

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

IET Intelligent Transport Systems

December 2018

Copyright 2018 Institution of Electrical Engineers All Rights Reserved

Section: Pg. 1421 - 1432; Vol. 12; No. 10; 1751-956X

Length: 8257 words

Byline: BingyuanHuang, b.huang@utwente.nl

TiagoFioreze

TomThomas

EricVan Berkum

Body

1

Introduction and background

Road transport contributes about one-fifth of the EU's total emissions of carbon dioxide according to the European Commission [1]. Another worrying societal issue is that the population in every EU country will be more obese by 2030, unless Europe's governments take immediate action, according to new projections released by the World Health Organisation [2]. Active forms of transport, especially cycling, can provide part of the solution for both challenges. Cycling is an environmentally friendly mode of transport and a very effective way to increase physical activity. Several studies have shown that cycling has a protective effect on cardiovascular outcomes [3] and is inversely associated with body mass index, obesity, triglyceride levels, and insulin levels [4]. Particularly cycling to work may be a feasible way to achieve the half hour of activity per day as commonly recommended [3, 5].

Cycling can be promoted through 'hard' measures (e.g. physical improvements to infrastructure, fiscal regulations, or even prohibition of car use) as well as by 'soft' measures (e.g. travel planning, subsidies, marketing, rewards, and discounts) to encourage citizens to reconsider their travel choices. Recently, it has become a common objective of transport authorities to reduce car use through the use of soft measure in the form of positive interventions [6–8].

In this study, we present results of a study in the use of positive interventions to promote sustainable travel behaviours, specifically cycling. Table 1 lists several case studies in which such incentives were employed to promote cycling.

Table 1 Overview of behavioural change techniques and intervention effectiveness

Study/sample sizes	Rewards/incentives/interventions	Effectiveness of intervention	Design
Baum [9] (600)	in-kind gifts, feedback, education, comparing with others and trip	increase of cycling and walking trips by 33% relative to the control	before-and-after survey with the control group; but different people

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Study/sample sizes	Rewards/incentives/interventions	Effectiveness of intervention	Design
Dubuy <i>et al.</i> [10] (110 joined)	diaries random monetary rewards, comparing with others	neighbourhood more than half participants reported no behaviour change. The barriers are mostly distant to work but not linked to the interventions.	after survey; before-and-after comparison; self-reported data
Steven and Avineri [11] (248 joined)	monetary rewards, personal goals, and planning	cycling to work increased. 51% were already cycling to work and continued to do so.	after survey; before-and-after comparison; self-reported data
Wen <i>et al.</i> [12] (68)	individualised marketing strategies: in-kind gifts and tailored travel plan	no significant results on changing active transport as the usual mode to work. Car trips have no significant decrease on working days but Sundays.	before-and-after survey and comparison; self-reported data
Usui <i>et al.</i> [13] (74)	personal goals and planning, feedback, and education	car use decreased by 20.1%. Travel on foot and by bicycle increased by 82.2%, while public transport use increased by 103%.	global positioning system (GPS) tracking without a control group; a before-and-after comparison
TravelSmart project [14] (1010)	social reward (praise), goals, and planning	the comparison among interventions shows the cycling and walking maps were the most effective tools to encourage people to walk more.	survey with stratified sampling method self-reported data
individualised Travel Marketing?IndiMarks [15] (?800 each study)	providing tailored information, advice, and incentives (such as a cycle trip computer or a pedometer)	travel-behaviour change achieved by IndiMark has consistently been in the range of a 5?15% reduction in car-as-driver trips. However, most of the mode change is the public transport increasing. no significant bike trip increase.	after survey; before-and-after comparison; self-reported data; few studies using GPS equipment.
Wardman <i>et al.</i> [16] (1000); Ryley [17] (654)	monetary rewards	first one proved that monetary reward is effective for traveller's intention behaviour change. Second one is on the contrary.	stated preference survey.

As Table 1 shows, tangible rewards such as money and in-kind gifts are often used to promote cycling, together with information that may motivate travellers to change their behaviour, such as feedback on past behaviour, setting of goals and planning behaviour change, and comparing their behaviour with that of others. In addition, at least three reviews have been carried out to investigate the effectiveness of such interventions on cycling [18–20]. Nearly all showed positive effects.

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

The majority of studies, which focused on positive interventions in Table 1, analysed interventions in field experiments. Most of them are general interventions that are the same for everyone, not personalised based on historic behaviour and personal needs. This is not the case for travel behaviour change schemes such as described by Wen *et al.* [12] and used in the TravelSmart project [14], which provide personalised travel plans and feedback by phone call interview and showed that individualised marketing of interventions helps change travel behaviour in an effective way. However, such programs are quite labour-intensive and therefore difficult to scale up to large numbers of participants.

This may be changing, though, with the aid of smartphone apps that can automatically detect travel behaviour and provide rewards accordingly, such as Strava, Fietstelweek, CycleMaps, and BetterPoints. However, so far only [13] used smartphone apps to study the effects of positive incentives on cycling in a field study. Similar studies that did not focus on cycling have proven that interventions through mobile technologies can successfully stimulate sustainable travel behaviour (e.g. [6, 21–23]).

Although field experiments with smartphones can measure behaviour change, they also have some drawbacks. They require a lot of commitment from participants. As a result, samples are relatively small (at most a few hundred respondents [6]), and are probably biased due to self-selection; i.e. participants who are already willing to cycle are more likely to participate. Moreover, external factors, such as weather [24] and events, have a strong influence on cycling demand. These factors interfere with the positive incentives. Control groups can be used to determine the external effects. In this type of experiment, the use of control groups is, however, quite hard (only one study has 23 participants in a control group [22]), because there is little incentive for people to participate; i.e. there is a burden of using the app, but no benefits in the form of positive incentives such as rewards.

Due to these drawbacks, it is difficult to make comparisons between incentives or between segments of the population. Only the TravelSmart project [14] made such comparisons. Comparisons between studies are even harder. For example, Ryley [17] found that a financial incentive of £2 per day would not induce or increase cycle commuting, while Wardman *et al.* [16] argued that an incentive of £2 per day can almost double the amount of cycling. It is not clear whether these differences are real or the result of the aforementioned selection and/or external effects. Furthermore, according to some studies, in-kind gifts can be a good alternative to money [6, 25]. However, Shaffer and Arkes [26] concluded that this is only the case when money and in-kind gifts are not offered simultaneously because a direct comparison between non-cash and cash incentives makes the fungibility of the cash reward more visible.

This study tries to overcome these issues by designing a controlled experiment using a stated intention survey with multiple incentives. Respondents got a neutral invitation to participate in a smart mobility experiment (without mentioning cycling), and the respondents' burden is limited. As a result, we obtain a relatively large sample, and we reduce the self-selection bias. To make the experiment as realistic as possible, we used mock-up apps with which participants could interact (as with a real app), and we personalised the incentives by including actual travel behaviour of the participants. In doing so, we can compare incentives and test which one may be most successful.

Overall, we think that people who never cycle (non-cyclists) may need other incentives to start cycling than people who already cycle but could still cycle more (occasional cyclists). We also expect differences between young and older people, between highly and lowly educated people, and between males and females, with the former groups probably more likely to cycle more when positive incentives are provided [27]. In this study, we test these assumptions with segmentation analyses that are mostly lacking in other studies.

The paper is organised as follows. Section 2 explains the methodology. Section 3 describes the design of the pilot study and data collection. Section 4 presents the results of the analyses and Section 5 provides conclusions.

2

Methodology and design

Section 2.1 introduces the positive incentive schemes and the mock-up apps, and the motivation for their design based on the literature. Section 2.2 details the multinomial logit model to quantify and interpret the outcomes.

2.1

Incentive schemes and mock-up design

In order to investigate the effect of different reward schemes delivered through smartphone technologies, we designed five intervention schemes. Based on the work of Zhang *et al.* [28] and Ben-Elia and Ettema [6], we included travel context, travellers' attitudes, and demographics as discriminating factors between groups. Fig. 1 summarises the research framework, including the interventions. We distinguished between respondents who never cycle (non-cyclist group (NCG)), respondents who cycle occasionally (occasional-cyclist group (OCG)), and respondents who cycle daily (daily-cyclist group (DCG)). This was done as, e.g. Oinas-Kukkonen and Harjumaa [29] and Khaled *et al.* [30] argued that incentives can be more effective when they relate to the actual behaviour of the user.

Fig. 1 Research framework

Table 2 lists the five intervention schemes, built on principles with a high potential according to our literature studies, such as goals, feedback, and rewards. According to goal setting theory [31], goals and planning, feedback and motioning, and rewards give the best results when they are combined [30, 31]. The types of rewards, however, were different in the various studies, such as cash rewards, in-kind gifts, and praise [6, 15, 28]. With this in mind, we composed our first three intervention schemes based on cash rewards, in-kind gifts, and praise. Furthermore, a study by Landers *et al.* [32] concluded that presenting specific goals on a leaderboard can have a similar effect as traditional goal setting and Dubuy *et al.* [10] showed that this also applies for the promotion of cycling. We, therefore, used individual tasks, combined with feedback, self-monitoring, rewards and social influence in intervention schemes 4 and 5. In scheme 4, we tested the potential of competition (individual goal), whereas, in scheme 5, we investigated the potential of cooperation (collective goal).

Table 2 Incentive schemes

Type of scheme	Scheme	Goals and planning	Feedback and motioning	Incentive s/rewards	Social influence	Target group	Mock-up
schemes 1, 2 & 3: private challenge	scheme 1: monetary reward	self-set challenge for increasing cycling frequency and distance	visual historical performance	monetary reward		non-cyclist and occasional cyclist	mock-up money
	scheme 2: tangible reward	self-set challenge for increasing cycling frequency and distance	visual historical performance	tangible reward points		non-cyclist and occasional cyclist	mock-up in-kind
	scheme 3: social reward	self-set challenge for increasing cycling frequency and distance	visual historical performance	social reward badges		non-cyclist and occasional cyclist	mock-up social

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Type of scheme	Scheme	Goals and planning	Feedback and monitoring	Incentive s/rewards	Social influence	Target group	Mock-up
scheme 4: competition (comp)		cycle more than others	leaderboard visual historical performance	tangible reward points for gifts	leaderboard competition	occasional cyclist and daily cyclist	mock-up competition
scheme 5: cooperation (coop)		work with others to increase cycling frequency and increase engagement	leaderboard progress bar of team performance visual historical performance	group tangible reward points for gifts, social rewards, personal performance with a prize	leaderboard cooperation	occasional cyclist and daily cyclist	mock-up cooperation

We created five mock-ups to visualise the incentive schemes in order to make the experience of interacting with the smartphone app as realistic as possible (Fig. 2). In general, the five mock-ups were similar, except for the screen with the incentives. Fig. 2*b* displays the home screen, which shows a fictional user's cycling stats. The bottom icons can be clicked to join a challenge (Fig. 2*a*), get feedback on bicycle commutes (Fig. 2*b*), and to check the user's rewards (Fig. 2*c*). Fig. 2*c* depicts a scenario in which the app user is rewarded with money. With respect to the incentive scheme using tangible rewards, the design of the mock-up is the same as for the monetary reward scheme, except that instead of money, points are awarded that can be exchanged for a real object from Fig. 2*f*. In the incentive scheme with social rewards, we replaced money by various levels of badges. Figs. 2*d* and *e* depict the challenge and leaderboard in the social influence schemes. The other parts in the social influence scheme mock-ups are the same as in the private challenge mock-ups.

Fig. 2 Screens in the mock-ups

(a) Goal/planning and reward system, (b) Feedback and monitoring, (c) Reward result, (d) Social influence intervention, (e) Social intervention leaderboards, (f) Variety of in-kind gifts scheme

2.2

Multinomial logit model

Our study examined how incentive schemes combined with current travel behaviour and personal characteristics may influence intentional travel behaviour changes and commuting app usage (cases 1 and 2 in Table 3), as well as how current travel behaviour and personal characteristics may relate to the choice for a certain incentive or reward (case 3 in Table 3). Those three cases contain the following choices: (i) considering using the app or not, (ii) motivated to cycle more or not, and (iii) the preferred incentive or reward. To make a quantitative analysis based on those choice-related cases, we used a multinomial logit model. Note that a positive response in cases 1 (app case) and 2 (cycle case) to the question listed in Table 3 can be either viewed as confirmative (i.e. 'consider' and 'yes', respectively) or as not negative (i.e. 'might or might not consider' + 'consider' and 'I don't know' + 'yes', respectively). We took the confirmative answers and the non-negative answers to indicate 'positive' responses.

Table 3 Description of three multinomial logit model cases

Case (choice action)	Question	Choice option	In-model choice option	Model
----------------------	----------	---------------	------------------------	-------

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Case (choice action)	Question	Choice option	In-model choice option	Model
(1) app usage (app case)	would you consider using this app to cycle to your workplace?	consider, might or might not consider, would not consider	consider, combined choice: consider and might or might not consider, wouldn't consider (reference)	three separate equations for three travel patterns
(2) motivation to cycle (cycle case)	would the interventions motivate you to cycle (more) to your workplace?	yes, I don't know, no	yes, combined choice: yes and i don't know, no (reference)	three separate equations for three travel patterns
(3) preferable incentive/reward (incentive case)	you have been introduced to one reward scheme. However, other reward schemes are being taken into consideration. Which kind of reward scheme would motivate you the most to cycle to your workplace?	no rewards. Personal recognition (i.e. compliments or badges, for example). In-kind gifts (i.e. redeeming points, which can be exchanged for products and/or experiences to your liking). Money. cooperation with others. Competition against others. Others	no rewards. In-kind gifts. Money. Gamifications: combined cooperation with competition. Others: combined others with personal recognition	one equation for all respondents

In the multinomial logit model, the probability of a respondent choosing alternative i , ($i = 1, 2, \dots, m$) is written as (1)

$$P_i = \frac{\exp(U_i)}{\sum_{j=1}^m \exp(U_j)}.$$

In (1),

U_i

is the systematic component of the utility of alternative (outcome) i . The utility function is given as (2)

$$U_i = \log \frac{P_i}{P_m} = \alpha_i + \beta T + \gamma IV + \delta AT + \theta AC + \omega SC + \epsilon_i.$$

In (2),

U_i

is an unobserved variable representing the utility of alternative i ,

α_i

is the alternative-specific constant for alternative i , β and T are the coefficients and attributes for the traffic characteristics (i.e. commuting distance and travel patterns), γ and IV are the coefficients and attributes for the intervention characteristics (namely social reward, in-kind gift reward, money reward, cooperation, and competition rewards), δ and AT are coefficients and attributes for the attitude characteristics (i.e. attitude about travel modes and attitude about cycling), θ and AC are the coefficients and attributes for the cycling app usage characteristics, ω and SC are the coefficients and attributes, respectively, for the demographic characteristics (i.e. gender, age, nationality, income, and education level), and

ϵ_i

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

is the random error term.

The coefficients of the utility functions were estimated with respect to a base case. The alternative m is the reference category or base case. All obtained choice actions have to be interpreted relatively to this reference, which is shown in (2). For example, in case 1 (see Table 2), the choice 'wouldn't consider using the app' is the reference. We used dummy variables to represent the factors considered in the analysis. If there were n dichotomous variables, $n - 1$ variables were used for each category to prevent multicollinearity. For example, with the gender category, the reference used was 'male' and the estimate for 'female' was analysed relative to the 'male' reference variable.

Coefficients were estimated for a large number of variables. Attributes for which the coefficients had p -values < 0.1 were included in the final model. If an attribute was included in one model, we also included it in the other models to make a fair comparison possible.

The coefficients of the utility functions can be interpreted as follows. A positive and significant coefficient of a variable for a particular outcome means that the explanatory variable increases the probability of that outcome relative to the base case. On the other hand, a negative and significant coefficient means that the variable decreases the probability of that outcome relative to the base case. Tables 4–7 contain all model results.

Table 4 NCG motivation to cycle and app usage reaction model

Non-cycling		Motivation		App usage	
Model χ^2 ()	χ^2 (23) 52.789	χ^2 (46) 85.305	χ^2 (23) 55.157	χ^2 (46) 66.912	
p -value	0.000	0.000	0.000	0.024	
Cox and Snell R^2	0.270	0.398	0.280	0.329	
Nagelkerke R^2	0.360	0.456	0.373	0.386	

explanatory variable	Base case: I could not be motivated to cycle (more) by the reward scheme				Base case: I would not consider using the app			
	Yes?+?maybe		Yes		Neutral?+?consider		Consider	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
constant	1.254	0.364	-0.458	0.800	0.579	0.682	-2.625	0.291
distance	-0.100	0.019	-0.106	0.035	-0.096	0.025	-0.095	0.152
interventions (ref: in-kind gift)								
mock-up social	-1.413	0.070	-1.632	0.095	-1.473	0.074	-2.053	0.086
mock-up money	-0.637	0.207	-0.445	0.452	-0.903	0.077	-2.163	0.012
mock-up cooperation	-0.992	0.084	-1.152	0.105	-0.664	0.244	-0.909	0.278
mock-up competition	-2.163	0.006	-2.423	0.013	-1.500	0.047	-2.461	0.075
statement travel cost (ref: no)								
yes	1.435	0.020	2.163	0.003	1.684	0.008	1.472	0.156
statement health								

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

explanatory variable	Base case: I could not be motivated to cycle (more) by the reward scheme				Base case: I would not consider using the app			
	Yes?+?maybe		Yes		Neutral?+?consider		Consider	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
(ref: no)								
yes	1.091	0.165	0.333	0.737	1.574	.054	2.533	0.054
statement travel time (ref: no)								
yes	0.249	0.724	0.188	0.829	0.770	0.325	2.166	0.129
statement convenience (ref: no)								
yes	-0.222	0.717	-0.512	0.473	-0.663	0.259	-0.373	0.709
statement relaxed (ref: no)								
yes	-0.622	0.140	0.397	0.457	0.115	0.792	0.429	0.551
statement environmentally (ref: no)								
yes	-1.292	0.224	-1.951	0.177	-1.435	0.147	-0.316	0.831
statement safety (ref: no)								
yes	-0.419	0.455	-0.258	0.714	1.172	0.038	1.664	0.083
talking about cycling (ref: never/seldom)								
sometimes	1.141	0.013	0.854	0.124	0.794	0.072	1.139	0.101
often/always	0.417	0.639	0.629	0.558	0.422	0.616	0.128	0.927
usage of cycle app(ref: no)								
yes	0.222	0.626	0.252	0.649	1.221	0.014	0.888	0.266
age (ref: 55?64)								
age 19?34	1.089	0.118	1.129	0.222	0.654	0.371	2.442	0.103
age 35?44	0.028	0.963	0.561	0.499	0.959	0.139	1.965	0.153
age 45?54	-0.911	0.135	-0.457	0.592	-0.062	0.923	1.073	0.424
nationality (ref: Dutch)								
foreigner	-0.031	0.965	0.438	0.578	1.009	0.161	1.207	0.273
education (ref: under college)								
hoger beroepsonderwijs (higher professional education) (HBO)	0.340	0.613	-1.052	0.277	-0.215	0.763	-0.857	0.485
middelbaar	0.216	0.757	-0.782	0.230	-1.033	0.183	-2.188	0.101

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

explanatory variable	Base case: I could not be motivated to cycle (more) by the reward scheme				Base case: I would not consider using the app			
	Yes?+?maybe		Yes		Neutral?+?consider		Consider	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
beroepsonderwijs (middle-level applied education) (MBO)								
Income (ref: above 3000)								
no answer	0.301	0.579	0.267	0.686	-0.913	0.097	-2.425	0.049
below 3000	0.115	0.812	0.062	0.913	0.391	0.436	0.020	0.979

Table 5 OCG motivation to cycle and app usage reaction model

Model χ^2 ()	χ^2 (23) 61.755	χ^2 (46) 88.911	χ^2 (23) 49.276	χ^2 (46) 77.072
p-value	0.000	0.000	0.001	0.003
Cox and Snell R^2	0.169	0.234	0.138	0.207
Nagelkerke R^2	0.229	0.266	0.199	0.233

explanatory variable	Base case: I could not be motivated to cycle (more) by the reward scheme				Base case: I would not consider using the app			
	Yes?+?maybe		Yes		Neutral?+?Consider		Consider	
	Coefficient	p-Value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
constant	-0.717	0.482	-3.489	0.012	0.359	0.759	-1.098	0.429
distance	-0.006	0.843	-0.008	0.805	0.053	0.094	0.047	0.206
interventions (ref: in-kind gift)								
mock-up social	-0.937	0.034	-1.233	0.015	0.170	0.748	0.355	0.539
mock-up money	-0.519	0.094	-0.539	0.108	-0.560	0.088	-0.646	0.088
mock-up cooperation	-1.904	0.000	-2.161	0.000	-0.825	0.058	-1.907	0.002
mock-up competition	-1.663	0.003	-2.168	0.002	0.151	0.810	0.201	0.775
statement travel cost (ref: no)								
yes	0.595	0.126	1.382	0.007	-0.527	0.236	-0.419	0.419
statement health (ref: no)								
yes	0.134	0.755	1.086	0.052	-0.307	0.530	-0.335	0.555

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

explanatory variable	Base case: I could not be motivated to cycle (more) by the reward scheme				Base case: I would not consider using the app			
	Yes?+?maybe		Yes		Neutral?+?Consider		Consider	
	Coefficient	p-Value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
statement travel time (ref: no)								
yes	0.189	0.652	1.033	0.056	-0.474	0.327	-0.259	0.646
statement convenience (ref: no)								
yes	0.054	0.893	0.670	0.195	-0.771	0.087	-0.638	0.224
statement relaxed (ref: no)								
yes	0.574	0.107	1.082	0.023	-0.320	0.430	-0.348	0.467
statement environmentally (ref: no)								
yes	0.342	0.386	0.930	0.066	-0.409	0.361	-0.511	0.335
statement safety (ref: no)								
yes	0.650	0.181	1.471	0.015	-0.116	0.828	-0.084	0.894
talking about cycling (ref: never/seldom)								
sometimes	-0.223	0.433	-0.077	0.810	0.034	0.907	-0.008	0.982
often/always	-0.420	0.321	-0.279	0.549	1.081	0.054	1.149	0.065
usage of cycle app (ref: no)								
yes	-0.062	0.830	0.060	0.852	0.807	0.020	1.221	0.002
age (ref: 55?64)								
age 19?34	1.472	0.001	1.666	0.001	1.342	0.004	1.203	0.027
age 35?44	1.125	0.002	1.210	0.004	1.001	0.011	0.935	0.050
age 45?54	0.998	0.004	1.027	0.011	0.744	0.044	0.821	0.066
nationality (ref: Dutch)								
foreigner	0.955	0.079	0.919	0.120	1.260	0.110	1.378	0.100
education (ref: under college)								
HBO	-0.176	0.671	-0.062	0.897	0.760	0.066	1.147	0.036
MBO	-0.100	0.822	-0.077	0.880	1.070	0.018	1.219	0.039
Income (ref: above 3000)								
no answer	0.489	0.141	0.363	0.331	-0.472	0.183	-0.320	0.453
below 3000	0.711	0.023	0.652	0.060	-0.144	0.670	0.260	0.510

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Table 6a DCG motivation to cycle and app usage reaction model

Model χ^2 ()	χ^2 (20) 101.604	χ^2 (40) 135.017	χ^2 (20) 76.408	χ^2 (40) 108.070
p-value	0.000	0.000	0.000	0.000
Cox and Snell R^2	0.150	0.195	0.115	0.159
Nagelkerke R^2	0.204	0.230	0.154	0.180

Table 6b

Explanatory variable ()	Base case: I could not be motivated to cycle (more) by the reward scheme				Base case: I would not consider using the app			
	Yes?+?maybe		Yes		Neutral?+?Consider		Consider	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
constant	-2.093	0.000	-2.450	0.001	-1.185	0.030	-1.793	0.012
distance	0.028	0.255	0.004	0.894	0.024	0.302	0.015	0.598
interventions (ref: competition)								
mock-up cooperation	0.600	0.010	0.597	0.030	0.236	0.269	0-0.077	0.767
statement travel cost (ref: no)								
yes	-0.335	0.485	0-0.560	0.363	0-0.010	0.981	-1.166	0.142
statement health (ref: no)								
yes	-0.138	0.584	-0.360	0.228	0.045	0.854	-0.048	0.878
statement travel time (ref: no)								
yes	-0.203	0.393	-0.403	0.161	0.177	0.436	-0.237	0.417
statement convenience (ref: no)								
yes	0.024	0.913	-0.094	0.722	-0.052	0.807	-0.256	0.347
statement relaxed (ref: no)								
yes	-0.287	0.172	-0.464	0.068	-0.092	0.649	-0.105	0.679
statement environmentally (ref: no)								
yes	0.236	0.297	0.188	0.491	0.156	0.475	0.036	0.897
statement safety (ref: no)								
yes	-0.219	0.600	0.047	0.920	0.034	0.933	-0.386	0.470
talking about cycling (ref: never/seldom)								

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Explanatory variable ()	Base case: I could not be motivated to cycle (more) by the reward scheme				Base case: I would not consider using the app			
	Yes?+?maybe		Yes		Neutral?+?Consider		Consider	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
sometimes	0.306	0.132	0.196	0.426	0.285	0.140	0.249	0.317
often/always	0.698	0.035	0.850	0.024	0.026	0.934	0.275	0.475
usage of cycle app (ref: no)								
yes	0.571	0.005	0.846	0.000	1.054	0.000	1.263	0.000
age (ref: 55?64)								
age 19?34	1.788	0.000	2.020	0.000	0.402	0.172	0.825	0.032
age 35?44	1.190	0.000	1.293	0.000	0.361	0.202	0.504	0.180
age 45?54	0.287	0.279	0.146	0.678	-0.140	0.552	0.208	0.513
nationality (ref: Dutch)								
foreigner	0.639	0.044	0.411	0.262	1.395	0.000	1.471	0.001
education (ref: under college)								
HBO	-0.425	0.146	-0.048	0.904	0.094	0.730	0.175	0.642
MBO	0.092	0.769	0.314	0.454	0.054	0.856	0.243	0.546
Income (ref: above 3000)								
no answer	0.380	0.162	0.140	0.680	0.243	0.338	0.169	0.612
below 3000	0.292	0.225	0.219	0.446	0.498	0.028	0.416	0.153

Table 7a Scheme preference reaction model

Model χ^2 (112) = 392.356

P-value 0.00

Cox and Snell R^2 = 0.294Nagelkerke R^2 = 0.313

Table 7b

Explanatory variable	Base case: money						Base case: no reward		Base case: in-kind gifts			
	No reward		In-kind gift		Gamification		Gamification		No rewards		Gamification	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
constant	1.69	0.017	-0.310	0.56	-2.79	0.008	-4.473	0.003	1.370	0.076	-3.39	0.025
distance	-	0.1	-	0.4	-	0.0	-	0.3	-	0.4	-	0.1

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Explanatory variable	Base case: money						Base case: no reward		Base case: in-kind gifts					
	No reward		In-kind gift		Gamification		Gamification		No rewards		Gamification			
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value		
	0.034	24	0.015	27	0.069	42	0.035	36		0.018	25	0.054	19	
interventions (ref: money)														
mock-up social	0.901	0.074	1.59	0.000	-0.872	0.433	-1.773	0.119	social	-0.062	0.903	-1.515	0.170	
mock-up in-kind	-0.420	0.238	0.205	0.476	-0.707	0.147	-0.287	0.606	money	0.624	0.106	0.911	0.071	
mock-up coop	0.302	0.394	0.408	0.245	-0.450	0.481	-0.752	0.262	coop	0.519	0.219	0.053	0.940	
mock-up comp	0.221	0.567	0.453	0.236	-1.117	0.105	-1.392	0.066	comp	0.393	0.389	-0.712	0.362	
travel patterns (ref: daily cyclist)														
non-cycling	1.18	0.003	-0.378	0.339	0.673	0.348	-0.504	0.499		1.555	0.000	1.015	0.154	
occasional cyclist	0.152	0.633	-0.058	0.850	-0.390	0.527	-0.542	0.400		0.209	0.544	-0.333	0.596	
statement travel cost (ref: no)														

Table 7c

Explanatory variable	Base case: money				Base case: no reward				Base case: in-kind gifts			
	No reward		In-kind gift		Gamification		Gamification		No rewards		Gamification	
	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue
yes	- 1.1 2	0.0 00	- 0.4 32	0.0 62	- 0.0 53	0.9 07	1.0 67	0.0 28	- 0.6 88	0.0 14	0.3 79	0.4 12

[illegible]

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Explanatory variable	Base case: money						Base case: no reward		Base case: in-kind gifts			
	No reward		In-kind gift		Gamification		Gamification		No rewards		Gamification	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
yes	-0.311	0.157	0.217	0.224	0.293	0.325	0.603	0.070	-0.527	0.019	0.076	0.799
gender (ref: female)												
male	0.069	0.731	-0.468	0.008	0.236	0.434	0.167	0.611	0.537	0.011	0.704	0.022
age (ref: 55?64)												
age 19?34	-0.668	0.033	-0.297	0.283	-0.247	0.598	0.421	0.404	-0.371	0.252	0.050	0.916
age 35?44	-0.650	0.022	-0.238	0.52	-0.431	0.326	0.219	0.640	-0.413	0.161	-0.193	0.662
age 45?54	-0.569	0.020	-0.284	0.219	-0.573	0.186	-0.004	0.993	-0.285	0.257	-0.289	0.506
nationality (ref: Dutch)												
foreigner	0.253	0.437	0.015	0.958	-0.296	0.532	-0.549	0.289	0.238	0.477	-0.311	0.514
education (ref: under college)												
HBO	-0.862	0.003	-0.333	0.213	0.435	0.466	1.298	0.034	-0.529	0.066	0.769	0.195
MBO	-0.522	0.092	-0.202	0.479	0.561	0.367	1.083	0.091	-0.320	0.302	0.763	0.217
income (ref: above 3000)												
no answer	-0.257	0.291	-0.268	0.241	-0.638	0.140	-0.381	0.404	0.012	0.964	-0.369	0.403
below 3000	-0.375	0.118	0.199	0.331	0.134	0.702	0.510	0.186	-0.575	0.021	-0.065	0.856
motivation (ref: no)												
maybe	-0.862	0.001	0.158	0.466	0.932	0.023	1.794	0.000	-1.02	0.000	0.775	0.062

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Explanatory variable	Base case: money						Base case: no reward		Base case: in-kind gifts			
	No reward		In-kind gift		Gamification		Gamification		No rewards		Gamification	
	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue	Co eff ici en t	P- val ue
yes	- 1.6 5	0.0 00	0.2 86	0.1 37	1.3 5	0.0 00	3.0 02	0.0 00	- 1.9 4	0.0 00	1.0 6	0.0 03

3

Survey design and data

We utilised a questionnaire to conduct the survey and obtain data. The survey was carried out online by means of the free and open-source survey application Lime Survey. The questionnaire was divided into four groups of questions: (i) current travel behaviour, (2) general opinion about cycling, (3) incentives to travel to work by bicycle, including mockups with personalised cycling incentives, and (4) demographic and psychographic information. Table 8 describes the sample of this study. In total, 1802 people took part in our online survey, of which 1401 had a commuting distance of ≤ 20 km. These are potential daily cyclists since a commuting distance above 20 km is considered physically demanding. Of these 1401 respondents, 1125 completed the survey, which was included in the analysis and modelling.

Table 8 Descriptive statistics of samples

Descriptive characteristics of sample $N=1125$

Categorie s	Variables	Proporti on	Categorie s	Variables	Proportio n, %
traffic- related	commuting distance		gender	gender male	45.3
	frequency			gender female	54.7
		TravelPattern non-cycling (NCG)			
		TravelPattern occasional (OCG)	age	age 19?24	2.2
interventio ns		TravelPattern daily (DCG)		age 25?34	21.9
	mock-up social	4.5%		age 35?44	22.3
	mock-up in-kind	13.7%		age 45?54	31.5
	mock-up money	15.8%		age 55?64 (reference)	22.1
	mock-up competition	50.1%	nationality	nationality foreigner	9.3

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Descriptive characteristics of sample $N=21125$

Categorie s	Variables		Proporti on		Categorie s	Variables	Proportio n, %
	mock-up cooperation		16.0%			nationality Dutch	90.7
attitude about travel mode	(question: which of the following statements are the most important for your mode choice when you travel to work?)	i want to travel conveniently	y e s n o %	38.1 % 61.9 %	education	education HBO or university	62.2
		i want to save on travel costs	y e s n o %	43.1 % 56.9 %		education MBO	25.6
		i want to feel relaxed	y e s n o %	27.7 % 72.3 %		education below college	12.1
		i want to behave environmentally friendly	y e s n o %	65.4 % 34.6 %	gross monthly income	income no answer	22.3
		i want to feel healthy	y e s n o %	51.5 % 48.5 %		income 999 or less	0.8
		i want to cut travel time	y e s n o %	10.1 % 89.9 %		income 1000?1999	14.5
		i want to travel safely	y e s n o %	10.1 % 89.9 %		income 2000?2999	30.3
attitude about cycling	how do you like cycling?	feelingCyc le neutral	17.4%			income 3000?3999	20.0
		feelingCyc le ?I like cycling?	79.6%			income 4000 or more (reference)	12.0
		feelingCyc le ?I don't like cycling?	3.0%		preferred incentives	no rewards	21.9

Descriptive characteristics of sample $N=21125$

Categorie s	Variables	Proporti on	Categorie s	Variables	Proportio n, %
cycling app	how often do you talk with others about cycling?	talking ?sometimes?		social rewards	1.6
		talking ?often/alw ays?		in-kind gift	29.0
		talking ?never/sel dom?		money	35.4
	UsageAppCycle no	73.2%		gamificatio n (coop & comp)	6.2
	UsageAppCycle yes	26.8%		others	6.0

As mentioned in the introduction, our study may be less sensitive to self-selection than field experiments. There is no evidence of self-selection among employees. For example, modal shares for the University of Twente sample were comparable to that of a general travel survey among University employees a few years earlier. However, there probably is a self-selection of employers [33]. Our sample also has a higher fraction of highly educated and high-income respondents compared to the Dutch Travel Survey 2015 [34]. We suspect that this type of study attracts employers whose workforce is more highly educated. Even though this study has statistically enough data for most segments, and the model is used to identify the impact of various incentives, we should take this into consideration when applying the results to the whole population.

Participants were randomly assigned to one of the five mock-ups based on their commuting frequency by bicycle. Participants who never or only occasionally cycled to work were randomly assigned to one of the intervention schemes (see Table 2). Participants who always cycled to work were randomly assigned to intervention scheme 4 or 5. Participants who always cycle to work do not need to improve their frequency of cycling commute and, therefore, were not offered the chance to interact with the remaining intervention schemes. Table 9 summarises the number of respondents randomly assigned to one of our rewarding schemes based on travel pattern segmentation.

Table 9 Reward schemes' respondents based on travel pattern segmentations

Cycling frequency	Social reward	In-kind gifts	Mon ey	Co op	Co m p	Total
NCG	16	40	58	35	19	576
OCG	35	113	119	45	21	445
DCG	0	0	0	48 4	14 0	781
total	51	153	177	56 4	18 0	1125

Once assigned, the participants could interact (e.g. by clicking on the smartphone screen) with the mock-up as if it was a real smartphone app. Moreover, this part was designed to be personalised. When participants clicked to join the challenge, the challenge was related to their commuting distance and frequency of cycling to work. The content of the challenges directly related to the cycling frequency to be increased. Participants could choose a challenge they thought was suitable for them and receive a corresponding reward based on the level of the challenge and the commuting distance. The amount of the rewards was based on a real budget for cycling promotion derived from an analysis of an existing local scheme [35].

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

After interacting with the mock-ups, the respondents were asked whether they would feel motivated to cycle more to work based on the personalised schemes offered to them. They were also asked whether they would consider using the app in real life. Additionally, we also asked the respondents' opinions about other interventions, since they could only interact with one mock-up. Those questions are vital for intervention-effectiveness checking because it reflects the respondents' stated preference of behaviour change by the provided interventions. The final part contained personal information related to the socioeconomic status of the respondents such as gender, age, annual income, education, and nationality.

4

Results

Section 4.1 presents the model estimation regarding app usage and a potential increase in cycling. We mainly discuss statistically significant results (i.e. using a significance level of $p=0.05$) and explicitly mention it when differences are not statistically significant. Tables 4–6 contain the model results. In Section 4.2, we discuss the model estimation results for the choice between different incentives (see Table 7).

4.1

App usage and cycling motivation result

As explained in Section 2.2, we used reference categories and estimated the utility of the other categories with respect to the reference. In general, we used the first or last variable in a category as the reference. For example, the highest age and highest income categories serve as references. For the incentive variable, we used the in-kind gifts category as a reference, as in-kind gifts have been shown to be a relatively good incentive to change behaviour.

The model results (see Tables 4–6) show that the probability of using the app (App case) is significantly lower for the competition ($p=0.047$) and money mock-ups ($p=0.012$) in the NCG and significantly lower for the cooperation mock-up ($p=0.002$) in the OCG. However, in the other cases, there is not enough evidence to claim that the in-kind gifts mock-up scores significantly better. The left panel of Fig. 3 displays the fraction of respondents who are willing to use the app, but from Fig. 3 it does not become immediately clear that the differences are significant. The reason for this is that there are actually three categories. Respondents could indicate that they would or would not consider using the app, but they could also indicate that they did not know whether they would use the app in the future. The percentage of respondents with inconclusive responses is more or less the same for the different incentive schemes, i.e. about 38.5% for the non-cyclists and about 40.0% for the occasional cyclists. The model used the 'not-considering' category as a reference, as it is a logical choice for a baseline, and the results are significant relative to this 'not-considering' category. In the OCG, neither the cooperation nor the competition mock-up attracted a significant fraction of potential app users.

Fig. 3 Interventions statistics of App case and Cycle case for NCG and OCG, with the error bars indicating the one sigma error

Regarding segmentation, we find that respondents who already used related apps are more likely to use the app provided to them ($p=0.014$). The difference between the NCG and OCG is that non-cyclists with short commutes who care about travel costs and safety are more likely to consider using the app ($p=0.008$ and 0.038). As expected [27], younger and higher educated travellers are more likely to use the new app. However, only respondents in the OCG confirm this hypothesis with statistical significance. It appears that non-cyclists tend to use the app for reasons related to travel situations, such as saving on costs and improving safety, whereas socio-demographic attributes are main drivers for occasional cyclists. Finally, foreign and low-income respondents who cycle daily are inclined to consider using the app ($p=0.001$ and 0.028). Regarding the latter group, this may be attributed to the fact that they are more economically vulnerable and therefore more open to tangible rewards.

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

With regard to respondents indicating that they would be motivated to cycle more (cycle case), the competition mock-up ($p = 0.006$) scores worse in the NCG, but there is no evidence that other mock-up scores are worse than the in-kind gift mock-up. This is illustrated by the right panel in Fig. 3, which shows the percentage of respondents who indicate that they would be motivated to cycle more in response to the given incentive. That the competition mock-up scores low is not strange, since non-cyclists are not likely to win a prize in a competition. However, the daily cyclists also tend to show a preference for the cooperation mock-up over the competition mock-up. This is somewhat surprising as we expected people who cycle daily to be more motivated to be directly compared with their peers (competition). In the OCG, all mock-ups except the money mock-up score worse than the in-kind gift mock-up ($p < 0.04$). These results suggest that tangible rewards are most likely to motivate people to cycle more, as there appears to be a slight, but non-significant preference for in-kind gifts over money.

Regarding segmentation, both non-cyclists and occasional cyclists who care about travel costs are more likely to be motivated to cycle more. However, travel costs seem to be less important for occasional cyclists than for people who never cycle. Specifically for the non-cyclists, respondents with short commutes are more inclined to be motivated to cycle more when they are rewarded ($p = 0.019$). This is in line with Dubuy *et al.* [10] who showed that the effect of interventions declined with increasing commute distance. For the occasional cyclists, respondents who care about travelling in a relaxed way ($p = 0.023$) or care about travel safety ($p = 0.015$), and are younger and have low incomes ($p = 0.03$) are more inclined to be motivated to cycle more. In contrast to the non-cyclists, commute distance does not seem to play an important role here. For people who never cycle, hard attributes such as travel costs and distance appear to be main drivers to get people onto the bicycle. For the occasional cyclists who already have some cycling experience, attributes related to the cycling itself (such as safety and whether the trip is relaxed) and socio-demographic attributes appear to be more important drivers to motivate them to cycle more.

For the respondents who cycle daily, we find that foreigners ($p = 0.044$), young people and people who use similar apps ($p = 0.000$) tend to be more motivated to cycle more. Talking about cycling also has a positive impact on cycling motivation ($p = 0.024$).

4.2

Incentive preferences model analysis

As Table 8 shows, we also asked people directly which reward scheme they would prefer, including the ones they were not introduced to (incentive case). Most people preferred the money incentive (35.4%), followed by the in-kind gift incentive (29.0%), and no rewards at all (21.9%). Therefore, we focused on comparing those three incentives.

Fig. 4 shows that money and in-kind gifts are the most preferable schemes for all groups except that for the non-cyclists no reward at all appears to be the most preferred option. Contrary to what we see in the App case and Cycle case (i.e. where people got to see one mock-up app), money incentives score significantly better than in-kind gifts for the NCG and OCG. The difference between the two schemes is particularly large for the NCG. Although this result appears to contradict the results from the mock-up app questions, it is important to stress that a mock-up app is not the same as the reward itself. The in-kind mock-up also provides a web-based shop, which contributes to the fun factor. This can be seen as a double reward, as after gaining points, you will also be able to shop with your points. However, when offered as an alternative to money, the comparison makes the fungibility of the money reward more visible. This is in line with results from Gneezy *et al.* [36], and Shaffer and Arkes [26]. Comparing no rewards with money or in-kind gift incentives, the results of Table 7 show that the respondents' attitude towards cycling has an impact on their preference. Respondents who were negative about cycling were inclined to choose no rewards. Also, non-cyclists ($p = 0.003$) and respondents who did not care about travel costs ($p = 0.000$) tended to choose no reward. This implies that behaviour change among non-cyclists with a negative attitude towards cycling is difficult, which is not surprising. Making them aware of the travel costs of their current travel mode can be a way to motivate them to change their behaviour. Respondents with higher education tend to prefer rewards instead of no rewards ($p = 0.003$). This is somewhat unexpected as we expected highly educated people to be less sensitive to tangible rewards. Maybe they opt for a tangible reward (instead of no reward) because they are more likely to use the corresponding app (see the previous subsection).

Fig. 4 Incentive preferences statistics, with the error bars indicating the one sigma error

The respondents who choose money or in-kind gift instead of no rewards tend to be female ($p=0.011$), young ($p<0.04$), care about travel time and travel costs ($p=0.014$ and 0.028), and have a low income ($p=0.021$). Interestingly, females are more inclined to choose in-kind gifts ($p=0.008$), whereas males opt for money. The latter was also found by Steven and Avineri [11] and Dickinson *et al.* [37].

Although gamification (competition or cooperation) was not preferred in general, we can distinguish some groups in this regard. Respondents with a positive attitude towards cycling, with short commute distances, and/or respondents who care about the environment have a higher probability of choosing the gamification incentives. Male respondents are also more likely to choose gamification over in-kind gifts, while respondents who care about travel costs, talk often about cycling and/or have a high-education level are more likely to choose gamification rather than no reward. It seems that these latter groups are more open to any incentive scheme.

From the respondents' intention about cycling behaviour change, we can see that respondents who are negative about the mock-up mostly choose another scheme in the general question, while respondents who are positive about the mock scheme tend to stick with this scheme. However, there is one notable exception. A significant fraction of respondents who are positive about the in-kind gift mock-up prefers a social reward scheme and vice versa. This result suggests that in-kind and social reward schemes are attractive to the same type of respondent. In contrast, there is almost no exchange between in-kind gifts and money, which suggests that these two schemes attract different types of people.

5

Conclusions

In this study, we have examined the potential impact of five positive incentive schemes, i.e. social rewards, in-kind gifts, monetary rewards, cooperation and competition on commuters' cycling behaviour and intention to accept a commuting app. We conducted a study in which these incentive schemes were delivered through a smartphone mock-up app, as part of a stated preference survey.

Intervention schemes on the basis of goal setting, feedback, and rewards had a positive effect on cycling motivation and potential app usage. Occasional cyclists were clearly more positive towards the various incentive schemes (with about 50% considering one of the mock-up schemes) than non-cyclists (with about 25% considering one of the mock-up schemes).

For the individual schemes, in-kind gifts and money (tangible rewards) were most likely to motivate people to cycle more and use the corresponding app. Money was the most preferred incentive when respondents chose between alternative incentives, but in-kind gifts scored better when the mock-up apps were considered separately. The latter is in line with the findings of Shaffer and Arkes [26], but having a web shop associated with in-kind gifts may also have made people more enthusiastic about the in-kind gift mock-up than about the money mock-up. We, therefore, suggest that in-kind incentives may be better for cycling promotion, as in reality, the incentive app will probably provide only one type of reward, and the impersonal character of money may partly demotivate (e.g. Gneezy *et al.* [36] and Shaffer and Arkes [26]). However, the picture is more nuanced as there are differences among the demographic groups. For example, men appeared more likely than women to opt for money.

Travellers who had experiences with related apps tended to consider using the app. For the non-cyclists, travel-related attributes such as travel costs and distance appeared to be important for considering the app. For occasional cyclists and daily cyclists, socio-demographic and socio-economic attributes appeared to be more important. Specifically, younger and higher educated occasional cyclists and foreign and low-income daily cyclists were more likely to use the new app. These results are quite in line what can be expected, and also confirm results reported by Chorus *et al.* [27].

Finally, our results suggest that positive incentives may encourage non-cyclists to start cycling if distances are short and travel costs are an important consideration in their travel choices. By contrast, when non-cyclists do not care about travel costs, they are most likely to choose no reward when asked directly. In other words, non-cyclists may be encouraged to start cycling when they are made more aware of the travel cost benefits, although this may only be true for low-income groups. While the attitude towards hard attributes such as travel costs are an important discriminator for behaviour change among non-cyclists, this is less true for occasional cyclists. They are more likely to change behaviour if they care about attributes related to cycling itself (such as safety and whether the cycling is relaxed), which is not surprising as they already have experienced cycling. However, these are important pre-conditions for encouraging cycling. Along with that line, it is interesting to focus on weather in a future study. Bad weather is an important barrier for cycling among occasional cyclists. Does the fact that this attribute is important for occasional cyclists to make it more likely for them to change behaviour when they receive incentives or not? This is an important question, which we can only test in real-world situations.

Regarding the meaningfulness of the observed results, one should be careful with drawing conclusions given the study context. Respondents were asked about their intentions and did not experience real cycling challenges. Inconsistencies between lab and field experiments have been reported in the literature, especially when social preferences are involved (see List and Levitt [38] for an overview). Nonetheless, even in cases where revealed and stated intention results are not exactly the same, some studies (e.g. [39]) find a clear relation between the two, suggesting that relative comparisons within a study are still valid. Moreover, inconsistencies between lab and field experiments may also be caused by the fact that the context of the stated intention survey does not match the real-world context. In this study, we simulate the reality as much as possible using mock-up apps. We show that this is important, e.g. when comparing in-kind gifts with money.

Throughout the study, we compared results with field experiments in the literature. Most of the results are in line with the literature. However, as mentioned in the introduction, comparisons between incentives and segments are rare in field studies. Although we cannot be sure about the absolute effects in a real-world implementation, this study provides valuable insight by comparing the potential effects of different incentives on different segments. In that sense, the use of mock-up apps can be viewed as complementary to field studies. Various features can be tested, and the most popular and/or effective ones can be implemented in a real app and tested in a field study.

The next step in this research will, therefore, be to implement the (most successful) incentive schemes in real-world conditions. Within the EMPOWER project, we have planned field experiments to do this, and see whether the results from this study will be confirmed.

Bibliography

REFERENCES

- 1 European Commission: 'Road transport: reducing CO2 emissions from vehicles | climate action'. Available at https://ec.europa.eu/clima/policies/transport/vehicles_en, accessed May 2017
- 2 World Health Organization: 'WHO Europe obesity data and statistics'. Available at <http://www.euro.who.int/en/health-topics/noncommunicable-diseases/obesity/data-and-statistics>, accessed May 2017
- 3 Hamer M., Chida Y.: 'Active commuting and cardiovascular risk: a meta-analytic review', *Prev. Med.*, 2008, 46, (1), pp. 9–13
- 4 Gordon-Larsen P., Boone-Heinonen J., Sidney S., : 'Active commuting and cardiovascular disease risk: the **CARDIA study**', *Arch. Intern. Med.*, 2009, 169, (13), pp. 1216–1223
- 5 Park S., Rink L.D., Wallace J.P.: 'Accumulation of physical activity leads to a greater blood pressure reduction than a single continuous session, in prehypertension', *J. Hypertens.*, 2006, 24, (9), pp. 1761–1770

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

- 6 Ben-Elia E., Ettema D.: 'Changing commuters' behavior using rewards: a study of rush-hour avoidance', *Transp. Res. F, Traffic Psychol. Behav.*, 2011, 14, (5), pp. 354–368
- 7 Bamberg S., Schmidt P.: 'Incentives, morality, or habit?: predicting students' car use for university routes with the models of Ajzen, Schwartz, and Triandis', *Environ. Behav.*, 2003, 35, (2), pp. 264–285
- 8 Cairns S., Sloman L., Newson C.: 'Smarter choices: assessing the potential to achieve traffic reductions using 'soft measures'', *Transp. Rev.*, 2008, 28, (5), pp. 593–618
- 9 Baum L.: 'Smart trips summit-U: an individualized marketing approach to changing travel behavior', 2008
- 10 Dubuy V., De Cocker K., De Bourdeaudhuij I.: 'Evaluation of a workplace intervention to promote commuter cycling: a RE-AIM analysis', *BMC Public Health*, 2013, 13, (1), p. 587
- 11 Steven F., Avineri E.: 'Has the introduction of the cycle to work scheme increased levels of cycling to work in the UK?'. 43rd Universities Transport Study Group Conf., Milton Keynes, UK, 5–7 January 2011
- 12 Wen L.M., Orr N., Bindon J.: 'Promoting active transport in a workplace setting: evaluation of a pilot study in Australia', *Health Promot. Int.*, 2005, 20, (2), pp. 123–133
- 13 Usui T., Miwa T., Yamamoto T.: 'Development and validation of internet-based personal travel assistance system for mobility management'. 15th World Congress on Intelligent Transport Systems and ITS America's 2008 Annual Meeting, New York, NY, USA, 2008
- 14 Zhang Y., Stopher P., Halling B.: 'An evaluation of TravelSmart tools for travel behaviour change', 2010
- 15 Brög W., Erl E., Ker I.: 'Evaluation of voluntary travel behaviour change: Experiences from three continents', *Transp. Policy*, 2009, 16, (6), pp. 281–292
- 16 Wardman M.R., Page M.R., Tight M.: 'Cycling and urban mode choice. results of behavioural mode and route choice models', 2000
- 17 Ryley T.: 'Estimating cycling demand for the journey to work or study in West Edinburgh, Scotland', *J. Transp. Res. Board*, 2006, 1982, (1), pp. 187–193
- 18 Yang L., Sahlqvist S., McMinn A.: 'Interventions to promote cycling: systematic review', *Br. Med. J.*, 2010, 341, pp. c5293–c5293
- 19 Pucher J., Dill J., Handy S.: 'Infrastructure, programs, and policies to increase bicycling: an international review', *Prev. Med.*, 2010, 50, (Suppl. 1), pp. S106–S125
- 20 Scheepers C.E., Wendel-Vos G.C.W., den Broeder J.M.: 'Shifting from car to active transport: a systematic review of the effectiveness of interventions', *Transp. Res. A, Policy Pract.*, 2014, 70, pp. 264–280
- 21 Hu X., Chiu Y., Zhu L.: 'Behavior insights for an incentive-based active demand management platform', *Int. J. Transp. Sci. Technol.*, 2015, 4, (2), pp. 119–133
- 22 Sanjust B., Meloni I., Spissu E.: 'An impact assessment of a travel behavior change program: a case study of a light rail service in Cagliari, Italy', *Case Stud. Transp. Policy*, 2014, 3, (1), pp. 12–22
- 23 Zhu C., Jia S.Y., Mandayam C.V.: 'Reducing road congestion through incentives: a case study'. Transportation Research Board 94th Annual Meeting, Washington, D.C, 2015
- 24 Thomas T., Jaarsma R., Tutert B.: 'Exploring temporal fluctuations of daily cycling demand on Dutch cycle paths: the influence of weather on cycling', *Transportation*, 2013, 40, (1), pp. 1–22

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

- 25 Presslee A., Vance T.W., Webb A.: 'The effects of reward type on employee goal setting, goal commitment, and performance', *Account. Rev.*, 2013, 88, (5), pp. 1–5
- 26 Shaffer V.A., Arkes H.R.: 'Preference reversals in evaluations of cash versus non-cash incentives', *J. Econ. Psychol.*, 2009, 30, (6), pp. 859–872
- 27 Chorus C.G., Molin E.J.E., van Wee B.: 'Travel information as an instrument to change car drivers travel choices: a literature review', *Eur. J. Transp. Infrastruct. Res.*, 2006, 6, (4), pp. 335–364
- 28 Zhang Z., Fujii H., Managi S.: 'How does commuting behavior change due to incentives? An empirical study of the Beijing Subway System', *Transp. Res. F, Traffic Psychol. Behav.*, 2014, 24, pp. 17–26
- 29 Oinas-Kukkonen H., Harjumaa M.: 'Persuasive systems design: key issues, process model, and system features', *Commun. Assoc. Inf. Syst.*, 2009, 24, (1), pp. 485–501
- 30 Khaled R., Barr P., Noble J., : 'Fine tuning the persuasion in persuasive games', *Persuasive Technol.*, 2007, 4744, pp. 36–47
- 31 Locke E.A., Latham G.P.: 'Building a practically useful theory of goal setting and task motivation. A 35-year odyssey', *Am. Psychol.*, 2002, 57, (9), pp. 705–717
- 32 Landers R.N., Bauer K.N., Callan R.C.: 'Gamification of task performance with leaderboards: a goal setting experiment', *Comput. Hum. Behav.*, 2017, 71, pp. 508–515
- 33 Fioreze T., Thomas T., Huang B., : 'How employees view smart cycling to work: A regional survey in the Netherlands', *Travel Behav. Soc.*, 2018, DOI: 10.1016/j.tbs.2018.04.002
- 34 'Research movements in the Netherlands (OVIN)'. Available at <https://www.cbs.nl/nl-nl/onze-diensten/methoden/onderzoeksomschrijvingen/korte-onderzoeksbeschrijvingen/onderzoek-verplaatsingen-in-nederland--ovin-->, accessed June 2018
- 35 'Twente mobile – together for your mobility policy'. Available at <http://www.twentemobiel.nl/>, accessed January 2017
- 36 Gneezy U., Meier S., Rey-Biel P.: 'When and why incentives (Don't) work to modify behavior', *J. Econ. Perspect.*, 2011, 25, (4), pp. 191–210
- 37 Dickinson J.E., Kingham S., Copsey S., : 'Employer travel plans, cycling and gender: will travel plan measures improve the outlook for cycling to work in the UK?', *Transp. Res. D, Transp. Environ.*, 2003, 8, (1), pp. 53–67
- 38 List J.A., Levitt S.D.: 'What do laboratory experiments tell us about the real world?', 2006, 9 (June)
- 39 Levitt S.D., List J.A.: 'What do laboratory experiments measuring social preferences reveal about the real world?', *J. Econ. Perspect.*, 2016, 21, (2), pp. 153–174

Classification

Language: ENGLISH

Publication-Type: Magazine

Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work

Subject: EUROPEAN UNION INSTITUTIONS (90%); OBESITY (90%); PUBLIC HEALTH (74%); COMMUTING (73%); ENVIRONMENTALISM (73%); EUROPEAN UNION (73%); INTERNATIONAL ECONOMIC ORGANIZATIONS (73%); MEDICAL RESEARCH (73%); EXERCISE & FITNESS (71%); CASE STUDIES (70%); EMISSIONS (68%); GRANTS & GIFTS (68%); HEALTH DEPARTMENTS (68%); SOCIETAL ISSUES (67%); ASSOCIATIONS & ORGANIZATIONS (66%); RESEARCH REPORTS (66%); WALKING & JOGGING (66%); SUSTAINABILITY (65%); SUSTAINABLE DEVELOPMENT (65%); PUBLIC HEALTH ADMINISTRATION (53%); incentive schemes (%); transportation (%); multinomial logit analysis (%); positive incentives (%); cycling behaviour (%); Twente region (%); reward schemes (%); social rewards (%); in-kind gifts (%); multinomial logit model (%); cycling frequency (%); app-based incentives (%)

Organization: EUROPEAN COMMISSION (84%); WORLD HEALTH ORGANIZATION (57%)

Industry: EMISSIONS (68%); HEALTH DEPARTMENTS (68%)

Geographic: EUROPE (92%); EUROPEAN UNION MEMBER STATES (87%)

Load-Date: November 25, 2018