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E-cycling intention versus behavioral change: Investigating longitudinal changes in e-cycling intention and actual behavior change in daily commuting

Joost de Kruijf[a,*], Dea van Lierop[a], Dick Ettema[a], Maarten Kroesen[b], Martin Dijst[c]

[a] Faculty of Geosciences, Utrecht University, PO Box 80115, 3508TC, the Netherlands
[b] Faculty of Technology, Policy and Management, Delft University of Technology, the Netherlands
[c] Luxembourg Institute of Socio-Economic Research (LISER), Luxembourg

A R T I C L E I N F O

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E-bike
Behavioral change
intention–behavior consistency

A B S T R A C T

By offering the opportunity to make longer trips at a lower level of physical activity, the e-bike provides a promising alternative to car use. Despite all advantages (e-)cycling brings to urban accessibility, the environment, physical and mental health, not all car commuters regard the e-bike as a suitable alternative yet in their daily activity patterns. This study reports on changes in behavioral intention and actual e-cycling brought about by an e-cycling incentive program in the province of Noord-Brabant, the Netherlands. The impact of the program on behavioral intention and the actual change to e-cycling were analyzed based on a longitudinal three-wave survey design on past, intended, and actual commuting behavior. To explore the changes in behavioral intentional, the differences between intention and actual behavior and the factors influencing them, descriptive and ordinal logistic regression analyses were conducted. To explore the dynamics between e-cycling intentions and behavior a longitudinal structural equation model was developed. In general, this study shows that the incentive program has a positive impact on participants' behavioral change to e-cycling during the incentive program. Results show that two-third of the participants actually use the e-bike as much as they intended at the start of the program. People who were used to taking the conventional bicycle to work before the stimulation program, are more consistent between their intention and behavior. Results also show that personal beliefs, habits, and goal-related variables do not influence the intention–behavior consistency.

1. Introduction

In order to promote more sustainable forms of mobility, policymakers aim to stimulate a change in behavior from current car-dependent lifestyles towards the use of travel modes that produce less noise, pollution, and greenhouse gasses (Commission of the European Communities, 2007). To achieve the necessary behavioral change, cities invest in motorized alternatives such as public transport, and non-motorized modes of transport such as cycling and walking. Over the last decade, cycling has received a growing interest in Western urban transport systems as an alternative to car use (Fishman and Cherry, 2016; Buehler and Pucher, 2012). In the year 2021, policies to stimulate cycling got additional traction during the COVID-19 pandemic, as the strong reduction in car traffic and health risks associated with public transport increased people's willingness to cycle. Obviously, cycling has positive environmental impacts and positive health effects through increased physical activity (Akar and Clifton, 2009; Badland and Schofield, 2008; Sugiyama et al., 2008). Despite the positive arguments related to cycling as a sustainable option for commuters, many still choose to use other modes of transport.

With the introduction of the bicycle-style (MacArthur et al., 2014; Dill and Rose, 2012) e-bikes (i.e., a bicycle with electric pedal assistance up to 25 km/h), factors like the required physical effort and greater range due to the higher speed compared to conventional bicycles offer new opportunities in the transition to sustainable mobility (Heinen et al., 2010; de Kruijf et al., 2018; Plazier et al., 2017). Compared to car travel, e-bikes are eighteen times more energy efficient (Shreya, 2010). Physical activity levels during e-bike use are lower than conventional cycling but markedly higher than during car use (Sundfør and Fyhri, 2017; Simons et al., 2009), implying that e-bike use also has positive

* Corresponding author.
E-mail address: j.kruijf@uu.nl (J. de Kruijf).

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health effects. Over the last couple of years, e-bikes have become more mainstream and popular, and extensive research has been conducted regarding various aspects of the use of the e-bike. Next to the effects of personal and technical factors such as gender, age, and perceived safety on e-bike use (Fishman and Cherry, 2016; Johnson and Rose, 2013; MacArthur et al., 2014; Popovich et al., 2014), the impact of e-bike promotion schemes on behavioral change has been investigated (de Kruijf et al., 2018; Kroesen, 2017; Plazier et al., 2017). Taken together, these studies suggest considerable potential for the e-bike to substitute for car use in commuting. Another relevant finding from previous research is that travel habits and previous experience play a significant role in e-bike use: those with a prior cycling habit are more likely to adopt and maintain e-bike commuting (de Kruijf et al., 2018).

A major challenge in bringing about a transition toward large-scale use of the e-bike in commuting remains to achieve actual behavioral change (and adherence to the changed behavior) of people to take up e-cycling. The challenge to achieve the behavioral change can be compared to other behavioral changes like increasing physical activity in general, changing to healthier eating patterns, and not smoking (Faries, 2016). The need to bring about behavioral change is especially apparent for programs to stimulate the use of conventional bicycles in daily commuting, such as bike-to-work days and public bicycle rental schemes (Buehler and Pucher, 2012; Pucher et al., 2010). Such programs typically recruit potential cyclists and stimulate them to cycle by providing information, support, and incentives, monitoring their behavior, and providing feedback.

While various studies have focused on the behavioral change brought about by e-cycling stimulation programs (Sun et al., 2020; Pucher et al., 2010), the underlying mechanism of behavioral change has received less attention. The widely known Theory of Planned Behavior (Ajzen, 1991) states that behavior is preceded by an intention toward this behavior, implying that behavior change is preceded by a change in intention. It is, however, also well documented that intention and behavior are often inconsistent because various factors prevent intention from being implemented (Sniehotta et al., 2005). In epidemiological studies, intention itself has already been proven to be a limited predictor of actual behavioral change (Faries, 2016; Norton et al., 2015; Grimmer and Woolley, 2014). Since policies to promote e-cycling affect e-cycling behavior via the intention to use the e-bike, insight into intention-behavior (in)consistency over time in this domain is important to design effective behavior change policies. Next, it can be argued that intentions, as well as the actual behavior, can change over time due to habituation, improvement of physical condition (de Kruijf et al., 2018), or other experiences during e-cycling. To better understand dynamics in e-cycling, insights into the intention–behavior gap and the development of this relationship over time are required, which are currently missing.

This paper reports on a study into the change in behavioral intention and actual engagement in e-cycling of participants of an e-cycling stimulation program. This study adds to the literature by exploring two specific novel aspects that give insights into the underlying mechanisms: 1) it investigates intention-behavior consistency and its influential factors in the context of an e-cycling stimulation program and 2) it investigates to what extent intention-behavior consistency changes over the course of a stimulation program, as experience with the adjusted behavior increases.

Regarding the relationship between behavioral intention and behavioral change from car commuting to e-cycling in daily practice, previous research has shown that participating in an e-cycling incentive program has positive effects on behavioral change towards e-cycling, where travel distances and the number of e-cycling trips increase over time (de Kruijf et al., 2018; Sun et al., 2020). In order to promote e-cycling, it is important to understand the mechanisms for over-performance or underperformance (actual behavioral related to one's intentions) of participants and how often this occurs. Next, insights into how behavior by participants changes and how the intention-behavior consistency is adjusted over time during the program are important, where most research is cross-sectional and focusses on behavioral intention or either focusses on behavior change itself. In line with the Theory of Planned Behavior (TPB) (Ajzen, 1991) and the Extended Model of Goal-directed Behavior (EMGB) (Perugini and Conner, 2000), we assume that behavioral intentions are influenced by factors relating to one's beliefs, social influences, anticipated emotions, and perceived level of control. In addition, it has been documented that prior cycling behavior, spatial context, and personal and household characteristics impact e-cycling behavior. Therefore, we investigate how both sets of variables influence intention–behavior consistency. The remainder of this paper is organized as follows. Section 2 reviews findings from other studies that were focused on behavioral modification. Section 3 describes the method and the data collection. Section 4 analyzes the results of the changes in intention and behavior. Section 5 concludes with the results of the research.

2. Literature review

2.1. Beliefs and behavioral change

Despite the many physical and mental health advantages and positive contributions to the environment that result from bicycle usage (Akar and Clifton, 2009; Sugiyama et al., 2008) a vast amount of people does not use the e-bike to commute to work. A comparison can be drawn to other physical activities such as healthy eating, maintaining a healthy weight, and giving up smoking, where changing behavior is favorable, but difficult to accomplish for many (Faries, 2016).

Behavioral changes related to transportation have been widely studied (Gärling and Fujii, 2009; Cairns et al., 2017; Fujii and Taniguchi, 2006). Because e-bike use in a cycling stimulation program can be regarded as part of a behavioral modification process, existing literature on travel behavior modification may provide insight into the reasons for enrollment in such a program. One often-used approach to the characteristics of the decision-makers and the decision-making process is the Theory of Planned Behavior (TPB) (Perugini and Conner, 2000). The TPB proposes that decisions about behavior (including travel) are driven by various personal beliefs: 1) beliefs about the outcome of the decision (attitudes), 2) beliefs about the norms held by oneself and others about the behavior, and 3) beliefs about the capabilities and inhibitions pertaining to the behavior (perceived behavioral control) (Ajzen, 1991). These beliefs determine, in combination, the intention to engage in the behavior, which logically influences whether the behavior is engaged in or not. For instance, Bamberg (2006) describes how a residential relocation combined with a public transport trial ticket leads to changes in attitudes, social norms, and perceived behavioral control, eventually leading to behavior change. Hunecke et al. (2001) describe how interventions aimed at influencing personal and social norms contribute to behavior change toward public transport. In the health domain, Hardeman et al. (2010) describe a series of interventions based on TPB, of which approximately two-thirds appeared to be successful. While the TPB is an important and relevant framework for understanding behavior change, there exist alternative behavioral frameworks that also provide starting points for behavior change interventions and intention–behavior inconsistency. According to these theories, the aim to increase affect and well-being during travel, or a state of (dis)satisfaction with the current travel behavior, could be triggers for behavioral change.

2.2. Affect, satisfaction, and behavioral change

Over the past decade, research on well-being has increasingly found its way into transportation research (Olsson et al., 2013; De Vos et al., 2018; De Vos et al., 2020; van Wee and Ettema, 2016). Put briefly, it is assumed that the act of traveling has a direct impact on travelers' well-being, which involves both an affective (i.e., emotional) and a cognitive component. Various measurement tools have been developed to measure well-being during travel. Some scholars have used single-item cognitive scales (e.g., ‘How satisfied were you with your trip’ (Abou-Zeid and Ben-Akiva, 2012). In contrast, other scholars have used multiple affective items (Morris and Guerra, 2015) or a combination of affective and cognitive items (Ettema et al., 2011). In addition, well-being related to travel can be measured during or immediately following the trip, in retrospect, thinking back of a trip, or more generally concerning a trip type (such as commuting). Travel-related well-being varies consistently across modes. In general, the affective state associated with the private car is positive due to the easy access to out-of-home mundane activities (Bergstad et al., 2012), non-instrumental factors such as joy, independence, freedom, mastery, and prestige, and car travel as an enjoyable activity in itself. The private car is also attractive because it provides privacy and security (Gatersleben et al., 2014). Research by Novaco and Gonzales (2009) shows that, in contrast to the positive effects mentioned above, some car drivers experience high levels of stress and that long commute trips in congested traffic cause residual stress in the working place. Relative to other modes of transport, commuting by car is experienced worse than active commuting (walking and cycling) and about the same (Olsson et al., 2013) or slightly better than public transport (Ettema et al., 2010; Friman et al., 2013; Tommy Gärling and Friman, 2018). Travel satisfaction by slow modes such as cycling and walking is consistently found to be higher than travel satisfaction by automobile and public transport (Olsson et al., 2013; St-Louis et al., 2014; Gatersleben and Uzzell, 2007; Martin et al., 2014).

The above indicates that the emphasis in existing studies has been on cross-sectional studies of how differences between travel modes and travel conditions lead to different levels of well-being during travel. However, scholars outside the transportation area suggest that affect may also be a driver of behavior change. Russell (2003) describes how individuals’ affective state is a core driver of action, in the sense that they seek to move away from negative affective states (avoidance) and seek positive affective states (approach). In a similar vein, negative affective states associated with a certain current travel mode may trigger individuals to explore and use alternative ways of travel, leading to better affective outcomes.

Another indication of the relevance of affect related to current behavior is obtained from the Extended Model of Goal-directed Behavior (EMGB) (Perugini and Conner, 2000), which suggests that goal-perceived feasibility, goal desire, and goal-anticipated emotions, along with cognitive factors such as attitude, subjective norms, and perceived behavioral control from the TPB, are drivers of decisions about, e.g., environmental behaviors. This mechanism also suggests that negative affect associated with one choice outcome based on previous experiences, may lead to an increased likelihood of changing one’s behavior. In transport marketing studies (Oliver, 1980) it has been found that satisfaction with a product or a service may influence the intention to consume the product a next time. Thus, both affective and cognitive assessment of prior experience may influence future intention and behavior, which can be regarded as loyalty to the product or service. Consequently, to keep e-cycling during an e-bike stimulation program may depend on both the affective and cognitive evaluation of the commute.

2.3. Intention–behavior gap

The situation where the transition from intentions to the actual behavioral change fails is called the intention–behavior gap. In socio-psychological models, intention is considered ‘the most immediate and important predictor of a person’s behavior’ (Sheeran, 2005). It is, therefore, important to understand the mechanisms behind intention and behavioral change. In order to understand and moderate the intention–behavior gap, there has been much discourse on variables beyond the commonly assessed belief-related variables within the TPB (subjective norms, perceived behavioral control, and attitude) (Armitage and Conner, 2001; Ajzen, 1991). First, implementation intention or behavioral volitions as concretization of the intention have been added to the TPB as mediating variables between intention and behavior (Sniehotta et al., 2005; Reuter et al., 2008; Wieber et al., 2015). In various transport planning studies aiming for a sustainable behavioral change, participant are asked to make detailed plans for how they aim to implement sustainable behavior where others did not do so. Such a detailed plan may entail a detailed plan for a commute trip by public transport. These studies found that making such a detailed plan led to a more likely behavioral change via strengthening the implementation intention (Kang et al., 2019; Bamberg, 2011; De Vet et al., 2011). Second, past behavior or habit is added as important factor to underpin behavior in a specific context (Gardner, 2015; Gardner and Rebar, 2019). Third, goal-related variables are added such as goal perceived feasibility as evaluation to what extent the intended goal is likely to be achieved, and goal desire as degree to which one is willing to achieve the goal from the Model of Goal-directed behavior (EMGB) (Perugini and Conner, 2000) which relates to the concepts of self-efficacy and action control (e.g., self-monitoring, effort) (Sniehotta et al., 2005) found in other research. Also goal-anticipated emotions are added as variables, which also relate to people’s personality (MacCann et al., 2014; Monds et al., 2016).

In line with the above insights, this study assumes that the relationship between intentions to e-bike and actual e-biking frequency is mediated by behavioral volition. In addition, we assume that the intention to e-bike is influenced by goal perceived feasibility, goal desire, and goal anticipated emotions (see Fig. 1).

3. Methods

3.1. Study context

To actively stimulate the behavioral change from car commuting to e-cycling, the collaborating regional and local road authorities in the province of Noord-Brabant developed a large-scale e-cycling incentive program (B-Riders). With approximately one million inhabitants (40% of the total regional population) living between five and fifteen kilometers from the main working locations and economic centers (Fig. 2), the long-term effects of the expected behavioral change were estimated to have a significant impact on the total regional modal split and reduction of congestion. The incentive program builds on previous projects in the Netherlands, in which participants received financial compensation upon changing their behavior in a more sustainable mode choice, such as the Spitsmijden (peak avoidance) project, which provided participants with financial compensation to travel out of the peak hours (Ben-Elia and Ettema, 2009).

The collaborative road authorities used a relatively new approach to stimulate behavioral change based on the actual e-cycling performance of participants instead of stimulating the purchase of regular e-bikes. All people working in Noord-Brabant were invited, via social media and regional newspapers, to participate for a year (twelve months) in a large-scale incentive program. Participants were allowed to make use of a regular e-bike or a speed pedelec, whereas in the practice of 2013, the number of speed pedelecs was limited. For this study, the behavior of all participants with a regular e-bike in the B-Riders program was monitored between September 2013 and September 2014. Three online surveys were developed and conducted to assess the development between the intended e-cycling and the actual behavioral change over time within the B-Riders program.

3.2. Study design

Because the incentive program focused on behavioral change of car users to (e-)cycling, participants had to meet several recruitment conditions. First, all participants at least had to travel to work for a minimum of 50% to work by car, with a minimum commute distance of three

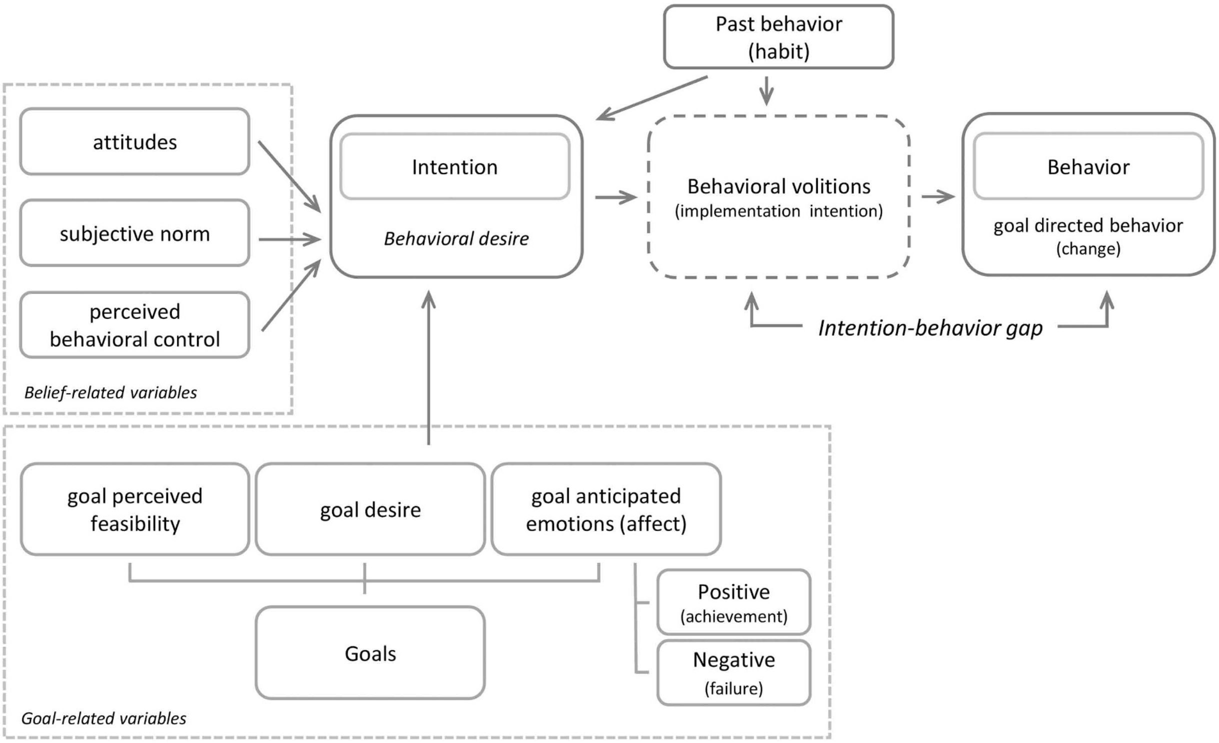

Fig. 1. Conceptual framework.

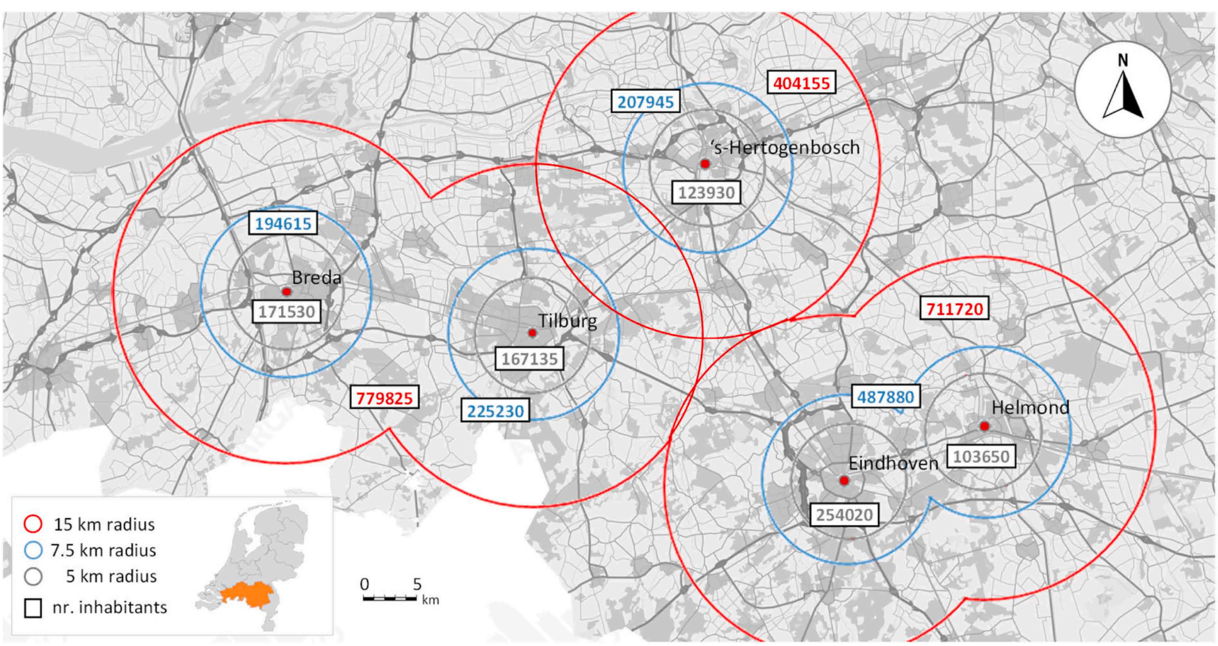

Fig. 2. Situational overview of the Province of North Brabant, with 5, 7.5, and 15 km radius from 5 main cities with the number of inhabitants per radius.

kilometers, and did not use the e-bike to commute prior to the program. The minimum share of working days per week by car was set this way due to the relatively new approach and the uncertainty about the number of participants willing to enroll in the program. During the enrolment process in the program, participants had to submit the proof of their e-bike purchase. Second, participants had to be between eighteen and sixty-five years of age (the retirement age at that time) with a working location within the province of Noord-Brabant. Finally, all participants agreed to actively participate in the study by filling out the three questionnaires throughout the experiment.

With the overarching program objective to reduce regional peak hour car congestion, participants received a €0.15 compensation per kilometer cycling during the morning and evening peak hours. Additionally, a compensation of €0.08 per kilometer at other times was set to make the program more appealing and encourage e-cycling for other purposes for trips. During the twelve months participation period, the total financial incentive per participant was capped at €1000 (one thousand euros). Based on a 10-kilometer average commuting distance, it would take participants approximately a year to reach this maximum financial compensation. Within the duration of the program, 25 participants (5%) cycled enough kilometers to reach the maximum financial incentive. The other participants received less compensation based on cycled less kilometers or ended participation in an earlier stage of the process. In total, €1000,000 (one million euros) was paid out to participants based on their performance. After finishing the program, the calculated effect was that more than one million trips by car during peak hours were avoided.

3.3. Longitudinal setup

To assess the behavioral change during the program, a series of three questionnaires were administered via the internet. At the start of participation in the program, a baseline questionnaire (T0) was conducted, where participants had to report the number of days using their habitual travel mode(s) for commuting in an average working week before entering the incentive program and making use of a e-bike to go to work. The options in the baseline questionnaire for the main mode of transport were car, carpool, motor, bus, tram, metro, moped/scooter, bicycle, and walking. Next, participants reported their behavioral intention to e-cycle to work expressed as the frequency in days of the week choosing the e-bike. In addition, participants reported on a series of constructs derived from the EMGB and TPB models, using established measurement scales, which is further explained below. Furthermore, questions were included to measure relevant personal and household characteristics, spatial characteristics, and work-related circumstances, which were suggested in previous e-cycling research (de Kruijf et al., 2018; Fishman and Cherry, 2016; Heinen et al., 2010; Plazier et al., 2017). Finally, as past behavior of people has frequently been demonstrated to predict changed behavior better than measures of intention and attitude (e.g. Bentler and Speckart, 1979; Verplanken and Aarts, 1999; Verplanken and Van Knippenberg al, 1997), participants were asked to report on their habitual travel behavior.

A second questionnaire (T1) was conducted one month after the starting date of all individual participants, where groups of participants started in batches at different start dates due to the organization of the program. Participants were invited to report again on the frequency of days using the main modes of transport for commuting in a working week over the last month. In this second questionnaire, e-bike was added as an optional main mode of transport going to work. This option was not applicable previously at T0 because as one of the recruitment conditions participants did not have an e-bike available prior to the start of the program. Similar to the baseline questionnaire, the behavioral intention for e-cycling in the number of days a week in an average week for the next period was asked together with all EMGB variables.

During the third and final questionnaires, which were conducted on each individual participant after six months of participation in the program, participants were asked again to report the intention of their commuting behavior in the number of days commuting by the different main modes of transport in an average week in the past period.

Of all 732 participants completing the first survey at the start of the program, 692 participants (a decrease of 5,5%) also completed the questionnaire at T2, and finally, with another decrease of 11,3%, a total of 614 participants completed the questionnaire at T3. In absolute number, the decrease in men (−47 participants) was less than in the female group (−71 participants) between T1 and T3. This study is eventually based on longitudinal responses from 547 participants after cleaning the survey for incomplete data.

3.4. Questionnaire development

3.4.1. Personal, household, and spatial characteristics

In addition, the questionnaire asked participants a set of questions about personal and household characteristics, including gender, age, educational level, income, car ownership, household composition, and subjective health status. The urbanization level for each participant was derived from each participant's home location postal code. Combined with the postal code of the working location, the e-bike distance was determined using the GIS (Geographical Information System) fastest path analysis based on the Open Street Map cycling network.

3.4.2. Intention-related determinants

In order to investigate behavioral intention, participants were questioned about their expected commuting trips during the incentive program in the next month. Therefore, the goal-related variables (perceived goal feasibility, goal desire, and goal-anticipated emotions) from the EMGB were used to measure intention, along with belief-related variables (attitude, perceived behavioral control, and subjective norms) from the TPB. In the EMGB section of the questionnaire, the goal behavior was defined as 'making use of the e-bike to go to work'. Next, all participants were asked to report the expected number of days a week to travel to work by e-bike in that period as their behavioral volition. Based on this behavioral volition or implementation-intention, participants reported on all nine EMGB (Perugini and Conner, 2000) determinants divided into the next main aspects: attitude, subjective norm, perceived behavioral control, past behavior, goal-perceived feasibility, goal desire, and goal-anticipated emotions (affect), where the latter is sub-divided into positive (achievement) and negative (failure) affect. Participants were asked to report on a seven-point Likert scale ranging from very unlikely (1 = very unlikely) to very likely (7 = very likely).

3.5. Sample demographic information

Based on e-cycling research showing that participants already making use of a conventional bicycle to commute to work exhibited different behavioral changes within an incentive program, participants were divided into car-commuters and multimodal car-commuters. The division between the two groups is based on their self-reported share of regular cycling commuting days in an average week. Car-commuters are the ones who never use the regular bicycle to travel to work in the baseline situation. Multimodal car-commuters reported (T0) to use different modes of transport to commute with a range of days using the regular bicycle. Table 1 specifies the total sample characteristics, including urbanization and the habitual cycling proportion before commuting by e-bike of all participants, car-commuters, and the multimodal car-commuters.

Table 1 shows that nearly half of the participants are between 50 and 65 years old and most have a university or higher vocational degree. This is consistent with the publications at the time of data collection reporting that the e-bike is especially popular in older cohorts and among higher educated segments (Fishman and Cherry, 2016; Johnson and Rose, 2013). More than 50% of the participants belonged to the category "couple with children living at home." Half of the sample (50.27%) owned at least two cars, and most participants (57.08%) were in the mid- to high-income categories (>3000 euro/month). Additionally, 77.15% of the participants had a cycle-commute distance of more than 10 kilometers, suggesting that the e-bike may be an important alternative to car-commuting, which also offers acceptable travel times for longer distances. Finally, 59.78% of the sample had flexible working hours.

The subdivision of all participants shows that the share of women within the unimodal car commuters' group (55.93%) is higher compared to (46.43%) in the multimodal car commuters group. The share of car ownership with two or more cars per household in the unimodal car-commuters group (52.54%) is higher than the 47.62% in the group of multimodal car commuters. Finally, the share of participants with cycle-commute distances of more than 10 kilometers is 87.81% for the unimodal car-commuters group compared to 64.68% for the multimodal car-commuters group.

Compared to the total population of the province of Noord-Brabant, the participants show a similar age and gender composition. However, couples with children at home, the higher income, as well as the higher

Table 1
Sample composition of all (547) participants; (295) unimodal car-commuter and (252) multimodal car-commuters (in %).

Variable	Category	Total	Car	Multimodal
Age	25–39 years old	12.07	14.24	9.52
	40–49 years old	36.38	35.93	36.90
	50–65 years old	51.55	49.83	53.57
Gender	Male	48.45	44.07	53.57
	Female	51.55	55.93	46.43
Education level	Lower education | primary and secondary	15.49	16.27	16.26
	Vocational education	27.61	26.10	28.86
	Higher education | (applied) scientific	56.90	57.63	54.88
Self-reported physical condition	Bad	13.39	15.36	11.11
	Neutral	18.53	19.11	17.86
	Good	33.03	34.47	31.35
	Excellent	35.05	31.06	39.68
Car ownership	1 car	49.73	47.46	52.38
	2 + cars	50.27	52.54	47.62
Net household income (in € per month)	< 3000	42.92	42.98	42.86
	3000 to < 4000	37.30	39.57	34.76
	> 4000	19.78	17.45	22.38
Household composition	Single	6.58	8.81	3.97
	Single parent	2.19	2.37	1.98
	Couple without children at home	34.92	34.24	35.71
	Couple with children at home	56.31	54.58	58.33
Urbanization level at home postal code	Highly urbanized	14.99	13.22	17.06
	Moderate urbanized	22.67	22.03	23.41
	Less urbanized	31.99	31.19	32.94
	Not urbanized	30.35	33.56	26.59
Cycle distance	0–5 km	3.66	1.69	5.95
	5 < 10 km	19.20	10.51	29.37
	10 < 15 km	30.53	32.20	28.57
	15 < 20 km	28.52	31.53	25.00
	20 + km	18.10	24.07	11.11
Flexibility working hours	Yes	59.78	58.98	60.71
	No	40.22	41.02	39.29

education level are overrepresented in the sample (CBS, 2023). It should be noted that our sample specifically targeted car commuters with commute distances of less than 25 kilometers, which have different characteristics as compared to the total population. However, due to this selection they will also differ from the.

whole Noord-Brabant working population, which might related to the type of job of the recruited people in the program.

3.6. Analytical approach

To explore the intentional and behavioral effects caused by the program, we conducted two descriptive analyses: one on the changes in behavioral intention between the start of the program and during participation, and one on the differences between intention and the actual behavior over the duration of the program. As regular cycling experience might have a different effect on intention and behavior between car commuters with and without the subdivision was added to the analyses.

In order to analyze the factors influencing the changes in intention, behavior, and the combination of both, we conducted ordinal logistic regression analyses. Therefore, we calculated the changes in intention of the number of days of e-cycling to the workplace between the situation after a month of participation (T1) and baseline (T0), where the outcome varies between an increase, no change, and a decrease. The same calculation was performed on the actual change in the number of days of e-cycling to the workplace between the situation after half a year of participation (T20) and the situation after a month of participation (T1). The outcome also varies between an increase, no change, and a decrease in days per week. Next to the EMGB variables, we incorporated personal, household, and commute characteristics as explanatory variables. This allows us to draw conclusions about the factors that stimulate a positive response to the e-bike incentive program.

Thirdly, to explore the dynamics between e-cycling intentions and behavior we developed a longitudinal structural equation model, depicted in Fig. 3. In the model we assume that behaviors and intention reciprocally influence each other over time. For the first point in time (T0) it is assumed that the commuting distance influences past bicycle and car commuting, which, in turn, are assumed to influence the intention to use the e-bicycle (at T0). The developed intention at the first point in time (T0) is then assumed to predict the e-cycling commuting in the first month (measured at T1). The e-cycling use is also assumed to be influenced by the past bicycle and car use directly. Should these paths prove non-significant, it can be concluded that the effects of the past behaviors are fully mediated by the e-cycling intention. Similar to T0, the intention to (keep) using the e-bicycle at T1 is assumed to be a function of the e-cycling behavior at T1, as well as the past e-cycling intention. Finally, the e-bicycle use at T2 (six months later) is assumed to be a function of the e-cycle intention at T1 and the past e-cycling use at T1. In addition, we assume that the e-cycle intention at T0 may also have an effect on the e-cycle use at T2. By exploring these dynamics, the model can shed light on the question at which specific points in time intentions and/or past behaviors are indeed relevant in the prediction of future behavior.

To control for possible spurious effects, we included gender, age and education level as additional exogenous variables to the model. These were assumed to influence all (endogenous) variables in the model. In addition, the error terms of car and bicycle commuting were allowed to correlate (given that these behaviors substitute for one another).

Given that the model contains ordered-categorical variables, weighted least squares was used for model estimation. Flora and Curran (2004) found, through a simulation study, that this estimation method demonstrates robust performance across diverse conditions. They particularly advocated its application in medium to large models involving ordinal variables. Mplus (version 8.5) was used for model estimation.

4. Results

4.1. Descriptive analyses

To address the longitudinal effect on intention–behavior consistency, Table 2 shows the relation between the reported e-cycling behavior and the intended number of working days using the e-bike to commute. The overview shows the difference between the stated intentions prior to the experiment and the actual behavior after a period of participation. The table describes the relationship between a) the stated intention (T0) and behavior (T1) and b) the intention (T1) and behavior (T2), expressed as the number of participants. Additionally, the shares of underperformance (less), overperformance (more), and corresponding intention–behavior (equal) were added.

First, comparing the stated e-cycling intention at the baseline and the actual behavior after one month of participation shows that 51% of all participants have an intention–behavior consistency and do what they intended in the first month of participation. The group of participants who intended to use the e-bike five or more days a week showed the lowest intention–behavior consistency with 37%. It is notable that there is actually a small group of participants who do not have an intention (anymore) to e-cycle to work. All other groups show between 47% and 57% intention–behavior consistency, where the majority of inconsistent participants are using the e-bike less than the intended number of days with 29–41% underperformance. Next to the general overview of all participants, Table 2 shows the difference between unimodal car-commuters and multimodal car-commuters. With a comparable

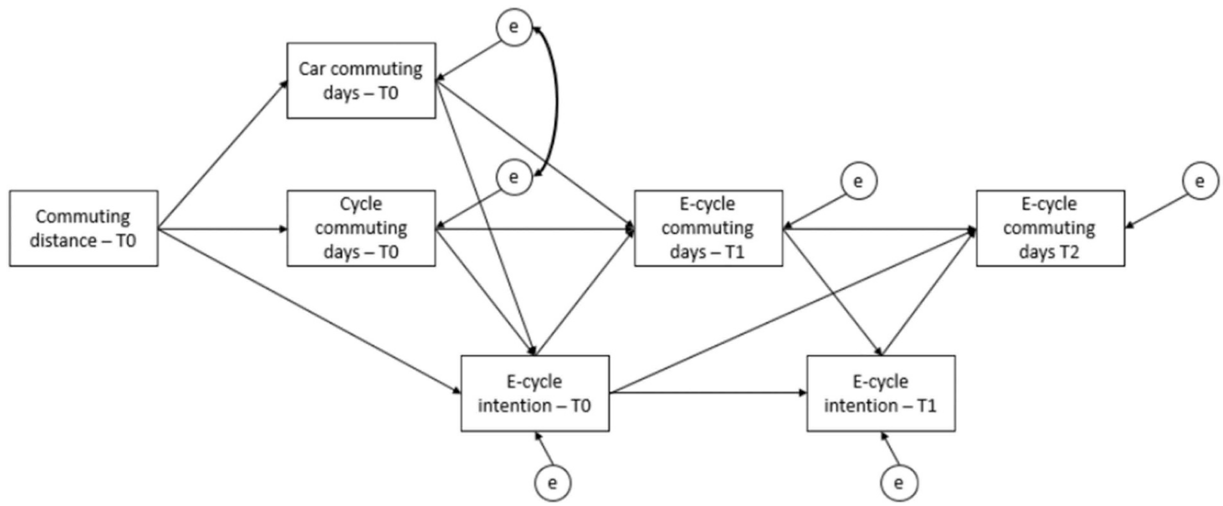

Fig. 3. Model structure of the longitudinal structural equation model.

number of participants in both groups, the overall average in similarity between baseline intention and e-cycling after a month higher for the multimodal commuters (55%) than the unimodal car-commuters (48%). The difference between the two groups is mostly in the limited number of multimodal participants overperforming. This can be understood from the habitual cycling experience of the group already commuting on the regular bicycle for some days in the week. Possibly, they are better able to envision what a specific e-biking frequency entails, so that it meets their expectations and they maintain their e-biking level.

Second, the difference between the stated e-cycling intention and actual e-cycling frequency one month and six months after the start of participation shows a comparable intention–behavior consistency of 50% on average. However, the shares of underperforming (less) and overperforming (more) are more balanced at T2 than at T1, where the group overperforming increased. This suggests that participants have had to get used to using the e-bike to travel to work. Maybe not surprisingly, the groups with the intention of e-cycling one of two days in the week showed overperformance of 53% and 42%, respectively. Most participants of these groups take the e-bike one more day than intended. The group of participants who intended to use the e-bike four to five days per week showed high consistency (47–60%), and when they differ, participants tend to only e-cycle one day less than intended. With comparable shares, both the group of unimodal and multimodal car-commuters show hardly changed intention–behavior consistency during participation. Both groups show a similar relative increase in overperformance in the second period.

To address the development of e-cycling intention, Table 3 shows the changes in behavioral intention by participants between T1 and the start of the program (T0). It may be assumed that expectations and intentions are more realistic after a month of participation in the program. A subdivision is presented, where participants were asked to indicate their use of the regular bicycle at T0. Given the Dutch context, one might assume that all participants in the program are capable of cycling in general but not all use the bike to go to work.

Overall, 68% of all participants did not change their intention over the duration of the program. The subdivision in self-reported regular cycling (T0) frequencies shows an increasing percentage of participants in the category 'equal'. Participants who reported a regular cycling frequency of zero days a week consisted of people who did not use the regular bicycle at all (unimodal car-commuters), together with people who used the regular bicycle irregularly and less than one day a week on average. Participants within the group of unimodal car-commuters show a 65% similarity in intention after one and six months. Of the remaining participants, 14% adjusted their intention positively to more e-bike commuting and 21% negatively, where most of these latter people adjusted their intention to one day a week.

The group of participants with one day a week of regular bicycle use shows an almost similar share in equal intentions of 63%. In comparison to the group without cycling commute habits with the regular bicycle (T0) only 7% adjusted their intention to e-bike more. This could be explained by their already developed (regular) cycling experience to work. The group of participants with two and three days of regular cycling behavior shows 72% to 77% of unchanged intention. The day-to-day cyclists with four or five days of regular cycling a week at the start of the program show a consistency of 83% in behavioral intention, which again can be explained by the experience in the past with regular cycling to work. From this group, most participants who changed, lower the intention, but not consistently with original cycling frequencies.

4.2. Regression models of e-bike intention and behavior

To investigate how both e-cycling intention and intention–behavior change over time, ordinal regression analyses were conducted in two models.

1. E-cycling intention T0 vs. behavior T1: model 1
2. E-cycling intention T1 vs. behavior T2: Model 2

The dependent variable per model is defined as the difference between actual and intended e-cycling frequency, where the outcome can be (1) overperformance, where the actual number of e-cycling days is more than intended, (2) a consistent situation, or (3) underperformance where the actual number of e-cycling days is less than intended.

As outlined in our conceptual framework, we hypothesize that goal-related variables, as defined in the EMGB and TPB, influence e-cycling intention and behavior (Dijst et al., 2008), we used goal desire, positive and negative anticipated emotions, past conventional cycling behavior, attitude, subjective norms, perceived behavior control and behavioral intention as independent variables. Moreover, independent variables like personal (gender, age, health status), household characteristics (household income, education, household composition, urbanization level, car ownership), and cycling commute distances were included. Table 4 shows the results of the two models.

In general, the goal-related variables do not show many structural significant relations throughout the models. Only a few variables have an impact on the changes in intention and behavior. Looking at the intention–behavior consistency (model 1), there is no significant relationship between the belief and goal-related variables. It might be speculated that intention–behavior consistency is a different process from the development of intention or behavior itself. The actual

Table 2
Overall e-cycling intention–behavior consistency, unimodal and multimodal car-commuters in workdays a week.

E-Cycle intention T0	Difference in e-cycling behavior T1 vs. intention T0										Difference in e-cycling behavior T2 vs. intention T1									
Total Group	**never**	**1 day**	**2 days**	**3 days**	**4 days**	**5 + days**	**Sum**	**Less**	**Equal**	**More**	**never**	**1 day**	**2 days**	**3 days**	**4 days**	**5 + days**	**Sum**	**Less**	**Equal**	**More**
0 workdays	4	2	1	0	0	0	7	-	57%	43%	1	5	0	2	1	1	10	0%	10%	90%
1 workday	6	9	3	0	0	1	19	32%	47%	210%	4	12	12	4	1	1	34	12%	35%	53%
2 workdays	3	21	46	12	2	0	84	29%	55%	17%	4	11	38	33	4	2	92	16%	41%	42%
3 workdays	4	10	46	85	19	1	165	36%	52%	12%	2	12	24	82	28	5	153	25%	54%	22%
4 workdays	1	2	8	59	95	5	170	41%	56%	3%	3	4	3	39	99	16	164	30%	60%	10%
5 + workdays	1	0	2	12	49	38	102	63%	37%	0%	2	0	1	11	36	44	94	53%	47%	0%
	3%	8%	19%	31%	30%	8%	547	41%	51%	8%	3%	8%	14%	31%	31%	13%	547	29%	50%	21%
Car-commuters	**never**	**1 day**	**2 days**	**3 days**	**4 days**	**5 + days**	**Sum**	**Less**	**Equal**	**More**	**never**	**1 day**	**2 days**	**3 days**	**4 days**	**5 + days**	**Sum**	**Less**	**Equal**	**More**
0 workdays	4	2	1	0	0	0	7	-	57%	43%	1	3	0	2	0	1	7	0%	14%	86%
1 workday	5	8	2	0	0	0	15	33%	53%	13%	4	8	11	2	1	1	27	15%	30%	56%
2 workdays	3	17	30	12	2	0	64	31%	47%	22%	4	9	27	21	4	2	67	19%	40%	40%
3 workdays	2	7	28	46	13	1	97	38%	47%	14%	2	8	16	47	10	2	85	31%	55%	14%
4 workdays	1	2	3	29	34	2	71	49%	48%	3%	1	3	2	23	37	6	72	40%	51%	8%
5 + workdays	0	0	1	6	18	16	41	61%	39%	0%	0	0	1	6	14	16	37	57%	43%	0%
	5%	12%	22%	32%	23%	6%	295	41%	47%	12%	4%	11%	19%	34%	22%	9%	295	32%	46%	22%
Multimodal commuters	**never**	**1 day**	**2 days**	**3 days**	**4 days**	**5 + days**	**Sum**	**Less**	**Equal**	**More**	**never**	**1 day**	**2 days**	**3 days**	**4 days**	**5 + days**	**Sum**	**Less**	**Equal**	**More**
0 workdays	0	0	0	0	0	0	0	-	-	-	0	2	0	0	1	0	3	-	-	-
1 workday	1	1	1	0	0	1	4	25%	25%	50%	0	4	1	2	0	0	7	0%	57%	43%
2 workdays	0	4	16	0	0	0	20	20%	80%	0%	0	2	11	12	0	0	25	8%	44%	48%
3 workdays	2	3	18	39	6	0	68	34%	57%	9%	0	4	8	35	18	3	68	18%	51%	31%
4 workdays	0	0	5	30	61	3	99	35%	62%	3%	2	1	1	16	62	10	92	22%	67%	11%
5 + workdays	1	0	1	6	31	22	61	64%	36%	0%	2	0	0	5	22	28	57	51%	49%	0%
	2%	3%	16%	30%	39%	10%	252	40%	55%	4%	2%	5%	8%	28%	41%	16%	252	25%	56%	19%

behavior might be determined by more practical factors, including preparation (putting on rain gear, getting the e-bike out of the shed), working conditions, and feedback from peers, among others. In the first month of participation, the group between 25 and 39 years old used the e-bike systematically less than intended (−0.644), less than people with an age over 50 years. Singles also are more likely to e-cycle less (−0.940) than intended in the first month. On the contrary, having one car available in the household only increases (0.393) e-cycling in the first month relative to their intention. Finally, in the cycling distances up to 10 kilometers, commuting participants significantly underperform (0 to 5 km. = −1.090 and 5 to 10 km. = −0.584) compared to the intended number of e-cycling days. It might be speculated that participants with a longer commuting distance have a stronger commitment or better preparation because of the impact of the related travel time.

In the second period, between a month and half a year after starting the program (model 2), the negative anticipated emotion of guilt (not achieving the goal) affects the consistency, where participants with anticipated guilt are more likely to underperform relative to their intention (−0.158). The perceived ease of using the e-bike affects intention–behavior consistency in e-cycling (0.232) in a positive way. Finally, male employees tend to significantly e-cycle less (−0.485) than intended in the second stage of the program. Notably, the physical condition of participants, urbanization level, income, and household composition do not significantly impact changes in intention-behavior consistency.

The model fitting data show the significance of the improvement of fit between the intercept-only model and the full model. The non-significant models are indicators that the models fit the data well (Petrucci, 2009). Despite the significance, the models can be used to evaluate the direction of effects.

4.3. Longitudinal Structural Equation Model

Fig. 4 shows the standardized parameters of the estimated longitudinal structural equation model. The path from car commuting at T0 to e-bicycle commuting at T1 was found to be insignificant and therefore fixed to zero. All other effects were found to be significant at the 1% significance level. With a chi-square value of 7.697 and 7 degrees of freedom the absolute fit of the model was found to be good ($p = 0.36$).

The results provide a plausible and intuitive picture as to how behaviors and intentions dynamically influence each other over time. In line with expectations the e-cycling intention at T0 is influenced positively by the levels of bicycle commuting (0.509) and -to a lesser extent- car commuting (0.338). The relative sizes of these effects reflect the levels of substitution from bicycle and car commuting respectively to e-bike commuting. The amount of e-cycling commuting at the second point in time (T1, one month from the start) is very strongly influenced by the developed intention at T0 (0.725). Only with respect to cycling does a small direct effect remain (0.101). This means that the effects of the past behaviors (car and cycling commuting) are almost fully mediated by the developed intention at T0. In line with the TPB, this means that the behavior is indeed the result of planned behavior (stated intentions) and not due to past behaviors (habits). Yet, if we move further down the causal chain, it can be seen that e-cycling commuting at T2 is most strongly influenced by e-cycle commuting at t1 (0.412) and to a lesser extent by past intentions at T1 (0.215) and T0 (0.117). Hence, whereas initially stated intentions play the strongest role in forming new behavior, at later stages the (past) behavior itself plays a larger role in its continuation. The choice to continue using the e-bicycle (at T2) is to a lesser extent determined by previously stated intentions (planned behavior) and more by past behavior (habitual behavior). These results effectively reconcile the opposing views on behavior as either primarily the result of reasoned action or primarily the result of habits (Bamberg et al., 2003). Our findings show that it depends on the moment in time, which of the two is actually more important.

Finally, the effects related to commuting distance are also worthy to

Table 3
Relationship between baseline use of regular bike and e-cycling intentions, unimodal and multimodal car-commuters.

	Difference in e-cycling Intention T1 vs. T0 (divided in regular cycling experience)											
Use of the regular bike T0	-4 days	-3 days	-2 days	-1 day	equal	+ 1 day	+ 2 days	+ 3 days	Sum	Less	Equal	More
0 workdays a week	3	2	9	48	192	32	9	0	295	21%	65%	14%
1 workday a week	0	2	4	21	56	6	0	0	89	30%	63%	7%
2 workdays a week	1	0	0	12	64	5	0	1	83	16%	77%	7%
3 workdays a week	0	0	0	4	28	7	0	0	39	10%	72%	18%
4 workdays a week	0	0	0	3	24	2	0	0	29	10%	83%	7%
5 + workdays a week	0	0	1	1	10	0	0	0	12	17%	83%	0%
Total	4	4	14	89	374	52	9	1	547	20%	68%	11%
	1%	1%	3%	16%	68%	10%	2%	0%				

highlight. In line with what can be expected, commuting distance has a positive effect on car commuting (0.144) and negative effect on bicycle commuting at T0 (−0.239). Interesting, because bicycle and car commuting are both positively associated with the e-cycling intention, these opposing effects also result in opposing (indirect) effects on the e-cycling intention. This makes intuitive sense; at shorter distances bicycle commuters are particularly attracted to the e-bicycle because there is little effort in switching (one is already using the bicycle) and the e-bicycle makes the commuting trip easier, whereas at higher commuting distances car commuters are mainly attracted by the e-bicycle, because the e-bicycle can cover longer distances with lower effort. Interestingly, in addition to the opposing indirect effects, a negative direct effect also remains (−0.190). It may be speculated that this is due to a mental effect of higher distance. At higher distances people may not even think the e-bicycle is indeed feasible alternative to use for the commute, while in practice it would be.

4.4. Conclusion and discussion

This study reported on the relation between the e-cycling intention and actual behavioral change within a large-scale e-cycling incentive program in the Netherlands, specifically in the province of Noord-Brabant. The main objective of the program was to incentivize car-commuters to use e-bikes in daily commuting as an alternative to car-commuting that causes congestion in the vicinity of the cities. For each kilometer commuted by e-bike, participants in the program earned monetary incentives. The incentive program was a collaboration of the national government, regional government, and the main cities aiming to reduce car commuting with target numbers on avoiding car commuting in peak hours. With a longitudinal three-wave survey design, this study observed the changes in e-cycling intention and the actual behavioral changes in order to understand the underlying mechanisms of behavioral change over time. Research on e-cycling has already shown that because of the electric peddle support of the e-bike, restrictions on range and physical effort are mitigated, as the main barriers to conventional bicycle use in daily commuting (Heinen et al., 2010; Heinen and Handy, 2012). In general, this study shows that the incentive program has a positive impact on the behavioral change to e-cycling of participants ' behavior during the incentive program. Results showthat the intention to e-cycle in daily commuting is positive and quite constant over a period of a month, with two-thirds of all participants actually use the e-bike as much as they intented at the start of the program as after a month of participation. One-fifth of all participants decreased their stated intention after the first month of experience, but most of this group only reduced e-cycling intention by one day a week. Especially in the groups of participants who were used to taking the conventional bicycle for more days a week, the changes in intention are less frequent, which might be explained by the habitual commuter-cycling experience. With respect to intention-behavior consistency, a distinction can be made between the experienced cyclists and participants without any or hardly any (one day a week) commuter-cycling experience (Gatersleben and Appleton, 2007). Comparing the e-cycling intention at the start of participation in the program to the behavior after a month shows that only half of the participants exactly meet their intention in the number of e-cycling days a week. Especially in the group of participants without conventional cycling experience for commuting, the use of the e-bike compared to their intention was higher, which might be explained by a very positive experience and satisfaction with their trip (de Kruijf et al., 2019). In the second stage (between a month and half a year of participation), the group with conventional cycling experience also more often showed an increase in e-cycling compared to the intention. The duration of the program to incorporate habituation is an important factor, while behavioral modification and adaptation take time. Overall, it can be concluded that a strong intention-behavior gap is not observed in the context of the e-cycling stimulation program. Most participants use the e-bike at least with the intended frequency or only slightly less. One explanation may be that the experience with e-cycling is positive and contributes to adherence to e-cycling. Another explanation is that enrollment in the program creates a strong incentive to continue e-cycling. In particular, the rewards per trip, needed to earn back the investment made in an e-bike may provide a strong incentive. Despite the limited overall significance, factors such as a relative young age, single car ownership, and living in a one person household significantly influence the intention-behavior consistency.

A question that remains is to what extent the effects on behavioral change by the incentive program are scalable to future incentive programs. The comparison was drawn between e-cycling and other favorite physical activities such as maintaining weight, healthy eating, and not smoking, which are challenging goals to accomplish (Faries, 2016). When the translation from intention to action fails, there is an intention–behavior gap. This study did not show convincing relations with belief-related variables as specified in the TPB and additional goal-related variables specified in the EMGB. It can be concluded that there are differences in intention–behavior consistency within the sample, which are, however, not directly related to the theoretical concepts of the TPB or EMGB. First, it can be argued if cycling to work is not that difficult in the Dutch context with its high-quality cycling infrastructure, positive cycling culture, and general cycling experience in society. Second, the monetary compensation within the program is introduced as an extrinsic incentive to motivate people to change their behavior. Participants in the program already had a positive mindset toward e-cycling and participating in an incentive program. One of the open questions still is how less motivated people can be persuaded to join such incentive programs. Third, participants can be influenced by outside pressure (Deci and Ryan, 1985). In that particular case, participants would feel pressured by people being important to them to show certain desired behaviors or be negatively influenced by the image of the e-bike as bicycle for the elderly only (Fishman and Cherry, 2016). The results do not show a significant relationship between the changes in intention or behavior, and outside pressure. It can be hypothesized that a specific group in society enrolled in the incentive program, which is less sensitive for negative outside pressure to demotivate people from participation. Because participants have already signed up voluntarily for the incentive program, the degree of self-selection of participants in the program can be questioned. Also, the initial purchase of an e-bike is

Table 4
Ordinal regression analysis of intention-behavior consistency.

			Model 21 Intention T0 vs. Behavior T1	Model 32 Intention T1 vs. Behavior T2
	minimum (1)	maximum (7)	Estimate	Estimate
Goal desire	very weak	very strong	0.035	-0.241
	strongly disagree	strongly agree	-0.039	-0.070
Positive anticipated emotions	excited	not excited	0.108	-0.168
	delighted	not delighted	-0.145	0.357
	happy	not happy	-0.077	-0.259
	satisfied	not satisfied	0.078	-0.024
	proud	not proud	-0.017	-0.053
Negative anticipated emotions	angry	not angry	-0.086	-0.030
	frustrated	not frustrated	0.043	0.066
	guilty	not guilty	-0.068	-0.158*
	sad	not sad	0.054	0.029
	disappointed	not disappointed	0.059	0.071
	worried	not worried	0.119	0.024
	uncomfortable	not uncomfortable	-0.035	0.035
Past behavior			-0.066	-
Attitude	useless	useful	-0.114	-0.164
	Ineffective	Effective	0.232	0.031
	expensive	cheap	-0.104	-0.139
	unpleasant	pleasant	0.063	0.014
	unattractive	attractive	0.303	-0.254
	unenjoyable	enjoyable	-0.314	-0.044
Subjective norms	people who are important to me, think I should/should not…		0.046	-0.100
	people who are important to me would (dis) apporve		0.091	0.112
	people who are important to me do not care whether I choose		0.014	-0.085
Perceived behavioral control	e-cycle n amount of days to work		0.082	-0.023
	if I wanted to, it would be easy to….		0.034	0.232*
	it is entirely up to me		0.121	-0.117
	I'm confident that I would use …		-0.034	-0.097
Behavioral intention	my desire to choose is …		-0.019	0.213
	I intend to choose ….		-0.105	0.058
	I gave it a good thought how I could use ….		0.115	-0.049
Age	25-39 years old		-0.644*	-0.208
	40-49 years old		-0.408	-0.053
	50 + years old		-	-
Gender	male		-0.343	-0.485*
	female		-	-
Physical condition	bad		0.091	-0.051
	neutral		-0.015	-0.267
	good		-0.125	0.011
	excellent		-	-
Car ownership	1 car		0.393*	0.178
	2 + cars		-	-
Household income (in € per month)	< 3.000		-0.419	-0.289
	3.000 - < 4.000		-0.197	-0.387
	> 4.000		-	-
Household composition	Single		-0.940*	-0.452
	Single parent		-0.654	0.965
	Couple without children		-0.172	-0.033
	Couple with children		-	-

Table 4 (*continued*)

			Model 21 Intention T0 vs. Behavior T1	Model 32 Intention T1 vs. Behavior T2
Residence urbanization	(very) strong Urbanized		-0.009	-0.102
	moderate urbanized		-0.290	-0.327
	Less urbanized		0.041	0.086
	Not urbanized		-	-
Cycle Distance (per commute trip)	0-5 km		-1.090*	-0.730
	5 < 10 km		-0.5840*	0.193
	10 < 15 km		-0.466	0.031
	15 < 20 km		0.039	0.287
	20 + km		-	-
Cycling Share	T0_CycleShare		0.327	-0.350
	Model fitting		0.352	0.004*
	Goodness of fit	Pearson	0.076	0.207
		Deviance	0.985	0.442

* Significant at $\alpha < 0.05$.

expensive compared to a regular bicycle, which could have been a restriction for lower income groups in society to enroll. In addition, the sales and use of e-bikes increased in the Netherlands over the last couple of years, (38% between May 2019 and 2020) (Bovag, 2020) which indicates an improvement of the image of the e-bike. Therefore, the question remains how to stimulate e-bike use among a wider audience to enroll in such an incentive program.

The question can be raised to what extent the results of the present study can be used to strengthen current (Dutch) cycling policies. From a policy perspective, the e-cycling incentive program is regarded as successful because the majority of participants intended, started, and persevered using the e-bike for one or more days a week to commute as an alternative to car-commuting. However, the question remains how people underperforming to their implementation intention can be stimulated to take up e-cycling more, as no clear indications have been found on the intention–behavior gap to enhance such an e-cycling incentive program.

Nevertheless, although it is likely that not all commuters will fully switch to using e-bikes in all weather conditions, a vast amount of car-commuting trips can be substituted with effective cycling policy measures (de Kruijf et al., 2018). Overall, the results indicate that e-bikes have a clear potential to substitute car use on commute trips. It is to be noted that over the last couple of years, regional policymakers in the Netherlands decided to decrease involvement in e-cycling incentive programs in general and particularly in monetary incentives. By shifting responsibility and facilities (increase in tax-related opportunities in facilitating the purchase of an e-bike) to employers, e-cycling is increasingly embedded in the mix of sustainable modal choices for employees. This studies shows that actively stimulating-bike use over time helps to sustain behavioral change towards e-bike use.

Finally, scaling the results of this study to a national level, the presented modal shift towards e-cycling to works is promising. With 74% of people in the Netherlands living in urban regions, the technical advantages of the e-bike with its greater range and increase of cycling comfort offer the majority of people a sustainable alternative living in the vicinity (< 15 km.) of work. With 64% of all car trips being shorter than 15 kilometer, 31% of all commuting trips falling in the five to ten kilometers range and 14% falling in the ten to fifteen kilometers range, the e-bike has still a lot of ground to gain (KIM, 2020).

Next to the reduction of congestion and environmental impact, the behavioral change towards e-bike use has proven to positively affect the mental and physical health status of people compared to car use. Overall, utilizing the Dutch standard societal cost-benefit method results

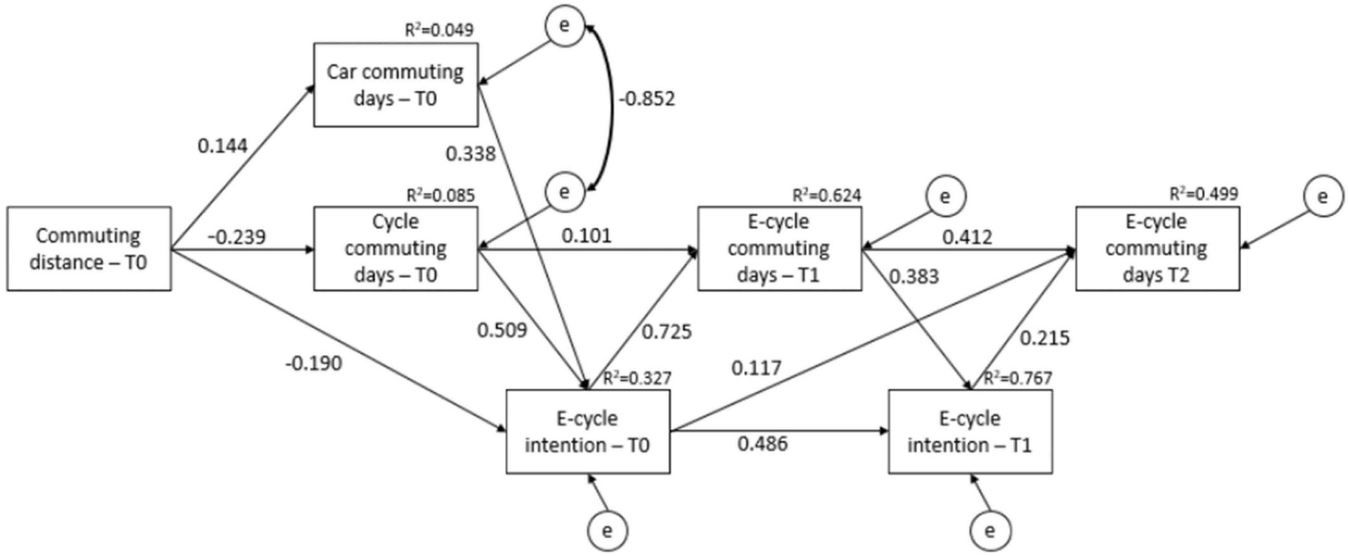

Fig. 4. Standardized parameters estimates of the longitudinal structural equation model. Note: all effects are significant at the 1% level.

in a positive benefit/cost ratio (Decisio, 2023). Even incorporating a negative health effect of the transition from the regular bicycle to the e-bike on the short distances and a decrease of traffic safety because of the behavioral change from car to e-bike, the net effect of the incentive program is positive. This result shows that investment stimulating in e-cycling has broader and positive societal impact than accessibility only.

Limitations

This study has offered new empirical based insights into the intention-behavior consistency over time during a large-scale e-cycling incentive program. However, this research also has limitations, which may have influenced the findings. The first limitation is the potential selection bias in the sample, since having an e-bike was one of the boundary conditions. Participants had to purchase a rather expensive e-bike prior to the start of participating in the program, as a result of which aspects such as perceived behavioral control and willingness to e-bike are likely to be considered in advance already, which may have affected our findings about intention-behavior consistency.

A second limitation are the program conditions which did not allow research of behavioral change after termination in the program. It remains unclear to what extent behavioral change towards e-cyling in daily commuting perpetuated and what the lasting effects are of the monetary incentives. It would have been interesting to determine factors influencing both the choice of dropping out in an early stage as well as continuation of behavior after the end of the incentive program.

A third limitation to the study is the particular Dutch cycling context. With its specific high quality cycling infrastructure, rather flat natural environment, temperate maritime climate, and well-developed cycling culture all cycling related circumstances in the Netherlands are likely to contribute to this behavioral change in positive manner. This study does not imply that similar e-cycling stimulation programs would show similar results in other regions and abroad considering variations in the natural and built environment, political, cultural and societal context. Therefore, future research on the effectiveness of the technical advantages the e-bike offers in a more hilliness environments in terms of increased speed and reduction of pedal effort could show positive modal shift effects compared to conventional cycling.

CRediT authorship contribution statement

de Kruijf Willem Johan: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Ettema Dick:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Conceptualization. **van Lierop Dea:** Writing – review & editing, Validation, Supervision. **Dijst Martin:** Supervision, Methodology, Conceptualization. **Kroesen Maarten:** Writing – review & editing, Visualization, Methodology, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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