The Influence of Interventions on Cycling

Bingyuan Huang

THE INFLUENCE OF POSITIVE INTERVENTIONS ON CYCLING

Bingyuan Huang

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DISSERTATION

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by

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Preface

Over 55 months, I have been in the group of Transport Engineering and Management at University of Twente to explore the topics of travel behavioral change and positive interventions. This was a challenging, valuable, and confused life stage that finally I seek meaning in life. Due to different cultural and educational background in China, It was during or after my bachelor study I started to explore what I really wanted as a future career. I got interested into transport related studies because of the impact from my grandfather (New China's first generation road builder and designer) and the rapid construction of highway in China. After the highway engineering study for my bachelor study in China, I found I was more interested into soft management or traffic planning instead of hard core civil engineering. Therefore, I decided to learn more traffic safety and design knowledge during my master study in China. However, during my master, I started to think about what transportation is in a big picture, how important it is in cities, how to choose where to build roads, and how citizens will be affected when building new roads. With these questions, I got the opportunity to study in the faculty of ITC, where I learned to apply the geoscience to solve urban planning issues. So finally, I moved from construction level to planning and management level. I quickly soaked lots of new knowledge that are all related to transportation in my master studies. After, I saw the PhD-project that focused on travel behaviour, which immediately attracted my attention because I wanted to continue explore new directions about transport system. I applied, got the funding, and that is how I started the PhD-life.

During my PhD, I gained experience in (concise) writing, publishing and (social) networking, and developed skills in conducting surveys, field experiments and data-analyses. Moreover, I was able to present my ongoing work at several international conferences. These conference visits did not only provide me with new insights, an extended network and revived motivation, it also provided me valuable life experience as they brought me to the best places in the world. Moreover, as part of the European Union's Horizon 2020 research, I had the opportunities to join a few project meetings and cooperated with other partners. I gained working experience, the general project running knowledge and social skills. Moreover, the governors and specialists from the project inspired me to think practically, and motive me to do research to solve real

social issues. This also inspired me about my future career, to provide knowledge for government and decision makers in the field of mobility and accessibility.

Now, I would like to take this opportunity to thank all those who have contributed to my research. First of all, I would like to express my gratitude to my promotor Prof. Dr. Eric van Berkum. He helped crystallize this research from the beginning and his time and expertise provided me with valuable insights at all stages of the project. He gave me a lot of freedom to do research, which helps me to develop myself. He helps me to know that I should understand the definitions and labels before I use them. This small details contributed substantially to my understanding of the topic and took my work to a higher level. I am further deeply grateful to my daily superior, Dr. Tom Thomas. First, your revisions and corrections of my texts have improved my writing skills significantly. Moreover, our discussions during the research process were very valuable to me. Your critical thinking kept me critical at my own work and made me realize to think more comprehensively. I learned from you how to do a research properly.

Besides my superior and promoter, many thanks to all colleagues of the CTS group at the University of Twente. You were of great support and helped in many ways. I especially like to thank Andani and Mariska. Andani, thank you for your discrete choice models on which you spend many hours. Without your help, it would have been difficult for me to start. You are my collage and my housemate as well. Thank you for your accompanying. And Mariska, our discussions on influencing travel behavior and discrete choice models helped me in reflecting on my own work, and you helped me to organize my research, which was really helpful in the beginning stage of my research. Also, Tiago, Bo, Oskar, Fransesco, Anika, Dorette, Lissy, Kostas, Karst, John and others, thank you for the nice conversations and fine times during and outside working hours.

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Finally, I would like to thank the my beloved family. First and foremost, my life partner, Chris, with whom I grew more Dutch and more logical. I am very grateful for your love, support and patience in the past years. I admire that you are a good listener who has wise and no prejudice, and can always solve my problems, often in a smart and high technical way. Thanks for sharing your life and growing together with me. I am looking forward to working with you for future life projects. This thesis also owns to the love and support of my dear parents in China: Huang Chunlin and Wei Shujin, they helped me to release my stress and give me endless support. Without my family in Netherlands: Frank and Roelien, things would have been much more difficult. You make me feel I have a family in the Netherlands and give me the feeling that I can always get coffee at home in Steenwijk.

Bingyuan Huang
November 2020

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1 Motivation, scope and methodology

1.1 Introduction

In many European cities, liveability is becoming a major issue. The use of the conventionally fueled vehicle (CFV) decreases liveability in cities by causing congestion, parking problems and accidents. Besides, according to the World Health Organization air pollution is a major environmental risk to health (WHO, 2010). Transport also contributes to climate change. For example, just by travelling to work the UK's commuters create 77.8 million tonnes of CO₂ emissions, which is a fifth of the UK's total emissions. Our use of the earth's resources to fuel our everyday lives is damaging us and the planet beyond repair. Hence, many cities across the world are committed to providing a new sustainable mobility system. Many policymakers are focusing on bicycles as their solutions (e.g. (Gerike, de Nazelle, Wittwer, & Parkin, 2019; Handy, van Wee, & Kroesen, 2014))

Over recent decades, there has been a dramatic increase in published research on cycling and bicycle use has been on the rise. Policymakers are trying to utilise this trend, as cycling is often seen as a relatively simple constituent in the complexity of urban mobility problems, that it is cost-effective, fast, clean, flexible and efficient. (Nijland & Van Wee, 2006; World Health Organization, 2014). Many policy measures have been used for cycling promotion, for example, adequate cycling infrastructure provision and financial disincentives to driving (e.g. road pricing, higher car parking charge). Moreover, resulting from the long-established perceptions and mobility habits (i.e. car dependence), there is a need to work substantially on the behavioural aspects of cycling. Responding, studies on travel behavioural change with non-positive interventions, such as fiscal regulations have been numerous. Yet, this approach might cause social inequality (Eliasson & Mattsson, 2006). This thesis analyses the positive 'carrot' type of interventions, for example, rewards, encouragements or subsidies, that are aimed at nudging individuals away from conventionally fuelled vehicles (CFV) towards cycling. The primary intended audience of this thesis is scientists within the field of traffic and behaviour as well as policy planners and decision makers. Nonetheless, this thesis might also be of interest to professionals who work at commercial travel information services and software companies. The purpose of this thesis is: 1) to provide empirical evidence to support the application of

information-based intervention strategies; 2) to demonstrate the short and long term effects of a positive intervention service on individual behaviour on modal change from car to bike. 3) to explain the motivators and barriers of cycling behavioural change by positive interventions through a smartphone app.

1.2 Problem statement

Cycling infrastructure has been implemented worldwide to promote bicycle use and to minimise injury risk. The successful example is the Netherlands, that is now the number one bicycling nation. However, still half of the short trips below 7.5 kilometres are made by car (Harms & Kansen, 2018). To further change those remaining car trips to bike trips, or to achieve a more sustainable transportation system, financial disincentives to driving has been found to be an effective tool (e.g. road pricing, or higher car parking charges). At the same time, it is noted that the implementation of financial disincentives to driving is not without controversy. For instance, in the Netherlands, discussions on such issues as social equity (stemming from the fact that individuals with a higher value-of-time receive larger benefits from road pricing than those with a lower value-of-time) (Eliasson & Mattsson, 2006) and public acceptance (Knockaert et al., 2012). In the context of this discussion, studies are undertaken to explore further the subjective reasons preventing bike use, and soft measures with the actions aimed at changing people's perceptions, beliefs and attitudes towards cycling appeared to be a solution (CIVITAS, 2013). Moreover, the consequences of those soft measures in terms of social effects and public acceptance are also investigated (Knockaert et al., 2012).

An idea that has been put forward (Ettema and Verhoef., 2006; Knockaert et al., 2007) is to investigate whether the behavioural change that is envisaged in the measures of financial disincentives to driving, can also be achieved by giving financial incentives to change travel behaviour. One successful example of peak hour travelling behavioural change is the Dutch Spitsmijden program by providing monetary and in-kind gift incentives (Ettema, Knockaert, & Verhoef, 2010; Knockaert et al., 2007). Meantime, there are also many voluntary travel behaviour change programmes (VTBC) that are designed to encourage, through information and communication, more efficient use of transport systems. (e.g. Brög et al. 2009; Sanjust et al. 2014, Lachapelle, 2013). These positive incentive projects show the potential to nudge behaviour change.

Conventional nudging approaches, such as rewarding system and VTBC, seem to have been successful in changing behaviour, yet, the evaluation of those intervention effects was questioned. Studies that reported significant changes in travel behaviour were mainly based on self-reported behaviour change (measured through surveys), and the sample sizes were sometimes rather small, and there was not always a control group (Stopher, Clifford, Swann, & Zhang, 2009). Moreover, traditional VTBC solutions require person-based interaction, either by phone or home interviews, which is inherently expensive and may induce biases stemming from social interaction and communication. The emergence of the social web and mobile applications for delivering interventions offers opportunities to reduce the costs and enables the use of ICT-based persuasion technology for influencing travellers (B. J. Fogg, 2002). With such advances in information & communication technology (ICT), the high accurate trip detection and interactive positive intervention application become more promising. This new technology may help to overcome several evaluation problems and has opened up new opportunities for influencing travellers. Nowadays, using smartphones to collect extensive and dynamic data for human travel behaviour has been proven in many ways better than traditional travel survey data research (Wesolowski et al., 2014; Palchykov et al., 2014). For example, travellers may forget

to report or not remember trips. Thus smartphone data provide greater accuracy for the locations of origins and destinations when compared to the self-reporting multiple addresses (Thomas, Geurs, Koolwaaij, & Bijlsma, 2018). Moreover, smartphone data is widely applied to estimate travel modes and travel routes, with high estimation accuracy (Wang, He, & Leung, 2017; Stopher et al., 2009).

Given the hyper-competitive nature of software and application market, designing successful apps is a challenge. Persuasive technology that is designed to change attitudes or behaviours based on interactive technologies, by incorporating and building on the results, theories, and methods of experimental psychology, rhetoric, and human-computer interaction, can aid in the design and evaluation of a travelling behavioural change app (Oinas-Kukkonen and Harjumaa 2009; Schneider et al. 2016; Brynjarsdóttir et al., 2012). Such technologies have been tested in smartphone apps (e.g. (Anagnostopoulou, Bothos, Magoutas, Schrammel, & Mentzas, 2018; Tsirimpa, Polydoropoulou, Pagoni, & Tsouros, 2019) intended to motivate a voluntary travel behavioural change. Common persuasive design features in those studies are personalized feedback, self-monitoring, challenge and goal setting, social comparison, and rewards. Moreover, the credibility of the app (high detection accuracy to create trustworthiness, third party endorsements, authority and surface credibility) is also an important persuasive element (Lehto & Oinas-Kukkonen, 2011). Ignorance or technical flaw may directly impact recruitment and engagement rate. In addition, given a successful app design, enabling cycling promotion needs local authorities, particularly policy executives and stakeholders to work together with good marketing, communication, and promotion techniques. These findings suggest that embedding new information technology based on persuasive intervention design into a well-organized cycling promotion campaign is able to motivate travel behavioural change. However, clear results on their effectiveness based on field evaluations is still missing. Most evaluations of behaviour change interventions proposed in this area are rather short-term, involve small groups of participants, and provide limited evidence of lasting behavioural impact (Dastjerdi et al., 2019; Gabrielli et al., 2014).

Besides new technology to support the successful travel behaviour change programs, providing positive intervention needs the understanding of individuals. Travel behavioural change intervention programs have been guided or evaluated by two theoretical models: the Theory of Planned Behaviour and Norm Activation, to explore the intention/attitudes-behaviour relationship. However, mobility is a highly habitual activity, which is not easily interrupted (Pronello, Simão, & Rappazzo, 2017). Instead of affecting attitude to occur behaviour change, Kroesen et al. (2017) claimed the effects of behaviours on attitudes are much larger than vice versa. In line with this, gamification provides a way to disturb current behaviour or to motivate changes (Bowden & Hellen, 2019; Sailer, Hense, Mayr, & Mandl, 2017). Moreover, many studies also highlight that long term involvement more often leads to positive results for behavioural change (Castellanos, 2016; Coombes & Jones, 2016; Pronello et al., 2017). Several studies are optimistic about gamification and its potential to extend the commitment of the user (e.g. (Andersson, Winslott Hiselius, & Adell, 2018; Bowden & Hellen, 2019;), however there is a lack of longitudinal study designs. Thus, more research is needed to discover the gamification effect on app involvement and commitment, and its impact on behaviour change, especially under a long term study period.

Different gamification strategies were involved in current travel apps. For rewards, tangible rewards such as money (e.g. (Ben-Elia & Ettema, 2011b; Tsirimpa et al., 2019) and in-kind rewards, i.e. points (e.g. (Bowden & Hellen, 2019; Poslad et al., 2015), and non-tangible rewards, i.e. praise (Gabrielli & Maimone, 2013; Mattheiss, 2015; Schrammel, Busch, & Tscheligi, 2013) were often used in current apps. Hence, it is necessary to analyse the effect of different types of rewards on cycling promotion. Challenges and goal-setting are also essential

features in gamification. Many goal-setting studies showed that specific and challenging tasks led to higher performance than easy or "do your best" tasks (Baretta, Bondaronek, Direito, & Steca, 2019; E. A. Locke, 1968; E. a Locke & Latham, 2002), however, current apps for cycling promotion reward users by directly calculating the kilometres they cycled, without a specific challenge, or massive challenges that are not suitable for every user. On the other hand, setting specific goals for long-term projects may be disadvantageous for the user participation, as users immediately tend to dropout upon finishing that goal (Habibipour, Bergvall-Kåreborn, & Ståhlbröst, 2016). Moreover, before considering personalised challenges or challenges that explicitly target a certain social-economic segment of travellers, it should be acknowledged that in many cases targeting specific segments or personalised targeting may be costly and even ethically troublesome. Hence, understanding of how to deal with gamification factors, such as rewards and challenges for involving users is important.

Overall, there is high hope on the potential of state-of-the-art ICT services (smartphone apps) based positive interventions on nudging travellers to have modal change and thereby support a cycling campaign. However, this policy measure needs the partnership between commercial parties, and transport authorities (like cities) or providers and the understanding of individuals, resulting in no firm evidence on the large-scale and long term impact of positive intervention.

1.3 Research objective and scope

The main objective of this research is 'to empirically determine the potential to use current state-of-the-art, information-based positive interventions to occur modal shift from car to bike in a short and longer term'.

Running such a cycling promotion project needs multidisciplinary cooperation, such as local authorities to manage, commercial parties to support rewards and IT company to support technology. I have cooperated with such parties that focus on intervention design and behaviour research. Information technology based on smartphones is the core to support this policy measure by providing those interventions and automated measurement of individual travel behaviour. For example, many researchers focus on improving the accuracy of trip detection or backend and frontend service infrastructure, which directly links to project recruitment and engagement. To consider these technical issues would make the behavioural change analysis based on positive interventions too complex to start with. Hence, a professional commercial company is in charge of developing and implementing interventions and measuring behaviour. My research findings and implications are based on multidisciplinary cooperation and I have focused on the design, evaluation and estimation of the positive intervention on cycling travel behavioural change.

Several positive interventions are generally applied to the VTBC projects, for example, rewarding sustainable behaviour, providing feedback about behaviour, encouraging behavioural change by goal setting and planning, and raising awareness of sustainable travel options by providing travel information. Those new ICT based interventions are in line with persuasion technology (Fogg, 2002), which uses interactive information technology services to change user attitudes and behaviours. However, cultural differences between countries as well as environmental and spatial differences between regions may have played a role in the effectiveness of these interventions. Existing literature also show controversial results about financial incentive. For example, recent travel apps suggests monetary and in-kind rewards are both effective on peak hour avoidance, but some VBTC projects (e.g. Brög et al. 2009; Sanjust et al. 2014, Lachapelle, 2013, Ampt, 2004) suggest in-kind reward or praise are more effective. Moreover, gamification of task performance with leaderboards shows a promising avenue to

increase employee task performance, for example, competition tasks or cooperation tasks (Landers, Bauer, & Callan, 2015). I argued that, in order to examine the potential of ICT-based interventions in the real-world environment, it is important to first identify how to design challenge and reward incentives according to the local environment and what incentives to apply.

Travel behaviour change can be incidental or sustained (new habits). The behavioural effect under longer periods of giving interventions have received limited attention in the literature but are crucial to the assessment of intervention strategies as a policy measure. For example, most of VBTC projects have run less than one year, and the current ICT services (apps) based studies have only run for less than two months. Several studies are optimistic about gamification and its potential to extend the commitment of the user (Andersson et al., 2018; Baranowski & Frankel, 2012; Berger & Platzner, 2015; Bowden & Hellen, 2019; Castellanos, 2016; Poslad et al., 2015)). This thesis focuses on the effects of positive interventions in the long term. Not only the effects on occurring incidental change have been analysed, but also whether a sustained behavioural change is achieved.

Finally, this thesis puts forward a strong focus on mediating factors and the possible moderators on cycling behaviour change. To better understanding ICT services (apps) based interventions in a real-world environment, I did not recruit travellers for an experiment only but simply because they wanted to. This also provided the possibility to see who did was willing to join the campaign and for how long. Further, it gave the possibility to analyse whether the interventions work differently for travellers in various travel pattern segmentations. Moreover, multiple types of interventions can be tested, and the effectiveness result can be used to update the intervention strategies

Resulting from the main research objective and scope, the following main research questions can be derived:

- 1) What are the effects of multiple types of challenge and reward incentives on travelling behavioural change, and what is the most effective challenge and reward?
- 2) What are the direct effects of the challenges on cycling and how is the behaviour change related to travel patterns and travellers' ways to deal with challenges?
- 3) What are the effects of positive interventions for behaviour change in a longer-term?

1.4 Research methodology

Figure 1.1 provides an overview of the research structure of this thesis. The research structure consists of three parts; incentive design research, living lab and research on behaviour change modelling. Each part will be explained in detail below.

1.4.1 Research on incentive design

According to my literature study, similar intervention strategies were applied for positive intervention studies, based on persuasive technology or goal-setting theory. Interventions such as challenges and tasks, feedback and motioning, and rewards give effective results when they are combined. However, the effects of different types of rewards remain controversial, i.e. to support monetary incentive or to support in-kind reward. Besides, competitive or cooperative gamification tasks shows a promising avenue to increase task performance in the commercial field. In order to obtain sufficient background knowledge about positive interventions, especially types of challenges and rewards, delivered via smartphone technology in the field of

cycling promotion, a stated choice experiment was conducted. First, to make the experience of interacting with the smartphone app as realistic as possible, I created mock-ups to visualize the incentive schemes. Second, the mock-ups were embedded in the survey and questions about travel pattern, cycling attitude, demographics and the opinions about the mock-ups were asked. The stated choice experiment can help to gain insights about the views of local travellers on the effectiveness of different incentive schemes. These insights provide valuable knowledge for interpretation and comparison of results in response to positive interventions.

After completion of this part of the research, insights into and understanding of the (stated) behavioural response of travellers to positive intervention for cycling promotion have been obtained, and recommendations for the design of an intervention strategy in a real-life experiment (living lab) with a smartphone app can be made.

Figure 1.1 Research structure consisting of three parts; incentive design research, real-world lab and research on behaviour change modelling.

1.4.2 Research on the real-world lab

Stated opinions about incentives obtained from the stated choice survey are translated into the smartphone app to apply in the real world. I have focused on setting up challenge intervention and evaluating the effect of the intervention strategies in the real world living lab. In order to assess the impact of each challenge intervention, I could have used a survey or stated choice experiments, just like how I did in the incentive design phrase. However, since tasks and challenges are directly linked to the real-world, hypothetical situations need to be built up in a

survey environment. Often respondents do not know what they would do if the hypothetical situation occurred in reality (e.g. Train, 2009). A major drawback of stated choice experiments in this situation is a potential discrepancy between stated behaviour and actual behaviour (Kroes & Sheldon, 1988). Therefore, I directly tested each challenge intervention in a real-world lab.

Two types of challenge interventions were set up. First, an intervention strategy combined with a hard measure and positive interventions. A hard measure, that refers to the provision and adaptation of physical infrastructure, has been seen to be more fundamental than other measures in increasing cycling share in a city. In a real-world experiment, the effects of new infrastructure can be evaluated with revealed travel data. Moreover, the integration of the hard measure with positive intervention can assess whether interventions can help hard measures increase behavioural changes. For this assessment, a challenge was designed for travellers to cycle through a newly designed cycling route (Boswinkel) ten times a month.

Second, a self-chosen challenge intervention strategy was conducted in the real world living lab. Many goal-setting studies showed that specific and challenging tasks led to higher performance than easy or “do your best” tasks. (E. A. Locke, 1968) (E. A. Locke & Latham, 2002) (Baretta et al., 2019). However, most applications for cycling promotion reward users by directly calculating the kilometres they cycled, without a specific challenge. Before considering personalised challenges or challenges that explicitly target a certain social-economic segment of travellers, it should be acknowledged that in many cases targeting specific segments or personalised targeting may be costly and even ethically troublesome. Instead, in this thesis, self-chosen cycling challenges were involved to make the task more specific and challengeable, along with the opportunity to research how travellers make a choice with the challenge and how will the choice impact their behavioural change. Moreover, the different types of challenges were designed and distributed throughout the years to encourage travellers to keep on participating (Dorn & Sahinyan, 2010). I designed all types of challenges for two weeks, in order to directly compare the actual behaviour with and without challenges. In this way, I can assess the short-term impact of interventions. The actual behaviour of each month was also compared throughout the whole experiment period to examine the long-term behavioural change.

In the real-world experiment, participants were recruited through a smartphone application, called ‘SMART Mobility’ (SMART in Twente, 2016). I targeted the whole population but not certain socio-demographic groups. Even though selecting target groups that are open for environmental argument and not determined to car use only, (e.g. shoppers of organic food, or parents of school children, who should learn to cycle) could be more efficient to achieve modal shift. However, this selection process generally needs travellers’ travel patterns beforehand, which inevitably involves questionnaires or real travel pattern tracking first without any incentives. Hence those travellers will be fully aware of the fact that they are participating in an experiment. This may induce them to behave more positively to please the experimenter, or they may try to control policies providing strategic responding (Train, 2002; Fujii & Gärling, 2003). Instead, a real-world experiment that protects traveller privacy and reducing experimental concepts could truly analyse the traveller’s behaviours, but this way resulted in no target group and no socio-demographic data of travellers.

This smartphone application automatically collects trip-data, i.e. origin, destination, departure time, arrival time, route and mode (-chain) for each trip. The SMART app is drawn on the achievements of other mobile app-based studies, in line with persuasive technology. Except delivering the interventions, the application also builds up high credibility by cooperating among different stakeholders (among which the mobile app company, the municipality, the university) and high detection accuracy. In addition, the application can be used for experience-

based sampling, asking a subject about its behaviour in a certain situation directly after that particular situation has revealed itself. Experience-based sampling through the app was used as a survey tool to assess motivations of (non-)completion with the received tasks, and it was also used to obtain participants' self-awareness of behaviour change. In this way, the gap between stated behaviour and actual behaviour can be further analysed.

After completion of this part of the research, insights into the short-term and long-term impacts of positive interventions on cycling behaviour change are obtained.

1.4.3 Research on behaviour change modelling

The challenge intervention design in the real-world environment is to reward cycling, rather than rewarding car reduces. This design makes sure that travellers would actively use the smartphone application, instead of turning off the app or not record trips to pretend have not made car trips. I expect the positive intervention measure is able to nudge modal shift from car to bike. However, may also motivate travellers to cycle additional trips without modal shift. In order to understand the individual behavioural change, I applied a behavioural change model to explain observed behavioural change obtained from the real-world experiment.

The behavioural change of individuals were observed each month, just as they made a decision on what changes to make each month. Their smartphone application usage information, chosen challenge information and travel pattern information would impact their decision to change. I applied a discrete choice modelling to investigate the relationship between travellers' behavioural change and their travel patterns, and how they response to the challenges and the types of challenges play a role in changing behaviour. Moreover, travellers can join the challenge or stop using the app freely. Therefore, the behavioural change decision for some individuals involved repeated choices. To explore the behaviour change over time when individuals' choices are repeated, I applied a panel-based mixed logit model (Bhat, 1999; Train, 1999; McFadden and Train, 2000).

After completion of this part of the research, insights into the behavioural change with panel effect, and how these changes related to travel pattern, intervention types and other mediating factors are obtained, and the research objective can be fulfilled.

1.5 Research relevance

The research that is presented in the next chapters has several contributions to the existing literature and society.

1.5.1 Scientific relevance

Since the late 1990s, using positive intervenes to occur voluntary travel behaviour change (VTBC) has been an increasingly popular strategy. In the age of big data, smartphone technology and software platforms are becoming useful tools to influence behavioural change. This thesis contributes to the literature on this topic as follows.

First of all, many researchers have proven the effectiveness of positive interventions for travel behavioural change, but there is an argument about the effects of different types of challenges and rewards. This thesis combined several types of challenges and rewards to make comparisons among them in the survey. Moreover, most VTBC studies did not involve new ICT technology, and only a few studies with ICT service-based interventions (e.g. Bie et al., 2012; Sanjust, Meloni, & Spissu, 2014; Gabrielli et al., 2014), generally faced the issues with the low recruitment and short running issues, due to the credibility of the app or marketing

strategies. This thesis had the opportunity to cooperate with multiple stakeholders using a smartphone application with broad recruitment in the long run. Hence, this thesis contributes to the research on long-term behavioural change, with a large sample size. Furthermore, the thesis had a quantitative analysis of the effect of an infrastructure-based challenge intervention on behavioural change in a real-world experiment. Moreover, since recent studies (e.g. Baretta, Bondaronek, Direito, & Steca, 2019) call for a stronger focus on specific and difficult challenge intervention design, this thesis answers to the call by designing a self-choice challenge intervention. Finally, this thesis developed an explanatory model for behavioural change to explain how the behavioural change is related to travel pattern, intervention types and other mediating factors and the possible moderators. As such, these challenge interventions provide suggestion in goal-setting literature and positive intervention design literature. Overall, this thesis provides evidence on positive intervention impact on cycling behavioural change by using a smartphone application, in the long term with high recruitment.

1.5.2 Societal relevance

Congestion, parking problems, accidents, air and noise pollution and climate change have pushed policymakers to focus on cycling promotion. With the consideration of social inequity and public acceptance issues, new policy measures have come up with the focus on nudging traveller voluntarily change behaviour. To that end, several governmental programmes are launched in which the implementation of ICT service-based positive interventions receives special attention. (e.g. Betterpoints app (Bowden & Hellen, 2019), OPTIMUM app (Tsirimpa et al., 2019), UbiGreen (Froehlich et al., 2009), Tripzoom app from SUNSET project (Broll et al., 2012; Bie et al., 2012; Poslad, Ma, Wang, & Mei, 2015), Peacox project (Schrammel, Busch, & Tscheligi, 2013; Mattheiss, 2015), MatkaHupi (Jylhä, Nurmi, Sirén, Hemminki, & Jacucci, 2013), SUPERHUB (Gabrielli & Maimone, 2013) Quantified Traveller (QT) (Jariyasunant et al., 2013; Jariyasunant, Sengupta, & Walker, 2014), and Metropia app (Hu, Chiu, & Zhu, 2015)).

Central to each of the abovementioned programmes is the provision of a positive intervention based on ICT services (apps). However, there is a lack of long-term evaluation and the potential to design interventions that focus on travellers who can change in the short term. A better understanding of these aspects might be crucial to the success of these programmes. As such, findings in this thesis enable these programmes to improve long-term behavioural change analysis.

1.6 Thesis outline

This is the final section of Chapter 1, the introduction. The research is introduced by putting forward the topic and defining the research problem and its relevance from a scientific and societal point of view. In addition, the research objective, research questions and the research methodology are provided. Finally, this thesis presents key conclusions, discusses results and implications and provides recommendations for future research.

Chapter 2 provides empirical insights into the effects of challenge and reward interventions on behaviour change. A survey is conducted to understand the (stated) behavioural response of travellers to positive intervention for cycling promotion. It answers whether travellers accept a smartphone app with positive interventions and whether this affects their modal shift from car to bike. Moreover, it distinguishes the acceptance of positive interventions based on several travel patterns and provides insights into how demographic factors explain individuals' adoption of a certain incentive.

Chapter 3 presents travellers' behavioural change by an infrastructure-based challenge intervention strategy. It introduces a monthly challenge to let travellers ride ten times a month on the newly designed Boswinkel cycling route, run by the SMART app. Finally, it provides insights into the effect of this type of challenge to help hard measures (the newly designed route) increase cycling.

Chapter 4 presents travellers' behavioural change by a self-chosen challenge intervention strategy, run by the SMART app. Both short and long term effects of the interventions are analysed. It answers whether challenge difficulty impacts the behavioural change. Additionally, the analysis of long term behavioural change sheds light on sustained behavioural change.

Chapter 5 provides insights into the behavioural change. It introduces an explanatory model to explain how individuals' behavioural change is related to their travel patterns, their smartphone application usage information and the chosen challenge information. Moreover, it provides insight into the behavioural change of individuals who repeatedly join the challenges. This chapter also investigates the association between stated behaviour and actual behaviour.

Chapter 6 answers the research questions by providing a comprehensive overview of the role of multiple types of challenges and rewards in the travel behavioural change. Moreover, travellers' short term behavioural change and the behavioural change impactors are discussed. Finally, the potential for positive interventions to obtain a sustained behavioural change in the longer term is analysed. Besides, this chapter discusses the usability of the results and their implications for transport policy and traffic management. Finally, it provides recommendations for future research.

2 Empirical insights into the effects of challenge and reward interventions on behaviour change

This chapter is based on the following: Huang, B., Fioreze, T., Thomas, T., & Van Berkum, E. (2018). Multinomial logit analysis of the effects of five different app-based incentives to encourage cycling to work. *IET Intelligent Transport Systems*, 12(10), 1421–1432. <https://doi.org/10.1049/iet-its.2018.5338>

Abstract

This paper presents results from an investigation into the effect of positive incentives on cycling behaviour among 1,802 commuters in the Twente region of the Netherlands. We used an on-line survey, which included mock-up apps with incentives to commute to work by bicycle. We tested five reward schemes, namely social rewards (such as badges), in-kind gifts, money, competition and cooperation. We used the survey data in a multinomial logit model to estimate to what extent travellers will use the app and increase their cycling frequency and which incentives they prefer. The model results show that respondents who sometimes cycle to work are more positive about incentive schemes than respondents who never cycle, and that offering an app with in-kind gifts is probably most effective. Interestingly, non-cyclists are more likely to change their behaviour for a reward if they care about travel costs, while occasional cyclists are more likely to cycle more often in response to incentives if they care about attributes that are related to the cycling itself. This also depends on attitudes towards cycling and on socio-demographic variables.

Keywords: challenge and reward, positive intervention, behavioural change

2.1 Introduction

Road transport contributes about one-fifth of the EU's total emissions of carbon dioxide according to the European Commission (European Commission, 2016). 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 Organization (World Health Organization, 2016). 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 (Hamer & Chida, 2008) and is inversely associated with Body Mass Index (BMI), obesity, triglyceride levels and insulin levels (Gordon-Larsen et al., 2009). Particularly cycling to work may be a feasible way to achieve the half hour of activity per day as commonly recommended (Hamer & Chida, 2008; Park, Rink, & Wallace, 2006).

Table 2.1 Overview of behavioural change techniques and intervention effectiveness

Study/sample sizes	Rewards/Incentives/Interventions	Effectiveness of intervention	Design
Baum (Baum, 2008) (600)	In-kind gifts, feedback, education, comparing with others, trip diaries	Increase of cycling and walking trips by 33% relative to the control neighbourhood	Before-and-after survey with control group; but different people
Dubuy et al. (Dubuy et al., 2013) (110 joined)	Random monetary rewards, comparing with others	More than half participants reported no behaviour change. The barriers is mostly distant to work but not linked to the interventions.	After survey; Before-and-after comparison; Self-reported data
Steven and Avineri (Steven & Avineri, 2011) (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 et al. (Wen, Orr, Bindon, & Rissel, 2005) (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 et al. (Usui et al., 2008) (74)	Personal goals and planning, feedback, education	Car use decreased by 20.1%. Travel on foot and by bicycle increased by 82.2 %, while public transport use increased by 103%.	GPS tracking without a control group; a before-and-after comparison
TravelSmart project. (Y. Zhang et al., 2010a) (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 (Brög, Erl, Ker, Ryle, & Wall, 2009) (≈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% to 15% reduction in car-as-driver trips. But 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 et al. (Wardman, Page, Tight, & Sin, 2000) (1000) Ryley (Ryley, 2006) (654)	Monetary rewards	First one proved that monetary reward is effective for traveller's intention behaviour change. Second one is on the contrary.	The stated preference survey.

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 (Ben-Elia & Ettema, 2011a), (Bamberg & Schmidt, 2003), (Cairns et al., 2008).

In this paper, we present results of a study into the use of positive interventions to promote sustainable travel behaviours, specifically cycling. Table 2.1 lists several case studies in which such incentives were employed to promote cycling.

As Table 2.1 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 (Yang, Sahlqvist, McMinn, Griffin, & Ogilvie, 2010), (Pucher, Dill, & Handy, 2010), (Scheepers et al., 2014). Nearly all showed positive effects.

The majority of studies, which focused on positive interventions in Table 2.1, 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. (Wen, Orr, Bindon, & Rissel, 2005) and used in the TravelSmart project (Y. Zhang, Stopher, & Halling, 2010), which provide personalised travel plans and feedback by phone call interview and showed that individualized 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 (Usui, Miwa, Yamamoto, & Morikawa, 2008) 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., (Ben-Elia & Ettema, 2011a), (Hu et al., 2015), (Sanjust et al., 2014), (Zhu et al., 2015)).

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 (Ben-Elia & Ettema, 2011)), and are probably biased due to self-selection; i.e., participants that are already willing to cycle, are more likely to participate. Moreover, external factors, such as weather (Thomas, Jaarsma, & Tutert, 2013) 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 (Sanjust et al., 2014)), 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 (Y. Zhang et al., 2010) made such comparisons. Comparisons between studies are even harder. For example, Ryley (Ryley, 2006) found that a financial incentive of £2 per day would not induce or increase cycle commuting, while Wardman et al. (Wardman, Page, Tight, & Sin, 2000) 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 aforementioned selection and/or external effects. Furthermore, according to some studies, in-kind gifts can be a good alternative to money (Ben-Elia & Ettema,

2011a),(Presslee, Vance, & Webb, 2012). However, Shaffer and Arkes (Shaffer & Arkes, 2009) 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 personalized 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 lower educated people, and between males and females, with the former groups probably more likely to cycle more when positive incentives are provided (Chorus, Molin, & van Wee, 2006). In this study, we test these assumptions with segmentation analyses that are mostly lacking in other studies.

The paper is organised as follows. Section 2.2 explains the methodology. Section 2.3 describes the design of the pilot study and data collection. Section 2.4 presents the results of the analyses and Section 2.5 provides conclusions.

2.2 Methodology and design

Section 2.2.1 introduces the positive incentive schemes and the mock-up apps, and the motivation for their design based on the literature. Section 2.2.2 details the multinomial logit model to quantify and interpret the outcomes.

2.2.1 Incentive schemes and mock-up design

In order to investigate the effect of different reward schemes delivered via smartphone technologies, we designed five intervention schemes. Based on the work of, e.g., Zhang et al. (Z. Zhang, Fujii, & Managi, 2014) and Ben-Elia & Ettema, 2011 (Ben-Elia & Ettema, 2011), we included travel context, travellers' attitudes, and demographics as discriminating factors between groups. Figure 2. 2.1 summarizes 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 (Oinas-kukkonen & Harjumaa, 2009) and Khaled et al. (Khaled, Barr, Noble, Fischer, & Biddle, 2007) argued that incentives can be more effective when they relate to the actual behaviour of the user.

Table 2.2 lists the five intervention schemes, built on principles with a high potential according to our literature study, such as goals, feedback and rewards. According to goal setting theory (Locke & Latham, 2002), goals and planning, feedback and motioning, and rewards give the best results when they are combined (McCalley & Midden, 2002), (Abrahamse, Steg, Vlek, & Rothengatter, 2005). The types of rewards, however, were different in the various studies, such as cash rewards, in-kind gifts and praise (Ben-Elia & Ettema, 2011a; Brög et al., 2009; Z. Zhang, Fujii, & Managi, 2014). 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, Bauer, and Callan (Landers, Bauer, & Callan, 2015) concluded that presenting specific goals on a leaderboard can have a similar effect as traditional goal setting and Dubuy et al. (Dubuy et al., 2013) 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).

Figure 2.1 Research framework

We created five mock-ups to visualize the incentive schemes in order to make the experience of interacting with the smartphone app as realistic as possible (Figure 2.2). In general, the five mock-ups were similar, except for the screen with the incentives. Figure 2.2(b) displays the home screen, which shows a fictional user's cycling stats. The bottom icons can be clicked to join a challenge (Figure 2.2(a)), get feedback on bicycle commutes (Figure 2.2(b)), and to check the user's rewards (Figure 2.2(c)). Figure 2.2(c) depicts a scenario in which the app user is rewarded with money, for example. 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 Figure 2.2(f).

In the incentive scheme with social rewards, we replaced money by various levels of badges. Figure 2.2(d) and 2.2(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.

Table 2.2 Incentive schemes

Type of scheme	Scheme	Goals and planning	Feedback and motioning	Incentives/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 & 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 & 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 & Occasional cyclist	Mock-up Social
Scheme Competition(Comp)	4:	Cycle more than others	Leaderboard Visual historical performance	Tangible reward Points for gifts	Leaderboard Competition	Occasional cyclist & Daily cyclist	Mock-up Competiti on
Scheme Cooperation(Coop)	5:	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 prize	Leaderboard Cooperation	Occasional cyclist & Daily cyclist	Mock-up Cooperati on

Figure 2.2 Screens in the mockups

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

2.2.2 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 2.3), 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 2.3). Those three cases contain the following choices: 1) considering using the app or not, 2) motivated to cycle more or not, and 3) 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., respectively ‘consider’ and ‘yes’) or as not negative (i.e., respectively ‘Might or might not consider’ + ‘Consider’ and ‘I don’t know’ + ‘yes’). We took the confirmative answers and the non-negative answers to indicate ‘positive’ responses.

Table 2.3 Description of three multinomial logit model cases

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 Wouldn't 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:

$$P_i = \frac{\exp(U_i)}{\sum_{j=1}^m \exp(U_j)} \quad (2.1)$$

In (2.1), U_i is the systematic component of the utility of alternative (outcome) i . The utility function is given as:

$$U_i = \log \frac{P_i}{P_m} = \alpha_i + \beta T + \gamma IV + \delta AT + \theta AC + \omega SC + \epsilon_i \quad (2.2)$$

In (2.2), 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 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 (2.2). For example, in case 1 (see Table 2.2), 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 smaller than 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. Table 2.6, 2.7, 2.8 and 2.9 contain all model results.

2.3 Survey design and data

We utilized 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: 1. 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 5 describes the sample of this study. In total, 1802 people took part in our online survey, of which 1401 had a commuting distance of less than or equal to 20 kilometres. These are potential daily cyclists, since a commuting distance above 20 kilometres is considered physically demanding. Of these 1401 respondents, 1125 completed the survey, which were included in the analysis and modelling.

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 employees (Fioreze, Thomas, Huang, & van Berkum, 2018). Our sample also has a higher fraction of highly educated and high-income respondents compared to the Dutch Travel Survey 2015 (“Research Movements in the Netherlands (OVIN),” 2015). We suspect that this type of study attracts employees whose workforce are 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 2.2). 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 2.4 summarizes the number of respondents randomly assigned to one of our rewarding schemes based on travel pattern segmentation.

Table 2.4 Reward schemes respondents based on travel pattern segmentations

Cycling frequency	Social reward	In-kind gifts	Money	Coop	Comp	Total
NCG	16	40	58	35	19	576
OCG	35	113	119	45	21	445
DCG	0	0	0	484	140	781
Total	51	153	177	564	180	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 (“Twente Mobile - Together for your mobility policy,” n.d.).

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.

2.4 Results

Section 2.4.1 presents the model estimation regarding app usage and 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. Table 2.6, 2.7 and 2.8 contain the model results. In Section 2.4.2, we discuss the model estimation results for the choice between different incentives (see Table 2.9).

2.4.1 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 reference, as in-kind gifts have been shown to be a relatively good incentive to change behaviour.

The model results (see Table 2.6, 2.7 and 2.8) 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 Figure 2.3 displays the fraction of respondents who are willing to use the app, but from Figure 2.3 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 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.

Figure 2.3 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 ($p = 0.008, 0.038$). As expected (Chorus, Molin, & van Wee, 2006), 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 ($p = 0.001, 0.028$). Regarding the latter group, this may be attributed to the fact that they are more economically vulnerable and therefore more open to tangible rewards.

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-ups scores are worse than the in-kind gift mock-up. This is illustrated by the right panel in Figure 2.3, 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. (Dubuy et al., 2013) 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 ($p = 0.024$).

2.4.2 Incentive preferences model analysis

As Table 2.5 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.

Figure 2.4 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. (Gneezy, Meier, & Rey-Biel, 2011), and Shaffer and Arkes (Shaffer & Arkes, 2009). Comparing no rewards with money or in-kind gift incentives, the results of Table 9 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).

Figure 2.4 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 ($p = 0.014, 0.028$), 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 (Steven & Avineri, 2011) and Dickinson et al. (Dickinson, Kingham, Copsey, & Hougie, 2003).

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 at. 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 prefer a social reward scheme and vice versa. This result suggests that in-kind and social reward schemes are attractive to the same type of respondents. In contrast, there is almost no exchange between in-kind gifts and money, which suggests that these two schemes attract different types of people.

2.5 Conclusions

In this paper, 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 via 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 (Shaffer & Arkes, 2009), 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. (Gneezy et al., 2011), and Shaffer and Arkes (Shaffer & Arkes, 2009).) 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. (Chorus et al., 2006).

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 like 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 (List & Levitt, 2006) for an overview). Nonetheless, even in cases where revealed and stated intention results are not exactly the same, some studies (e.g. (Levitt & List, 2016)) 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, for example, when comparing in-kind gifts with money.

Throughout the paper, 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 between 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.

2.6 Acknowledgements

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Table 2.5 Descriptive statistics of samples

Descriptive characteristics of sample N=1125								
Categories	Variables		Proportion		Categories	Variables	Proportion	
Traffic-related	Commuting distance				Gender	Gender male	45.3%	
	Frequency	TravelPattern Non cycling (NCG)	15.0%			Gender female	54.7%	
		TravelPattern Occasional (OCG)	29.7%		Age	Age 19-24	2.2%	
		TravelPattern Daily (DCG)	55.3%			Age 25-34	21.9%	
Interventions	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%	
	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	Yes	38.1%	Education	Education HBO or university	62.2%	
			No	61.9%		Education MBO	25.6%	
		I want to save on travel costs	Yes	43.1%		Education Below college	Education Below college	12.1%
			No	56.9%			Gross monthly income	Income No answer
		I want to feel relaxed	Yes	27.7%	Income 999 or less			0.8%
			No	72.3%	Income 1000-1999			14.5%
		I want to behave environmentally friendly	Yes	65.4%	Income 2000-2999	30.3%		
			No	34.6%	Income 3000-3999	20.0%		
		I want to feel healthy	Yes	51.5%	Income 4000 or more (reference)	12.0%		
			No	48.5%	Preferred incentives	No rewards	21.9%	
		I want to cut travel time	Yes	10.1%		Social rewards	1.6%	
			No	89.9%		In-kind gift	29.0%	
		I want to travel safely	Yes	10.1%		Money	35.4%	
			No	89.9%				
Attitude about cycling	How do you like cycling?	FeelingCycle Neutral	17.4%			Gamification (Coop & Comp)	6.2%	
		FeelingCycle 'I like cycling'	79.6%			Others	6.0%	
		FeelingCycle 'I don't like cycling'	3.0%					
	How often do you talk with others about cycling?	Talking 'Sometimes'	40.9%					
		Talking 'Often/Always'	9.9%					
		Talking 'Never/Seldom'	49.2%					
Cycling app	UsageAppCycle No		73.2%					
	UsageAppCycle Yes		26.8%					

Table 2.6 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	.000		.000		.000		.024	
Cox and Snell R2	.270		.398		.280		.329	
Nagelkerke R2	.360		.456		.373		.386	
	Base case: I could not be motivated to cycle (more) by the reward scheme				Base case: I would not consider using the app			
explanatory variable	Yes+maybe		Yes		Neutral+Consider		Consider	
	Coefficient	p-Value	Coefficient	p Value	Coefficient	p Value	Coefficient	p Value
Constant	1.254	.364	-.458	.800	.579	.682	-2.625	.291
Distance	-.100	.019	-.106	.035	-.096	.025	-.095	.152
<i>Interventions (ref: In-kind gift)</i>								
Mock-up Social	-1.413	.070	-1.632	.095	-1.473	.074	-2.053	.086
Mock-up Money	-.637	.207	-.445	.452	-.903	.077	-2.163	.012
Mock-up Cooperation	-.992	.084	-1.152	.105	-.664	.244	-.909	.278
Mock-up Competition	-2.163	.006	-2.423	.013	-1.500	.047	-2.461	.075
<i>Statement Travel Cost (ref: No)</i>								
Yes	1.435	.020	2.163	.003	1.684	.008	1.472	.156
<i>Statement Health (ref: No)</i>								
Yes	1.091	.165	.333	.737	1.574	.054	2.533	.054
<i>Statement Travel Time (ref: No)</i>								
Yes	.249	.724	.188	.829	.770	.325	2.166	.129
<i>Statement Convenience (ref: No)</i>								
Yes	-.222	.717	-.512	.473	-.663	.259	-.373	.709
<i>Statement Relaxed (ref: No)</i>								
Yes	-.622	.140	.397	.457	.115	.792	.429	.551
<i>Statement Environmentally (ref: No)</i>								
Yes	-1.292	.224	-1.951	.177	-1.435	.147	-.316	.831
<i>Statement Safety (ref: No)</i>								
Yes	-.419	.455	-.258	.714	1.172	.038	1.664	.083
<i>Talking about cycling (ref: Never/Seldom)</i>								
Sometimes	1.141	.013	.854	.124	.794	.072	1.139	.101
Often/Always	.417	.639	.629	.558	.422	.616	.128	.927
<i>Usage of Cycle App(ref: No)</i>								
Yes	.222	.626	.252	.649	1.221	.014	.888	.266
<i>Age (ref: 55-64)</i>								
Age 19-34	1.089	.118	1.129	.222	.654	.371	2.442	.103
Age 35-44	.028	.963	.561	.499	.959	.139	1.965	.153
Age 45-54	-.911	.135	-.457	.592	-.062	.923	1.073	.424
<i>Nationality (Ref: Dutch)</i>								
Foreigner	-.031	.965	.438	.578	1.009	.161	1.207	.273
<i>Education (ref: Under college)</i>								
HBO	.340	.613	-1.052	.277	-.215	.763	-.857	.485
MBO	.216	.757	-.782	.230	-1.033	.183	-2.188	.101
<i>Income(ref: above 3000)</i>								
No answer	.301	.579	.267	.686	-.913	.097	-2.425	.049
Below 3000	.115	.812	.062	.913	.391	.436	.020	.979

Table 2.7 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	.000	.000	.001	.003				
Cox and Snell R2	.169	.234	.138	.207				
Nagelkerke R2	.229	.266	.199	.233				
	Base case: I could not be motivated to cycle (more) by the reward scheme		Base case: I would not consider using the app					
explanatory variable	Yes+maybe		Yes		Neutral+Consider	Consider		
	Coefficient	p-Value	Coefficient	p Value	Coefficient	p Value	Coefficient	p Value
constant	-.717	.482	-3.489	.012	.359	.759	-1.098	.429
distance	-.006	.843	-.008	.805	.053	.094	.047	.206
Interventions (ref: In-kind gift)								
Mock-up Social	-.937	.034	-1.233	.015	.170	.748	.355	.539
Mock-up Money	-.519	.094	-.539	.108	-.560	.088	-.646	.088
Mock-up Cooperation	-1.904	.000	-2.161	.000	-.825	.058	-1.907	.002
Mock-up Competition	-1.663	.003	-2.168	.002	.151	.810	.201	.775
Statement Travel Cost (ref: No)								
Yes	.595	.126	1.382	.007	-.527	.236	-.419	.419
Statement Health (ref: No)								
Yes	.134	.755	1.086	.052	-.307	.530	-.335	.555
Statement Travel Time (ref: No)								
Yes	.189	.652	1.033	.056	-.474	.327	-.259	.646
Statement Convenience (ref: No)								
Yes	.054	.893	.670	.195	-.771	.087	-.638	.224
Statement Relaxed (ref: No)								
Yes	.574	.107	1.082	.023	-.320	.430	-.348	.467
Statement Environmentally (ref: No)								
Yes	.342	.386	.930	.066	-.409	.361	-.511	.335
Statement Safety (ref: No)								
Yes	.650	.181	1.471	.015	-.116	.828	-.084	.894
Talking about cycling (ref: Never/Seldom)								
Sometimes	-.223	.433	-.077	.810	.034	.907	-.008	.982
Often/Always	-.420	.321	-.279	.549	1.081	.054	1.149	.065
Usage of Cycle App(ref: No)								
Yes	-.062	.830	.060	.852	.807	.020	1.221	.002
Age (ref: 55-64)								
Age 19-34	1.472	.001	1.666	.001	1.342	.004	1.203	.027
Age 35-44	1.125	.002	1.210	.004	1.001	.011	.935	.050
Age 45-54	.998	.004	1.027	.011	.744	.044	.821	.066
Nationality (Ref: Dutch)								
Foreigner	.955	.079	.919	.120	1.260	.110	1.378	.100
Education (ref: Under college)								
HBO	-.176	.671	-.062	.897	.760	.066	1.147	.036
MBO	-.100	.822	-.077	.880	1.070	.018	1.219	.039
Income(ref: above 3000)								
No answer	.489	.141	.363	.331	-.472	.183	-.320	.453
Below 3000	.711	.023	.652	.060	-.144	.670	.260	.510

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	.000		.000		.000		.000	
Cox and Snell R2	.150		.195		.115		.159	
Nagelkerke R2	.204		.230		.154		.180	
	Base case: I could not be motivated to cycle (more) by the reward scheme				Base case: I would not consider using the app			
explanatory variable ()	Yes+maybe		Yes		Neutral+Consider		Consider	
	Coefficient	p-Value	Coefficient	p Value	Coefficient	p Value	Coefficient	p Value
constant	-2.093	.000	-2.450	.001	-1.185	.030	-1.793	.012
distance	.028	.255	.004	.894	.024	.302	.015	.598
Interventions (ref: Competition)								
Mock-up Cooperation	.600	.010	.597	.030	.236	.269	-.077	.767
Statement Travel Cost (ref: No)								
Yes	-.335	.485	-.560	.363	-.010	.981	-1.166	.142
Statement Health (ref: No)								
Yes	-.138	.584	-.360	.228	.045	.854	-.048	.878
Statement Travel Time (ref: No)								
Yes	-.203	.393	-.403	.161	.177	.436	-.237	.417
Statement Convenience (ref: No)								
Yes	.024	.913	-.094	.722	-.052	.807	-.256	.347
Statement Relaxed (ref: No)								
Yes	-.287	.172	-.464	.068	-.092	.649	-.105	.679
Statement Environmentally (ref: No)								
Yes	.236	.297	.188	.491	.156	.475	.036	.897
Statement Safety (ref: No)								
Yes	-.219	.600	.047	.920	.034	.933	-.386	.470
Talking about cycling (ref: Never/Seldom)								
Sometimes	.306	.132	.196	.426	.285	.140	.249	.317
Often/Always	.698	.035	.850	.024	.026	.934	.275	.475
Usage of Cycle App(ref: No)								
Yes	.571	.005	.846	.000	1.054	.000	1.263	.000
Age (ref: 55-64)								
Age 19-34	1.788	.000	2.020	.000	.402	.172	.825	.032
Age 35-44	1.190	.000	1.293	.000	.361	.202	.504	.180
Age 45-54	.287	.279	.146	.678	-.140	.552	.208	.513
Nationality (Ref: Dutch)								
Foreigner	.639	.044	.411	.262	1.395	.000	1.471	.001
Education (ref: Under college)								
HBO	-.425	.146	-.048	.904	.094	.730	.175	.642
MBO	.092	.769	.314	.454	.054	.856	.243	.546
Income(ref: above 3000)								
No answer	.380	.162	.140	.680	.243	.338	.169	.612
Below 3000	.292	.225	.219	.446	.498	.028	.416	.153

Table 2.9 Scheme preference reaction model

Model χ^2 (112) = 392.356			p-Value 000											
Cox and Snell R2 = .294			Nagelkerke R2 = .313											
Explanatory variable	Base case: money						Base case: No reward		Base case: In-kind gifts					
	No reward		In-kind gift		Gamification		Gamification		No rewards		Gamification			
	Coe	p-V	Coe	p-V	Coe	p-V	Coe	p-V		Coe	p-V	Coe	p-V	
Constant	1.69	.017	-.310	.656	-2.79	.058	-4.473	.003		1.370	.076	-3.39	.025	
Distance	-.034	.124	-.015	.427	-.069	.042	-.035	.336		-.018	.425	-.054	.119	
Interventions (ref: Money)														
Mock-up Social	.901	.074	1.59	.000	-.872	.433	-1.773	.119	Social	-.062	.903	-1.55	.170	
Mock-up In-kind	-.420	.238	.205	.476	-.707	.147	-.287	.606	Money	.624	.106	.911	.071	
Mock-up Coop	.302	.394	.408	.245	-.450	.481	-.752	.262	Coop	.519	.219	.053	.940	
Mock-up Comp	.221	.567	.453	.236	-1.17	.105	-1.392	.066	Comp	.393	.389	-.712	.362	
Travel patterns (ref: Daily cyclist)														
Non-cycling	1.18	.003	-.378	.339	.673	.348	-.504	.499		1.555	.000	1.05	.154	
Occasional cyclist	.152	.633	-.058	.850	-.390	.527	-.542	.400		.209	.544	-.333	.596	
Statement Travel Cost (ref: No)														
Yes	-1.12	.000	-.432	.062	-.053	.907	1.067	.028		-.688	.014	.379	.412	
Statement Health (ref: No)														
Yes	-.123	.663	.320	.207	.545	.281	.667	.213		-.443	.135	.224	.662	
Statement Travel Time (ref: No)														
Yes	-.345	.199	.273	.263	.305	.527	.650	.200		-.618	.028	.031	.949	
Statement Convenience (ref: No)														
Yes	.240	.346	-.083	.725	.024	.958	-.216	.662		.323	.233	.108	.822	
Statement Relaxed (ref: No)														
Yes	-.025	.913	.071	.745	.268	.539	.293	.519		-.096	.695	.196	.658	
Statement Environmentally (ref: No)														
Yes	.369	.172	.438	.076	1.30	.005	.935	.057		-.069	.804	.866	.066	
Statement Safety (ref: No)														
Yes	-.035	.916	.377	.224	.190	.746	.225	.715		-.412	.240	-.187	.752	
Talking about cycling (ref: Never/Seldom)														
Sometimes	-.105	.599	.172	.322	-.080	.802	.025	.941		-.277	.179	-.251	.434	
Often/Always	-.804	.027	-.157	.573	.442	.294	1.245	.013		-.647	.088	.599	.163	
Usage of Cycle App (ref: Yes)														
Yes	-.311	.157	.217	.224	.293	.325	.603	.070		-.527	.019	.076	.799	
Gender (ref: Female)														
Male	.069	.731	-.468	.008	.236	.434	.167	.611		.537	.011	.704	.022	
Age (ref: 55-64)														
Age 19-34	-.668	.033	-.297	.283	-.247	.598	.421	.404		-.371	.252	.050	.916	
Age 35-44	-.650	.022	-.238	.352	-.431	.326	.219	.640		-.413	.161	-.193	.662	
Age 45-54	-.569	.020	-.284	.219	-.573	.186	-.004	.993		-.285	.257	-.289	.506	
Nationality (Ref: Dutch)														
Foreigner	.253	.437	.015	.958	-.296	.532	-.549	.289		.238	.477	-.311	.514	
Education (ref: Under college)														
HBO	-.862	.003	-.333	.213	.435	.466	1.298	.034		-.529	.066	.769	.195	
MBO	-.522	.092	-.202	.479	.561	.367	1.083	.091		-.320	.302	.763	.217	
Income (ref: Above 3000)														
No answer	-.257	.291	-.268	.241	-.638	.140	-.381	.404		.012	.964	-.369	.403	
Below 3000	-.375	.118	.199	.331	.134	.702	.510	.186		-.575	.021	-.065	.856	
Motivation (ref: No)														
Maybe	-.862	.001	.158	.466	.932	.023	1.794	.000		-1.02	.000	.775	.062	
Yes	-1.65	.000	.286	.137	1.35	.000	3.002	.000		-1.94	.000	1.06	.003	

3 Travellers' behavioural change by an infrastructure-based challenge intervention strategy

This chapter is based on the following: Huang, B., Thomas, T., Groenewolt, B., Fioreze, T., & van Berkum, E. (2018). The Effect of Incentives to Promote Cycling: a Mobility Living Lab. *Transportation Research Board 97th Annual Meeting*

Abstract

As part of the Horizon 2020 project EMPOWER, this paper presents results from a case study on the impact of positive incentives on cycling behaviour for around 70 participants in the Twente region of the Netherlands. This was done by using the SMART app in a real-world living lab environment. The SMART app uses challenges with rewards, feedback, and message functions to promote cycling. In this particular case, participants were challenged to cycle at least 10 times along a newly paved cycling road and get rewarded upon completion of the challenge. A post-challenge survey was sent through the app to evaluate participants' behaviour. We found that the campaign resulted in new bike trips, on the newly paved road, made by users who completed the challenge, even after the campaign had ended. According to the survey, 44% of participants responded that their behaviour had changed due to the campaign, and that they would keep on cycling more often after the campaign. Most users who did not complete the challenge said they do not need to use this road, but 20% of them indicated that they would cycle more if they got challenges and rewards more suited to their personal situation. This implies that challenges are more effective when they are customized based on individuals' historical travel patterns

Keywords: Travel behaviour, Living lab, Smartphone, challenge and rewards, soft measures

3.1 Introduction

Road transport contributes to about 25% of the EU's total emissions of CO₂ (European Commission, 2016a). As the main component of global greenhouse gas (GHG), CO₂ emission is the main contribution to global warming. Therefore, the European Union stressed the urgent need to reduce the levels of CO₂ emission. In addition to the negative impact for the environment, car driving is also associated with unhealthy behaviour (e.g., Gordon-Larsen et al., 2009 (Gordon-Larsen et al., 2009)). Active modes of transport (i.e., cycling and walking) are not only environmentally friendly, but also seen as healthy alternatives (Park et al., 2006)(Hamer & Chida, 2008), in particular for relatively short trips within cities.

Fiscal regulations to discourage car use are effective measures to stimulate alternative transport modes, but are sometimes controversial regarding socio-economic equity (i.e. poor people cannot afford to use the car anymore, whereas rich people are less affected or not at all) and often lack public support. Instead of 'stick' measures, positive incentives such as travel planning, subsidies, marketing, rewards, and PT discounts could also stimulate the use of sustainable transport options. Positive interventions or "soft measures" are used within voluntary travel behaviour change (VTBC) programs or active traffic and demand management (ATDM). We found several case studies in which such interventions were used to promote cycling (e.g., (Baum, 2008; Dubuy et al., 2013; Steven & Avineri, 2011) and (Y. Zhang, Stopher, & Halling, 2010b)).

However, in most of the cases, stated preference surveys were used to measure the intention for change, which is not the same as actual changing behaviour. This situation is improving and changing with the use of information technologies, such as smartphones, where high-bandwidth connectivity and the growing adoption rate are said to be transforming the public realm and the way we live and interact in urban areas (Schaffers, Ratti, & Komninos, 2012). These rapidly advancing technological are able to automatically detect travel behaviour, offer real-time information about the traffic and provide rewards accordingly. There are some positive incentive programs that used mobile technologies to provide interventions for travel behaviour change studies (e.g.,(Hu et al., 2015), (Sanjust et al., 2014), (Ben-Elia & Ettema, 2011b), (Usui et al., 2008) , and (Zhu et al., 2015)), which all have proven that interventions through mobile technologies can successfully raise sustainable travel behaviour change. These interventions are: rewarding sustainable behaviour, providing feedback about behaviour, encouraging behavioural change by goal setting and planning, and raising awareness of sustainable travel options by providing travel information. For example, the Spitsmijden (Ben-Elia & Ettema, 2011b) focused on the effectiveness of rewards, CAPRI (Zhu et al., 2015) used feedback by comparing behaviour with others and by giving rewards accordingly. Casteddu Mobility Styles programs (Sanjust et al., 2014), Osaka, Japan, and Metropia (Usui et al., 2008)(Hu et al., 2015) used a combination of incentives.

One of the problems of aforementioned studies is that subjects are fully aware of the fact that they are participating in an experiment. This may induce them to behave in a more positive way in order to please the experimenter (List & Levitt, 2006). Furthermore, direct measurements of the effects are often lacking and behavioural change is often measured indirectly. For example, Metropia sent emails during the experiment to ask participants about their habitual behaviour, and Casteddu Mobility Styles program used surveys to ask participants' potential behaviour change, without using smartphone sensors to track the real behaviour change. The smartphone app usage inconvenience, the experimental look and feel of the used apps, and the use of surveys to measure effects, are limitations of these studies. Even though those studies are valuable, they do not gain rich insights into the complex interactions of the user with the environment, or the user context (List & Levitt, 2006) (Mulder & Stappers, 2009). Living lab

experiments, on the other hand, can overcome those limitations and provide real-life contexts (Pallot, Trousse, Senach, & Scapin, 2010) (Mulder & Stappers, 2009). Living Labs are a rather new phenomenon which started to emerge in the beginning of 2000. The initial focus of Living Lab was to test innovative technologies in home-like environments (Bergvall-Kåreborn, Holst, & Ståhlbröst, 2009). As the concept has grown, a real-world context is one precondition in a Living Lab experiment.

Last but not least, aforementioned studies were not specifically focusing on cycling. Metropia and Spitsmijden analyzed peak hour avoidance, CAPRI studied a parking behaviour program, Casteddu Mobility Styles programs focus on mode change to a light rail service. Osaka, Japan involved cycling behaviour analysis, but the main focus was all non-auto transport modes. This is unfortunate, because as mentioned earlier, cycling (and walking) can capture a significant share of car trips within cities. Therefore, there are already numerous commercial apps such as Strava, CycleMaps that promote cycling by using gamification methods. Other apps such as BetterPoints, Fietstelweek, CommuteGreener are providing real rewards to promote cycling. All those projects show a potential to encourage cycling, but lack rigorous scientific analysis to evaluate their effects.

This study is part of the Horizon 2020 project EMPOWER ("EMPOWER," 2016), in which positive interventions are used in real-world Living labs to promote sustainable travel behaviour (change), such as cycling. Within EMPOWER, the SMART (jointly developed by Mobidot and the municipality of Enschede) app has been used to promote cycling. The objective of this paper is to test the effectiveness of positive interventions in a living lab environment.

The paper is organized as follows: Section 3.2 explains the methodology and the design of the interventions strategies, the SMART system, and reviews the pilot study; Section 3.3 presents the results of the discussions; and Section 3.4 provides conclusions and future works.

3.2 Method

3.2.1 SMART App

The positive incentives were provided through the SMART app ("SMART," 2017). In this subsection, we describe the SMART app based on the principles of persuasive technology. TravelSmart (Seethaler & Rose, 2005) and Casteddu Mobility Styles programs (Sanjust et al., 2014), for example, have successfully adopted the principle of persuasion (Cialdini, 2001) to promote travel behaviour change. The persuasive system design (Oinas-Kukkonen & Harjumaa, 2008) is used for the design of software and information systems to reinforce, change and / or shape attitudes and behaviour. The design consists of four principles and the application of the persuasive design principle in the SMART app is shown in Figure 3.1, Figure 3.1(a) depicts the SMART app dashboard. Users can explore the whole functions of the app from this page. The remaining figures are enlarged screenshots from other pages of the SMART app. The following shows the four design principles.

First, the principle of task support design presents the user's primary task and supports the user in finalizing this task. In the SMART app, we present the task by challenges, and we provide feedback on historical behaviour (i.e. on trips made in the previous days and weeks). In doing so, we provide the user with information on the progress of the challenge (Figure 3.1(a, b)). This is done by continuously tracking (using GPS, accelerometer data, etc.), and using advanced algorithms that combine travel speeds and travel routes to determine which transportation mode the traveller is using. The observed trips (including route and mode) of the user are shown in

a)

d)

f)

b)

c)

e)

Figure 3.1 a) Dashboard, task support, feedback and monitoring; b) Task support, monitoring; c) Task/challenge, d) Dialogue support, reward result, e) Dialogue support, messages, f) System credibility, third party redeem stores ; g) Social support

the front end. The operator can provide challenges and messages to users, which also will be shown in the front end (Figure 3.1(c)).

Secondly, the principle of dialogue support stimulates users to keep moving towards their goal or target behaviour. In SMART, rewards are provided upon completion of the challenge (Figure 3.1(d)). If the challenge is accepted by the user, the system starts to keep track of the targeted behaviour, and shows the process in the front end. When the challenge is fulfilled, the system will immediately give the corresponding amount of points. The earned points can then be redeemed for various discounted products and services. Note that non-cash incentives may ultimately make users more satisfied (Shaffer & Arkes, 2009), and that from an earlier study we also concluded that in kind gifts from a web shop have a more positive impact than cash rewards (Huang, Fioreze, Thomas, & Berkum, n.d.). Furthermore, event and traffic information are also offered through messages (Figure 3.1(e)). SMART can give useful information about the actual local traffic situation and notifies users in case of road works or large scale events that lead to extra traffic. Based on this, SMART can also suggest travel alternatives to help the user to optimize their travel plans.

Thirdly, the principle of system credibility provides to the user with credible and authentic information from an acknowledged source. For example, a mobile application with good reviews that is regularly updated by its developer(s) and supported by trustworthy source(s) is expected to be credible. The SMART app is regularly updated and maintained by Mobidot and supported by the municipality of Enschede. Moreover, its users are informed in advance about privacy protection and the travel mobility data is updated every day. At last, there are new challenges updated regularly as well as well-known shops to redeem vouchers (Figure 3.1(f)). All these features help to support the system credibility of the SMART app.

Finally, social support motivates users by leveraging social influence. The SMART app involves group challenges in which participants can invite friends to fulfil the challenge together (Figure 3.1(g)). However, in the Boswinkel campaign, social support was not included.

3.2.2 Case study design

The case study includes two parts, first the implementation, monitoring and evaluation of the challenge and rewarding scheme, and secondly post-challenge survey to evaluate the participants' view on their behaviour. The whole case study was designed and carried out through the SMART app.

In this cycling promotion campaign, named the Boswinkel challenge, participants were challenged to cycle at least 10 times along a newly paved cycling road (in the Boswinkel neighborhood). The campaign period was from the beginning of October to the beginning of December 2016 (week 41-49 in 2016). During this time period, there were no other challenges. Users who downloaded the SMART app needed to select and join the challenge. After finishing the challenge, a voucher was awarded to the user who could redeem it in the local shops. The case study was carried out in the city of Enschede, a mid-sized city in the Netherlands with approximately 158,000 inhabitants.

Participants who used the SMART app were recruited via different municipal communication channels in which the main objective was to promote the cycling city ambition in general, and to promote the use of the newly opened Boswinkel route in particular.

Participants were not told that they were participating in an experiment and could join at any time within the duration of the campaign through the SMART app. As a result, we created a real-life context—a living lab to truly analyse the traveller's behaviours. However, as the participants could immediately use all functionalities of the SMART app, we are not able to do a before measurement, which is an important drawback of this study. Moreover, we cannot

disentangle in this experiment whether either the added comfort of the new route itself or the challenge with reward lead to extra cycling trips.

To tackle the question whether and why participants change their behaviour, we used the SMART experience sampling question service, which allows to send personal questions triggered by specific events. The questionnaire was sent out immediately after completion of the challenge or after the campaign for participants that did not complete the challenge. First, participants received the question why they did or did not complete the challenge. Then they were asked whether they had cycled more along the Boswinkel route during the challenge and whether these trips were new trips, trips that were previously made by car or public transport, or trips that were previously made by bike but along a different route. In the case that participants had indicated that they had cycled more along the Boswinkel route, they received two follow-up questions. In the first question, they were asked about the reasons to cycle more (due to the new infrastructure, due to the challenge & reward, or due to some other external factors). In the second question, they were asked whether they would keep on cycling more often.

3.3 Results

3.3.1 Trip data

In total, 139 SMART users joined the Boswinkel challenge. However, 59 users did not have more than 4 weeks continuously GPS travelling data, and were therefore excluded from the analysis. Of the remaining 70 users, 32 completed the challenge. Those users were labeled as Finish Group (FG). The other 38 users who did not complete the challenge were labeled as Did Not Finish Group (DNFG).

As mentioned earlier, due to the set-up of this campaign, we do not have measurements before week 41 when the campaign officially started. However, we have measurements after the campaign ended in week 49. Users downloaded the app over the entire course of the experiment, where almost all 70 users accepted the challenge immediately when they downloaded and registered for the App. Unfortunately, this means that the challenge period is not the same for each user as most users downloaded the app after the start of the campaign. Although this mimics realistic real-world behaviour, it complicates the evaluation. Only 14 users in FG and 14 users in DNFG have participated during the whole campaign. This first sample was used to evaluate the campaign period. Fortunately, as most people only started in the second half of the campaign, more people were tracked during the end and after the campaign. To compare the behaviour during and after the campaign, we used a five week period from week 46 until week 51. For this second sample, we had 24 users in FG and 24 users in DNFG. The two samples do not overlap completely for FG, 11 users in challenge period sample were in the during and after challenge sample. For DNFG, all users in challenge period sample were also in the second sample.

In Figure 3.2, we show the weekly average trip frequencies per person for the first sample from week 41 – 49, and the same trip frequencies for the second sample from week 46 - 51. We distinguish between bike trips and short car trips (smaller than 7.5 km) that could in principle be made by bike. We also show the bike trips that didn't go along the Boswinkel. The difference with the total bike frequency indicates to what extent the Boswinkel challenge was successful. Remember that the campaign promotes cycling along the Boswinkel route, not necessarily cycling in general.

Figure 3.2 Trip frequencies during the campaign and Trip frequencies during the last few week of the campaign and after the campaign

Figure 3.2 shows the difference between the cycling frequencies of both groups. This difference is statistically significant for the second sample (week 46 – 51), which can be seen from the standard error bar in Figure 3.2. For car trips, the standard error is bigger than bike trips, so the difference between the two groups are not significant.

For both samples, the cycling frequency is consistently higher for FG than for DNFG. This difference can be attributed to cycling trips along the Boswinkel route, given that when we exclude the Boswinkel cycling trips, there is no significant difference in cycling frequency between the two groups. However, the fact that half of FG participants did not cycle more to finish the challenge (as reported from the post-challenge survey), gives a bit of uncertainty to our behaviour change analysis with respect to the FG group. Nevertheless, the effectiveness of the campaign is supported by the post challenge survey. For the 24 users in the second half of the campaign, 14 out of the 24 users answered the survey, and 9 out of 14 users reported that they cycled more on the Boswinkel route under the challenge, which implies that the campaign has likely resulted in new bike trips. Additionally, in case that there are users who did not cycle more on Boswinkel route in FG, so to exclude the extra new bike trips made on the Boswinkel route, FG made more cycling trips than DNFG. This suggests that FG is more cycle minded than DNFG.

However, there is no statistical evidence that the campaign had an effect on the number of (short) car trips. Although car trip frequency is on average higher for the DNFG group, this result is not statistically significant. Moreover, it is not clear if such a difference could be solely the result of the challenge. The DNFG group also has a somewhat higher rate of long distance trips (> 20 km). For example, 4.4 trips per person for DNFG (which corresponds to 12.6 % of the total number of trips) versus 2.6 trips for FG (which corresponds to 8.5 % of all trips). These trips are typically made by car. When people use the car more often for longer trips, they may also be inclined to use the car for short trips.

When comparing the situation during and after the campaign, results are inconclusive. Figure 2 shows there is some indication that the bike frequency decreases and car frequency increases for DNFG after the campaign. This might be related to the fact that the challenge has ended. However, again this result is not significant. There is no evidence for a steep decline in cycling trips along the Boswinkel route after the end of the campaign. On the contrary, during the short

measurement period (of two weeks) after the campaign, participants of the FG keep cycling along the Boswinkel route.

One of the reasons results are inconclusive is that there is quite some natural variation from week to week in the trip frequency. The relative week-to-week variation for is more than 10% (standard deviation with respect to the mean) and about 20% for the bike and short car trips respectively. This result suggests that it is quite hard to disentangle the effect of positive incentives from natural variation. Traditional before and after measurements of one day (or a few days) may only prove an effect when it is very large. For smaller effects, before and after measurements of weeks are needed to provide enough data to prove a positive incentive has an effect. Of course, the relatively small sample size may amplify the natural variation. However, there are indications that some (significant) part of this variation is caused by external effects that influence the whole group rather than a few individuals. Although not statistically significant due to the limited number of weeks, there seems to be a negative correlation ($r = -0.6$) between the weekly car and bike frequency for FG, and a positive variation between the weekly bike frequencies of both groups ($r = 0.5$). Such correlations are expected due to, for example, changing weather conditions. For example, week 43 showed quite some precipitation, coinciding with an increase in car trips and a decrease in the number of bike trips.

3.3.2 Post-challenge survey

Post-challenge survey was sent out through the SMART app for all participant immediately after the campaign. In total, 43 out of 139 participants took part in the post-challenge survey of which 23 participants completed the challenge, and 20 did not. The results are shown in Figure 3.3. For FG, half of the users (12 users) found the challenge too easy, and 7 of those 12 did not even need to cycle more to complete the challenge. Furthermore, 5 out of 23 users claimed they had to use the Boswinkel route quite often anyway and therefore they completed the challenge without changing their behaviour. The remaining 6 participants indicated that they were motivated by the challenge and the reward, and 5 of them cycled more often along the Boswinkel route during the challenge.

Summarizing, 10 out of 18 users (55.6%) indicated they have changed their behaviour, and all of them said they would keep on cycling more often (50% also claimed to cycle more on other routes). Furthermore, half of them gave the challenge & reward as the sole reason for their behavioural change, whereas the other half claimed that both the newly paved route and the challenge & reward were the reason for behavioural change. In other words, all participants indicated that the challenge and reward played a role for them to cycle more. However, all 10 users changed their behaviour to choose the Boswinkel route more often, but not related to mode change.

For the participants that did not complete the challenge, half of them (10 participants) did not need to use Boswinkel the route at all, and therefore could not complete the challenge. Others claimed external factors such as illness and weather (4 persons), the limited challenge period (4 persons) and malfunctioning of the tracking tool of the app (2 persons) as reasons for non-completion. It is worth noting that in the latter case, the participants complained about the GPS trajectory accuracy. However, it turned out that they only cycled through a small part of the Boswinkel route which was excluded by the algorithm, but which was not reflected in the textual explanation of the challenge. This is of course an issue when considering the trustworthy and credibility of the app. For the participants that did not complete the challenge, still 6 out of 20 persons indicated they had changed their behaviour, and were planning to cycle more. In other words, if we would customize the challenges to the personal situation of the participant

such that the challenge is perceived as not too easy or too difficult, high rates of behavioural change are likely based on these results.

Figure 3.3 Reasons for completing (left) or not completing (right) the challenge.

3.4 Conclusion and future work

In this study, we examined the potential impact of interventions to promote cycling by using the SMART app in a living lab environment. The intervention in this case study is the Boswinkel challenge in which participants were challenged to cycle along a newly paved cycling road (Boswinkel route) with rewards.

From our analysis, we can draw three main conclusions. First, the new paved Boswinkel route alone did not have a significant effectiveness to promote cycling. In other words, the challenge and reward played a role for travellers to cycle more, which is supported from the survey that no users claimed the new route resulted in their behaviour change, but resulted from the combination of the new paved route with challenge and rewards. Second, extra bike trips were made on the Boswinkel route during the campaign, as participants who completed the challenge made more cycling trips than participants who didn't complete the challenge, and the users who finished the challenge and joined the survey claimed they made more bike trips on the Boswinkel route. Additionally, the extra bike trips on the Boswinkel route were mostly created by change in route choice, since users who completed the challenge mostly live nearby the Boswinkel route and already cycled often. The effectiveness of the interventions for modal shift is not significant, however, some users who did not finish the challenge claimed they had modal shift from car to bike. The modal shift analysis needs a bigger sample size. Third, participants who completed the challenge kept cycling along the Boswinkel route after the campaign. These results were confirmed by the post-challenge survey, in which 56% of users indicated they have changed their behaviour and planned to continue cycling more often after the campaign.

Moreover, from the survey we found that 20% of participants who didn't complete the challenge, still indicated they had changed their behaviour and / or were planning to cycle more in the future. In fact, most people that indicated they had not changed their behaviour either found the challenge too easy (or did not need to adapt their behaviour) when they completed

the challenge or found the challenge too difficult or not appropriate (because they did not need to use the Boswinkel route) when they had not completed the challenge. This clearly shows that personalized challenges, customized to the individual's need, i.e., based on the travel context of the individual (which can be derived from historic trip patterns), could significantly increase the amount of behavioural change. Moreover, respondents who either claim the challenge is too easy or too difficult / not appropriate to them, may be discouraged to participate in future challenges.

Due to natural variation in weekly trip patterns (partly due to small sample sizes), it is quite hard to disentangle the effect of positive incentives from external effects (such as weather). These external effects may have influenced modal split, i.e. the percentages of cycle and car trips (for example more car trips at the expense of bike trips during bad weather), or total demand (for example more traffic during events, or less during holidays). Although the data shows a slight decrease and increase respectively of the average numbers of car and bike trips, these findings are not statistically significant. In addition, as we used a living lab setting, it is hard to do (controlled) experiments with before and after measurements. To overcome these drawbacks, we are planning to monitor the participants over longer periods of time, in which they get multiple challenges, so that we have multiple outcomes. This will enable us to look for behavioural change over a longer period, distinguishing between challenges, in which we control for external effects such as weather or seasonality by for example using traffic counts (both for car and bicycles).

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4 Travellers' behavioural change by a self-chosen challenge intervention

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Abstract

Reduction of car use is one of the most effective ways to tackle congestion-related problems. Using positive incentives to stimulate bicycle use is one possibility to reduce car use. Cycling is a sustainable transport mode that uses little space and is healthy. There is evidence that positive incentives may be more effective than punishing travellers for undesirable behaviour, and the emergence of mobile applications for delivering interventions has opened up new opportunities for influencing travellers. So far, few studies have focused on exploring the effectiveness of positive incentives on long-term behavioural change. We used the SMART app to deliver positive incentives to more than 6,000 travellers in the Dutch region of Twente. The app automatically tracks users and provides incentives such as challenges with rewards, feedback, and messages. This study covers the period from March 2017 to June 2018, in which more than 1,000 SMART users participated in monthly challenges. We evaluated the effects of the challenges and rewards and found that the challenges did encourage cycling and reduced car use in the short term. There is also some evidence for behavioural change over a longer time period.

Keywords: Real-world experiment, travel behaviour, challenge and rewards, positive interventions

4.1 Introduction and background

Traffic and its externalities, such as the emission of greenhouse gases, is increasingly causing problems for almost all major cities. One of the challenges for transportation researchers is to change people's travel choices, and getting them to use sustainable transport modes. The negative health effects of a sedentary lifestyle provide another compelling reason to encourage active transport modes. In the Netherlands, people cycle about 10% of all trip kilometres, which is a significantly larger fraction than in other countries. The Dutch government wants to encourage cycling even more and aims to increase the cycled distance by 20% between now and 2027 (Rijksoverheid, 2016).

Offering positive incentives is a relatively cheap way to encourage cycling because it does not require infrastructure investment. Voluntary travel behavioural change (VTBC) schemes that use incentives such as rewards, feedback, subsidies and public transport discounts can result in a shift from car use towards more sustainable travel modes, see e.g. the work of Brög et al. 2009 (Brög et al., 2009), Sanjust et al. 2014 (Sanjust et al., 2014), Ben-Elia & Ettema, 2011 (Ben-Elia & Ettema, 2011a), Lachapelle, 2013 (Lachapelle, 2013). Such schemes work better than fiscal measures in the sense that they do not encourage socioeconomic inequity (Eliasson & Mattsson, 2006).

Traditional VTBC solutions require person-based interaction, either by phone or home interviews, which is inherently expensive and may induce biases stemming from social interaction and communication. The emergence of the social web and mobile applications for delivering interventions offers opportunities to reduce the costs and enables the use of ICT-based persuasion technology for influencing travellers (B. J. Fogg, 2002). Table 1 lists eight mobile app projects intended to encourage voluntary travel behaviour changes (Anagnostopoulou et al., 2018; Bie et al., 2012; Broll et al., 2012; Froehlich et al., 2009; Gabrielli & Maimone, 2013; Hu et al., 2015; Jariyasunant et al., 2013, 2014; Jylhä et al., 2013; Mattheiss, 2015; Poslad et al., 2015; Schrammel et al., 2013; Tsirimpa et al., 2019). The app design of those studies followed or fitted in the Persuasive Systems Design model (PSD) (Brynjarsdóttir et al., 2012; Oduor & Oinas-Kukkonen, 2019; Oinas-kukkonen & Harjumaa, 2009; Schneider, Moser, Butz, & Alt, 2016), which offers a way to analyse, design and evaluate the persuasion context. Common persuasive design features used in those studies were personalised feedback, self-monitoring, challenges and goal-setting, social comparison, and rewards. Field experiments provide evidence that these features are important for influencing users to change their travel behaviour; however, clear results on their effectiveness based on field evaluations is still missing (Table 1). Most evaluations of behaviour change interventions proposed in this area are rather short-term, involve small groups of participants, and provide limited evidence of lasting behavioural impact. (Brynjarsdóttir et al., 2012; Gabrielli et al., 2014). (Dastjerdi et al., 2019).

This paper focuses on exploring positive incentives on behaviour change, especially for modal shift from car to bike, by using a mobile app (SMART app) in Enschede, the Netherlands. The new travel app includes persuasive design features such as feedback, travel information, self-monitoring, nudging and gamification elements. Due to the collaborative feature of VTBC-based travel apps, a critical is to develop the travel app or the experiment to get broad engagement and run for a long time. A better grasp of the behaviour change for the long term

Table 4.10 Overview of software and information systems based interventions for travel behavioural change

Study	Sample sizes	Experiment period	Result	Credibility system
UbiGreen 2009	14	four weeks	As an early-stage study, it cannot reasonably be expected to confirm that behavior change occurred. The qualitative results indicate that participants did start new behaviours.	Not functioning optimally .
Tripzoom, SUNSET project 2012	108 Enschede, NL 6 Leeds, UK 95 Gothenburg, SE	Multiple experiments: Each lasted from two weeks to two months.	The main findings support the effectiveness of the incentives to encourage travel behavior change.	The clear system architecture of the app, Security layer, Third-party services, City authorities, High accuracy of trip, modes, location recognition (need improvement), around 25% total corrections.
SUPERHUB app 2013	8	Four weeks	A modest increase (14%) in “sustainable transport choices”	No automatic tracking data, No detail of support systems.
Quantified Traveler (QT) 2013	135	Three weeks	QT is useful to significantly reduce the car mileage, and to a lesser extent to encourage walking/cycling	Clear system architecture, Third-party services, High accuracy of trip, modes, location recognition (need improvement). 13.5% total corrections.
MatkaHupi app, SUPERHUB project 2013	8	Four weeks	Challenges were, in general, perceived positively.	No detail of support systems.
Peacox project 2015	37	Eight weeks	Findings show that persuasive approaches have the potential to influence users' attitude towards sustainable mobility.	Clear system architecture, More than 40% total corrections, indication low detection accuracy, Bugs and app crash problems.
Metropia app Los Angeles pilot 2015	36	Ten weeks	20% travel time can be saved for people who changed their travel behavior	High accuracy. Government authorities.
OPTIMUM project	76	Six weeks	Apps were used to reward sustainable transport, including cycling. The amount of cycling respectively almost doubled or even more than doubled as a result.	No detail of support systems.

by using mobile app, will aid authorities and private entrepreneurs to design effective and appealing apps, eventually translating into a broader potential of VTBC.

Mobility is a highly habitual activity, which is not easily interrupted, except for short periods (Pronello et al., 2017). Many studies also highlight that long term involvement more often leads to positive results. (Castellanos, 2016; Coombes & Jones, 2016; Pronello et al., 2017). Several studies are optimistic about gamification and its potential to extend the commitment of the user (Andersson et al., 2018; Baranowski & Frankel, 2012; Berger & Platzer, 2015; Bowden & Hellen, 2019; Castellanos, 2016; Poslad et al., 2015)). That gamification would have a positive impact on participants' involvement is also supported by Seaborn & Fels (Seaborn & Fels, 2014); however, Seaborn & Fels also implied that there is a lack of longitudinal study designs. Thus, more research is needed to discover the gamification effect on app involvement and commitment, and its impact on behaviour change, especially under a long term study period.

Different gamification strategies were involved in current travel apps. For rewards, tangible rewards such as money (Tsimpa et al., 2019) (Ben-Elia & Ettema, 2011b) and in-kind rewards, i.e. points (Hu et al., 2015) (Broll et al., 2012) (Bie et al., 2012) (Poslad et al., 2015) (Bowden

& Hellen, 2019), and non-tangible rewards, i.e. praise (Gabrielli & Maimone, 2013) (Mattheiss, 2015) (Schrammel et al., 2013) were often used in current apps. Based on our previous study, in-kind rewards are suggested for travel apps. In reality, by having a web shop associated with in-kind rewards may make people more enthusiastic about the in-kind reward than about the money, because money has an impersonal character, which would decrease the feeling of enjoyment. (Gneezy et al., 2011; Huang, Fioreze, Thomas, & Berkum, 2018; Shaffer & Arkes, 2009). Challenges and goal-setting are also essential features in gamification. Many goal-setting studies showed that specific and challenging tasks led to higher performance than easy or "do your best" tasks (Baretta et al., 2019; E. A. Locke, 1968; E. a Locke & Latham, 2002), however, current apps for cycling promotion reward users by directly calculating the kilometres they cycled, without a specific challenge, or massive challenges that are not suitable for every user. On the other hand, setting specific goals for long-term projects may be disadvantageous for the user participation, as users immediately tend to dropout upon finishing that goal (Habibipour et al., 2016). Moreover, before considering personalised challenges or challenges that explicitly target a certain social-economic segment of travellers, it should be acknowledged that in many cases targeting specific segments or personalised targeting may be costly and even ethically troublesome. Hence, understanding of how to deal with challenges of involving users is important.

App credibility is an essential persuasive element which was often not achieved in mobile phone related studies. Ignorance or technical flaw may directly impact recruitment and engagement rate. Gamification may increase involvement and support long term interest, but app credibility can be more crucial to lead a successful app. The current travel mobile apps are often related to technology, privacy and reliability issues (Table 4.1, column "Credibility system") (Gadziński, 2018), which can decrease the credibility of a mobile app (Lehto & Oinas-Kukkonen, 2011; Pornpitakpan, 2004; Sillence, Briggs, Harris, & Fishwick, 2006; Wathen & Burkell, 2002)). Since users will engage with apps that they perceive as credible but navigate away from those they do not consider credible, high detection accuracy and also security features are therefore important, so that the app does not award incentives unfairly or inappropriately. The greater the app's accuracy and security, the more users it will attract. Besides, social trust is important as a motivator for sustainable behaviour change, since trust reinforces peoples' engaging behaviour, i.e. acceptability and public involvement (Hsu, Chiang, & Huang, 2012; Steg, Perlaviciute, & van der Werff, 2015). Therefore, third-party endorsements, authority and surface credibility to increase the trust between individuals and the community at large can also enhance app credibility (Lehto & Oinas-Kukkonen, 2011). Thus, a travel app engaging in encouraging sustainable behaviour for a society, need multidisciplinary cooperation, such as local authorities to manage, commercial parties to support rewards and I.T. company to support technology.

Given the gap in current literature, this study contributes to the body-of-knowledge by designing a monthly self-chosen challenge and by analysing travel behaviour tracked by the SMART app in a real-world environment for over a year, supported by local government, commercial parties and I.T. companies. The main aim of this paper is to analyse and explore the app users' changes in travel behaviour and changes in interest and commitment, both in a short and long term. Also, to identify key factors that influence the response to gamification (challenge and reward), and to explore whether the type of challenge played a role in the change in behaviour. The hypotheses related to the objective are proposed as follow:

- H1: The app has broad recruitment and high retention, and the user who has high challenge commitment stays longer in the app.
- H2: The challenges and rewards as gamification mean motivate travel behaviour change for a short-term, and travel patterns, users challenge commitment impact behavioural change.

- H3: There is long term sustained behaviour change, but for users with high engagement.

The paper is organised as follows: Section 4.2 provides methods about the SMART app, the case study and introduces the data. Section 4.3 presents the results, and finally, section 4.4 presents the discussions, limitations and concludes the paper.

4.2 Methods

This research is based on the SMART application, which records the users' mobility on their mobile phones. Everyone can download and use this app and choose to participate in monthly cycling-related challenges.

4.2.1 SMART app

The SMART app attempts to nudge travellers towards sustainable transport modes, especially cycling, by providing incentives ("Mobidot," 2017). It runs on the Android and IOS platforms and records the users' trips. We designed our interventions by drawing on other mobile app-based studies, which aimed to inspire voluntary travel behavioural changes and contained common persuasive design features (personalised feedback, self-monitoring, challenges and goal-setting, social comparison, rewards and praise, traffic information and travel suggestions) (Cialdini, 2001; Oinas-Kukkonen & Harjumaa, 2008). The cooperation between different stakeholders (among which the ICT company behind the app, the city of Enschede, the university) supports the app's credibility.

Figure 4.1a shows the SMART app's dashboard, from which users can explore all functions. The following persuasive strategies are used.

1) Self-monitoring and feedback: On the SMART home page and "my mobility" page, users can see their trip history per travel mode and daily CO2 emission.

2) Challenge and goal setting: In SMART, the living lab operator (municipality) sets up challenges to promote cycling. Users who download the SMART app need to select and join challenges on the challenge page ("take a new challenge" in Figure 4.1a), which shows all available challenges. Users are able to choose any suitable challenge. When a user accepts a challenge, the system starts to keep track of the targeted behaviour and shows the progress. This is done by continuous tracking (using GPS, accelerometer data, etc.) and by using advanced algorithms that combine travel speeds and travel routes to determine which transportation mode the traveller is using..

3) Rewards and praise: Rewards are provided upon completion of the challenge. The SMART app starts tracking the user's target behaviour when a challenge is chosen. When the challenge is completed, the system immediately awards the corresponding number of points,

Figure 4.1. SMART app screenshots

(a) Left: Dashboard, (b) Right: System credibility and third-party web shop

which is also shown in the dashboard. On the “reward” page, the earned points can then be redeemed towards discounted products and services (Figure 4.1b). Multiple stakeholders joined the project to support the web shop in the app, which created a win-win, for the municipality (funding) and for the participating shops (sales). Huang et al. (Huang et al., 2018) concluded that in-kind gifts from a web shop have a more positive impact than cash rewards, and may ultimately make users more satisfied (Shaffer & Arkes, 2009). Additionally, the SMART app is able to pop up notifications to praise the users if they travel sustainably.

4) Traffic information and suggestions: Event and traffic information are also offered through messages (“messges” in Figure 4.1a). SMART is able to give useful information about the actual local traffic situation and notifies users of road works or large-scale events that lead to extra traffic. Based on this, SMART may also suggest travel alternatives to enable the users to optimise their travel plans.

5) System credibility: System credibility provides users with credible and authentic information so that it decreases the dropout rate. The SMART app is updated regularly and maintained by Mobidot, and supported by the city of Enschede. Moreover, its users are informed in advance about the app’s privacy protection, and the travel mobility data is updated every day. Finally, new challenges are updated regularly and the shops where vouchers can be redeemed are all well known (Figure 4.1b).

4.2.2 Recruitment

Enschede (the municipality in question) used Facebook, flyer actions on the streets, digital advertisements, and cooperation with local employers to promote the SMART app, aiming to help the traveller to minimize travel time and cost, or/and travel sustainably and healthily. To decrease the risk of selection bias, we emphasised that the SMART app can help travellers to travel smarter and make them more aware of the region.

The recruited users were not asked to provide extra information (such as age or gender), and could participate in challenges immediately. In other words, they were not recruited for an

experiment but simply used the app because they wanted to. This way, we created a realistic real-life context to analyse the travellers’ true behaviours. However, as the users could immediately use all functionalities of the SMART app, we were not able to do a “before” measurement, which is an important drawback of this study.

4.2.3 Case study: Monthly choice challenges

From March 2017, SMART users could join a cycling promotion named “monthly choice challenge”; those who joined were challenged to accomplish a certain cycling distance or frequency or cycle to a certain location. The monthly choice challenge is still ongoing, but we were allowed to use data from March 2017 until June 2018 for this study. Every month, one monthly choice challenge is offered. In the first two weeks of each month, the SMART users can choose one challenge out of five or six; the challenge immediately starts when a SMART users clicks to join the challenge. The duration of the challenge is up to two weeks; participants can complete their challenge in less time.

We introduced different types of choice challenges: frequency challenges, distance challenges, mixed challenges (combined frequency and distance challenge), minimum-distance challenges (on certain days, cycle a minimum distance) and location challenges. The five different types of challenges were designed and distributed throughout the year to see which type is more effective. Rotating challenges may also encourage users to keep participating (Dorn & Sahinyan, 2010).

Table 4.2 Monthly choice challenge options and rewards

Challenge types	Challenge options (related reward in points)		Month
Frequency challenge	The number of bike trips to be made within 14 days		May, August 2017; June 2018
	Choice:	2, 5, 10, 25, 50 trips	
	Rewards	60, 90, 150, 330, 630	
Distance challenge	The number of bike kilometres to be ridden within 14 days		December 2017; May 2018
	Choice:	5, 20, 50, 100, 200 km	
	Rewards	50, 110, 230, 430, 830	
	The number of bike kilometres to be ridden within xx days		January 2018
	Choice:	30, 60, 90 km in 14 days or 60 km in 3 or 7 days	
	Rewards	150, 270, 390, 510, 390	
Mixed challenge: Frequency & distance	The number of bike trips or kilometres to be made within 14 days		April, July, October 2017; April 2018
	Choice:	5, 10, 50, trips, or 5, 50, 200 km	
	Rewards	90, 150, 630, or 50, 230, 830	
Minimum distance challenge	The number of days to ride a bike for at least 10 kilometres		February 2018
	Choice:	1, 3, 6, 9, 12 days	
	Rewards	70, 150, 270, 390, 510	
	The number of bike kilometres to be ridden on at least 10 out of 14 days.		November 2017 March 2018
	Choice:	1, 2, 5, 10, 15 km per day	
	Rewards	70, 110, 230, 430, 630	
Location	The number of bike trips to go to a certain location within 14 days		March, June, September 2017

Table 4.2 lists the options and related rewards. The more difficult the challenge that the user chooses, the more points the user can gain by completing that challenge. The relation between challenge difficulty and reward is a simple linear function, with a constant (baseline points) to ensure that users who rarely cycle can still collect a reasonable number of points if they cycle

a short distance or a few times. Choosing a difficult challenge means more rewards; however, if the participant fails to complete the challenge within the challenge period (two weeks), he or she will not receive any points. Participants therefore have to choose between an easy challenge with a relatively small reward but a greater chance to be successful or a difficult challenge with a relatively high reward but a greater chance of failing. Participants immediately are awarded if they meet their chosen challenge in time. They can redeem the points in the app's web shop (see Figure 4.1b).

A post-survey was sent through the SMART experience sampling question service, to collect more information on the reasons why users did or did not change their behaviours. The post-survey questionnaire was sent out immediately after completion of the challenge or after the challenge period if participants did not complete the challenge.

4.2.4 Data

Data resource

We used SMART data of between March 2017 and June 2018. The data consists of trip data, postsurvey data, and information about when users started and completed a particular challenge. The trip data contains origin, destination, departure time, arrival time, transport mode, activity, average speed, and trip distance. The transport mode and trip activity are determined in the back-end by processing and learning algorithms (see (Thomas et al., 2018)). When a user uses the functions of the SMART app, trigger data are generated. These contain the user's ID, type of trigger (challenge, survey question, message), status of trigger (accepted, answered, awarded, read), response to the trigger (number of points awarded, reply to a survey question), trigger date and trigger time.

Indicators and segments

The indicators we chose to evaluate behavioural change are distance-based mode share and daily distance per mode. We inspected these indicators by aggregating data on a monthly level. We chose a period of a month because a new set of choice challenges was offered each month. We thus had data points per month for each user ("person-month data"). The distance-based mode share is the percentage of the total distance that is covered by each mode during the measurement period. We used distance rather than trip frequency, because the latter might be disproportionally influenced by people shifting from walking to cycling for the shortest trips. The daily mode distance is the total distance covered by a certain mode divided by the number of days in the measurement period. We considered several measurement periods per month, i.e., the whole month, the period during the challenge, the period outside the challenge period. Note that the latter two are variables among users, dependent on when participants started and completed a challenge. In the long-term analysis, we also used the last week of each month (corresponding with days outside the challenge period for almost all users) to determine the sustained effect of the campaign.

We also performed segmentations to analyse differences between challenge and trip types. As mentioned earlier, we did not have data on personal characteristics of users. However, we made a distinction between users who chose easy challenges and users who chose difficult challenges and checked whether behavioural changes occurred in both groups. We defined the difficulty of the challenge by comparing the challenge against the user's behaviour in the previous month. In other words, if a challenge required the user to cycle more than in the previous month, we assessed the challenge as (relatively) difficult. By contrast, if a challenge required less effort than before, we considered the challenge (relatively) easy. In addition, we distinguished

between different types of trips. For example, commuting behaviour may be more difficult to change than recreational travel behaviour (Harms & Kansen, 2018). More generally, we assumed that habitual or regular trips may be more difficult to change. If more than eight trips were made between the same origin and destination in one month, then we considered these trips regular trips. This criterion was chosen to obtain more or less equal sample sizes per group.

Data selection

In total, 6,214 users downloaded and used the SMART app between March 2017 and June 2018, with 23,233 person-months of data. To make sure that the tracking data from the SMART app reflected the real travel behaviour, we excluded person-months that had fewer than 15 days of recorded trips. Moreover, only trips below 20 kilometres were counted for travel behaviour analysis, as cycling is not a viable option beyond 20 km (Gatersleben & Appleton, 2007). These trips cover almost all trips within the urban area of Enschede (and the neighbouring city of Hengelo) and therefore can be regarded as urban trips. By selecting these trips, we also neutralised the disadvantage of distance-based mode share in which non-recurrent long-distance trips have a disproportionally large effect on mode shares.

After error-checking, cleaning and filtering the data based on the above criteria, 5,525 users remained with data for in total 22,174 person-months. In total, 1,868 out of 5,525 users joined the monthly choice challenge at least once. We call those users “participants”; they make up the “experiment group”. The other 3,657 users never joined a challenge but used the SMART app regularly for other incentives, such as trip history, and travel information. They are in the No Challenge group. The 1,868 participants had 11,076 person-months in total, but the participants only participated in the monthly choice challenge about every other month on average (50%). To check whether participants perhaps only used SMART during challenges and turned off the app to extend battery life after a challenge, we compared the days with recorded trips inside and outside challenge periods. Figure 4.2a shows the average proportion of days with trips recorded. Figure 4.2b displays the distribution of the differences between days inside and outside the challenge periods for the participants.

As the top panel in Figure 4.2a shows, there was a significantly higher number of days with recorded trips in the challenge period. This may imply that some participants turn off SMART when there is no challenge. Figure 4.2b shows a clearly skewed distribution, with a peak located around 0. In most cases, SMART reports more or less the same fraction of days with trips inside and outside of the challenge period. However, the mean is significantly greater than 0 (greater than 0.15). For some participants, trips appear to have been underreported outside the challenge period. To correct for this possible bias, we only included participants who had a smaller than 0.2 average difference on both sides of the distribution. This left us with 1,056 participants and 3,269 person-months data. The bottom panel of Figure 4.2a shows the results after the correction. The figure shows there are still more days with recorded trips in the challenge periods. The remaining difference may be attributed to the fact that there were more workdays in the challenge periods, and days without trips are relatively rare during workdays. The

Figure 4.2. Differences between behaviour inside the challenge periods and outside the challenge periods

(a) Proportion of days with trip recorded, (b) Histogram of proportion difference

remaining difference may also represent a real effect of the challenges, namely that participants might have become encouraged to cycle on days on which they normally would not make a trip

Data analysis

To analyse short-term behaviour, we compared the users' travel behaviour inside and outside the challenge period for each month. This analysis was done using descriptive statistics. We compared the behaviours in the groups to gain a better understanding of the influence of the monthly challenges on cycling.

The longitudinal analysis focused on quantifying the traveller's behaviours across the months. To capture long-term behavioural change, we only included users who used SMART for at least six months. All users have continued 6 months of data; therefore, there is no missing data.

As already explained, we had no "before" data as users could immediately use all functionalities of the SMART app upon downloading. We used ANOVA tests in the SPSS software package to identify statistically significant differences between time series averages.

Figure 4.3 The distribution and cumulative user distribution of SMART app usage times or joined the monthly choice challenge times

Table 4.3 Number of users who continuously used the SMART app in these periods, with challenge participation and total SMART app usage information

Continuously used SMART app during	Number of users				
	No Challenge Group	Use SMART ≥ 12 months,	Participants	Joined challenge ≥ 3 times	Use SMART ≥ 12 months, Joined ≥ 3 times
Jun 2017-Jun 2018 (13 months)	36	36	68	52	52
One year (12 months)	52	52	89	69	69
8 months	150	66	261	184	65
6 months	280	63	526	375	71

4.3 Result

This section begins with an analysis of the users, followed by a description of the short-term effects of incentives. Finally, long-term behavioural changes are analysed. This is mainly limited to statistically significant results, i.e. using a significance level of $p = 0.05$. We mention it explicitly when differences are not statistically significant. The figures include error bars values and indicate two times the standard deviation of the mean.

4.3.1 Participants and SMART usage

After data selection, 1,057 participants remained in the experiment group and 3,657 users in the No Challenge group. Figure 4.3 shows the distribution over the number of months. Participants on average used SMART over a longer period than users in the No Challenge group. About 40% of the 1,057 participants used SMART for six months or longer. However, around 40% of the 1,057 participants joined a challenge only once, while 10% joined six times or more. In other words, we could only use a small part of the sample for the long-term analysis. In the whole 18-month period, only 68 participants and 36 users in the No Challenge group continuously used the SMART app for more than one year. Table 4.3 shows how long users used the SMART app continuously. For example, we had 526 active participants and 196 users in the No Challenge group who used the app for six continuous months. We used the data in Table 4.3 to examine long-term trends.

4.3.2 The direct effects of monthly challenges

The No Challenge group had an average bike share of 37.8%. The bike share for participants of monthly choice challenges, at 47.4%, is clearly higher. This implies that the monthly choice challenge might attract travellers who are already interested in cycling. Hence, there may be some self-selection among participants. However, it should be noted that for the other SMART users, the observed car mode shares for trips shorter than 20 km are lower than what is found in National Travel Surveys. Even so, the participants still have a high car mode share, that has the potential to get further decreased.

Table 4.4 shows the travel behaviour changes and allows comparing differences between inside and outside the challenge period. On average, the bike mode share was higher and car share was lower in challenge periods. The daily bike distance was also greater in challenge periods. However, the car distance was not significantly lower.

In Table 4.4, we distinguish between regular and non-regular trips. Around 30% of the total covered distance was made by regular trips (at least eight trips per month between the same origin and destination), 65% by non-regular trips, and the rest by round trips. Table 4.4 shows that regular trips had a higher bike share and a lower car share, mostly because trip distances on average are shorter for regular trips. However, behavioural changes were greater for non-regular trips. This suggests that positive incentives to encourage cycling may be more effective for non-regular trips.

In SMART, participants can freely select any monthly challenge. The question is how participants choose and what the effect may be on behavioural change. Therefore, we used challenge difficulty and challenge accomplishment to categorize person-months into four groups: (1) a participant chose a difficult challenge and accomplished the challenge in the corresponding month (DiffACP), (2) a participant chose a difficult challenge but did not accomplish the challenge (DiffNotACP), (3) a participant chose an easy challenge and accomplished the challenge (EasyACP), and (4) a participant chose an easy challenge but did not accomplish the challenge (EasyNotACP). We also excluded the first month for each participant because it was not possible to assess the relative difficulty of the challenge based on previous behaviour.

Table 4.4 Behavioural change for regular and non-regular trips between the inside and outside the challenge periods, with the two sigma error

		Regular			Non-Regular			ΔTotal
		In	Out	Δ In Out	In	Out	Δ In Out	Δ In Out
Mode Share	Bike	70% (0.01)	66% (0.01)	3.4% (0.007)	46% (0.01)	41% (0.01)	3.4% (0.008)	3.4% (0.007)
	Car	18% (0.01)	21% (0.01)	-3.1% (0.007)	41% (0.01)	46% (0.01)	-4.9 % (0.008)	-4.8 % (0.006)
Daily Distance	Bike	3.76 (0.13)	3.01 (0.11)	0.75 (0.08)	4.59 (0.13)	3.81 (0.10)	0.78 (0.10)	1.54 (0.13)
	Car	1.34 (0.12)	1.39 (0.11)	-0.04 (0.08)	5.04 (0.19)	5.26 (0.17)	-0.22 (0.14)	-0.33 (0.16)

Figure 4.4 Behavioural change inside and outside the challenge periods, with mode share change on the left, and daily distance change on the right, the error bars indicating the two-sigma error

Figure 4.4 shows the travel behavioural changes for the four groups. More than 90% of the participants who chose easy challenges also accomplished the challenge, while the completion rate was about 50% for participants who chose difficult challenges. On the other hand, the strongest behaviour change occurred for participants who accomplished difficult challenges.

This suggests that participants need to choose difficult challenges to obtain large positive effects. However, bike and car shares also increased and decreased, respectively, when participants accomplished easy challenges. The observed overall behaviour change was more or less the same, regardless of whether participants chose easy or difficult challenges. While the change in behaviour was relatively large when participants completed difficult challenges, difficult challenges were completed much less frequently.

These results were unexpected. Obviously, participants who choose easy challenges do not need to change their behaviour to accomplish the challenge. The fact that they did suggests that the challenges in themselves encourage participants to change their behaviour. Perhaps participants are more aware of their behaviour when they participate in a challenge and therefore more likely to change their behaviour even when they can accomplish the challenge without behaviour change. This would be a positive result and suggests that choice challenges encourage behaviour change in the short term even when participants do not need to change their behaviour to accomplish the challenge.

4.3.3 Longitudinal analysis

New users downloaded and started using the SMART app throughout the whole study period. Figure 4.5 shows the retention rate of users over time after they start using the app. For both participants in choice challenges and users in the No Challenge group, most of the dropouts occurred in the first six to nine months. After this period, retention rates tended to stabilize. The average retention rate was greater than 50% for participants, but around 30% or even lower for the No Challenge group. Importantly, users who started using the SMART app after September had a higher retention rate, which appeared to be linked to an update of the SMART app (updated on 13 August 2017).

Figure 4.5 User retention

(a) Participant group, (b) No Challenge group

Table 4.5 details the number of participants in different stages, i.e., those using the app for 6 months, 7 to 9 months, 10 to 12 months, and more than 12 months (13 or more). We only included the participants who were still using the app in June 2018 (at the end of the study period). Since the retention rates tended to stabilize after six months, Table 4.5 contains almost all participants who used the app for six months or longer, and we assume that most of the participants in Table 4.5 have continued using the app afterwards. For the long-term analysis, it therefore makes sense to compare these groups in the January to June 2018 period, because they more or less represent the same type of participants but who are in a different stage of usage.

Table 4.5 Descriptive information under different SMART usage conditions and segmentations

<i>Usage</i>	<i>Experiment group</i>	<i>Diff</i>	<i>Easy</i>	<i>Active Participants</i>	<i>Final week</i>
6 months	105	52	53	66	109
7-9 months	57	27	28	39	48
10-12 months	64	26	37	46	52
≥13 months	66	29	36	41	60

(Control group: 87 users who used the app for 6 months.)

Diff: More than half of the chosen challenges were difficult.

Easy: More than half of the chosen challenges were easy.

Active group: Participants who joined the monthly challenge more than three times in the final six months of the study.

Final week: Participants with trips in the final week of each month.

In Figure 4.6, we show the modal shares for the different groups of participants (right panel) and for the control group. The control group consisted of users who did not participate in the challenges (“No Challenge group”), but still may have been influenced by other features of the app over a longer period of time. To exclude those potential effects and enable a fair comparison between the groups of participants, the control group only includes users who started using the app in January 2018. Figure 4.6 reveals similar seasonal effects for all groups of participants and for the control group. Due to increasingly favourable weather conditions, bike shares increased during the first six months, while car shares declined. As mentioned earlier, participants in challenges tended to have a higher bike share and lower car share than users in the control group, as Figure 4.6 shows. The difference is about 15 percent points. We assume that this is mainly due to self-selection, but we cannot exclude the possibility that there was also some increase in bike share (and decrease in car share) when participants started choosing monthly challenges. Unfortunately, we were not able to verify this as we had no “before” measurements.

Figure 4.7 shows the bike and car mode share difference between the participants and the control group from January to June. We defined groups in the different stages of app usage, as follows:

- 6 months (group 1);
- 7 to 9 months (group 2);
- 10 to 12 months (group 3);
- More than 12 months (group 4).

We compared each group with the control group, separately for bike share difference and car share difference. Therefore, we run eight repeated-measures ANOVA for the experimental group with the control group. Moreover, we have four segmentations as experimental subgroups. Thus there were 40 ANOVA tests in total. Table 6 presents the repeated-measures ANOVA results related to Figure 4.7. The challenge join rate, and the share of easy and difficult challenges for each group are also shown in Table 6. Power analysis was operated by the program GLIMMPSSE, as recommend by Guo et al. (Guo, Logan, Glueck, & Muller, 2013). The result shows that a sample size of 40 travellers per group, or a total of 80 travellers, would give a power of at least 0.8 for testing the hypothesis of whether there is a time $\times$ intervention interaction. For our study, all ANOVA tests fitted this requirement. Users in all groups had continuously six months of data. Therefore, there is no missing data

The upper panel of the figure displays the trends for all participants per group (green lines). Groups 2 and 3 showed a slow increase in bike share and a decrease in car use over time, relative

to the control group. We found a significant linear increase ($p < 0.05$ in corresponding ANOVA tests) in bike share and a decrease in car use after the first month. However, there is no significant trend for groups 1 and 4. This suggests that sustained behaviour change may only take place after several months, and tends to be stable after one year, which would be in line with the theory of sustained behaviour change. As a result, the bike share fractions are on average about 4 percent points higher for groups 2, 3 and 4, while car shares are about 3 percent points lower relative to group 1. However, this difference is only significant for the month of May. In this month, bike shares were 6 percent points higher for groups 2, 3, and 4 (combined).

Figure 4.7 presents a long-term analysis. The upper panel of Figure 4.7 also shows highly active participants who entered the monthly challenge more than three times in the last six months (blue lines). After more than a year of using the app, there was a significant increase and decrease in bike and car shares, respectively, for the participants in group 4 relative to the control group. Bike shares were also higher in group 4 than for non-active users. This may suggest that sustained behaviour change may be more likely for the most active participants.

To have enough trips in our sample, we took all the data for each month. This means that we also included trips that took place in the challenge periods. When considering long-term trends, it is useful to exclude short-term effects due to the challenges. During the final week of each month, almost all participants are outside of the challenge period. Therefore, we also looked at trips from the final week of each month only (yellow lines). However, the trip sample sizes then became so small that the total variation mostly reflected random variation, making significant differences harder to detect. We, therefore, did not find significant trends over the months. However, for group 1, the participants' bike and car shares appeared to be lower and higher, respectively, during each month's final week. This was expected because this final week was outside the challenge period. Interestingly, this difference became smaller after six months, again suggesting that if sustained behaviour change takes place, this may only happen after several months.

In the lower panel of Figure 4.7, we distinguish between easy and difficult challenges. The group "difficult challenges" includes users who entered a difficult challenge more than half of the times. For the long-term behaviour change, Figure 4.7b basically shows the same trends for all the participants. In the first six months (far left), there is no clear trend, while there is an increase over time for groups 2 and 3, while bike shares seem to be higher for groups 2, 3 and 4 (relative to the control group). There also appears to be some difference depending on whether participants chose mainly difficult or mainly easy challenges. The bike distance difference between group 1 and the control group is slightly larger for those who predominantly chose

Figure 4.6 Control and experiment groups last six months of travel behaviour under app usage conditions

b

Figure 4.7 Long-term analysis: comparison of different types of participants with No Challenge group under app usage conditions

(a) Active participants and NonActive participants, (b) easy-challenge, difficult-challenge participants

difficult challenges. However, for groups 3 and 4, it is the other way around. Bike shares are higher and car shares are lower for the easy challenges (relative to the control group). In fact, for the difficult challenges, mode shares are almost the same for groups 2, 3, and 4 relative to group 1. On the other hand, for the choosers of easy challenges, bike shares are on average about 6 percent points higher and car shares are about 7 percent points lower for groups 2, 3 and 4 relative to group 1. This result suggests that sustained behaviour is mainly achieved through easy challenges that are also much more often accomplished. However, the results are not conclusive as none of the differences are significant (with a significance level of 0.05) because of the small sample size. However, these differences are still substantial, i.e., they are

of the same magnitude as the differences between inside and outside the challenge period (slightly above 5 percent points). The main difference between the short-term and long-term behaviour analysis is the sample size. The sample size is still relatively large compared with other studies, and a substantial fraction of the app users participated in at least one monthly challenge. However, although the retention rates are relatively high among the active participants, the number of participants that used the app over a longer period was relatively low as many users joined in a late stage of the study. Moreover, not all of the longer-term users showed sustained behaviour change. Therefore, if substantial sustained behaviour changes occurred, this would only be seen in a small fraction of the users, namely the ones who downloaded the app and used it for more than six months.

4.4 Discussion

In this study, we examined the impact of monthly challenges on travellers' cycling behaviour. In the SMART app, participants were able to choose a cycling-related challenge each month and received points upon completion of a challenge. The app also provided other incentives such as feedback, messages and traffic information.

Over 6,000 users downloaded the SMART app with a steady 51% half-year retention rate. About 25% of these users joined the monthly choice challenge, indicating that other interventions, such as self-monitoring and feedback, are also important for attracting users. The users who participated in monthly challenges tended to cycle more, suggesting some form of self-selection among the participants in the monthly challenges. (For the other users, the mode shares were similar to those found in the National Travel Survey). While car use was still substantial among this group of participants, retention rates were relatively high. This shows that there is the potential, at least in theory, to encourage more cycling and reduce car use.

We found no clear evidence for behaviour change among users who never joined any of the monthly challenges, which indicates that for behavioural change, they need to become actively involved.

During the monthly two-week challenge periods, the intervention caused a modal shift from car to bike, suggesting that challenge-and-reward interventions are effective for short-term behavioural change. However, the differences between inside and outside the challenge periods were still relatively small. The distance-based modal shift rate was about 5% points. Interestingly, short-term changes appeared to be greater for non-regular trips than for regular trips. One reason may be that the car mode share for non-regular trips is greater than for regular trips, which would create more room to change.

We assumed users who have high challenge commitment would have more significant change; however, we observed the overall behaviour change was more or less the same, regardless of whether participants chose easy or difficult challenges. These results were unexpected. Obviously, participants who choose easy challenges do not need to change their behaviour to accomplish the challenge. The fact that they did suggests that the challenges in themselves encourage participants to change their behaviour. Perhaps participants are more aware of their behaviour when they participate in a challenge and therefore more likely to change their behaviour even when they can accomplish the challenge without behaviour change. This would be a positive result and suggests that choice challenges encourage behaviour change in the short term even when participants do not need to change their behaviour to accomplish the challenge. In a longer-term, users tend to choose easier challenges, and sustained behaviour is more likely achieved through easy challenges that are also much more often accomplished,

There is some indication that the interventions were effective for some long-term behavioural changes. In general, we observed some increase in cycling (relative to the control group) after between 6 and 12 months of usage. After 12 months, the bike share remained slightly larger for participants in the monthly challenges, even more so for highly active challenge participants. This pattern is in accordance with the transtheoretical model, which states that sustained behaviour is only observed after some time (often after one year). However, our sample sizes were too small to arrive at definitive conclusions. If sustained behaviour changes occurred, this may only have been the case for a small fraction of the app's users.

Behaviour change has often been equated with action, since action is observable, but decisions to change a habit are preceded by a change in awareness (H. C. Triandis, 1980; Harry Charalambos Triandis, 1977) as habitual behaviour is relatively unintentional (Gärling & Garvill, 1993; Ronis, Yates, & Kirscht, 1989). The change in awareness before action is often ignored in studies because the monitoring periods when incentives are offered are relatively short. This limits the potential for understanding awareness changes and why people may revert to old habits in the long term. We found that different users may take action over different time periods, and that some people may not consciously change behaviour but will return to their old habit after a short period of behaviour change related to an incentive. This suggests that in order to cause conscious changes, experiments need to run long enough to cover all the early stages.

One way to raise awareness is to provide feedback and education; the SMART app does this. In addition, Geller (Geller, 2001) has found that several small incentives can be more effective than one large incentive since this causes individuals to develop internal motivation for behavioural change. In SMART, incentives are relatively small and recurrent. At first sight, it is therefore not obvious how sustained behaviour change could still be increased within the context of our experiment. Also, it is quite hard to control for all these parameters in a real-world environment. However, the interventions had a strong impact on the most active participants and accomplished long-term behavioural changes. Increasing the variety of challenge types and making the challenges feasible for all types of travellers might increase retention (Dorn & Sahinyan, 2010) and increase the challenge join rate, and lead to more sustained behaviour change.

The limitation of this study is that we only analysed the period during which challenges were provided. We did not have "before" data and had no information on the behaviour after no more monthly challenges would be provided. Moreover, there is self-selection for SMART users in the experiment group. Yet, the self-selection group still had a significant car mode share that can be decreased further and this study proves that the behaviours of the self-selection group have the potential to be changed in the long term by the interventions. Moreover, some SMART users were in the control group who did not join the challenge yet but used the app for other functions and can join the challenge later. In line with this, future research could focus on to design apps to attract travellers who do not cycle often, or focus on an even longer-term experiment, because these users may need longer interventions to change in awareness. In addition, in order to let travellers truly behave as in a real-life environment, the real-world experiment was controlled not to involve privacy issues. As a result, there is no socio-demographic data of travellers

However, this study does show the realistic potential of using positive interventions via a commercial app in the real world. The SMART app provides larger samples than most studies have so far and makes it possible to monitor behaviour continuously over a more extended period of time. As Prochaska & Velicer (Prochaska & Velicer, 1997) found with regards to quitting smoking, the so-called maintenance period lasts from six months to about five years. Therefore, we will monitor SMART users for an even longer period of time in a future study.

In conclusion, our study has shown that monthly challenges can be effective persuasive interventions to accomplish short-term change. The effects on the long term are less clear, and suggest that behaviour change is a gradual and cyclical process, in line with the transtheoretical theory. VTBC schemes need to pay more attention to the different stages of behaviour change and monitor them accordingly. Results from short-term studies probably overestimate the change that can be sustained.

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5 Explanatory model to estimate behavioural change

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Abstract

Reducing car use by positive interventions with the aid of smartphone technology is attracting attention, for example, to promote bicycle use, which is cost-effective, fast, clean and healthy. So far, the potential effects of positive interventions on cycling behaviour have not been well explored. We used the SMART app to deliver positive incentives to more than 6,000 travellers in the Dutch region of Twente. This app automatically tracks users and provides incentives such as challenges with rewards, feedback and messages. Our study covers the period from March 2017 to June 2018, in which more than 1,000 SMART users participated in monthly challenges. Four types of cycling-related challenges, to be chosen by the user, were designed and provided every month. A mixed logit model was deployed to explain the behavioural changes. We found that challenge type and travel pattern impacted behaviour change differently. Overall, the cycling challenges were effective in nudging people from cars to bikes. However, the challenges also had the effect of causing additional bike use without a modal shift.

Keywords: Travel behavioural change; positive incentives; mixed logit model; challenge and reward

5.1 Introduction

Transport is responsible for about 25% of Europe's greenhouse gas (GHG) emissions and is the main cause of air pollution in cities; in 2014, road transport contributed more than 70% to these GHG emissions from transport (European Commission, 2016b). Motoring is associated with unhealthy behaviours (e.g., (Gordon-Larsen et al., 2009), whereas active modes of transport (i.e., cycling and walking) are not only environmentally friendly, but are also healthier (Park, Rink, and Wallace 2006, Hamer and Chida 2008). As they may be easy to incorporate into a daily routine, in particular for short trips within cities, there is a large potential for accomplishing a lasting shift towards these healthier travel modes.

Positive interventions or “soft measures”, such as personal travel planning, subsidies, providing feedback, and rewards as well as public transport (PT) discount can stimulate the use of sustainable transport options (e.g. Ben-Elia, Ettema, & van Delden, 2013; Bamberg, & Schmidt, 2003, Cairns, et al., 2008). Unlike fiscal regulations to discourage car use, positive interventions promote behavioural changes in a way that prevents increasing socio-economic inequity (i.e. poor people can no longer afford to use the car, whereas rich people are less affected or not at all) (Eliasson & Mattsson, 2006). Such soft measures can result in a significant reduction of car use as has been proven in several voluntary travel behaviour Change (VTBC) schemes. For example, the Spitsmijden project (peak hour avoidance) in the Netherlands (Ben-Elia & Ettema, 2011a), the Travel Marketing–IndiMark projects in Europe (focused on individualised travel) (Brög et al., 2009) (Y. Zhang et al., 2010a), and the Casteddu Mobility styles program in Italy (to promote the use of light rail) (Sanjust et al., 2014) applied several similar interventions, such as rewarding sustainable behaviour, providing feedback about behaviour, encouraging behavioural changes by goal-setting and planning, as well as raising awareness of sustainable travel options by providing travel information. However, most of these VTBC schemes did not focus on cycling.

In the age of big data, mobile phones and software platforms are becoming useful tools to collect travel behaviour data and deliver interventions. Using smartphones to collect extensive and dynamic data for human travel behaviour has proven to be better than traditional travel surveys. For example, travellers may forget trips or forget to report them. Smartphone use also provides greater accuracy for the locations of origins and destinations when compared with the self-reporting of multiple addresses (Thomas et al., 2018). Moreover, smartphone data is widely applied to estimate travel modes and travel routes, with high estimation accuracy (Stopher et al., 2009; Wang et al., 2017).

Many recent research projects have involved mobile phone in delivering interventions and collecting travel data (Bie et al., 2012; Broll et al., 2012; Carreras et al., 2012; Froehlich et al., 2009; Gabrielli et al., 2014; Hu et al., 2015; Jylhä et al., 2013; Poslad et al., 2015; Sanjust et al., 2014). This approach is generally inspired by Fogg's framework (B. Fogg, 2009; B. J. Fogg, 2002), in the integration and design of the successful intervention schemes, intended to convince users to behave more sustainably. Common persuasive design features used in those studies were personalised feedback, self-monitoring, challenges and goal-setting, social comparison, and rewards. App credibility (high detection accuracy and security features) is also an important persuasive element. Users will engage with apps they perceive as credible but navigate away from those that they do not consider credible. However, app credibility was often not achieved in mobile phone related studies, and this resulted in small sample sizes (Brynjarsdóttir et al., 2012; Gabrielli et al., 2014).

Commercial apps that focus on behavioural changes generally seamlessly serve end-users, have thoughtful app credibility design and are supported by business models, all leading to successful

recruitment. There are already numerous commercial apps such as Strava, CycleMaps, Cyclemeter, which promote cycling by using gamification methods or persuasive solutions. Other apps, such as BetterPoints and CommuteGreener are providing real rewards to promote cycling. BetterPoints recruited 15,000 active users for a six-month pilot and CommuteGreener engaged with 50,000 users via Facebook still 2015. All those projects (see Table 5.1) show a potential to encourage cycling, but a rigorous scientific analysis to evaluate their effects is still missing.

Moreover, these apps involve different intervention strategies. Strava, CycleMaps and Cyclemeter work as fitness apps, that track and analyse cycling or running trips, explore new routes, and provide the social network for competing with friends. Without challenges and rewards, these apps only target regular cyclists who already cycle a lot. The CommuteGreener app targets all types of travellers, and rewards them if they travel more sustainably relative to the baseline, which is an ideal behavioural change design. However, it is difficult to define the baseline and measure changes in reality. Therefore, CommuteGreener asks users to self-report the baseline and the changes they implement, which results in a high number of registered users but a low rate of real participants (10% of registered users) (Matushkina & Nevalennaya, 2010). BetterPoints automatically tracks users' travel behaviour, and reward them for each mile of cycling, walking or running, which makes it also attractive for car users. However, the challenge in BetterPoints is to encourage users to do their best to gain as many rewards as possible, i.e., rewarding each kilometre that travellers cycled. Many goal-setting studies have shown that specific and challenging goals lead to higher performance than easy or "do your best" goals (E. A. Locke, 1968; E. A. Locke & Latham, 2002). Last but not least, BetterPoints and other apps show that a commercial app can provide anonymity and create a real-world context, which means that the participants forget that their behaviour is being monitored (List & Levitt, 2006). Thus, real behaviour can be detected.

Based on existing cycling promotion apps, we introduced the SMART app (jointly developed by the company Mobidot and the municipality of Enschede). It focuses on all types of travellers and draws on the achievements of other mobile app-based studies. The SMART app automatically tracks travel behaviour in a real-world environment and includes personalised feedback, self-monitoring, challenge and goal setting, rewards and praise, traffic information and travel suggestions. It also offers a self-chosen cycling challenge intervention to make the cycling task more specific and challenging, along with the opportunity to investigate how travellers choose challenges and how their choices influence their behavioural changes. In addition, different types of challenges are designed and distributed throughout the year to encourage travellers to keep on participating. The cooperation between various stakeholders (among which the mobile app company, the municipality and the university) supports the app's credibility.

We assumed that the positive interventions introduced by the use of this app could nudge travellers away from cars to bikes and have broader recruitment. The main aim of this paper is to examine this hypothesis. We identified different travel change segments based on bike and car distance share changes and investigated the relationship between the travellers' change in behaviour and their travel patterns, how they responded to the challenges and whether the type of challenge played a role in the change in behaviour. The paper addresses the following research questions:

- Does this smartphone positive intervention app have high engagement and what is the effect on behavioural change?
- If engagement is high, how do different travel patterns relate to behavioural change?

- Does the way in which travellers deal with challenges and the type of challenge impact behaviour differently?

The paper is organised as follows. Section 5.2 sets out the case, with the description of the design of the interventions. Section 5.3 presents the data, followed by section 5.4, which covers the methodology. Section 5.5 presents the results of the analyses as well as the discussion. Section 5.6 provides conclusions.

Table.5.1 Overview of Apps focus on cycling promotion

Apps	Target users	Purposes	Interventions	Challenge types	Disadvantage
Strava	Athletes (cyclist and runners)	Social fitness network, primarily used to track cycling and running	Explore new routes, compete with friends, provide feedback		Cannot attract habitual car users
CycleMaps Cyclometer	Normal cyclists	Fitness tracking and planning app	Provide bike route information, explore and plan bike routes, compete with friends.		Cannot attract habitual car users
BetterPoints	Cyclists or runners	Deliver sustainability, CO2 emission reduction, improved resident self-health and social care.	Challenge and goal setting, Provide feedback, Show progress, providing incentives.	Earn a reward for each mile walked, cycled or run.	Simple goal-setting scheme. Cannot show trip routes but only total distances travelled.
Commute Greener	All types of travellers	Motivate to travel to work more sustainably. Reduce CO2 emission and improve health.	Provide traffic information, public transport alternatives, suggest rideshare partners, compete with friends, providing incentives.	Earn incentive points if travel greener than baseline.	No automated tracking (self-reporting).
SMART	All types of travellers	Motivate to travel in a sustainable and healthy way.	Challenge and goal setting, provide feedback and self-monitoring, provide incentives, provide traffic information and messages.	Self-chosen cycling challenges for each month.	

5.2 Case study

5.2.1 Recruitment

The municipality involved in the development of the app used Facebook, on-street leaflet distribution, digital advertisements and cooperation with local employers to promote SMART app usage, aiming to help the traveller minimise travel time and travel cost and/or to travel sustainably and healthily.

The recruited users could immediately participate in challenges and did not need to provide extra information (such as age or gender). In other words, they were not recruited for an experiment but simply used the app because they wanted to. Thus, we created a realistic real-life context enabling us to analyse true travel behaviour. However, as the users could immediately use all functionalities of the SMART app, we were not able to do a “before” measurement (baseline), which is an important drawback of this study.

5.2.2 Incentive design

We included a series of self-chosen challenges in a monthly choice challenge campaign. Each month, the app offered one type of challenge that contained five options ranging from easy

(“low”) to difficult (“high”). We created four types of challenges: frequency challenges (Fre), distance challenges (Dis), minimum distance per day challenges (DayKm) and location challenges (Loc). The different types of challenges were designed and distributed across the year to see which type would be more effective. Rotating challenges may also encourage users to keep on participating (Dorn & Sahinyan, 2010).

There were four types of challenges. Each type contained five options ranging from easy to difficult with an associated number of points to be obtained. The more difficult the challenge, the more points the participant was able to gain by completing that challenge. No reward was given if the participant did not complete the chosen challenge. Therefore, participants had to choose between easier challenges with fewer points but a greater chance of gaining them and more difficult challenges with more points but a greater chance of failing.

- •Fre: The number of trips to be made within 14 days;
- •Dis: The number of kilometres to be cycled within 14 days;
- •DayKm: The number of days to cycle at least 10 kilometres;
- The number of kilometres to be cycled on at least 10 out of 14 days;
- •Loc: The number of bike trips to go to a certain location within 14 days

In these monthly choice challenges, a bicycle trip (>2km) equalled 12 SMART credits and a cycled kilometre translated into 4 SMART credits. For each challenge, 30 SMART credits could be earned to motivate users, especially car users, to join the challenge actively. The challenge was open in the first two weeks of each month. The SMART users could choose one option; the challenge started immediately after her or she clicked to join the challenge. The duration of the challenge had a maximum of two weeks and participants were allowed to complete their challenge in less than two weeks. Participants immediately were rewarded if they met their chosen challenge in time. They then could redeem the points in the app’s web shops. For example, a free coffee in the SMART web shop cost 150 SMART points. There were also various discounts and other forms of commercial services, each requiring a certain number of credits.

We sent a post-survey through the SMART experience sampling question service to collect the users’ experiences with the challenges and obtain more information on the reasons why users did or did not change their behaviours. The survey aimed to assess the participants’ motivations behind (non-)completion of challenges and the participants’ self-awareness of behavioural change. This enabled a further analysis of the gap between stated behaviour and actual behaviour.

The monthly choice challenge started in March 2017, has been going on for several years and is still ongoing. However, we only used data from March 2017 until June 2018 for this study.

5.3 Data

5.3.1 Data sets and data selection

Data types

We used SMART data between March 2017 and June 2018. The research used the SMART app to deliver incentives and to track travel behaviour. Therefore there are two data sets: trip data and mobile app trigger data. Users' smartphone will automatically sense trip start, movement and trip end, so the trip data contains the origin, destination, departure time, arrival time, transport mode, activity, average speed, trip distance, and sensor data quality. The transport mode and trip activity are generated in the back-end by processing and learning algorithms, more detailed description can be found in Thomas, Geurs, Koolwaaij, & Bijlsma, (2018). In terms of the mobile app trigger data, when a user uses the functions of the SMART app, trigger data are generated. These contain the users' ID, type of triggers (challenge, survey questions, message), the status of triggers (accepted, answered, awarded, read), responses of the triggers (number of points awarded, reply to a survey question), trigger time and dates. The challenge trigger data and the post-survey question trigger data respectively correspond to monthly choice challenges and the post-survey.

Data to define behaviour and challenge period

The indicators we chose from the trip data to evaluate behaviour and behavioural change are distance-based mode share and daily distance per mode. We inspected these indicators by aggregating data on a monthly level; we chose a monthly level because a new set of choice challenges was offered each month. Thus, each user had one or more monthly data ("person-month data"). The distance-based mode share is the percentage of the total distance that is covered by each mode during the measurement period. We used distance rather than trip frequency because the latter might be disproportionally influenced by people shifting from walking to cycling for the shortest trips. The daily mode distance is the total distance covered by a certain mode divided by the number of days in the measurement period. We considered several measurement periods per month, i.e., the whole month, the period inside the challenge and the period outside the challenge period.

For each month, we defined the challenge period as 14 days, starting from the date on which the user joined the challenge. The remaining days in the month were defined as "outside the challenge period". (In practice, we chose two weeks and deleted the duplicated days.) That we chose a fixed challenge period but not the exact challenge period (i.e., users could complete the challenge within less than 14 days) was to ensure that the challenge period and the remaining period contained the same number of weekends and weekdays for a better comparison of the behaviour inside the challenge periods and outside the challenge periods. For users who only used the SMART app but did not pick a challenge, we defined the second and third week as the hypothetical challenge period and the first and fourth week as the hypothetical period outside the challenge. More than 60% of the participants' challenge periods were hypothetical, which made it possible to compare the behavioural changes between challenge participants and users who did not join any challenges.

Data sample and data selection

A total of 5,531 individuals downloaded and used the SMART app between March 2017 and June 2018, resulting in 22,203 person-months of data. Figure 5.1 shows the timeline for the

SMART app's usage, the number of users steadily increasing with a spike at the beginning of 2018. This spike may be explained by the start of several recruitment campaigns around that time. The fraction of dropouts was relatively low, indicating that most users actively or passively continued to use SMART. Half of the SMART users joined at least a challenge, with an average 50% participation rate. Thus overall, the monthly challenge join rate was around 25%. The lower line in Figure 5.1 depicts the number of users who joined challenges over time. After the increase at the start of 2018, the challenge participation rate dropped from 25% to 20%.

Figure 5.1 The timeline of app users and users who joined the challenges.

To ensure that the tracking data from the SMART app reflected the real travel behaviour, we excluded person-months that had fewer than 16 days of trip recording. Moreover, only trips below 20 kilometres were counted for our travel behaviour analysis, as cycling is not a viable option beyond 20 km (i.e., Fioreze, Thomas, Huang, & van Berkum, 2018). Almost all of these trips were trips within the urban area of Enschede (and the neighbouring city of Hengelo) and therefore can be regarded as urban trips. We also avoided irregular SMART app usage and tried to exclude users who turned off SMART when there was no challenge. This was done by excluding users that had a greater-than-20% difference in the fraction between days with trips inside and outside of the (hypothetical) challenge periods (often abbreviated to “Inside” and “Outside”).

After cleaning and filtering the data based on the above criteria, 2,111 users with data for in total 10,499 person-months remained. In total, 996 out of these 2,111 users joined the monthly challenge choice at least once. We called this group the “Experiment” group. The other 1,115 users never joined a challenge but used the SMART app regularly for other incentives, such as trip history and travel information. They are in the “No Challenge” group.

5.3.2 Measure and indicators

Behaviour and behavioural change

The travel behaviour in Table 5.2 shows the difference of modal share between the groups, e.g., the No Challenge group had a greater car mode share (52.1%) than the Experiment group (35.2%). Even the No Challenge group travelled a slightly shorter distance by car compared with what was found by the Dutch National Travel Survey (about 60%) (Statistics Netherlands, 2015.). This indicates the existence of self-selection for SMART users, in particular for the Experiment group. In spite of that, the participants still had a significant car mode share that can be decreased further.

The app users in the Experiment group (see Table 5.2) cycled more inside the challenge periods than outside the challenge periods. They also increasingly favoured bicycle use, although the decrease in average daily car distance is not statistically significant. If more than eight trips in one month took place between the same origin and destination, then we defined these trips as regular trips, otherwise as non-regular trips. Table 5.2 also shows the changes in total distance and purpose of trips. The “Inside” period shows a greater total distance and a greater fraction of regular trips than the “Outside” period. This implies that the challenge had the effect of nudging travellers towards using the bicycle, but it may partly have come from new trips rather than from a shift from car to bike.

Participants in the Experiment group did not join all the challenges. Table 5.3 contains the behaviours of 663 participants who joined challenges at least once but who also used the app without joining challenges for a few months. The aggregated results from these person-months (not-join challenge periods compared with outside the challenge periods) show that there was no significant difference in mode share. It is remarkable that the average daily travel distances are smaller during months without challenge. One reason can be that there were fewer trips in months without challenges. Therefore, instead of comparing behaviours between months with challenges and months without challenges, the comparison between “Inside” and “Outside” within the challenge months may reflect the actual behavioural change accomplished by the challenge intervention.

Table 5.2 number of different users and their behaviour

(one sigma error)	No Challenge group	Experiment group			
No. users	1115	996	<i>Behavioural change</i>		
		All	Inside	Outside	Δ
Bike distance based share	34,9% (0,7%)	45,9% (0,7%)	50,9% (0,8%)	48,3% (0,8%)	2,6% (0,4%)
Car distance based share	52,1 % (0,8%)	35,2% (0,7%)	36,4% (0,8%)	38,4% (0,8%)	-2,0% (0,4%)
Bike Daily Distance	4,62 (0,10)	7,07 (0,13)	7,94 (0,15)	7,21 (0,14)	0,73 (0,07)
Car Daily Distance	8,54 (0,20)	6,51(0,20)	6,94 (0,01)	7,00 (0,21)	-0,06 (0,09)
Regular trip distance percentage	26,0% (0,5%)	27,2% (0,5%)	30,3% (0,6%)	28,8% (0,5%)	1,5% (0,3%)
Total distance	448,7 (6,2)	498,8 (6,7)	236,76 (3,28)	227,28 (3,10)	9,49 (1,59)

Table 5.3 Users with both participating and non-participating status

(one sigma error)	663	
No. users	Not Join challenge	Outside
Bike distance based share	44,4%(0,9%)	45,8% (0,9%)
Car distance based share	42,2%(1,0%)	40,4% (0,9%)
Bike daily Distance (km)	6,11 (0,16)	7,01 (0,17)
Car daily Distance (km)	6,93 (0,23)	7,42 (0,25)
Regular trip distance percentage	26,6% (0,6%)	28,0% (0,6%)
Total distance	446,1 (7,1)	231,78 (3,70)
Average number of trips per month	131.5 (1.7)	137.6 (2.2)

In order to understand the impact of the different types of changes better, we divided the behavioural change of each person-month into three groups: the modal shift group, the additional bike increase group and the reference group. As Figure 5.2 shows, behavioural changes in area A fall in the modal shift group, the changes in area B form the additional bike

increase group and the remainder forms the reference group. The boundaries in Figure 5.2 are based on the self-reported behavioural change from the post-survey.

- Modal shift (MS in Table 5.5): The area (A) between $x=0$ and $y=-0.5x$ in the bottom window of the coordinates. If during the challenge the bike distance increased and the car distance decreased by more than half of the bike kilometres, we call this a modal shift.
- Additional bike increase (IN in Table 5.5): The area (B) between $y=-0.5x$ and $y=x$ in the right window of the coordinates. If during the challenge the bike distance increased while the car distance decreased less than half of the bike kilometres and the car distance did not increase more than the bike distance, we called this a change in bike increase. (We assumed that the challenge only led to an increase in cycling, not an increase in car trips, and that the latter would simply be caused by the participant travelling more.)
- Reference (Ref): The remaining area.

Figure 5.2 Behavioural change segments, showing the difference in behaviour inside and outside the challenge periods.

Challenge and app indicators

The challenge is the essential intervention and app usage determines the success of the experiment. Therefore, we extracted challenge and app indicators to find out how the participants' app use and their way of choosing challenges affected their behavioural changes.

First, we analysed the difficulty of the chosen challenges to check whether behaviour changed differently between participants who chose easy challenges and those who selected difficult challenges. We defined the difficulty of a chosen challenge by comparing the challenge with the participants' behaviour in the previous month. In other words, if the challenge required the participant to cycle more than in the previous month, the challenge was considered to be (relatively) difficult and if the challenge required less effort from the participant relative to the month before, we considered the challenge to be (relatively) easy. As a result, the first month for each participant had no difficulty value, because the relative difficulty could not be estimated based on previous patterns.

Second, we looked at the chosen challenge option as an impact factor for behavioural changes. We assumed that the "cycling a lot" option ("high") is more challenging than the "cycling a

little” option (“low”), even though the former option might still be an easy challenge for active cyclists.

Third, we looked at the type of challenge. As described in Section 5.2.2, we designed four types of challenges. The behavioural changes seen for the location challenge were significantly different, which may result from the fact that a location might be an unattractive destination for the participants. Also, there was a technical issue with properly defining the area of a certain location. Therefore, we excluded the person-months with the location challenge. As a result, 2,189 person-months for 856 users who joined the challenge contained challenge difficulty information.

Fourth, by comparing the number of months in which an individual joined the challenge and the entire months which he or she used the app, we extracted the join rate.

Travel patterns

To analyse the relationships between travel patterns and travel behavioural changes, we derived mode uses and mode purposes from the SMART trip data. We used bike, car, public transportation and walking as travel modes. Besides, we distinguished different types of trips. For example, the trip purpose was likely different on weekdays and weekends and commuting behaviour may be more difficult to change than recreational travel behaviour (Harms & Kansen, 2018). More generally, we assumed that habitual or regular trips might be more difficult to change. If in one month, more than eight trips were made between the same origin and destination, then we defined these trips as regular trips, otherwise as non-regular.

The total distance travelled per month may also impact behavioural changes. For example, travellers who make more trips have more opportunities to change. Therefore, combined with mode share, type of trip and total travel distance, 22 variables were formulated to reflect travel patterns (see Table 5.4). We conducted a common factor analysis (principal components analysis with Varimax with Kaiser normalisation) to explore if there were unobserved (latent) variables that described the variation. We identified eight underlying factors (based on eigenvalues greater than 1), reflecting travellers’ travel patterns, sorted by effect size: *Regular car, long-distance travellers (F1)*, *Weekdays, non-regular car, long-distance travellers (F2)*, *weekends, non-regular car travellers (F3)*, *Non-regular bike, long-distance travellers (F4)*, *PT user (F5)*, *Weekdays, regular bike travellers (F6)*, *Walking enthusiast (F7)*, *Weekends, regular bike traveller (F8)*. These factors explain 82% of the total variance. Table 5.4 presents a list of all variables and the corresponding factor loadings. We saved each respondents’ latent factor scores on each of the eight factors reflecting their travel patterns in the database.

Post survey

There were 660 person-months responses about whether they had cycled more during the monthly choice challenge. Of those responses, 40% claimed they had cycled more, 21% of this 40% said they switched from car to bike. We compared these self-reported behavioural changes (i.e., average modal shift) with actual changes collected through the SMART app to find the gap between stated behaviour and actual behaviour.

Table 4 Factor loadings from the factor analysis (N = 2189).

Factors	variables	Factor loading
F1: Regular car, long-distance traveller	Car regular weekdays daily distance	0,821
	Car regular weekends daily distance	0,753
	Car regular weekdays mode Share	0,753
	Car regular weekends mode Share	0,619
	Bike regular weekdays mode Share	-0,591
	Total distance	0,511
F2: Weekdays, non-regular car, non-bike, long-distance traveller	Car non-regular weekdays mode Share	0,855
	Bike non-regular weekdays mode Share	-0,840
	Car non-regular weekdays daily distance	0,768
	Bike non-regular weekdays daily distance	-0,407
	Total distance	0,403
F3: Weekends, non-regular car, non-bike traveller	Car non-regular weekends mode Share	0,857
	Bike non-regular weekends mode Share	-0,835
	Car non-regular weekends daily distance	0,765
	Bike non-regular weekends daily distance	-0,462
F4: Non-regular bike, long-distance traveller	Bike non-regular weekdays daily distance	0,781
	Bike non-regular weekends daily distance	0,675
	Total distance	0,584
	Total proportion of non-regular trips	0,403
F5: PT user	PT distance	0,975
	PT mode share	0,968
F6: Weekdays, bike regular travellers	Biker weekdays mode share	0,513
	Bike regular weekdays daily distance	0,924
	The total proportion of non-regular trips	-0,751
F7: Walking enthusiast	Walk distance	0,947
	Walk mode share	0,907
F8: Weekends, regular bike traveller	Bike regular weekends daily distance	0,867
	Bike Regular weekends mode share	0,863

5.3.3 Sample description

Table 5.5 shows characteristics of the selected sample with behavioural change distribution, SMART app usage information, challenge related information and sample post survey results. This final sample contained 2,189 person-months from 856 users. Around half of the person-months had behavioural changes, in which 26% had a modal shift and around 23% had additional bike increase. Second, the challenge and app usage information shows that most participants joined fewer than three monthly challenges as only 304 participants joined three or more monthly challenges. In reality, participants may have joined challenges more often, but may have been removed from the sample because those months did not fit the selection requirement. However, we also had the real join frequencies of the participants in the sample and this confirmed that the number of participants joining challenges over a longer period was relatively low. Partly, this can be contributed to the fact that many users joined in a late stage of the study. This could also explain why almost 80% of participants still had a join rate of greater than 50%.

Furthermore, the challenge information shows that around half of the chosen challenges were difficult relative to the observed travel patterns. However, the more challenging options were chosen more often than the less challenging options, reflecting the fact most participants in the

sample are (active) cyclists. The comparison with the previous challenge shows that participants tended to choose the same challenge option or a slightly more difficult option for the next challenge. The sample had a high challenge accomplishment rate. Most participants joined KM challenges and the DayKM challenges had the least participation. This is probably due to the challenge design, as we repeated KM and Fre challenges more often than DayKM challenges.

Table 5 Descriptive statistics of samples N=2189, from 856 users

variables		N (M)	Percent (SD)	variables	N (M)		Percent(SD)
Behaviour	Behavioural change	Modal Shift (MS)	575	26.3%	Times	participants	
		Bike Increase (IN)	496	22.7%		373	43,6%
		Reference (Ref)	1118	51.1%		179	20,9%
	Difficulty	Difficult (DIFF)	1110	50,7%		120	14,0%
		Easy	1079	49,3%		51	6,0%
	Choice	1 Low	233	10,6%		50	5,8%
		2 Low	296	13,5%		21	2,5%
		3	870	39,7%		23	2,7%
		4 High	310	14,2%		13	1,5%
		5 High	480	21,9%		14	1,6%
	Finish status	Finish (FIN)	1588	72,5%		7*	0,8%
		Unfinished	601	27,5%		3	0,4%
Challenge & App usage	Pre-Finish	Others	1317	60,2%	Survey	Reason why they had cycled more	NoData
		Pre-Finish (PreFin)	872	39,8%			ExtraBike
	Pre-Unfinished	Others	1636	74,7%			CarShift
		Pre-Unfinished	553	25,3%			NoChange
	Type	Daykm	458	20,9%			270
		Fre	729	33,3%			mean 0
		km	1002	45,8%			std 1
	PreChoice compared with current choice	Easier (PreEasyChoice)	492	22,5%			min
		More Difficult	395	18,0%			Max
		No Info. Equal	856	39,1%			F1: Regular car, long distance traveller
	JoinRate	<50% LowJoinRate	313	14,3%			F2: Weekdays, non-regular car, non-bike, long distance traveller
		50%~80%	943	43,1%			F3: Weekends, non-regular car, non-bike traveller
		>=80% HighJoinRate	933	42,6%			F4: Non-regular bike, long distance traveller
Join	<=3	4~6	559	25,5%			F5: PT user
		>=7	382	17,5%			F6: Weekdays, bike regular travellers
							F7: Walking enthusiast
							F8: Weekends, regular bike traveller

5.4 Methods

5.4.1 Modelling approach

For each month, we obtained the individuals' differences between their behaviour inside the challenge periods and outside the challenge periods. We classified these behavioural changes as a modal shift from car to bike (MS), bike distance increase without modal shift (IN) or as falling into the rest (Ref). Based on those three types of changes, we can say that individuals made a "decision" on what changes to make each month with the highest utility (which effort to make to obtain rewards). Their SMART app usage information, chosen challenge information and travel pattern information would impact that "decision". Additionally, individuals could either join the challenge or even stop using the app freely. Therefore, the behavioural change decision for some users involved repeated choices. To explore the behavioural change over time when respondents' choices are repeated, we applied a panel-based mixed logit model (Bhat, 1999; Train, 1999; McFadden and Train, 2000).

Mixed logit models are highly flexible and can approximate any random utility model (McFadden and train 2000). A standard logit model accounts for heterogeneity in unobserved utility by lumping all heterogeneity together in the iid-distributed error. However, in these panel data, the users' choice or preference for a certain behavioural change could vary across individuals. Different than in the standard logit model, in the mixed logit model, this specification is

generalised by allowing c_n to be random, following a distribution $f(c|\theta)$ where c_i is the mean and variance σ_n . The utility from alternative i in choice situation t by person n is:

$$U_{nit} = c_{ni} + \beta_{nj}x_{nit} + \varepsilon_{nit} \quad (5.1)$$

$$c_{ni} \sim f(c_i, \sigma_n^2)$$

with ε_{nit} being iid extreme value over time, people, and alternatives. The unconditional probability that the person makes this sequence of choices is the integral product over c_{ni} :

$$P_{ni} = \int \prod_{t=1}^T \left[\frac{e^{c_{ni} + \beta_{nj}x_{nit}}}{\sum_j e^{c_{nj} + \beta_{nj}x_{njt}}} \right] f(c_{ni}) dc_{ni} \quad (5.2)$$

$$L_{ni}(C) = \prod_{t=1}^T \left[\frac{e^{c_{ni} + \beta_{nj}x_{nit}}}{\sum_j e^{c_{nj} + \beta_{nj}x_{njt}}} \right] \quad (5.3)$$

where x is a vector of explanatory variables, β , is a vector of fixed coefficients. We had a real-world experiment, with revealed preference data, that were limited to choice situations and attributes of the alternatives. In our case, we had no attributes of the alternatives. All attributes in our model come from decision makers, that do not vary over alternatives. They were specified in such a way that they created differences in utility over alternatives.

The choice probability is not a closed form for the integral, thus we specified that $f(c|\theta)$ has a normal distribution, and estimated θ to simulate P_{ni} . R values of θ can be drawn from its distribution, and the probability in (5.2) is calculated conditional on each realisation. The simulated probability (SP) is the average of the conditional probabilities over R draws:

$$SP_{ni} = \frac{1}{R} \sum_{r=1}^R L_{ni}(c^r) \quad (5.4)$$

Then, the simulated log-likelihood function is constructed as, $SLL = \sum_n \ln(SP_{ni})$, and the estimated parameters are those that maximise SLL. We also compared the estimates obtained by model runs with 100, 200 and 800 Halton draws in the SLL estimation to verify their stability. Estimation of the model parameters was conducted with the PandaBIOGEME software (Bierlaire, 2003).

To discover and compare behavioural changes over a certain period, several multinomial logit models were applied to the sample with the same variables under various conditions. For example, participants that joined the challenges more than three times, or participants who joined only once or twice were further analysed.

5.4.2 Specification

The model specification applied for our case study, in the multinomial choice among the Modal Shift (MS), the additional bike increase (IN), and the rest (Ref) changes, included three “linear in the parameters” utility functions. The reference choice (i.e., choice = 0) was always Ref and all alternative-specific constants were specified in the other two utility functions, but not in Ref. Constants were included to capture the average impact of unobserved factors. Furthermore, panel effects were accounted for by using random parameters with constant variables with a normal distribution for the disturbance. The formal specification (5.5) was followed by a description of the different factors included in the model. Table 5 contains the definitions of the factors. Coefficients in parenthesis indicate the standard deviations of the random parameter to the left. As noted, the model includes attributes of the person (participants) but no attributes of

the alternatives. We assumed that the utility for all alternatives depends on the same variables, but that the coefficients are different for different alternatives, as follows:

$$U_i = ASC_i(\sigma_i) + \beta_{DIFF_i} DIFF + \beta_{FIN_i} FIN + \beta_{LJR_i} LowJoinRate + \beta_{HJR_i} HighJoinRate + \beta_{km_i} KM + \beta_{DayKM_i} DayKM + \beta_{LowChoice_i} LowChoice + \beta_{HighChoice_i} HighChoice + \beta_{PreFin_i} PreFin + \beta_{PreEasyChoice_i} PreEasyChoice + \beta_{JoinTime_i} JoinTime + \sum_{j=1}^8 \beta_{FA_ji} FAj \quad (5.5)$$

$$U_{NEG} = ASC_{Ref}(\sigma_{Ref}) \quad ASC_{NEG} = 1 \text{ and } i \text{ is } MS, IN \quad (5.6)$$

We used a mixed logit model to estimate the behavioural change for the whole sample (Main model). Moreover, to discover behavioural changes of participants who had a high join rate, we estimated participants with more than three person-months with the same model (RepeatAll). Additionally, to gain an understanding of behavioural changes as join time increasing, we applied a the multinomial logit model. The MNL model includes the same attributes as the mixed logit model, but without random parameters. The following MNL models were applied:

- For participants who only joined once (JoinOnce).
- For participants who at least joined three times (JoinOften), a model was estimated for
 - The first time participants joined (Repeat1st);
 - The second time participants joined (Repeat2nd);
 - The third time participants joined (Repeat3rd);
 - All the first three times participants joined (RepeatThree).

5.5 Results and discussion

5.5.1 Main model results and comparison with other models

Table 6 displays the estimation results of two mixed logit models (Main model and JoinOften model) and one MNL model (JoinOnce). First of all, the models show similar results, except the model for participants who only joined once, which implies that participants who joined more challenges often had a different behavioural change tendency than participants who joined only once. More specifically, the coefficients related to the challenge itself for the JoinOnce model is less significant. This implies a relatively low engagement for this group, which is not surprising.

For both behavioural changes (Modal shift and Additional Bike increase) in the Main model, the positive and significant coefficients of challenge accomplishment (β_{FIN}) implies that, unsurprisingly, the commitment of fulfilling a challenge had a positive effect on behavioural change. The effects of β_{FIN} were greater for the JoinOften model than for the Main model, and were not significant on MS change for the JoinOnce model. This suggests that the commitment to changing one's behaviour is weaker for participants who only joined once. The coefficient for challenge difficulty (β_{DIFF}) was not significant, which is surprising. Overall, high commitment (difficult challenge) was accompanied by a low accomplishment rate. This could be one of the reasons that the β_{DIFF} was not significant. However, β_{DIFF} was significant in the JoinOften model, which implies that participants with high engagement may have a greater commitment towards changing their behaviour, which is in line with the finding that high

engagement (joining more than three times) is associated with a 51% accomplishment rate, and low engagement with an accomplishment rate of 47%.

We also found that distance-related challenges (β_{DayKM} and β_{KM}) and a preference for more challenging options ($\beta_{\text{HighChoice}}$) were more likely to result in a change in behaviour. By contrast, participants who preferred less challenging options ($\beta_{\text{LowChoice}}$) were not willing to adapt their behaviour. The preceding challenge situation ($\beta_{\text{PreEasyChoice}}$, β_{PreFIN}) had no significant impact on behavioural change.

Travel patterns had a different effect on the two types of behaviour change (MS and IN). PT users and people who walk more often were more inclined to cycle more than to shift from the car to the bike. Conversely, travellers with many irregular car trips tended to shift from the car to the bike, in line with the expectation that a modal shift can be more easily accomplished for those trips. Travellers with high bike shares tended to show no change in behaviour.

Different challenge types also had different effects on the type of behavioural change. First of all, distance-related challenges were more effective than frequency challenges. Of the distance-related challenges (β_{DayKM} and β_{KM}), daily cycling distance challenges (β_{DayKM}) motivated users towards a shift in travel mode more effectively than weekly distance challenges (β_{KM}). This indicates that this strategy may be more effective for accomplishing a modal shift from car to bike, as it did not yield extra bike kilometres while the other challenges did.

The constant random parameters (σ_i) reflect the panel effect. None of the sigma values are significant, which implies that participants tended not to stick with a change. Alternatively, it could be that participants maintained the change, resulting in no difference between inside and outside the challenge periods.

5.5.2 Repeat Three Times models

Table 5.7 contains the RepeatThree MNL model and the separate models for each number of repeats. The results of the RepeatThree model show no significant differences compared with the Main model, except that the challenge difficulty had a significant positive effect. This effect became stronger in the Repeat3rd mode, suggesting that the effect of challenge difficulty appears only after joining the challenge multiple times. Moreover, the real join frequency (β_{JoinTime}) was significant in the RepeatThree model, especially in the Repeat3rd mode, which implies that the more often people participated in challenges, the more they tended to change their behaviour. However, this effect may only start to show up after users participate in challenges many times.

Travellers with high shares of bike trips tended not to change their behaviours in the Main model. However, for travellers who repeatedly joined the challenge, this tendency weakened. This implies that long-term engagement may even encourage frequent cyclists to cycle more.

Table 5.6 The Main model and other models

	MainModel			JoinOften			JoinOnce		
	Value	Std err	Sig.	Value	Std err	Sig.	Value	Std err	Sig.
Modal Shift MS									
ASC_MS	-2,46	0,23	***	-3,00	0,31	***	-1,80	0,52	***
β DIFF	0,24	0,16		0,42	0,20	*	-0,58	0,37	
β JoinHighRate	-0,12	0,14		-0,05	0,17		-0,08	0,50	
β JoinLowRate	-0,14	0,18		-0,34	0,28		0,14	0,33	
β DayKM	0,78	0,20	***	0,87	0,25	***	1,17	0,53	*
β KM	0,35	0,14	*	0,43	0,18	*	0,66	0,32	*
β Fin	1,15	0,16	***	1,43	0,21	***	0,64	0,35	
β HighChoice	0,92	0,17	***	0,93	0,20	***	1,21	0,42	**
β LowChoice	-0,50	0,16	**	-0,44	0,20	*	-0,80	0,38	*
β PreEasyChoice	-0,08	0,16		0,00	0,18				
BPreFin	0,21	0,13		0,23	0,16		-0,66	0,68	
β FA1	0,19	0,06	***	0,16	0,07	*	0,24	0,13	
β FA2	0,73	0,07	***	0,76	0,09	***	0,83	0,15	***
β FA3	0,70	0,07	***	0,73	0,08	***	0,62	0,15	***
β FA4	-0,55	0,07	***	-0,56	0,09	***	-0,57	0,19	**
β FA5	0,13	0,06	*	0,10	0,08		0,10	0,18	
β FA6	-0,29	0,07	***	-0,35	0,08	***	-0,30	0,17	
β FA7	-0,02	0,06		-0,08	0,08		0,13	0,16	
β FA8	-0,11	0,06		-0,14	0,08		-0,09	0,15	
β JoinTime	0,03	0,02		0,03	0,03		0,13	0,20	
Additional Bike Increase IN									
ASC_IN	-2,58	0,23	***	-2,67	0,31	***	-2,35	0,61	***
β DIFF	0,24	0,16		0,45	0,19	*	-0,57	0,40	
β JoinHighRate	-0,05	0,15		-0,17	0,17		0,94	0,52	
β JoinLowRate	-0,24	0,20		-0,21	0,28		-0,22	0,39	
β DayKM	0,26	0,21		0,34	0,25		0,20	0,65	
β KM	0,29	0,14	*	0,27	0,17		0,66	0,34	
β Fin	1,40	0,17	***	1,50	0,22	***	1,15	0,41	**
β HighChoice	1,20	0,17	***	1,18	0,20	***	1,78	0,45	***
β LowChoice	-0,72	0,18	***	-0,63	0,22	**	-0,46	0,45	
β PreEasyChoice	-0,16	0,16		-0,25	0,18				
BPreFin	-0,07	0,14		-0,09	0,15		-0,28	0,60	
β FA1	-0,18	0,08	*	-0,14	0,10		-0,27	0,20	
β FA2	-0,09	0,07		-0,10	0,09		0,08	0,17	
β FA3	-0,01	0,07		-0,07	0,08		-0,07	0,16	
β FA4	-0,73	0,08	***	-0,73	0,09	***	-0,98	0,21	***
β FA5	0,21	0,06	***	0,21	0,07	**	0,05	0,19	
β FA6	-0,23	0,07	***	-0,26	0,08	**	-0,31	0,18	
β FA7	0,22	0,06	***	0,19	0,07	**	0,09	0,18	
β FA8	-0,12	0,06	*	-0,15	0,07	*	0,01	0,14	
β JoinTime	0,03	0,02		0,03	0,03		-0,18	0,23	
σ _IN	0,33	0,20		-0,26	0,27				
σ _MS	-0,27	0,25		0,31	0,24				
σ _Ref	-0,25	0,22		0,26	0,23				
N	2189			1458			373		
Rho-square	0,19			0,19			0,24		

* p < 0.05

** p < 0.01

*** p < 0.001

Table 5.7 Repeat Three Times models

	RepeatThree			Repea t1 st			Repe at2 nd			Repe at3 rd		
Modal Shift MS	Value	Std err	Sig.	Value	Std err	Sig.	Value	Std err	Sig.	Value	Std err	Sig.
ASC_MS	-3,42	0,40	***	-3,92	0,79	***	-3,86	0,96	***	-3,34	0,92	***
βDIFF	0,65	0,24	**	0,39	0,43		0,66	0,47		1,02	0,47	*
βJoinHighRate	0,00	0,21		-0,08	0,42		-0,04	0,42		-0,26	0,36	
βJoinLowRate	-0,29	0,30		-0,27	0,50		0,27	0,53		-0,77	0,61	
βDayKM	0,73	0,32	*	0,42	0,59		1,40	0,62	*	0,29	0,55	
βKM	0,56	0,22	**	0,28	0,40		0,74	0,42		0,71	0,37	
βFin	1,40	0,25	***	1,95	0,50	***	2,07	0,48	***	0,62	0,44	
βHighChoice	0,78	0,26	**	0,96	0,48	*	1,34	0,48	**	0,37	0,48	
βLowChoice	-0,33	0,24		0,07	0,43		-1,17	0,48	*	-0,19	0,44	
βPreEasyChoice	0,06	0,24		0,00	0,00		-0,44	0,41		0,24	0,39	
BPreFin	0,28	0,20		0,68	0,43		0,45	0,38		0,09	0,33	
βFA1	0,18	0,08	*	-0,01	0,17		0,51	0,16	**	0,06	0,14	
βFA2	0,70	0,10	***	0,58	0,19	**	0,87	0,19	***	0,76	0,17	***
βFA3	0,66	0,10	***	0,75	0,18	***	0,72	0,17	***	0,62	0,18	***
βFA4	-0,51	0,10	***	-0,26	0,19		-1,05	0,22	***	-0,46	0,17	**
βFA5	0,14	0,09		-0,14	0,18		0,16	0,17		0,27	0,16	
βFA6	-0,35	0,10	***	-0,62	0,19	**	-0,53	0,19	**	-0,06	0,17	
βFA7	-0,12	0,10		-0,45	0,21	*	0,03	0,18		0,05	0,17	
βFA8	-0,08	0,10		-0,22	0,19		-0,14	0,18		-0,03	0,17	
βJoinTime	0,14	0,07	*	0,29	0,23		0,02	0,22		0,28	0,17	
Additional Bike Increase IN												
ASC_IN	-3,02	0,39	***	-3,35	0,76	***	-2,35	0,82	**	-3,76	0,91	***
βDIFF	0,69	0,24	**	0,65	0,42		0,13	0,47		0,65	0,45	
βJoinHighRate	-0,30	0,21		-0,28	0,45		-0,10	0,43		-0,28	0,35	
βJoinLowRate	-0,16	0,30		-0,83	0,52		0,46	0,52		0,04	0,58	
βDayKM	0,37	0,32		0,05	0,62		1,57	0,63	*	-0,05	0,59	
βKM	0,33	0,21		0,14	0,38		0,68	0,44		0,40	0,34	
βFin	1,42	0,26	***	2,24	0,54	***	1,07	0,48	*	1,23	0,46	**
βHighChoice	0,94	0,26	***	1,42	0,49	**	0,86	0,47		1,00	0,46	*
βLowChoice	-0,69	0,27	*	-0,29	0,46		-0,67	0,49		-1,08	0,51	*
βPreEasyChoice	-0,28	0,24		0,00	0,00		-0,34	0,39		-0,12	0,38	
BPreFin	0,00	0,19		-0,08	0,45		-0,08	0,36		0,17	0,32	
βFA1	-0,03	0,11		-0,11	0,20		0,19	0,19		-0,14	0,19	
βFA2	-0,15	0,10		-0,26	0,20		-0,05	0,19		-0,19	0,17	
βFA3	-0,11	0,10		-0,12	0,19		-0,02	0,17		-0,19	0,17	
βFA4	-0,57	0,11	***	-0,99	0,23	***	-0,40	0,20	*	-0,51	0,17	**
βFA5	0,19	0,08	*	0,07	0,12		0,31	0,15	*	0,28	0,17	
βFA6	-0,22	0,10	*	-0,46	0,19	*	-0,02	0,17		-0,12	0,18	
βFA7	0,18	0,08	*	-0,08	0,19		0,44	0,15	**	0,22	0,15	
βFA8	-0,01	0,08		-0,05	0,16		0,10	0,16		0,00	0,15	
βJoinTime	0,17	0,07	*	0,00	0,24		-0,08	0,20		0,36	0,16	*
N	912			304			304			304		
Rho-square	0,19			0,25			0,25			0,20		

* p < 0.05

** p < 0.01

*** p < 0.001

5.5.3 Effects on behavioural changes

The Rho-square of all model fits was below or around 0.20, which is not very high. One reason for this is the large natural variation in total trip distance and modal split due to external effects such as weather. This may also explain some differences between reported (from the experience sampling) and observed behavioural change. For example, 44% of travellers who reported a modal shift change also showed a modal shift in the real-world experiment (see Table 5.8). However, 32% of the travellers who claimed to have no behavioural change did display some modal shift. To interpret the significance of the results from Section 5.5.2 (with many results being statistically significant) in more detail, we aggregated person-months in specific bins.

Table 5.8 observed behavioural change compared with reported behavioural change.

Reported Observed	MS	IN	Ref
MS	44,2%	28,0%	31,9%
In	22,1%	33,3%	24,1%
Ref	33,7%	38,7%	44,1%
Total number	86	93	270

The left panel in Figure 5.3 shows the effects of the chosen challenge option on the daily bike and car distance. The (in absolute sense) more difficult challenges yielded a greater change in bike distance. The most challenging option had a bike distance increase of 1.9 km per day. However, the reduction in car distance is much less clear than the increase in bike distance. This indicates that participants also cycled more without a modal shift taking place, especially when they chose the greatest challenge option. The right panel shows the effects of challenge type on the daily bike and car distance. Relative to frequency challenges, distance challenges seem to lead to larger increases in bike distance and reductions in car distance. However, the differences are small and because of the large natural variation, these results are not statistically significant.

Figure 5.3 Effects of different variables on daily distance change (a) challenge option, (b) challenge type

Table 5.9 shows the behavioural change based on the modal shift probability from the mixed logit model. By sorting the modal shift probability from high to low, we divided travellers into four groups. Half of the travellers who have a high modal shift probability (group 1 and 2) included 71% of all the travellers who reported a modal shift. Hence, the observed and self-reported behavioural change gap is smaller when considering high versus low modal shift probability, implying that on an aggregated level observed and reported modal shifts are correlated. Those travellers with a high modal shift probability had a more than 10% modal shift from car to bike per month, corresponding to a 1.5 km per day bike increase, as well as 1.5 km per day car decrease. Hence, for this group of people, the intervention strategy could be decisive in accomplishing a modal shift from car to bike.

Table 5.9 Behavioural changes based on model shift probability from mixed logit model, compared with reported behavioural changes.

Modal shift probability based on the logit model, Groups are based on sorting the modal shift probability from high to low	Reported behavioural change			Mode share change		Daily distance change	
	IN	MS	Ref	Bike	Car	Bike	Car
Group 1 (high 25%)	20,4%	41,9%	23,7%	12%	-12%	1.82	-2.55
Group 2(middle high 25%)	26,9%	29,1%	24,1%	7%	-7%	1.28	-0.41
Group 3 (middle low 25%)	23,7%	19,8%	26,3%	3%	0%	0.73	0.53
Group 4(low 25%)	29,0%	9,3%	25,9%	-5%	7%	-0.28	1.14

5.6 Conclusions

A cycling-positive intervention strategy was set up in a real-world environment, by means of the SMART app. Analysis of the strategy of including cycling challenges to be chosen by users shows that these challenges had a positive effect on behavioural change. That is, it can effectively cause a modal shift from car to bike every month. However, the challenges also had the effect of causing additional bicycle use without a modal shift (i.e., the decreased car distance can explain more than half of the increased cycling distance, but some of the bike use increase is not accompanied by a decrease in car use). This is good from a health perspective, but does not have any other of the desired effects.

Behavioural change models were used to explain these two types of behavioural changes. More specifically, the models explained how individuals' behavioural change is related to their travel patterns, their smartphone application usage information and the chosen challenges. We found that public transport users and people who walk more often were more inclined to increase the number of bike trips than to shift from car to bicycle. Conversely, travellers with a high frequency of irregular car trips did tend to display a modal shift. Also, the way travellers faced and chose challenges and the type of challenge they chose played a role in changing behaviour. More specifically, travellers who completed the challenges, those who challenged themselves with difficult challenges or selected the most challenging option were more willing to change their behaviour. By contrast, the relative difficulty level does not seem to have had a significant effect. We contribute this to the relatively low accomplishment rate for difficult challenges, which might actually work as discouragement when aiming for behavioural change. However, this changed with increasing number of joined challenges.

In addition, we saw that rewarding travellers for cycling longer distances can be more effective than rewarding them for cycling more trips. Importantly, daily cycling distance challenges can motivate a modal shift more effectively than weekly challenges. These findings indicate that some parts of this strategy are effective for accomplishing a modal shift from car to bike. Overall, it appears unavoidable to cause an increase in the number of bike trips without accomplishing a modal shift. However, this measure has the potential to achieve sustained behavioural change, provided that it motivates travellers to keep participating in the challenges.

Comparison of the observed behaviour with experience sampling (post-survey) revealed that the travellers' self-reported behavioural change matched the observed behavioural change, but with some discrepancies. These discrepancies imply a large natural variation in total trip distance and modal split. However, the discrepancy was smaller for travellers with a high modal shift probability as seen in the behavioural change model. Importantly, the intervention had a

promising effect in terms of behavioural change for half of the users with a high modal shift probability, that is, the daily distance shift from car use to bike use was around 1.5 km. This implies a decisive role for this intervention strategy in nudging users out of their cars and onto bicycles.

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6 Conclusions, implications and future research

In this thesis, the potential of smartphone-based positive interventions to nudge modal shift from car to bike in the long term is examined. To that end, a stated choice experiment, two intervention strategies in a real-world experiment and an explanatory model for behavioural change were conducted. This final chapter presents conclusions that consist of three sections. First, it presents the conclusions of this research, based on the research questions. The second section describes the policy implications. Finally, the study's recommendations for further research are given in the last section.

6.1 Conclusions

- 1) What are the effects of multiple types of challenge and reward incentives on travelling behavioural change, and what is the most effective challenge and reward?

Based on the stated preference survey, it is found that challenges in combination with rewards, especially individual challenges (e.g. increase cycling frequency) and in-kind rewards (e.g. points), can motivate travellers to change travel behaviour by cycling more. A variation was found in terms of the incentive effects among different travel patterns. Overall, the occasional cyclists are more positive towards various incentives (with about 50% consideration) than non-cyclists and are more willing to change their behaviour. More specifically, it is found that travellers that rarely cycle tend to have a negative attitude towards cycling. They do not prefer any incentive, and not willing to make any behavioural change towards more bike use, as a result of any incentives. For those travellers, a interventions strategy that focuses on changing attitude is essential. For example, showing information or travel cost savings or designing short distance challenges can help change their attitudes. Moreover, young and higher educated travellers, as well as low-income travellers, are more easily to accept this new technology (recording trips and providing rewards via smartphone apps) to make a change.

Analysis of the rewards shows that in-kind reward and monetary reward are most likely to motivate people to cycle more and to use the corresponding app. For challenges, the gamification challenge (i.e. competitive and cooperative challenges) had less motivational

effect compared with an individual challenge. In terms of rewards, more specifically, money was the most preferred reward when respondents chose among alternative incentives, but in-kind gifts scored better than money when incentives were considered separately without information about other incentives. Such inconsistencies often occur when social preferences are involved (e.g. Levitt & List, 2007) (i.e. to reward travellers for a better and greener society). However, when travellers used the mock-up app in the survey that conveys the incentives to simulate the reality as much as possible, the in-kind rewards motivated more travellers to consider to cycle more often than money. This fact implies that in-kind rewards should be more effective than monetary reward in the real-world environment. Moreover, in reality, the incentive app will probably provide only one type of reward, thus by having a web shop associated with in-kind gifts may make people more enthusiastic about the in-kind gift incentive than about the money, because money has an impersonal character, which would decrease the feeling of enjoyment. (Shaffer & Arkes, 2009), (Gneezy et al., 2011).

Although this study is not absolutely sure about effects in a real-world implementation, it 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 real-world experiments. Various features can be tested, and the most popular and/or effective ones can be implemented in a real app and tested in a real-world experiment.

Overall, findings from this stated preference survey indicate that different strategies are needed for different travellers. For example, to provide an individual cycling challenge for occasional cyclists, but an attitude change strategy with information about travel cost savings for non-cyclists. Moreover, this new technology attracts specific travellers. Besides proving interventions to concern those travellers, more attention needs to be paid for the self-selection effect for cycling promotion in reality. Regarding that social preferences are involved in the survey, which causes inconsistencies between lab and field experiments, a real-world experiment is needed to validate the survey observations.

- 2) What are the direct effects of the challenges on cycling and how is the behaviour change related to travel patterns and travellers' ways to deal with challenges?

Two types of challenge intervention strategies were set up in a real-world environment. First, the infrastructure-based cycling challenge intervention shows that the challenges and rewards play a role in motivating travellers to cycle more on the newly designed cycling route. In other words, the newly designed route alone did not have significant effects to promote cycling. The change in behaviour by this intervention is mainly caused by changing route choices and making additional bike trips. However, the intervention effect of modal shift is not significant. Yet, the challenge and reward can motivate participants who complete the challenge to keep cycling along the newly designed route after the campaign. Apart from the positive aspects of this intervention, it is only feasible for travellers who live nearby. Additionally, participants who either claimed the challenges were too easy, too difficult or not appropriate for them may be reluctant to participate in future challenges.

Analysis of the strategy about self-chosen cycling challenges shows that the challenges had a positive effect on behavioural change. That is, it can effectively nudge a modal shift from car to bike every month. However, the challenges also had the effect of causing additional bike increase without modal shift (i.e. the decreased car distance can explain more than half of the increased bike distance, but some of the bike increase is without car decrease.). Results from the behavioural change model show that public transport users and people who walk more often are more inclined to increase additional bike trips than to have a modal shift. Conversely, travellers with a high frequency of irregular car trips tend to have a modal shift.

Also, how travellers face and choose challenges and the types of challenges play a role in changing behaviour. More specifically, travellers who can complete the challenges, and those who challenge themselves with difficult challenges or select the highest challenge option are more willing to change. However, difficult challenges are with low accomplishment rate, that the difficult uncompleted challenges may result in no behavioural change. Moreover, rewarding travellers for cycling more distance is more effective than rewarding them for increasing cycling frequency. Importantly, daily cycling distance challenges can motivate modal shift more effectively than weekly challenges. Also, travellers who get rewarded are more inclined to have modal shift again in the next participation. The findings indicate that some parts of this strategy are effective for modal shift from car to bike, but overall it is unavoidable to affect increasing additional bike trips.

In terms of challenge difficulty effects on behavioural change, it is found that the strongest behavioural change is from travellers who accomplished difficult challenges, which is in line with results obtained from the behavioural change model. This suggests travellers need to choose difficult challenges to get large positive effects. However, there is also direct behavioural change when travellers accomplished an easy challenge, with less change degree compared with the difficult one. The fact that behavioural change is relatively large when participants accomplish a difficult challenge is compensated by the fact that difficult challenges are accomplished much less frequently. Thus, the overall short term behavioural change is more or less the same for easy and difficult challenges. However, travellers that choose easy challenges do not need to change their behaviour to accomplish the challenges. The fact that they did suggests that the challenges in themselves encourage travellers to change their behaviour. Perhaps travellers are more aware of their behaviour when they participate in a challenge and therefore are more likely to change their behaviour even when they can accomplish the challenge without behavioural change. This positive result suggests that self-chosen challenges encourage behavioural change in the short term even when travellers do not need to change their behaviour to accomplish the challenges.

Comparison of the observed behaviour with experience sampling shows that travellers' self-reported behavioural change are consistent with the observed behavioural change, but with some discrepancies. The discrepancies imply a large natural variation in total trip distance and modal split. Therefore, even though the effects of positive interventions on behavioural change in the short term is significant, the significance may get weaker by analysing the changes within subgroups (modal shift group and additional bike increase group). As a result, the behavioural change explanatory model has a slightly low model fit, but it's still possible to estimate the systematic modal shifts. Anyhow, findings based on the behavioural change explanatory model show that half of the travellers that have a high modal shift probability had on average more than 10% modal shift from car to bike per month, corresponding with 1.5 km per day bike increase, as well as 1.5 km per day car decrease. Hence, the intervention strategy is decisive in nudging modal shift from car to bike.

3) What are the effects of positive interventions for behaviour change in a longer-term?

The self-chosen challenge strategy successfully recruited a high amount of participants and maintained a steady retention rate (51% of users stayed after half a year). However, about two-thirds of all the application users that never participated in challenges also had a steady retention rate, indicating that other interventions, such as self-monitoring and feedback, are also important to attract users. However, without challenge and reward interventions, there is no clear evidence for behavioural change among those users, even after using the app long-term.

Behavioural change is associated with the challenge and reward interventions, and there are some indications that interventions are effective for long-term behavioural change. In general,

in the last six months of the experiment, participants that used the application for more than six months and less than one year had cycling increase (relative to the control group). After 12 months of usage, the bike share of participants remained 4% higher than participants with six months of usage, which is even more evident for active challenge participants (users that joined more than half of the time). This pattern is in accordance with the transtheoretical model, which states that sustained behaviour is only observed after some time (often after one year). In which sustained behaviour is only observed after some time (often after one year). However, travellers can join during the experiment (mostly in the late stage of the research), resulting in a small sample size of participants that used the application for more than one year. However, with the high retention rate, it seems that a more significant effect can be obtained if an even longer experiment can be performed to wait for most travellers to use the application for more than one year.

Main objective: ‘to empirically determine the potential to use current state-of-the-art, information-based positive interventions to occur modal shift from car to bike in a short and longer term’.

Several studies provided theoretical evidence for the effective application of positive interventions to voluntarily change travel behaviour (e.g. Ampt, 2004, Bamberg, Fujii, Friman, & Gärling, 2011). Others provide commercial ways to apply this new technology, or in slightly small sample research experiments (e.g. Bie et al., 2012, Poslad, Ma, Wang, & Mei, 2015). This thesis complements these studies by providing empirical evidence of the potential of smartphone-based positive interventions in a real-world environment over a longer period for the possibility to observe sustained behavioural change. Findings suggest that positive interventions (individual distance challenges and in-kind rewards), do have the effect of promoting cycling by nudging travellers away from car to bike in a short-term, but this measure can also lead additional bike trips to increase without a mode change. Results suggest to focus on travellers with particular travel pattern characteristics by applying daily challenging cycling tasks can increase the willingness to have a modal shift. Moreover, this measure has the potential for the sustained behavioural change over a longer-term, provided that it attracts travellers to keep using the app for at least for one year.

6.2 Research implications for transport policy

The findings on the potential of information-based positive interventions to nudge travellers to have modal change from car to bike have several implications for transport policy.

First of all, governments intervene in transport, they provide and own transport infrastructure, tax car owners, subsidize public transport, implement emission standards, and so forth. It's the role of the government to concern over environmental problems caused by modern transportation, based on the consumption of oil. In order to consider social equity and liveability, it is important to nudge travellers away from fuel transportation not through hard measures, but by positive intervention to make them voluntarily change behaviour. In this thesis, an information-based positive intervention smartphone application was used, which fits the current trend of smartphone applications that are nowadays being developed with the aim to solve societal issues. This thesis provides evidence for transport policy measures the potential of applying this positive intervention by new technology to society.

Several design considerations for the positive intervention measures could be derived from the findings. First of all, it is crucial to provide tailored positive intervention to travellers with different willingness to change. As such, it is essential to know travellers' characteristics and their travel pattern. The smartphone can automatically track the travel pattern. An approach to

get travellers' characteristics is to create user profiles by asking a few questions upon registration for the application, although users might not be really keen on this. Other approaches might be to use a self-learning algorithm or to extract user characteristics from social media or Google.

It is found that younger and higher educated and low-income occasional cyclists are more likely to use this type of intervention application. For those travellers, the challenge and reward interventions can directly be applied. However, travellers who rarely cycle, that have the largest potential to change behaviour, tend to have low engagement. One way for the government to recruit those travellers is to have marketing about the benefits of cycling leisure trips and cycling travel cost. Moreover, after recruitment, an intervention strategy in the application that focuses on their cycling awareness-raising and cycling attitude change is essential.

The design of challenge and reward interventions is essential for behaviour change. Logically, the challenge and reward interventions are designed to reward cycling, rather than rewarding for reducing car, because to reward reducing car can result in not using the smartphone to record trips. However, as a result, the interventions partly have the effect of increasing additional bike trips without shifting modes. One approach to enlarge the modal shift effect of interventions is to focus on travellers that have a high amount of irregular car trips. Moreover, to apply cycling distance challenges with daily tasks might be more effective than weekly tasks, and in-kind rewards are suggested to be applied to the challenges. Finally, if the (local) government wants to occur route choice change by new infrastructure, a challenge intervention related to the new infrastructure might be applied to expand the effect of the new infrastructure.

Moreover, in order to have a sustained behavioural change, it is recommended to apply the positive intervention for more than one year to each individual. Also, increasing the challenge join rate (e.g. expanding the variety of challenge types and making the challenges feasible for all types of travellers) could enlarge sustained behavioural change. One should realise that the sustained behavioural change might only be the case for a small fraction of all the users that join the application.

6.3 Recommendations for future research

The findings reported in this thesis show the potential of positive interventions for promoting cycling. As such, they motivate future research into positive interventions, especially from a behavioural point of view.

A unique real-life experiment was conducted in this thesis, to gain actual travel behaviour based on the complex interactions of travellers with the environment. In order to let travellers truly behave as in a real-life environment, the real-world experiment was controlled not to involve privacy issues. As a result, there is no socio-demographic data of travellers and no significant period of data before travellers start the first challenge since the travellers could immediately use all functionalities of the application when they downloaded the application. In line with this, future research could involve socio-demographic data to analyze behaviour further, and the socio-demographic variables can be used to explain the behavioural change.

This thesis monitored behaviour (change) via a smartphone app continuously over a long period, and the app retention rate is high. Future research could implement a longer experiment period because sustained behaviour may need a longer time to maintain. For example, (Prochaska & Velicer, 1997) show that for smoke quitting habitual analysis, the maintenance period lasts from six months to about five years. As such, a more sufficient observation of sustained behaviour will be obtained. Moreover, some indications show that sustained

behavioural can be achieved with the challenge and reward intervention. Future research could recruit more users to increase analysis significance and effect size. Furthermore, the research is not long enough to analyse how will sustained behaviour change after the challenge and reward stop. Besides, to implement a longer experiment period, further research could design a controlled study to analyse sustained behaviour change after rewards stop.

There is an indication that shows that the long-term behavioural change is following the different phases of the theory. That behavioural change is to be a progression through a sequence of degrees of motivation (Prochaska and DiClemente, 1982). Recently, studies have applied the stages of change model based on travel surveys. (e.g. Nkurunziza, Zuidgeest, & Van Maarseveen, 2012, Biehl, Ermagun, & Stathopoulos, 2019). Future research could implement the stages of change model in a real-world environment. By identifying the stage that traveller belongs, targeted personalized interventions can be provided, and behavioural change at different stages can be tracked and analysed.

An explanatory model is conducted to estimate individuals' behavioural change. Future research could implement this model, including individual characteristics, to predict the change. Moreover, the predicated individual behaviour could further be simulated in the transport system as a whole, so to assess the effect on the whole transport system. To extract user characteristics from social media could be considered in the future, and a personalised incentive works on recording trips for users just join the application could be applied to get travel behaviour before the interventions for behavioural change.

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Appendix: Questionnaire “Monthly cycling challenges”

This appendix provides the questions of the post survey for the Monthly cycling challenges. All questions were send out through the SMART app. The survey was conducted in Dutch and translated into English for inclusi9on in this thesis.

Questions	You have reached the choice challenge. Can you indicate what has been decisive for this?
Choices	<p>The challenge was relatively easy.</p> <p>I was very motivated to complete this challenge.</p> <p>The conditions (such as the weather) were very favorable.</p> <p>The reward was very attractive to me.</p> <p>Other: accidently met the challenge, not intention/Accidentally choose. wrong challenge.</p> <p>Other: cycle regularly.</p> <p>Other: fun to do.</p>
Questions	You did enter into the choice challenge but did not complete it. What was the reason for this?
Choices	<p>The reward was too low to motivate me to continue until the end.</p> <p>Due to external circumstances (such as bad weather, illness, holidays, etc.) I could not meet the challenge.</p> <p>I found the challenge too difficult.</p> <p>SMART did not do my tracking properly; I think I have completed the challenge.</p> <p>Others: Not recognize home - work trips due to multiple locations.</p> <p>Others: Started too late.</p> <p>Others: Not register trips.</p> <p>Others: no mobile phone with.</p>

	The challenge end to early.
Questions	Have you started cycling more often during the duration of the choice challenge?
Choices	<p>No.</p> <p>Yes, because I now make extra trips that I take on the bike.</p> <p>Yes, instead of taking public transportation.</p> <p>Yes, instead of taking the car.</p> <p>Yes, instead of walking.</p>
Questions	What was the reason to cycle more often?
Choices	<p>Move more..</p> <p>Because of good weather.</p> <p>Because of the SMART challenge and reward that I could win.</p> <p>All above.</p> <p>Other: New bike and school.</p> <p>Other: health.</p> <p>Other: like cycling.</p> <p>Other: more meeting.</p> <p>Other: cycling buddy program.</p> <p>Other: colleague collective cycling.</p> <p>Because of the opening of new bicycle routes that make cycling more attractive.</p>
Questions	Are you planning to continue cycling more often?
Choices	<p>Yes.</p> <p>Yes, but only with good weather.</p> <p>Yes, but only with challenges and rewards.</p>

Summary

In many European cities, liveability is becoming a major issue, resulting from congestion, parking problems, accidents and air and noise pollution. Moreover, worldwide transportation is responsible for approximately 60 per cent of oil consumption, resulting in air pollution. Hence, many cities across the world are committed to providing a new sustainable mobility system. Many policymakers are focusing on the bicycles as their solutions since it is cost-effective, fast, clean, flexible and efficient and healthy for short-distance urban trips. An important question in this regard is how to motivate those car travellers to cycle.

Conventional financial disincentives to driving approaches, such as road pricing, lead to resistance and cause social equity and public acceptance issues. Thus, soft measures with the actions aimed at changing people's perceptions, beliefs and attitudes towards cycling appeared to be a solution. According to this, voluntary travel behaviour change (VTBC) studies show the potential to apply positive intervention, such as challenges, rewards, feedback and self-monitoring to nudging behavioural change. However, traditional VTBC solutions require person-based interaction, either by phone or home interviews, which is inherently expensive and may induce biases stemming from social interaction and communication. Meanwhile, advances in information & communication technology (ICT) opened up new opportunities for influencing travellers. As a result, many commercial apps are working on changing behaviour by applying design technology, derived from human-computer interaction and psychology (e.g. Nike fitness app). However, the effect of those apps in travelling behavioural change is not well analysed. Moreover, the mobile apps' long-term effects to change and maintain the desired behaviour is not well researched, mostly due to short-term experiment and low participants' involvement issues. Overall, firm evidence that empirically supports behavioural change by the potential of positive interventions through smartphone does not exist.

The main objective of this thesis is to empirically determine the potential to use current state-of-the-art, information-based positive interventions to occur modal shift from car to bike in a short and longer-term'. Positive interventions, based on previous VTBC studies and current mobile apps based studies, included self-monitoring and feedback, challenge and goal

setting, rewards and praise, and traffic information and suggestions. Moreover, the success to run a long term experiment is supported by long term involvement. Interventions, especially the challenges and rewards, have been proven to have the potential to extend the commitment and have a positive impact on participants' involvement. Therefore, the design and testing of the effects of challenges and rewards in both the stated choice experiment and the real-world mobile app-based experiment is my main focus.

Chapter 2 examines the impacts of different challenge and reward schemes for behavioural change. Before designing and operating a real mobile app, there is a need for a better understanding of which challenges and rewards are most preferred in an app for behavioural change, since the effects of different types of rewards remain controversial, i.e. to support monetary incentive or to support in-kind reward. In order to obtain sufficient background knowledge about positive interventions, especially types of challenges and rewards, delivered via smartphone technology in the field of cycling promotion, a stated choice experiment was conducted. In detail, mock-ups were designed and embedded in the survey, which were used to visualize different challenges and rewards and questions about travel patterns, cycling attitude, demographics and the opinions about the mock-ups were asked.

Based on the stated preference survey, it is found that challenges in combination with rewards, especially individual challenges (e.g. increase cycling frequency) and in-kind rewards (e.g. points), can motivate travellers to change travel behaviour by cycling more. A variation was found in terms of the incentive effects among different travel patterns. Overall, the occasional cyclists are more positive towards various incentives (with about 50% consideration) than non-cyclists and are more willing to change their behaviour. More specifically, it is found that travellers that rarely cycle tend to have a negative attitude towards cycling. They do not prefer any incentive, and not willing to make any behavioural change towards more bike use, as a result of any incentives. For those travellers, an interventions strategy that focuses on changing attitude is essential. For example, showing information or travel cost savings or designing short distance challenges can help change their attitudes. Moreover, young and higher educated travellers, as well as low-income travellers, are more easily to accept this new technology (recording trips and providing rewards via smartphone apps) to make a change.

Analysis of the rewards implies that in-kind rewards should be more effective than monetary reward in the real-world environment. Moreover, in reality, the incentive app will probably provide only one type of reward, thus by having a web shop associated with in-kind gifts may make people more enthusiastic about the in-kind gift incentive than about the money, because money has an impersonal character, which would decrease the feeling of enjoyment.

Although this study is not absolutely sure about effects in a real-world implementation, it 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 real-world experiments. Various features can be tested, and the most popular and/or effective ones can be implemented in a real app and tested in a real-world experiment.

Overall, findings from this stated preference survey indicate that different strategies are needed for different travellers. For example, to provide an individual cycling challenge for occasional cyclists, but an attitude change strategy with information about travel cost savings for non-cyclists. Moreover, this new technology attracts specific travellers. Besides proving interventions to concern those travellers, more attention needs to be paid for the self-selection effect for cycling promotion in reality. Regarding that social preferences are involved in the survey, which causes inconsistencies between lab and field experiments, a real-world experiment is needed to validate the survey observations.

Chapter 3 presents travellers' behavioural change by an infrastructure-based challenge intervention strategy. The provision and adaptation of physical infrastructure, has been seen to be more fundamental than other measures in increasing cycling share in a city. The integration of the hard measure with positive intervention can assess whether interventions can help hard measures increase behavioural changes. For this assessment, participants were recruited through a smartphone application, called 'SMART Mobility', and a challenge was designed for travellers to cycle through a newly designed cycling route (Boswinkel) ten times a month. Findings show that the challenges and rewards play a role in motivating travellers to cycle more on the newly designed cycling route. In other words, the newly designed route alone did not have significant effects to promote cycling. The change in behaviour by this intervention is mainly caused by changing route choices and making additional bike trips. However, the intervention effect of modal shift is not significant. Yet, the challenge and reward can motivate participants who complete the challenge to keep cycling along the newly designed route after the campaign. Apart from the positive aspects of this intervention, it is only feasible for travellers who live nearby. Additionally, participants who either claimed the challenges were too easy, too difficult or not appropriate for them may be reluctant to participate in future challenges.

Chapter 4 explores the changes in behaviour and the relation with challenge commitment and participants' involvement, under a comprehensively designed travel mobile app, during the one-year-long pilot study. A self-chosen challenge strategy was designed to analyse the participants' commitment. Also, the key factors that influence the response to challenge and reward were identified. Findings show that the self-chosen challenge strategy successfully recruited a high amount of participants and maintained a steady retention rate (51% of users stayed after half a year). However, about two-thirds of all the application users that never participated in challenges also had a steady retention rate, indicating that other interventions, such as self-monitoring and feedback, are also important to attract users. However, without challenge and reward interventions, there is no clear evidence for behavioural change among those users, even after using the app long-term.

Behavioural change is associated with the challenge and reward interventions, and there are some indications that interventions are effective for long-term behavioural change. In general, in the last six months of the experiment, participants that used the application for more than six months and less than one year had cycling increase (relative to the control group). After 12 months of usage, the bike share of participants remained 4% higher than participants with six months of usage, which is even more evident for active challenge participants (users that joined more than half of the time). However, travellers can join during the experiment (mostly in the late stage of the research), resulting in a small sample size of participants that used the application for more than one year. However, with the high retention rate, it seems that a more significant effect can be obtained if an even longer experiment can be performed to wait for most travellers to use the application for more than one year.

Chapter 5 provides insights into the behavioural change, and its association with travel patterns and challenge types. This was obtained by a cycling-positive intervention strategy which was set up in a real-world environment, by means of the SMART app. The findings show that these challenges had a positive effect on behavioural change. That is, it can effectively cause a modal shift from car to bike every month. However, the challenges also had the effect of causing additional bicycle use without a modal shift (i.e., the decreased car distance can explain more than half of the increased cycling distance, but some of the bike use increase is not accompanied by a decrease in car use). This is good from a health perspective, but does not have any other of the desired effects.

Behavioural change models were used to explain these two types of behavioural changes. More specifically, the models explained how individuals' behavioural change is related to their travel patterns, their smartphone application usage information and the chosen challenges. We found that public transport users and people who walk more often were more inclined to increase the number of bike trips than to shift from car to bicycle. Conversely, travellers with a high frequency of irregular car trips did tend to display a modal shift. Also, the way travellers faced and chose challenges and the type of challenge they chose played a role in changing behaviour. More specifically, travellers who completed the challenges, those who challenged themselves with difficult challenges or selected the most challenging option were more willing to change their behaviour. By contrast, the relative difficulty level does not seem to have had a significant effect. We contribute this to the relatively low accomplishment rate for difficult challenges, which might actually work as discouragement when aiming for behavioural change. However, this changed with the increasing number of joined challenges.

In addition, we saw that rewarding traveller for cycling longer distances could be more effective than rewarding them for cycling more trips. Importantly, daily cycling distance challenges can motivate a modal shift more effectively than weekly challenges. These findings indicate that some parts of this strategy are effective for accomplishing a modal shift from car to bike. Overall, it appears unavoidable to cause an increase in the number of bike trips without accomplishing a modal shift. However, this measure has the potential to achieve sustained behavioural change, provided that it motivates travellers to keep participating in the challenges.

Comparison of the observed behaviour with experience sampling (post-survey) revealed that the travellers' self-reported behavioural change matched the observed behavioural change, but with some discrepancies. These discrepancies imply a large natural variation in total trip distance and modal split. However, the discrepancy was smaller for travellers with a high modal shift probability as seen in the behavioural change model. Importantly, the intervention had a promising effect in terms of behavioural change for half of the users with a high modal shift probability, that is, the daily distance shift from car use to bike use was around 1.5 km. This implies a decisive role for this intervention strategy in nudging users out of their cars and onto bicycles.

In conclusion, this thesis demonstrated in a real-world context, that the smartphone-based positive interventions have the potential to nudge modal shift from car to bike, even to some extent over a longer time period. Several design considerations can be derived from the findings presented. The most important consideration is to provide tailored positive intervention to travellers with different willingness to change, and in order to have a sustained behavioural change, it is recommended to apply the positive intervention for more than one year to each individual. Our findings motivate future research into positive interventions, from a behavioural point of view. One future challenge is to upscale the experiments to an even longer experiment period. Moreover, identifying travellers socio-demographic data in which they are not aware of taking part in an experiment, and obtaining individuals' degrees of motivation to change, can give more insight into understanding behaviour change.

Samenvatting in het Nederlands

In veel Europese steden is leefbaarheid een groter probleem aan het worden door files, parkeerproblemen, ongevallen en lucht- en geluidsoverlast. Bovendien is wereldwijd transport verantwoordelijk voor ongeveer 60 procent van het verbruik van fossiele brandstoffen, wat resulteert in luchtvervuiling. Daarom zetten veel steden over de hele wereld zich in voor een nieuw duurzaam mobiliteitssysteem. Veel beleidsmakers richten zich op de fiets als hun oplossing, omdat deze kosteneffectief, snel, schoon, flexibel en efficiënt en gezond is voor korte stadsritten. Een belangrijke vraag daarbij is hoe je die automobilisten kunt motiveren om te fietsen.

Conventionele financiële maatregelen voor het ontmoedigen van autorijden, zoals kilometerheffing, leiden tot weerstand en veroorzaken problemen met sociale gelijkheid en publieke acceptatie. Zachte maatregelen die richten op het veranderen van zienswijzen, overtuigingen en houdingen van mensen ten opzichte van fietsen leken dus een oplossing. Volgens dit onderzoek tonen vrijwillige reisgedragsverandering (VTBC) het potentieel aan om positieve interventie toe te passen, zoals uitdagingen, beloningen, feedback en zelfmonitoring om gedragsverandering te stimuleren. Traditionele VTBC-oplossingen vereisen echter persoonlijke interactie, via telefoongesprekken of thuisinterviews, wat inherent duur is en kan leiden tot vooroordelen die voortvloeien uit sociale interactie en communicatie. Ondertussen hebben de ontwikkelingen in de informatie- en communicatietechnologie (ICT) nieuwe mogelijkheden geopend om reizigers te beïnvloeden. Als gevolg hiervan werken veel commerciële apps aan gedragsverandering door design technology toe te passen vanuit mens-computerinteractie en psychologie (bijv. Nike fitness-app). Het effect van die apps op gedragsverandering tijdens reizen is echter niet goed geanalyseerd. Bovendien zijn de langetermijneffecten van de mobiele apps om het gewenste gedrag te veranderen en in stand te houden niet goed onderzocht, vooral vanwege korte-termijn experimenten en lage betrokkenheid van deelnemers. Over het algemeen bestaat er geen hard bewijs dat empirisch ondersteunt dat positieve interventies via de smartphone gedragsverandering bewerkstelligen.

Het hoofddoel van dit proefschrift is om empirisch het potentieel te bepalen om de huidige state-of-the-art en op informatie gebaseerde positieve interventies te gebruiken om op korte en langere termijn een modale verschuiving van auto naar fiets te bewerkstelligen. Positieve interventies, gebaseerd op eerdere VTBC-onderzoeken en huidige op mobiele apps gebaseerde onderzoeken, omvatten zelfcontrole en feedback, het stellen van uitdagingen en doelen, beloningen en complimenten, en verkeersinformatie en suggesties. Bovendien wordt het succes van een langdurig experiment ondersteund door langdurige betrokkenheid. Het is bewezen dat interventies, met name de uitdagingen en beloningen, het potentieel hebben om het engagement uit te breiden en een positieve impact hebben op de betrokkenheid van de deelnemers. Daarom is het ontwerpen en testen van de effecten van uitdagingen en beloningen in zowel het stated choice experiment als het real-world mobiele app-gebaseerde experiment mijn belangrijkste focus.

Hoofdstuk 2 onderzoekt de impact van verschillende uitdagingen- en beloningsschema's voor gedragsverandering. Alvorens een echte mobiele app te ontwerpen en te gebruiken, is er behoefte aan een beter begrip van welke uitdagingen en beloningen de meeste voorkeur hebben in een app voor gedragsverandering, aangezien de effecten van verschillende soorten beloningen controversieel blijven, d.w.z. ter ondersteuning van financiële prikkels of om in natura beloning te ondersteunen. Om voldoende achtergrondkennis te verkrijgen over positieve interventies, met name soorten uitdagingen en beloningen, geleverd via smartphonetechnologie op het gebied van fietspromotie, werd een stated choice experiment uitgevoerd. Meer specifiek, er werden mock-ups ontworpen en ingebed in de enquête, die werden gebruikt om verschillende uitdagingen en beloningen te visualiseren en er werden vragen gesteld over reispatronen, houding t.o.v. fietsen, demografie en de meningen over de mock-ups.

Uit de stated preference-enquête blijkt dat uitdagingen in combinatie met beloningen, met name individuele uitdagingen (bijv. verhoging van de fietsfrequentie) en beloningen in natura (bijv. punten), reizigers kunnen motiveren om het reisgedrag te veranderen door meer te fietsen. Er werd een variatie gevonden in de stimulerende effecten tussen verschillende reispatronen. Over het algemeen staan de gelegenheidsfietsers positiever tegenover verschillende prikkels (met ongeveer 50% overweging) dan niet-fietsers en zijn ze eerder bereid hun gedrag te veranderen. Meer specifiek blijkt dat reizigers die zelden fietsen een negatieve houding hebben ten opzichte van fietsen. Ze geven de voorkeur aan geen enkele prikkel, en zijn niet bereid om als gevolg van eventuele prikkels gedragsverandering door te voeren in de richting van meer fietsgebruik. Voor die reizigers is een interventiestrategie gericht op attitudeverandering essentieel. Het tonen van informatie of besparingen op reiskosten of het ontwerpen van uitdagingen op korte afstand kunnen hun houding helpen veranderen. Bovendien accepteren jonge en hoger opgeleide reizigers, evenals reizigers met een laag inkomen, deze nieuwe technologie (ritten registreren en beloningen aanbieden via smartphone-apps) gemakkelijker om iets te veranderen.

Analyse van de beloningen impliceert dat beloningen in natura effectiever zouden moeten zijn dan geldelijke beloningen in de echte wereld. Bovendien zal de incentive-app in werkelijkheid waarschijnlijk maar één soort beloning bieden, dus door een webshop te hebben die is gekoppeld aan cadeaus in natura, kunnen mensen enthousiaster worden over de incentive in natura dan over het geld, omdat geld een onpersoonlijk karakter heeft, wat de lol zou verminderen.

Hoewel deze studie niet absoluut zeker is van effecten in een praktijkimplementatie, biedt het waardevol inzicht door de potentiële effecten van verschillende prikkels op verschillende segmenten te vergelijken. In die zin kan het gebruik van mock-up-apps worden gezien als complementair aan experimenten in de echte wereld. Er kunnen verschillende functies worden

getest, en de meest populaire en/of effectieve functies kunnen in een echte app worden geïmplementeerd en in een echt experiment worden getest.

Over het geheel genomen geven de bevindingen van dit verklaarde voorkeurenonderzoek aan dat verschillende strategieën nodig zijn voor verschillende reizigers. Bijvoorbeeld om een individuele fietsuitdaging voor gelegenheidsfietsers te bieden, maar een attitudeveranderingsstrategie met informatie over reiskostenbesparingen voor niet-fietsers. Bovendien trekt deze nieuwe technologie specifieke reizigers aan. Naast het aantonen van interventies die reizigers aangaan, moet er meer aandacht worden besteed aan het zelfselectie-effect voor fietspromotie in de praktijk. Vanwege het feit dat sociale voorkeuren betrokken zijn bij het onderzoek, dat inconsistenties veroorzaakt tussen laboratorium- en veldexperimenten, is een real-world experiment nodig om de onderzoeksobservaties te valideren.

Hoofdstuk 3 presenteert de gedragsverandering van reizigers door middel van een op infrastructuur gebaseerde uitdagingsinterventiestrategie. Het aanbieden en aanpassen van fysieke infrastructuur wordt gezien als fundamenteeler dan andere maatregelen om het fietsaandeel in een stad te vergroten. De integratie van de harde maatregel met positieve interventie kan beoordelen of interventies kunnen helpen bij het vergroten van gedragsveranderingen door harde maatregelen. Voor deze beoordeling werden deelnemers geworven via een smartphone-applicatie, genaamd 'SMART Mobility', en werd een uitdaging ontworpen voor reizigers om tien keer per maand een nieuw ontworpen fietsroute (Boswinkel) te fietsen. Uit bevindingen blijkt dat de uitdagingen en beloningen een rol spelen bij het motiveren van reizigers om meer te fietsen op de nieuw ontworpen fietsroute. Met andere woorden, de nieuw ontworpen route alleen had geen significant effect op het fietsen. De gedragsverandering door deze ingreep wordt voornamelijk veroorzaakt door veranderende routekeuzes en het maken van extra fietstochten. Het interventie-effect van modal shift is echter niet significant. Toch kunnen de uitdagingen en beloningen deelnemers, die de uitdaging aangaan, motiveren om na de campagne langs de nieuw ontworpen route te blijven fietsen. Afgezien van de positieve aspecten van deze interventie, is het alleen haalbaar voor reizigers die in de buurt wonen. Bovendien kunnen deelnemers, die beweerden dat de uitdagingen te gemakkelijk, te moeilijk of niet geschikt voor hen waren, terughoudend zijn om deel te nemen aan toekomstige uitdagingen.

Hoofdstuk 4 onderzoekt de gedragsveranderingen en de relatie met uitdagingsbetrokkenheid en de betrokkenheid van deelnemers, onder een uitgebreid ontworpen mobiele app voor reizen, tijdens de eenjarige pilotstudie. Er werd een zelfgekozen challenge-strategie ontworpen om de betrokkenheid van de deelnemers te analyseren. Ook werden de sleutelfactoren geïdentificeerd die de reactie op uitdaging en beloning beïnvloeden. Uit de bevindingen blijkt dat de zelfgekozen challenge-strategie met succes een groot aantal deelnemers heeft gerekruteerd en een stabiel retentiepercentage heeft behouden (51% van de gebruikers bleef na een half jaar). Ongeveer tweederde van alle applicatiegebruikers die nooit deelnamen aan uitdagingen had echter ook een gestage retentie, wat aangeeft dat andere interventies, zoals zelfmonitoring en feedback, ook belangrijk zijn om gebruikers aan te trekken. Zonder uitdagings- en beloningsinterventies is er echter geen duidelijk bewijs voor gedragsverandering bij die gebruikers, zelfs niet na langdurig gebruik van de app.

Gedragsverandering houdt verband met de uitdagings- en beloningsinterventies, en er zijn enkele aanwijzingen dat interventies effectief zijn voor gedragsverandering op de lange termijn. Over het algemeen hadden deelnemers die de applicatie langer dan zes maanden en minder dan een jaar gebruikten in de laatste zes maanden van het experiment een toename van het aantal fietsbewegingen (ten opzichte van de controlegroep). Na 12 maanden gebruik bleef het fietsaandeel van deelnemers 4% hoger dan dat van deelnemers met zes maanden gebruik, wat

nog duidelijker is voor actieve challenge-deelnemers (gebruikers die meer dan de helft van de tijd meededen). Reizigers kunnen echter tijdens het experiment meedoen (meestal in de late fase van het onderzoek), wat resulteert in een kleine steekproef van deelnemers die de applicatie langer dan een jaar hebben gebruikt. Met het hoge retentiepercentage lijkt het er echter op dat een groter effect kan worden verkregen als een nog langer experiment kan worden uitgevoerd om te wachten tot de meeste reizigers de applicatie langer dan een jaar gebruiken.

Hoofdstuk 5 geeft inzicht in de gedragsverandering en het verband met reispatronen en soorten uitdagingen. Dit werd bekomen door een fiets-positieve interventiestrategie die werd opgezet in een real-world omgeving, door middel van de SMART app. De bevindingen laten zien dat deze uitdagingen een positief effect hadden op gedragsverandering. Dat wil zeggen, het kan elke maand effectief een modal shift van auto naar fiets veroorzaken. De uitdagingen hadden echter ook het effect dat ze extra fietsgebruik veroorzaakten zonder modal shift (dat wil zeggen, de afgenomen auto-afstand kan meer dan de helft van de toegenomen fietsafstand verklaren, maar een deel van de toename van het fietsgebruik gaat niet gepaard met een afname van het autogebruik). Dit is vanuit gezondheidsperspectief goed, maar heeft verder niet de gewenste effecten.

Er werden gedragsveranderingsmodellen gebruikt om deze twee soorten gedragsveranderingen te verklaren. Meer specifiek legden de modellen uit hoe de gedragsverandering van individuen verband houdt met hun reispatronen, de gebruiksinformatie van hun smartphone-app en de gekozen uitdagingen. We ontdekten dat OV-gebruikers en mensen die vaker lopen meer geneigd waren om het aantal fietsverplaatsingen te vergroten dan om van auto op fiets over te stappen. Omgekeerd vertoonden reizigers met een hoge frequentie van onregelmatige autoritten wel een modal shift. Ook de manier waarop reizigers uitdagingen aangingen en kozen, en het type uitdaging dat ze kozen, speelden een rol bij het veranderen van gedrag. Meer specifiek waren reizigers die de uitdagingen voltooiden, degenen die zichzelf uitdaagden met moeilijke uitdagingen of de meest uitdagende optie kozen, meer bereid om hun gedrag te veranderen. Daarentegen lijkt de relatieve moeilijkheidsgraad geen significant effect te hebben gehad. We dragen dit bij aan het relatief lage succespercentage voor moeilijke uitdagingen, wat in feite zou kunnen werken als ontmoediging bij het streven naar gedragsverandering. Dit veranderde echter met het toenemende aantal gezamenlijke uitdagingen.

Daarnaast zagen we dat het belonen van reizigers voor het fietsen van langere afstanden effectiever zou kunnen zijn dan het belonen van meer reizen. Belangrijk is dat dagelijkse uitdagingen op het gebied van fietsafstand een modal shift effectiever kunnen motiveren dan wekelijkse uitdagingen. Deze bevindingen geven aan dat sommige onderdelen van deze strategie effectief zijn om een modal shift van auto naar fiets te bewerkstelligen. Al met al lijkt het onvermijdelijk om een toename van het aantal fietsritten te veroorzaken zonder een modal shift te bewerkstelligen. Deze maatregel heeft echter het potentieel om duurzame gedragsverandering te bewerkstelligen, op voorwaarde dat het reizigers motiveert om te blijven deelnemen aan de uitdagingen.

Vergelijking van het waargenomen gedrag met ervaringssteekproeven (post-survey) onthulde dat de zelfgerapporteerde gedragsverandering van de reizigers overeenkwam met de waargenomen gedragsverandering, maar met enkele discrepanties. Deze discrepanties impliceren een grote natuurlijke variatie in de totale reisafstand en modal split. De discrepantie was echter kleiner voor reizigers met een hoge waarschijnlijkheid om modal shift te vertonen zoals te zien in het gedragsveranderingsmodel. Belangrijk is dat de interventie een veelbelovend effect had in termen van gedragsverandering voor de helft van de gebruikers met een hoge kans voor modal shift, dat wil zeggen dat de dagelijkse afstandsverschuiving van auto- naar

fietsgebruik ongeveer 1,5 km bedroeg. Dit impliceert een doorslaggevende rol voor deze interventiestrategie om gebruikers uit hun auto en op de fiets te krijgen.

Concluderend, dit proefschrift toonde in een reële context aan dat de op smartphones gebaseerde positieve interventies het potentieel hebben om de modale verschuiving van auto naar fiets te stimuleren, zelfs tot op zekere hoogte over een langere periode. Uit de gepresenteerde bevindingen kunnen verschillende ontwerpoverwegingen worden afgeleid. De belangrijkste overweging is om op maat gemaakte positieve interventie te bieden aan reizigers met een verschillende bereidheid tot verandering, en om een duurzame gedragsverandering te bewerkstelligen, wordt aanbevolen om de positieve interventie gedurende meer dan een jaar op elk individu toe te passen. Onze bevindingen motiveren toekomstig onderzoek naar positieve interventies, vanuit een gedragsperspectief. Een toekomstige uitdaging is om de experimenten op te schalen naar een nog langere experimentperiode. Bovendien kan het identificeren van sociaal-demografische gegevens van reizigers waarvan ze niet weten dat ze aan een experiment deelnemen, en het verkrijgen van de mate van motivatie van individuen om te veranderen, meer inzicht geven in het begrijpen van gedragsverandering.

About the author

Bingyuan (Amelia) Huang was born in China where she received the bachelor's and master's degrees in highway engineering and traffic engineering. She received another master's degree in Urban planning and management (2015) at the University of Twente. She joined in the Centre for Transport Studies, University of Twente, as a PhD student in 2015. Since 2020, she has worked in the Netherlands Institute for Transport Policy Analysis (KiM) as a researcher. Her current research focuses on mobility and sustainable transport policy.

She got interested in transport-related studies because of the impact of her grandfather (New China's first-generation road builder and designer) and the rapid construction of the highway in China. After the highway engineering study for her bachelor study in China, she found she was more interested in soft management or traffic planning instead of hardcore civil engineering. During her master in China, she started to think about big pictures about transportation: how important it is in cities, how to choose where to build roads, and how citizens will be affected when building new roads. With these questions, she got the opportunity to study in the faculty of ITC, where she learned to apply the geoscience to solve urban planning issues. So finally, she moved from construction level to planning and management level. A curiosity for travel behaviour and the keen interest in exploring new directions about transport system led her to pursue a PhD at the Centre for Transport Studies, University of Twente.

Due to the impact of different cultures, she gets the advantage to understand the world from more angles. This becomes her hobby for her spare time: to know the world. Of course, she also joins parties, sports activities, and she likes travelling and cooking.

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Huang, B. (2016) On personalized positive interventions to reduce car use: a micro-experiment to promote cycling. *Presented at the TRAIL congress*. November 15th, 2016, Utrecht, the Netherlands.

Huang, B., Fioreze, T., Thomas, T., & Van Berkum, E. (2016). On personalised positive incentives to reduce car use: a microexperiment to promote cycling on the campus of the University of Twente. *Presented at the Mobile Tartu 2016 conference*, June 2, 2016, Tartu, Estonia.

Huang, B & Van Essen, M.(2016). Empower travel behaviur change. *Poster presented at the CTIT symposium "Citizenship in a digital society"*, Novermber 1st, 2016, Enshcedede, The Netherlands.

Huang, B & Van Essen, M.(2016). Empower travel behaviur change. *Poster presented at the Your reseach @CITI"-Event 2016*, October 17th, 2016, Enshcedede, The Netherlands.

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Summary

Reducing car use by positive interventions with the aid of smartphone technology can be a potential policy measure. Stated choice experiment and a real-world experiment based on a smartphone app provide insights into the interventions design and travel behavioural change. Results show that cycling challenges and rewards can nudge travellers away from cars to bikes in a short-term and have the potential for the sustained behavioural change over a longer-term.

About the Author

Bingyuan (Amelia) Huang carried out her PhD research from 2015 to 2020 at the centre for transport studies, University of Twente. She currently works for the Netherlands institute for transport policy analysis (KIM), where she is involved in mobility studies. Amelia holds a Master's degree in Geo-information science and earth observation with specialization urban planning and management.

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