 kilometres per person and day. As a result, the modal share of cycling, expressed in distance, went from 4% before the intervention to 23% during. The increase was accompanied by a significant decrease in car trips and car mileage. Since no other mode of transport decreased significantly, one can say that principally, the whole increase was at the expense of car use. However, the large reduction in car distance was mostly due to a decrease in total kilometres travelled (14 kilometres or 30%). This was more than for the participants in the control group when they got access to the e-bikes, as well as the results obtained for both the treatment and control group (with e-bikes) in Skövde [4]. For these three groups, the reduction in total travel distance was around 20%. Nevertheless, the question arises why the participants reduced their amount of travel so extensively? There are two possible explanations, the first being that the participants switched to more proximal destinations when having access to the e-bikes, or secondly, that they intentionally cut back on driving due to participating in the trial. If it were to be the latter, would the observed travel behaviour hold over time, with the assumption that the participants acquired an e-bike post-intervention? Recent studies suggest, contrary to common prejudice, that eventual changes in travel behaviour from behavioural interventions tend to last over time [71,72]. The next question would then be how many actually acquired an e-bike, and how many kept cycling, after the trial? Due to time constraints, the researchers within the project did not conduct any more evaluations than already reported. However, the partner organisation VGR (Västra Götalandsregionen) conducted a survey 4–5 months later with the participants in Skövde. Of 98 contacted, 81 individuals responded to the survey, of which 44% stated that they cycled more to everyday activities than before the trial, and 16–26% that they bought an e-bike after the intervention.

5.2. Psychological Constructs Determining E-bike Use

To get an insight into why the observed changes occurred, psychological constructs were measured alongside the collection of travel data. This allows us to see beyond the average effect that came with the e-bike trial and form a better understanding of which determinants influence the decision to e-cycle.

The proposed path-analytic model was able to predict the extent to which the participants e-cycled, although explained variance was not very high. Intention explained around 20% of the variance in behaviour and mediated the effects of attitudes and self-efficacy, which were the two most important determinants predicting intention. The effect on intention from self-efficacy was partly mediated by attitudes, suggesting that higher perceived ability to e-cycle is related to more favourable attitudes towards e-bikes, which influence intention to e-cycle positively. Consequently, more favourable attitudes toward e-cycling and higher perceived self-efficacy for e-cycling positively influenced e-cycling, supporting the theories by Ajzen [25] and Bandura [27]. Perceived behavioural control and social norm did not significantly predict intention which could be due to their low internal consistency. The two items that constituted PBC were partly pulling in opposite directions, demonstrating the weakness in combining perceived difficulty with perceived control in one composite construct [37]. An individual might feel perfectly confident in her ability to use the e-bike, while at the same time being uncertain about external factors, such as family needs, which may not be under complete volitional control. Future studies might therefore benefit from separating perceived difficulty and perceived control.

Habit was expected to influence intention to e-cycle and observed e-bike use; however, this was not supported by the empirical model. The non-significant path from habit to intention and e-bike use could be due to the nature of the intervention, in which all participants had already adjusted their automatic travel habit by signing up for the trial. Personal norm, on the other hand, did have a negative influence on habit, suggesting that strong moral concerns about the environment dampen the strength of habitual, non-reflective, car use. Personal norm further had an indirect effect on intention to e-cycle more for work, and its effect was partly mediated through attitudes. This goes in line with earlier studies demonstrating that moral concerns exert an indirect effect on pro-environmental behaviours [36], and increase the predictability of modal shift intentions, motivation and travel behaviour [46,50,73,74]. The role played by personal norm may thus be twofold, on the one hand strengthening pro-environmental attitudes while at the same time reducing habit strength, which is important for modal shift to take place [32,75].

According to Bandura [28], perceived collective efficacy fosters a group's motivational commitment to their missions, resilience to adversity, and performance accomplishments. Believing in the capability of others could also lead to increased self-confidence, and, indeed, it was found that the effect of self-efficacy on the intention to e-cycle was moderated by collective efficacy. In other words, an important indirect effect was that collective efficacy amplified the relationship between perceived self-efficacy to use the e-bike and intention to e-cycle. This finding not only lends support to the suggestion that perceptions of individual ability are elevated when people perceive their group as efficacious [43] but further demonstrates that this relationship also has an indirect effect on pro-environmental travel behaviour. Exchanging car trips for cycling is at least partly associated with environmental action, which in turn suffers from the social dilemma issue, where one's efforts to tackle climate change may feel worthless by the inaction of others [76]. Thus, a strong sense of collective efficacy is essential for turning perceived individual powerlessness in the face of global climate change into personal action [39]. For any individual, using an e-bike instead of a car does not solve the climate change issue, but acting as part of a group, be it within the household, the workplace, an online community, or society at large, people may feel that their actions matter.

5.3. Implications for Policy

This study provides a strong case for policy makers that seek to promote e-cycling as a sustainable mode of transport. The results show that e-bikes can be a realistic alternative to the car, even for habitual car users, and that large potentials for environmental gains (not to mention physical activity) exist due to a significant substitution effect from car to the e-bike. The focus of this study was commuting trips and this particular errand could be a good starting point for promoting e-cycling [4]. Planners can facilitate e-bike use by crafting campaigns that strengthen favourable attitudes towards e-cycling and perceived abilities to e-cycle. Further, intention to e-cycle could be increased by promoting it as a green modal choice and making it social so that individuals feel part of a collective when choosing to e-cycle. For company managers, offering e-bikes to employees to be used for business trips or as a benefit could result in more sustainable commuting trips.

5.4. Limitations

Some limitations of the present study should be mentioned. The sample of participants in this study was not representative of the general population in the examined municipalities, but rather, reflected a car-oriented segment willing to participate in the e-bike trial. As such, the substitution effect reported here may be in the upper bound, as the potential for substitution was high. On the other hand, these kinds of samples are often the target population in real-life interventions to decrease car use, and therefore, the results of this study are of high relevance in practice. Another limitation is that the analysis was constrained for commuting trips, meaning that the results from the path analysis might not be the same for other types of trips, for instance, recreational trips. More research is needed on what motivates other types of e-bike trips. Further, the low internal consistency of social norm and perceived behavioural control makes it difficult to establish the influence that these components could have had in the path analysis. Conducting a path analysis as done in this study warrants a note on cause and effect. To establish causality, four conditions must be present [65]: (1) covariation, (2) temporal sequence, (3) nonspurious association, and (4) theoretical support. A limitation is that the possibility of spurious relationships cannot be ruled out due to some lurking variables not measured in the study. However, for the significant effects obtained in the model, the assumptions of covariation and theoretical support were met, and for the intention-behaviour effect temporal sequence can be added, since the survey items were measured before the collection of travel data, which makes the causal inference more robust.

6. Conclusions

The aggregated results from two randomised controlled e-bike trials with a sample of frequent drivers showed that total cycling increased by 4.5 kilometres per person and day and its modal share measured in distance went up from 4% pre-intervention to 23% during the trial. A larger significant reduction in car use, both in the number of trips and distance, was observed, which was partly attributed to the e-bike substitution but mainly to a reduction in total trips and distance travelled. E-bike use was predicted by the intention to bike to work, which in turn mediated the effects of attitudes and self-efficacy on e-cycling. Attitude mediated the indirect effect of personal norm on intention, and collective efficacy moderated (strengthened) the effect of self-efficacy on intention. Thus, campaigners could increase the use of e-bikes by strengthening individuals' attitudes toward cycling as well as perceived self-efficacy with e-cycling. Further, making personal norms more salient by emphasising environmental consequences in choosing modes of transport, and highlighting collective action within this context, could boost pro-environmental behaviours.

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Author Contributions

A.S. developed the study design and the survey, analysed the data, did the modelling and wrote the original manuscript as was responsible for the review and editing work.

Conflicts of Interest

The author declares no conflict of interest.

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Appendix A

Table A1. Composition of the factors used in the path-analysis, with Cronbach alpha, mean, and standard deviation.

	Mean	SD
Intention [a] (α = 0.90)	4.25	1.19
I will try to use the bike more to get to work from now on		
I intend to cycle more to work from now on		
Attitude [a] (α = 0.77)	4.54	0.69
You think that taking the bike to work would…		
… be inconvenient		
… be relaxing		
… be good for the environment		
… give me a sense of freedom		
… take long time (reversed)		
… save me money		
… be boring (reversed)		
… be good for my health		
Subjective Norm [a] (α = 0.54)	2.58	0.86
It is common for people I know to cycle to work		
The people whose opinions I value highly cycle to work		
I am expected to cycle to work by my peers		
The people whose opinions I value highly think that I should cycle to work		
Perceived Behavioural Control [a] (α = 0.40)	3.99	1.03
Cycling to work would be easy for me		
It is entirely up to me to decide whether I cycle to work or not		
Habit [a] (α = 0.73)	3.91	1.49
I take the car to work without thinking much about it		
Taking the car to work is done automatically for me		
Personal Norm [a] (α = 0.89)	3.73	1.42
I personally feel that it is important to think about the environment in my everyday behaviour		
Personally, I feel that it is important to travel as little as possible with vehicles that run on fossil fuels		
I feel a moral responsibility to reduce my greenhouse gas emissions by driving less		
I get a bad conscience when I take the car to work		
Self-efficacy [b] (α = 0.89)	59.55	22.01
Assuming I have access to a bicycle, I can…		
… start a new habit where I cycle to work more often than I take the car		
… keep that habit for an extended period of up to 6 months		
… cycle to work on a rainy day		
… cycle to work a stressful morning		
… contribute to a better environment by cycling more instead of driving		
… reduce the climate impact by cycling more instead of driving		
Collective Efficacy [b] (α = 0.86)	53.46	16.64
In general, we as a group can…		
… start a new habit where we cycle to work more often than we take the car		
… keep that habit for an extended period of up to 6 months		
… cycle to work on a rainy day		
… cycle to work a stressful morning		
… contribute to a better environment by cycling more instead of driving		
… reduce the climate impact by cycling more instead of driving		

[a] = 1 (strongly disagree) to 7 (strongly agree); [b] = 0 (no confidence) to 100 (complete confidence)