Walking on Sunshine or on the Highway to Hell?

Predicting Willingness to Participate in an Online Intervention to Walk or Cycle more

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Walking on Sunshine or on the Highway to Hell? Predicting Willingness to Participate in an Online Intervention to Walk or Cycle More

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Research questions: This thesis aims to predict intentions to walk and cycle more and willingness to participate in an online intervention by analyzing sociodemographic characteristics and past behavior collected in a large recruitment survey.

Abstract

Increasing walking and cycling is important both for population health and, if done through active transportation, for the local and global climate. In addition to infrastructural and regulatory measures, voluntary behavior change interventions are used to increase physical activity and active mobility. The impact of such interventions depends on their reach, both in total and whether they reach the groups that would benefit most. I collaborated with the Institute of Transport Economics and used data from a large survey used to recruit participants to different projects. I analyzed which sociodemographic characteristics and past behavior could predict intentions to walk and cycle more ($N = 4195$), willingness to participate in an intervention to do so ($N = 2862$), how ($N = 1092$) they wanted to participate (walking/cycling, leisure activity/active transportation) and what predicted completion of the intervention ($N = 1092$). Results show that usual travel mode can predict both intentions to walk and cycle more and willingness to participate. Car and motorcycle commuters had both lower intentions and less willingness to participate than active commuters and public transport users. This indicates that public transport commuters are the most promising group to reach with self-regulation interventions, while car and motorcycle commuters might need other approaches. Higher intentions to walk and cycle more were positively associated with willingness to participate in the intervention, as were being female and having more children under 18 in the household. People with children have been found to cycle less, but in this sample had higher intentions to cycle, were more likely to say yes to participating and more likely to choose cycling over walking. This indicates that people with children are promising groups to reach with interventions using self-regulatory strategies. The only variable significantly associated with completion of the intervention was physical activity, with inactive people being less likely to complete the intervention than moderately active people. This is consistent with previous findings and illustrates the difficulty related to reaching the groups that would benefit most from the intervention.
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Introduction

Many of the challenges facing the world and its inhabitants today are consequences of people’s behavior. What they eat, how they travel and how little they move relate to both health concerns and the emission of climate gases. Some ways to change these behaviors include regulations, structural changes, taxes and incentives of different kinds. While measures such as car-free streets, decreased parking and increased tolls are used to decrease car traffic (Klimaetaten Oslo kommune, 2016), these measures depend on political agreement on controversial subjects and face backlashes from the population (Vikøyr, Thanem, & Giæver, 2018). Psychological strategies for voluntary behavior change could represent quickly implemented and cost-efficient solutions (Hoffmann, Abraham, White, Ball, & Skippon, 2017) that could supplement other measures without increasing conflict. The way governments have adopted the concept of nudging (e.g., by creating ‘nudge units’ in the UK, Australian and US governments) shows the popularity and attractiveness of being able to achieve policy goals without using regulations or incentives (Benartzi, Beshears, Milkman, Sunstein, & Thaler, 2017).

In Norway, only 32% of the adult population satisfy the minimum recommendation of 30 minutes of physical activity each day (Norwegian Directorate of Health, 2016). At the same time, more than half of all trips of 1-3km are done by car and the percentage of trips taken by car only increases with the distance of the trip (Hjorthol, Engebretsen, & Uteng, 2014). Active transportation represents a way to combine the goals of decreasing car pollution and increasing physical activity. One study found that 29% of people using public transit met their daily recommended physical activity level solely from walking to and from the transit stops (Besser & Dannenberg, 2005).

Combining exercise with daily activities (such as commuting) can make the physical activity behavior more durable and successful (Lawlor et al., 2003) and active transportation has been associated with significant health gains in the population (Norwood, Eberth, Farrar, Anable, & Ludbrook, 2014). Norway has set goals to increase active mobility in the form of both walking and cycling (Samferdselsdepartementet, 2016-2017). These active mobility goals are founded on the government’s targets of improved public health through physical activity, more environmentally friendly transportation and improved local climate in cities and towns (Berge, Haug, & Marshall, 2012).

Traditional measures (e.g., structural changes, regulations, information campaigns) often focus on changing people’s motivation to walk or cycle, but changing intentions does not necessarily lead to corresponding changes in behavior (Sheeran & Webb, 2016). People
who want to change their behavior but fail to do so are known as ‘inclined abstainers’ (Sheeran, 2002). The context for this thesis is a planning intervention created to help people follow-through on their intentions to walk and cycle more. The effectiveness of the intervention will be evaluated as a part of a PhD project and is not the subject for this thesis.

Instead, this thesis will investigate to what extent sociodemographic characteristics and past behavior can be used to predict willingness to participate in, and completion of, the intervention. These findings have implications for the expected effectiveness of future interventions and the external validity of results of both this and similar interventions.

**Physical Activity and Active Transportation**

The Norwegian Directorate of Health (2016) states on its website that approximately one in three adults in Norway satisfy the minimum recommendations for physical activity. That is, 75 minutes of rigorous physical activity or 150 minutes of moderate physical activity per week (Norwegian Directorate of Health, 2016). Physical inactivity is estimated to cause approximately 3.2 million deaths per year and is the fourth highest risk factor for mortality globally (World Health Organization, 2018). Regular physical activity, for example walking and cycling, can reduce the risk of several diseases such as cardiovascular diseases, diabetes and some forms of cancer (World Health Organization, 2018).

There’s a Norwegian adage that ‘public transport takes you from where you aren’t to where you aren’t going’, illustrating the fact that people need to get to and from the public transportation stop. Getting exercise through active transportation may for some people be a way to incorporate physical activity into their day without having to dedicate too much time to it. One study of physical activity and public transportation found that Americans who used public transport spent a median of 19 minutes per day walking to and from public transportation, and that 29% of public transport users met the recommended daily amount of physical activity solely through transit related walking (Besser & Dannenberg, 2005). Multivariate analyses showed that people in low-earning households, minorities, rail users and people from high-density urban areas were more likely to spend more than 30 minutes each day walking to and from transit (Besser & Dannenberg, 2005). As low socioeconomic status (SES) groups are less active in their leisure time (Stalsberg & Pedersen, 2018), facilitating walking to and from public transportation may promote active lifestyles in low income and minority groups (Besser & Dannenberg, 2005).

**Potential Health Impact.** The impact of active transportation on public health depends in part on how increasing active travel influences total amount of physical activity, as some people might replace other activities with walking or cycling (Veisten, Flügel,
Ramjerdi, & Minken, 2011). A cross-sectional self-report study estimated that approximately 30% of new regular cyclists would obtain net health gain, while for new regular pedestrians this number was only 15% (Veisten et al., 2011). However, a longitudinal study found that there was no correlation between change in active travel and change in recreational activity, but that changes in active travel were associated with changes in total physical activity (Sahlqvist, Goodman, Cooper, & Ogilvie, 2013). These findings suggest that promoting active travel is likely to increase total amount of physical activity and thus be beneficial for public health overall, but that not all people will benefit this way (Sahlqvist et al., 2013; Veisten et al., 2011). To improve health, reaching the threshold for moderate physical activity is considered more important than increasing activity beyond that point (World Health Organization, 2010). The health impact of the intervention therefore also depends on whether sedentary individuals join the intervention or whether it’s mostly already active people who participate.

People who intend to exercise, but don’t do so (inclined abstainers) have been found to view exercise behavior as more physically demanding and time-consuming than people who act on their intentions (Godin, Shephard, & Colantonio, 1986). If sedentary people have increased perceptions of barriers related to exercise, this might indicate that being physically inactive can predict lower intentions to walk and cycle more. However, being overweight and having health issues, especially combined with health literacy, has previously been associated with increased willingness to participate in health programs (You et al., 2011) and the same effect could be found for sedentary people who are aware of the health risks associated with inactivity. Previous research has found that inactive people are less likely to complete exercise programs (Arikawa, O'Dougherty, Kaufman, Schmitz, & Kurzer, 2012; Jancey et al., 2007), but I have not found studies including physical activity when predicting attrition from travel mode interventions.

Inactive people’s participation and completion in such programs are essential for the health impact of interventions, and I will examine whether level of physical activity at baseline can predict intentions to walk and cycle more, willingness to participate in an online intervention and completion of the intervention.

**Travel Mode Choice**

There are several determinants involved in travel mode choice and a range of theories to explain them (Chng, Abraham, White, Hoffmann, & Skippon, 2018). I will discuss the behavior change process in the next section, but first present some factors that are relevant for shaping the beliefs that eventually lead to explicit intentions regarding travel mode choice.
Many travel mode studies seem to assume that mode choices are made by making a cost-benefit analysis of each mode and choosing the one that performs best. Instrumental aspects of a trip include speed, cost, convenience, comfort, privacy, protection, freedom and control (Anable & Gatersleben, 2005). Longer distance is negatively associated with active travel modes (Heinen, van Wee, & Maat, 2010; Ton, Duives, Cats, Hoogendoorn-Lanser, & Hoogendoorn, 2018) and trip time is negatively associated with cycling (Ferrer & Ruiz, 2013). Da Penha Sanches and Serra de Aruda found that once trips exceed 4kms, the probability of walking is almost zero (as cited in Ferrer & Ruiz, 2013).

Active mobility is further reduced for trips with the purpose of taking children or other people to places (e.g., children to school or other activities, parents to the hospital). Such trips are mostly done by car and have a very low (2%) share of cycling (Ellis, Amundsen, & Høyem, 2016). Similarly, previous research has found that having children is negatively associated with both cycling (Heinen et al., 2010; Ryley, 2006) and walking (Hamre & Buehler, 2014). An explanation for this, especially for small children, could be that they both need to be transported (the physical act of moving them influencing mode choice) and that time-constraint for pick-up and delivery can result in both tighter schedules and increased trip-linking (Hamre & Buehler, 2014). Consistently, households with children have been shown to favor leisure cycling trips (Ryley, 2006). Based on such findings, I expect that having children in the household will be a barrier for participating in the intervention and that those parents who do choose to participate will prefer to do so as a leisure activity rather than as active transportation.

Travel mode choice can also be influenced by the affective experience of a trip (Anable & Gatersleben, 2005) and people’s sense of identity and status (Gatersleben, 2011; Heinen, 2016). People who identify with their travel mode might feel threatened by attempts to have them switch to active modes and experience psychological reactance that then prohibits change (Murtagh, Gatersleben, & Uzzell, 2012). In addition, in cases where people experience difficulty changing their behavior, they might instead change their attitudes and beliefs about the consequences of the behavior (Festinger, 1957; Stone & Fernandez, 2008). The same way a smoker might convince herself that smoking is not as harmful as people say or that the benefits outweigh the risk (Festinger, 1957) a person who depends on his car might convince himself that the impact of him commuting by car is so very little that it doesn’t matter.

Past behavior has been shown to be an important predictor of travel mode choice and relates to the formation of habits (Verplanken, Walker, Davis, & Jurasek, 2008). When a
person first decides on a travel mode or route, the decision is made as a rational choice based on available options, expected outcomes and the person’s own attitudes, values, etc. (Lanzini & Khan, 2017). Once this behavior has been established it is unlikely to change unless the person does a new deliberate evaluation. As an example, people might initially choose a car over public transportation or active mobility as they believe the car to be more accessible, faster and reliable (Gatersleben, 2011) and habit might keep them driving a car despite changes in public transportation availability and cycling paths that would have led to a different choice had the person truly reconsidered.

To summarize, research indicates that travel mode choice depends on more than just a cost-benefit analysis of each available mode. Participants’ affective experiences, past behavior, values and habit also influence mode choice but have not been measured in the survey used in this thesis. To capture such additional influences, I will use participants’ usual travel mode as a predictor of their intentions to walk and cycle more and their willingness to participate in the intervention. I expect that people who usually commute by car or motorcycle will be more connected to their mode (e.g., because of instrumental aspects, values, sense of identity, habits, etc.) than people who commute by public transportation, and that car/motorcycle commuters therefore will have both lower intentions to walk/cycle more and be less likely to agree to participate in an intervention to do so.

Transport or leisure. The health outcome of a walking or cycling trip is not affected by the purpose of the trip, and government recommendations for physical activity promote both active travel and recreational walking and cycling (Norwegian Directorate of Health, 2016). People might also want to walk or cycle more due to any combination of reasons, but very few studies combine active mobility and leisure walking/cycling. The former is often treated as travel behavior and the latter as physical activity in the same way as other forms of exercise.

While many studies examine travel mode choice, I have not found any that look at choice of purpose (leisure or utilitarian) for people who know they want to walk or cycle more. A couple studies have distinguished between transportation and recreational walking and found that walking trips with different purposes differ in location, speed and distance (Kang, Moudon, Hurvitz, & Saelens, 2017) and that different factors have different impacts on transportation and recreational walking trips (Mirzaei, Kheyroddin, Behzadfar, & Mignot, 2018). Participants of the current intervention were asked to choose between walking or cycle as active transportation or in their leisure time and I will explore whether past behavior and sociodemographic characteristics predict the choice of purpose. Such findings could have
important implications for future interventions attempting to increase either one or both types of activity.

**The Behavior Change Process**

Psychology can contribute to improving public health and limiting climate change by increasing the understanding of why people do, or don’t do, relevant behaviors like choosing active mobility (Stern, 2011). When comparing groups segmented on attitudes with groups segmented on sociodemographic or geographic factors, Hunecke, Haustein, Böhler, and Grischkat (2010) found that attitude-based groups were more predictive of travel mode choice, distances traveled and ecological impact than the other groups. Many theories have been used to explain travel behavior, but the Theory of Planned Behavior (TPB) is most widely used (Donald, Cooper, & Conchie, 2014; Lanzini & Khan, 2017). It was created by Icek Ajzen and views intention as the most immediate predictor of behavior (Ajzen, 1991).

According to the TPB, subjective norms, attitudes and perceived behavioral control predict intentions, and perceived behavioral control is also directly associated with behavior (Ajzen, 1991). While there is consensus that intention serves as an essential variable in explaining and predicting behavior there are limitations to its predictive value (Schwarzer, 2016). As many interventions and measures essentially aim at changing people’s intentions to walk and cycle (though the ways of influencing intentions vary widely from information campaigns and financial incentives to regulations making it difficult or costly to travel by car), it is important to be aware of how well changes in intentions translate to changes in behavior.

**Intention-behavior gap.** In 1996, Godin and Kok (as cited in Schwarzer, 2016) reviewed 19 studies and found a mean correlation of .46 between intention and various health behaviors. A few years later, Abraham and Sheeran (2000) stated that intentions can be expected to account for 20-25% of variances in health behavior. However, as these findings are based on correlational research, the interpretation is subject to issues such as third-variables and direction of causality (Rhodes & Dickau, 2012). To account for this issue, Webb and Sheeran (2006) conducted a meta-analysis of 47 experimental tests where participants were randomly assigned to a test group whose intentions were significantly increased compared to a control group, and where subsequent differences in behavior were compared. They found that inducing medium-to-large changes in intention ($d = .66$) only leads to small-to-medium changes in behavior ($d = .36$) (Webb & Sheeran, 2006).

Inspired by the findings of Webb and Sheeran, Rhodes and Dickau (2012) conducted a similar meta-analysis but included only experimental studies on physical activity. This was
done because they suspected that physical activity would have an even larger intention-behavior gap than behaviors in general (Rhodes & Dickau, 2012; Webb & Sheeran, 2006). As expected, they found that there was an even weaker relationship than in the previous meta-analysis, with changes in intention not resulting in corresponding changes in behavior (Rhodes & Dickau, 2012).

To my knowledge no review has been conducted on the magnitude of the intention-behavior gap for commuting behavior and little on cycling or walking outside a physical activity context. One study distinguishing between lifestyle activities (commuting, but also housekeeping, gardening, etc.) and exercise activities found that the TPB model predicted exercise activities better than lifestyle activities and that perceived behavioral control was only significantly associated with exercise activity and not with lifestyle activity (Bellows-Riecken, Rhodes, & Hoffert, 2008). Rebar, Maher, Doerksen, Elavsky, and Conroy (2016) examined walking separately from moderate and vigorous physical activity and found a larger intention-behavior gap for walking than vigorous activity. They contribute this finding to the fact that vigorous activity requires more preparation and planning than walking, which can be done spontaneously, and therefore depends more on the person having intentions to be active (Rebar et al., 2016).

Even though intentions are considered to be the most proximal predictor of behavior, a meta-analysis of physical activity interventions found that 39% of total participants had intentions to be active but failed to translate those intentions into behavior (Rhodes & de Bruijn, 2013). In the same meta-analysis, only 54% of those who intended to act were successful in doing so (Rhodes & de Bruijn, 2013). To identify the source of the intention-behavior gap, Sheeran (2002) split the intention-behavior relationships into a 2 by 2 matrix (intent or not, act or not). The analysis showed that it is people who intend to act and don’t follow-through (inclined abstainers) who are chiefly responsible for the discrepancy. Across six studies of health behavior, the median proportion of people who failed to act on their intentions was 47% (Sheeran, 2002).

While meta-analyses have shown that there’s a large percentage of inclined abstainers, the same analyses have shown that very few people act without intending to do so, and disinclined actors make up only 7% (Sheeran, 2002) or 2% (Rhodes & de Bruijn, 2013). This is strong evidence that intentions are necessary to produce behavior change, even though intentions on their own are not sufficient (Rhodes & de Bruijn, 2013). It is important to acknowledge the consistency between intentions and behavior and the utility of intentions for predicting different behaviors (Sheeran & Webb, 2016). Even though intentions aren’t enough
for a behavior to be enacted, they are important prerequisites for behavior change. Pinpointing groups with different intentions can be essential for targeted campaigns and interventions. I expect that usual travel mode can be used to identify groups with lower or higher intentions to walk/cycle more and that people’s usual travel mode also represents a potential way to reach them with tailored information (e.g., posters at parking lots or on subway stations with mode-specific messages). Recruiting participants based on past behavior and sociodemographic information might be more feasible than recruiting based on psychological constructs, as the former is more easily available information. I will therefore explore whether sociodemographic characteristics can predict intentions to walk/cycle more.

**Overcoming the gap.** Knowing that intentions don’t always lead to a corresponding change in behavior, and aiming to bridge the intention-behavior gap, implies that there are at least two different phases of behavior change. Heckhausen and Gollwitzer (1987) tested a distinction between two different states of mind and found that participants’ thought content varied depending on whether participants were contemplating which goal to pursue or whether they already had an established goal. In the motivational state, the individual deliberates which goal to pursue and what the outcomes would be, while in the volitional state such questions are disregarded in favor of how to implement the behavior and follow-through on the decision (Heckhausen & Gollwitzer, 1987). Several theories encompass at least this distinction between two stages, though the number of stages varies with the theory (e.g., Rubicon Model of Action Phases, Stages of Change model and the Health Action Process Approach).

The Health Action Process Approach (HAPA) is not strictly a stage model, but can be used that way when planning interventions (Schwarzer & Luszczynska, 2008). Basing an intervention on (at least) two separate stages of behavior change makes it possible to target the intervention to people with different needs. As an example, people in the motivational phase (pre-intenders) would benefit from a change in their outcome expectancies and risk perception, while people with intentions have moved beyond this and should instead benefit from interventions that help them plan how to translate their intentions into actions.

Matching interventions to the stage people are in should therefore improve the effectiveness of interventions. Bamberg (2013) compared a stage-matched dialog with a standardized information packet and found that the stage-matched dialog resulted in car use reduction while the information packet did not. Similarly, Lippke, Schwarzer, Ziegelmann, Scholz, and Schüz (2010) tested a volitional intervention that either matched (inclined abstainers) or did not match (non-intenders) the stage of the participants and found that the
stage-matched intervention moved significantly more participants forward a stage than what the mismatched intervention did.

Translating intentions into action requires several self-regulatory strategies and the volitional phase includes several factors that are important for self-regulation, such as action control, volitional self-efficacy, planning and social support (Schwarzer & Luszczynska, 2008). The planning intervention that participants were recruited to in this thesis uses implementation intentions. Implementation intentions are plans that specify ahead of time how a person will act in a given situation, thus inducing automatic control and circumvent the negative effects of habits or competing goal intentions (Gollwitzer, 1993). Implementation intentions are meant to help people act on their existing goal intentions and were used in the present intervention as the target participants were inclined abstainers.

**Willingness to Participate**

Interventions using implementation intentions have been found to have medium-to-large effects on behavior in general (Gollwitzer & Sheeran, 2006) and small-to-medium effects on physical activity specifically (Bélanger-Gravel, Godin, & Amireault, 2013). As web-based interventions can reach very large segments of the population, small-to-medium effects on walking/cycling behavior can have a substantial impact on climate issues and public health.

The effectiveness of all interventions depends on the participation rate in the population and the participation rate is generally low (Petter, Reitsma-van Rooijen, Korevaar, & Nielen, 2015). Depending on who doesn’t participate, this has implications not only for the impact of the intervention (small-to-medium effects on 1/5 of the population is far less than on 4/5) but also for the external validity of the results (Robroek, van Lenthe, van Empelen, & Burdorf, 2009). If some segments of the population are hard to reach and rarely interested in participating, we cannot say that the intervention would be equally effective for these groups or even that we would be able to recruit them at all. Lack of knowledge about participation rates also makes it unclear whether the people who would most benefit from the intervention (e.g., inactive people in a physical activity intervention) are less likely to participate than groups who would benefit little (You et al., 2011). This makes it important to look at the sociodemographic characteristics and prior behavior of both participants and those who decline. Such findings can be used in further research to discover why certain groups are less likely to participate and if interventions can be targeted to their needs, as well as guide researchers when designing interventions.
Despite the importance of the subject, few studies investigate willingness to participate and most of those that do are centered on limited populations, such as workplace health promotion programs (Röttger et al., 2017; You et al., 2011), patient groups (van Gils et al., 2011), or members of a consumer panel (Petter et al., 2015). Across different studies, participation rates in interventions are usually low. A study on lower socioeconomic status adults in Singapore found that of the 50% who responded to the survey, approximately 36% were willing to participate in at least one health promotion program (Ng et al., 2012).

Participation rates vary for workplace health promotion (WHP) programs, but are generally below 50% (Robroek et al., 2009; You et al., 2011). The variables examined vary with the subject of the intervention, ranging from the importance of health concern (Petter et al., 2015) to gender differences, with women generally being more likely to participating in WHPs (Robroek et al., 2009; You et al., 2011). This gender difference in WHP participation disappeared for the sub-category “fitness center studies”, indicating that men might be more sensitive to the content of the program (Robroek et al., 2009). While You et al. (2011) found that participants were generally inactive, Ng et al. (2012) found that respondents who did not exercise were less willing to participate than people who exercised regularly. These studies are based on widely different samples (Southwest Virginia and Singapore, respectively) and they also differ in that the former was a WHP while the latter would be conducted in low SES respondents’ leisure time and one of the most common reasons given for not participating was “not enough time” (Ng et al., 2012).

To my knowledge, no studies have been conducted on willingness to participate in interventions that specifically focus on walking or cycling. My hypotheses are therefore based on past behavior and known barriers to walking and cycling, and I will also conduct exploratory analyses to see whether general sociodemographic characteristics (e.g., gender and age) are associated with willingness to participate in web-based interventions to walk and cycle more.

**Attrition in Interventions**

Interventions often experience that participants are lost to attrition and this might introduce bias if the people lost differ systematically from those that completed the intervention (Dumville, Torgerson, & Hewitt, 2006). A systematic review of behavioral interventions to increase active mobility found that of the 13 unique studies included, only four described sample attrition adequately (Arnott et al., 2014). Of two car use reduction studies, neither found any systematic difference between those who completed the intervention and those lost to attrition (Bamberg, 2013; Eriksson, Garvill, & Nordlund, 2008),
indicating that attrition bias might not be an issue in car reduction interventions, though more studies should examine this. Systematic differences have been found, however, in interventions targeting exercise behavior, with drop-out rates ranging from 22 to 76% within the first year of exercise programs (Schmidt, Gruman, King, & Wolfson, 2000). Participants lost to attrition have been found to differ from retained participants by having greater disease burden, lower endurance and physical function (Schmidt et al., 2000), being from areas of lower socioeconomic status, having higher loneliness scores and being overweight (Jancey et al., 2007) as well as being less physically active (Arikawa et al., 2012; Jancey et al., 2007).

A suggested guideline for troublesome attrition states that attrition of less than 5% is usually unproblematic and a loss of 20% or more should invoke concerns of possible bias (Dumville et al., 2006). Eysenbach (2005) argues that though many eHealth trials experience substantial attrition this might reflect not a failure of the intervention, but rather a natural and typical feature of web-based interventions, particularly those with self-help applications. Instead of rejecting the trial or glossing over attrition, one should analyze and discuss determinants of attrition and highlight challenges with real-life adoption (Eysenbach, 2005). Identifying important characteristics associated with attrition will make it possible for future interventions to include countermeasures designed to keep these participants, thereby improving the reach and effectiveness of the programs. There’s little research into what predicts attrition in walking/cycling interventions specifically, and I will conduct exploratory analyses to address this lack of knowledge.

Aims of the Thesis

Much of the research done on willingness to participate has been done on either workplaces or patient groups, as these are settings where much information is available on those who say no. This thesis examines participation rates in a broader, and more varied, segment of the population. As participation rates (both total and for sub-groups of the population) have strong implications on both the generalizability and the effectiveness of such interventions it is important to examine what characterizes those who say yes to an intervention and those who complete it. In addition, identifying groups that differ in their intentions to walk/cycle more represents a way to conveniently reach groups with targeted information.

My hypotheses were pre-registered at aspredicted.org at an early stage of the process and as I’ve gained more understanding of both the topic and research methods I have deviated from the pre-registration. The full pre-registration with explained deviations can be viewed in
Appendix A. The following research questions, with pre-registered hypotheses indented beneath associated research questions, will be examined in this thesis:

1. What predicts intentions to walk and cycle more?
   a. People who commute by walking will have lower intentions to walk more, and people who commute by cycling lower intentions to cycle more, than people who don’t commute by the mode specified in the intention measure
   b. People who mainly travel by car or motorcycle will have lower intentions to walk/cycle more than people who commute by public transportation

2. What predicts willingness to participate in an online intervention to walk and cycle more?
   a. People with higher intentions to walk and cycle more will be more likely to participate
   b. More children in the household will predict less likelihood of participating
   c. Distance between home and work/school will be negatively associated with likelihood of participating
   d. People who mainly commute by car or motorcycle will be less likely to participate than people commuting by other modes

3. Participants in the intervention were asked to choose what active mode they wanted to focus on (walking or cycling) and whether to do so as transportation or leisure (choice of purpose) and I will explore which background variables can predict these choices.
   a. Participants with children who choose to participate in the intervention will to a greater degree choose to walk/cycle as a leisure activity rather than as transportation.

4. What predicts completion of the intervention?
   a. There are no pre-registered hypotheses for this topic, but I will explore whether physical activity and sociodemographic characteristics can predict who completed the intervention

In addition to the specified hypotheses I will explore whether past behavior and sociodemographic characteristics contribute to explain variances in the dependent variables. Such knowledge is an important addition to knowledge of the effectiveness of volitional interventions, as it can indicate which population groups are more susceptible to participate in interventions to increase their walking or cycling, as well as which groups are promising targets for future interventions.
Method

The data used in this thesis was collected in a large survey used for recruiting participants to three different projects. The design of the recruitment survey made it so that even people who declined to participate in any projects had already answered many questions related to sociodemographic characteristics and travel behavior.

The recruitment survey was shared between several projects in a larger project called “Push & Show” at the Institute of Transport Economics (TØI), funded by the Research Council of Norway. One of these projects was an internet-delivered planning intervention to help people walk and cycle more over the next month. Both the intervention and the recruitment survey were created during the spring and summer of 2018 and I contributed to the creation of the intervention through an internship in one of my courses. It was later decided that I would not evaluate the effectiveness of the intervention and instead utilize the design of the recruitment survey to predict willingness to participate in the intervention. I participated in a couple meetings discussing the questions to be included, but the survey was designed by researchers at TØI.

Recruitment

Respondents were first and foremost recruited through the Norwegian Automobile Federation (NAF) who agreed to send an e-mail invitation to 40 000 of their members. In addition, the recruitment survey was shared on Facebook, TØIs own website, sent to previous survey respondents who had agreed to be contacted in the future and (with a link that promoted another part of the project) to students at the University of Oslo and published in an online newspaper. The survey invitation included mention of a 5000 NOK gift card participants could win if they completed the survey and supplied their e-mail. Recruitment via social media makes it impossible to say how many had the opportunity to respond to the first survey and to calculate an initial response rate, but of the 40 000 who received an e-mail from NAF, 2288 (5.72%) completed the first survey, though many of these e-mails might have gone straight to people’s promotion or trash folders. The recruitment texts sent to NAF-members and shared on social media are shown in Appendix B. E-mails were sent on August 21, 2018, with social media sharing the following days.

Recruitment survey design. The first survey contained three parts that are relevant for my thesis. The first part was shared for all participants and included sociodemographic information (gender, age, income, place of residence, job status) and travel information (access to different modes, distance and time of work commute, etc.). This section also included questions of intentions to walk and cycle more and if respondents gave a score
higher than 1 (completely disagree) on either of these, they qualified for the planning intervention. Depending on different requirements, participants could qualify for none or all the three different projects. Each respondent could only participate in one project, so if they qualified for more than one project they were asked about each project in a randomized order until they said yes or ran out of projects they qualified for.

Respondents who said yes to the planning intervention and one other project were then redirected to a detailed travel diary of the last day, as well as questions about walking, cycling and other physical activity during the previous seven days. After this, participants who said yes to the planning intervention were redirected to an intervention specific part of the survey. This section asked them to choose between walking or cycling as the intervention focus and then whether they wanted to walk or cycle in their leisure time or as a way to replace trips by other travel modes. The design of the intervention, with different sections and filtered depending on previous answers, is the main reason number of cases differs for different variables.

**Operationalization**

As the recruitment survey was shared among three different projects it was quite long and contained many variables which are not used in this thesis and therefore not described. Respondent fatigue was also a concern and researchers from each project had to minimize the number of questions to be included. Some questions were filtered depending on previous responses to ensure that respondents weren’t exposed to irrelevant questions. Appendix C shows the survey questions used in this thesis.

**Intentions.** Intentions to walk and cycle more were measured with two items each. The items were worded as «I want to walk more the next month than I currently do» (Jeg har lyst til å gå mer den neste måneden enn jeg gjør nå) and «I want to walk more the next month than I did same time last year» (Jeg har lyst til å gå mer den neste måneden enn jeg gjorde på samme tid i fjor), and the same with cycling instead of walking. We chose the wording “jeg har lyst” as this was considered to be the most natural translation of “I intend” and the wording “I want” has previously been used in intention items (e.g Donald et al., 2014; Elliott & Armitage, 2009; Verhoeven, Adriaanse, de Vet, Fennis, & de Ridder, 2014). The intention measures included “more” as a qualifier as we wanted to capture not their intention to walk and cycle period, but their intention to do more of it. The aim was to identify inclined abstainers. Two items were considered enough as we believed that other nuances would not increase validity enough to compensate for the increased burden on participants. As the scales consisted of only two items, Spearman-Brown was used to calculate reliability rather than
Cronbach’s alpha, as the former has been shown to be less biased for two-item scales (Eisinga, Grotenhuis, & Pelzer, 2013). Internal consistency was quite high for both intentions to cycle more (Spearman-Brown = .925) and intentions to walk more (Spearman-Brown = .946), and an average was computed for each and used in analyses.

**Willingness to participate.** Willingness to participate was measured by whether respondents said “yes” or “no” when they were invited to participate. The description of the planning intervention was the following (translated from Norwegian):

Some of the people who respond to this survey will be offered the opportunity to use a short, research-based planning tool to help you walk or cycle more in your daily life. The tool is web-based and you can choose whether you want to focus on cycling or walking. Is this something you would want to participate in?

This general and sparse description meant that participants didn’t have the opportunity to evaluate the content or comprehensiveness of the project before indicating their interest. It might therefore be possible to generalize the results to other web-based interventions.

**Completion of the intervention.** The recruitment survey was the first contact point with participants (T0) and those who said yes to participate (N = 1092) completed an additional part of the survey specific to the intervention. Three weeks later, participants were sent either the intervention (test group) or information about the benefits of cycling and walking (control group) and both groups reported behavior the past week. The first follow-up (T2) was sent out three weeks after the intervention and the second follow-up (T3) a few weeks after that, after the fall break in October 2018. Completion of the intervention was defined as participants who responded at T1 (intervention or control) and at either one or both follow-ups (T2/T3).

**Job status.** Respondents were asked about their daily activities and based on their answer coded as “working”, “student” or “other”. The other category included everything from being retired, on disability, jobhunting or simply not wanting to answer. Only students and those working were asked about their usual travel mode and their distance between home and work/school, as people categorized as other were assumed to not have a regular commute.

**Travel behavior.** The recruitment survey was primarily designed with closed-ended questions. These are easier to analyze and made it impossible for respondents to complete the survey with many missing values, but they restrict responses to the provided alternatives. This also meant that distance was measured as a categorical variable despite being continuous.
The question was: “Approximately how long is the route you usually choose from home to work/school?” and the response alternatives were: Less than 3km, 3-5km, 5-7km, 7-10km, 10-15km, 15-20km and more than 20km. As distance is continuous by nature, but was reported categorically, I tested some analyses with distance first as continuous and then as categorical. There were no substantial differences in results and distance was therefore used continuously to ease interpretability.

Participants were also asked what travel mode they usually use for commuting to work/school “this time of year” (August/September). The response alternatives were car, motorcycle/moped, bicycle, electric bike, walking, public transportation, work from home and “other”, which was open-ended. Those who chose other were coded as missing and removed from analyses as they did not belong in a clear category. The “work from home” group could potentially be an interesting comparison to the others, as they don’t have a work commute, but due to few cases (n = 29) this group was not included in analyses. Bicycle and e-bike were combined as one mode as they were assumed to be similar and the same was done for car and motorcycle/moped as the essential difference was considered to be whether people used a “personalized motorized vehicle” and the motorcycle/moped group was quite small compared to the other groups (n = 76).

**Physical activity.** Responders were asked about their walking, cycling and other moderate or vigorous physical activity last week. In all cases they were asked which days they conducted at least 10 minutes of the specified activity. For walking they were asked about how many trips of at least 10 minutes per day, as well as total minutes per day on average. For cycling and physical activity (moderate and vigorous) they were asked about total minutes per week. These questions were based on the short form of IPAQ, but cycling was separate instead of included with general physical activity. Due to filtering in the survey, not all respondents were asked about their physical activity last week (n= 3260). To combine the different forms on physical activity I calculated metabolic equivalent (MET) minutes by multiplying the minutes given with the estimated MET for each category. Based on previous MET estimations used for IPAQ scoring (Patterson, 2010) I multiplied each walking minute with 3.3, each cycling minute with 6 and each minute moderate and vigorous physical activity with 4 and 8, respectively.

The variable was then grouped based on MET minutes per week, with an “inactive” group (n = 796) being those who do not fulfill the Norwegian health directorate’s recommendation of 150 minutes of moderate or 75 minutes of vigorous activity (= 600 MET minutes) per week, a “highly active” (n = 458) group from 3000 MET minutes per week
(similar to IPAQ recommendations, but only concerning total minutes, not number of days) and a “moderately active” group \((n = 2006)\) in-between. Some people had first answered that they had walked/cycled/done physical activity on some days, filled in minutes, and then gone back and changed their original answer to “on none of these days”. In those cases, the minute-value they had were changed to zero, as I assumed that their last response was the correct one. Beyond that, values were checked to see if they were impossible (e.g., someone saying they walked 24 hours a day) and since none were, no further changes were made.

### Statistical Procedures

All analyses were conducted using IBM SPSS Statistics version 24, with all tests being two-tailed and a pre-determined alpha level of .05. For linear regressions, effect sizes are reported with \(r\) for continuous variables and Cohen’s \(d\) for categorical variables.

**Inclusion criteria.** To be included in the analyses, respondents had to complete the recruitment survey and give their e-mail address. Respondents gave their email for a chance to win a gift certificate of 5000 Norwegian kroner and this cut-off means that some people who were genuine respondents might have been excluded because they didn’t want to give their email address for a chance to win. However, including respondents without email addresses ran the risk of including duplicate responders or someone testing the survey. As the sample was quite large either way, I preferred to be conservative with the cut-off, resulting in a total sample of 4814.

**Assumptions for analyses.** The analyses were conducted using multiple linear regressions (when predicting intentions) and logistic regression (for willingness to participate, completion of the intervention and choice between walking/cycling and leisure/transport), in addition to one Chi-square test of independence. For the logistic regressions I tested for multicollinearity and linearity of log odds, with no issues, and assumptions were met for the chi-square test of independence. There was a little more uncertainty regarding normal residuals and homogeneity of variance for the linear regressions. Inspection of normal probability plots of standardized residuals showed that there was some curvature in the residuals, but they adhered quite close to the line. In addition, the samples are quite large and normality therefore not so much of an issue due to the central limit theorem (Field, 2018). Due to the dichotomous nature of the independent variables a scatterplot wasn’t helpful in determining homogeneity of variance. While Levene’s test provides a statistical test of homogeneity of variance, it (like all other statistical tests) tends to become significant for small effects when the sample size is large. Instead, I calculated the variance ratio and the largest variance ratio was 1.49 (for working from home compared to bicycle/e-bike), while
most were below 1.2. Field calls a variance ratio of 1.2 very small and uses it as an example of why not to use significance tests of homoscedasticity in large samples (Field, 2018).

Tabachnick and Fidell (2018) point out that if group sizes are roughly equal (within a ratio of 4 to 1) an Fmax as great as 10 is acceptable, and that as the discrepancy between group sizes increases an Fmax as small as 3 can be troublesome. The largest group size ratio is 4.45 (between those who cycle and those who walk) and all other group size ratios are below 2. As there was some uncertainty related to normal residuals and heteroscedasticity, I chose to conduct the linear regressions with bias corrected accelerated bootstrapping enabled since bootstrapping is not as sensitive to issues of normality and heterogeneity of variance (Field, 2018). Mersenne twister seed was set to 2.000.000 to enable replication of the bootstrap results.

**Procedure for exploratory analyses.** As a rule, exploratory analyses were conducted on an arbitrary half of the sample. This half was determined by using SPSS’s “random sample of cases” and “approximately 50% of all cases” function which created a filter variable that was used consistently. All variables were first tested solo and significant (p < .05) predictors were then combined in models that were also tested on half of the sample. Only the variables that were still significant when combined were included in a model that was tested on the full sample. This was done to reduce the likelihood of Type 1 errors while exploring the data. An overview of all exploratory analyses is shown in Appendix E. For the sake of brevity, only the complete models, with variables that were significant predictors when combined with other predictors on the full sample, are reported in the results. It therefore varies which sociodemographic variables are included.

**Power and sample size.** To determine the necessary sample sizes for discovering small effects, I conducted power-analyses using G*Power version 3.1 with two-tailed test, .05 alpha level and .8 power as the basis for all calculations. For multiple linear regressions I would need a sample size of at least 343 to detect a small effect and as the smallest group (“walking”) contained 255 cases this was not an issue for the linear regressions. Logistic regression power calculations require more information about expected probabilities than I had available and I therefore used G*Power to construct graphs of sample size requirements for odds ratios of different magnitudes. These are shown in Appendix D. The sample used to analyze willingness to participate is large enough (N = 2842) to have sufficient power to discover quite small effects, also when splitting the sample in half for exploratory analyses.

Based on previous attrition analyses (e.g., Eriksson et al., 2008; Jancey et al., 2007) I expected small, if any, effects when predicting completion of the intervention. As this sample
was limited to those who said yes to participate \((N = 1092)\) I decided to use the full sample when exploring. By exploring on the full sample, I deviated from the procedure for exploratory analyses described above and increased the risk of Type 1 errors. I therefore applied a Bonferroni correction according to the number of analyses conducted \((.05/14 = .004)\) and used the adjusted alpha level when evaluating the results. Predicting the choices between walking/cycling and leisure/transport was based on the same sample, but in these cases I judged it to be more important to reduce the likelihood of Type 1 errors. With many exploratory analyses conducted, using half the sample \((n = 546)\) made it more likely that only practically meaningful effects, i.e. medium-large effect sizes, would be statistically significant.

**Results**

**Description of Sample**

The research questions and hypotheses are based on different parts of the recruitment survey, meaning that the available sample changes with the dependent variable. In addition, in-survey filters were used for some questions, further reducing the sample when those variables are included. An overview of important variables for each cut-off point in the survey is shown in Table 1.

Table 1

*Means and Frequencies of Variables at Different Parts of the Survey*
<table>
<thead>
<tr>
<th>Variables</th>
<th>Recruitment survey ((N = 4814))</th>
<th>Invited to participate ((N = 3419))</th>
<th>Yes to participate ((N = 1092))</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intentions to walk</strong></td>
<td>(4.2 \pm 1.9)</td>
<td>(4.6 \pm 1.7)</td>
<td>(4.9 \pm 1.7)</td>
</tr>
<tr>
<td><strong>Intentions to cycle</strong></td>
<td>(3.8 \pm 2.1)</td>
<td>(3.8 \pm 2)</td>
<td>(4.4 \pm 2)</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>(47 \pm 13)</td>
<td>(49 \pm 13)</td>
<td>(47 \pm 13)</td>
</tr>
<tr>
<td><strong>Gender (men)</strong></td>
<td>57</td>
<td>57.1</td>
<td>50.8</td>
</tr>
<tr>
<td><strong>Have children</strong></td>
<td>42.5</td>
<td>40.2</td>
<td>44.4</td>
</tr>
<tr>
<td><strong>Job status</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>11.8</td>
<td>14.4</td>
<td>13.6</td>
</tr>
<tr>
<td>Student</td>
<td>4.5</td>
<td>3</td>
<td>4.1</td>
</tr>
<tr>
<td>Employed</td>
<td>83.7</td>
<td>82.7</td>
<td>82.3</td>
</tr>
<tr>
<td><strong>Physical activity</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>((n = 3260))</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inactive</td>
<td>24.4</td>
<td>27.5</td>
<td>23.5</td>
</tr>
<tr>
<td>Moderate</td>
<td>61.5</td>
<td>60.2</td>
<td>61.2</td>
</tr>
<tr>
<td>High</td>
<td>14</td>
<td>12.3</td>
<td>15.3</td>
</tr>
<tr>
<td><strong>Usual travel mode</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>((n = 4195))</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car</td>
<td>27.2</td>
<td>31</td>
<td>22.3</td>
</tr>
<tr>
<td>Mc</td>
<td>1.8</td>
<td>1.9</td>
<td>1.2</td>
</tr>
<tr>
<td>E-bike/bike</td>
<td>41.4</td>
<td>28.3</td>
<td>40.8</td>
</tr>
<tr>
<td>Walking</td>
<td>9.3</td>
<td>10.4</td>
<td>11.6</td>
</tr>
<tr>
<td>Public Transportation</td>
<td>19.6</td>
<td>21.3</td>
<td>23.8</td>
</tr>
<tr>
<td>Work from home</td>
<td>0.7</td>
<td>0.8</td>
<td>0.4</td>
</tr>
<tr>
<td><strong>Achieved education</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle school</td>
<td>2.5</td>
<td>2.7</td>
<td>2.7</td>
</tr>
<tr>
<td>High school</td>
<td>17.5</td>
<td>17.8</td>
<td>15.8</td>
</tr>
<tr>
<td>Lower degree</td>
<td>36.5</td>
<td>38.3</td>
<td>40.4</td>
</tr>
<tr>
<td>Higher degree</td>
<td>43.5</td>
<td>41.2</td>
<td>41.4</td>
</tr>
<tr>
<td><strong>Yearly income</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than 299k</td>
<td>8.4</td>
<td>7.2</td>
<td>9.1</td>
</tr>
<tr>
<td>300-499k</td>
<td>22.1</td>
<td>23.4</td>
<td>25.1</td>
</tr>
<tr>
<td>500-699k</td>
<td>34.8</td>
<td>33.6</td>
<td>34.1</td>
</tr>
<tr>
<td>700-899k</td>
<td>16.8</td>
<td>17.2</td>
<td>16.6</td>
</tr>
<tr>
<td>More than 900k</td>
<td>13.8</td>
<td>14</td>
<td>10.5</td>
</tr>
<tr>
<td>Won't say</td>
<td>4.1</td>
<td>4.6</td>
<td>4.7</td>
</tr>
<tr>
<td><strong>Distance</strong></td>
<td>((n = 4202))</td>
<td>((n = 2897))</td>
<td>((n = 932))</td>
</tr>
<tr>
<td>Less than 3km</td>
<td>18.1</td>
<td>18.5</td>
<td>19.7</td>
</tr>
<tr>
<td>3-5km</td>
<td>20.4</td>
<td>19.1</td>
<td>19.5</td>
</tr>
<tr>
<td>5-7km</td>
<td>13.6</td>
<td>12.5</td>
<td>11.1</td>
</tr>
<tr>
<td>7-10km</td>
<td>16.6</td>
<td>16.8</td>
<td>17.6</td>
</tr>
<tr>
<td>10-15km</td>
<td>15.6</td>
<td>15.7</td>
<td>14.5</td>
</tr>
<tr>
<td>15-20km</td>
<td>7.6</td>
<td>8.2</td>
<td>7</td>
</tr>
<tr>
<td>More than 20km</td>
<td>7.9</td>
<td>9.2</td>
<td>10.6</td>
</tr>
</tbody>
</table>

*Note.* Values are expressed as mean ± SD for continuous variables and % frequency for categorical variables. Due to in-survey filtering some variables (physical activity, usual travel
mode, distance) have consistently fewer cases than the full sample, correct n is given in parentheses.

**Intentions to Walk and Cycle More**

**Active commuters versus all other modes.** I hypothesized that people who already travel by active transportation would have lower intentions to increase their walking/cycling compared to people commuting by other modes. I conducted multiple regressions with dummy variables for all travel modes, with the intention-congruent mode as the baseline (walking as baseline for intention to walk and bicycle/e-bike as baseline for intention to cycle). Results from multiple linear regressions testing this hypothesis are shown in Table 2 and Table 3.

**Table 2**

*Multiple Linear Regression Predicting Intentions to Walk for Walking Commuters Versus Other Modes*

<table>
<thead>
<tr>
<th>Item</th>
<th>B</th>
<th>95% Confidence interval</th>
<th>p</th>
<th>β</th>
<th>d</th>
<th>F</th>
<th>Adj. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.56</td>
<td>4.37 - 4.74</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car/mc</td>
<td>-0.34</td>
<td>-0.56 - 0.14</td>
<td>0.004</td>
<td>-.08</td>
<td>0.017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bicycle/e-bike</td>
<td>-0.74</td>
<td>-0.95 - 0.53</td>
<td>0.001</td>
<td>-.19</td>
<td>0.039</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public transport</td>
<td>0.11</td>
<td>-0.13 - 0.33</td>
<td>0.336</td>
<td>.02</td>
<td>0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>45.28***</td>
<td>.031</td>
</tr>
</tbody>
</table>

*Note.* Confidence intervals and p-values based on 1000 bias corrected and accelerated bootstrap samples. N = 4166. Dummy coded 0 and 1 with walking as reference. *** = p < .001.

**Table 3**

*Multiple Linear Regression Predicting Intentions to Cycle for Cycling Commuters Versus Other Modes*
<table>
<thead>
<tr>
<th>Item</th>
<th>B</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>p</th>
<th>β</th>
<th>d</th>
<th>F</th>
<th>Adj. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.23</td>
<td>4.14</td>
<td>4.33</td>
<td>.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car/mc</td>
<td>-0.91</td>
<td>-1.04</td>
<td>-0.77</td>
<td>.001</td>
<td>-.20</td>
<td>0.044</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Walking</td>
<td>-0.58</td>
<td>-0.83</td>
<td>-0.35</td>
<td>.001</td>
<td>-.08</td>
<td>0.029</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public transport</td>
<td>-0.18</td>
<td>-0.34</td>
<td>-0.02</td>
<td>.042</td>
<td>-.03</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
<td></td>
<td>50.10***</td>
<td>.034</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Confidence intervals and p-values based on 1000 bias corrected and accelerated bootstrap samples. N = 4166. Dummy coded 0 and 1 with bicycle/e-bike as reference. *** = p < .001.

Opposite of what expected, I found that people who already walk or cycle as their usual travel mode had higher intentions to increase their walking or cycling than most other travel mode groups. For intentions to walk more, those who usually commute by walking had higher intentions to walk more than all other groups, except for public transportation, which was non-significant. According to the power analysis conducted, the public transportation group was large enough (n = 823) that a genuine difference between groups should have been detected. For intentions to cycle, those who usually commute by e-bike or bicycle had higher intentions to cycle more than all other travel modes, though the effect size varied. The difference between cycling/e-bike commuters and public transport commuters is barely significant and with a beta of merely -.03, indicating that it contributed far less to the model than the difference between cyclists and car/mc commuters, which had a beta of .20.

**Predicting intentions from past behavior and sociodemographic characteristics.**

In addition to my hypothesis about car/mc commuters having lower intentions than people commuting by public transportation, I wanted to explore whether other factors could be used to predict intentions to walk and cycle more the coming month. Exploratory analyses were conducted according to the procedure described previously and only the variables that remained significant predictors of intentions to walk or cycle when combined into complete models are reported here. The exception is job status as the response to this question determined whether people were asked about their usual travel mode. Job status could therefore not be combined with usual travel mode, as listwise deletion of cases would have excluded everyone in the *other* group. Instead, job status was tested on the full sample (N = 4814) in simple linear regressions. I used *other* as the reference group as it was assumed that...
both people in the working and student categories had a regular commute that other did not, which might impact intentions. Compared to the other group, workers had significantly lower intentions to walk \((b = -.296, p = .001, d = 0.015)\) while there was no significant effect of being a student. Overall, job status was a statistically significant predictor of intentions to walk, but explained a minimal proportion of the explained variance in intentions to walk \(R^2 = .003, F(2, 4811) = 6.17, p = .002\). Job status explained more of the variance in intentions to cycle, \(R^2 = .013, F(2, 4811) = 31.96, p < .001\), with both working \((b = .483, p < .001, d = 0.23)\) and being a student \((b = 1.326, p < .001, d = 0.65)\) being significant predictors of higher intentions to cycle more compared to the other group.

The combined models for predicting intentions to walk and intentions to cycle can be found in Table 4 and Table 5, respectively.

### Table 4

**Multiple Linear Regression Analysis of Intentions to Walk with all Significant Predictors**

<table>
<thead>
<tr>
<th>Item</th>
<th>B</th>
<th>95% Confidence interval</th>
<th>p</th>
<th>β</th>
<th>d</th>
<th>F</th>
<th>Adj. (R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
<td>4.49</td>
<td>4.36 to 4.62</td>
<td>.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Usual modea</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bicycle/e-bike</td>
<td>-0.44</td>
<td>-0.58 to -0.29</td>
<td>.001</td>
<td>-.11</td>
<td>0.021</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Walking</td>
<td>0.25</td>
<td>0.03 to 0.48</td>
<td>.022</td>
<td>.08</td>
<td>0.017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public transport</td>
<td>0.37</td>
<td>0.21 to 0.54</td>
<td>.001</td>
<td>.08</td>
<td>0.024</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Genderb</td>
<td>-0.42</td>
<td>-0.54 to -0.30</td>
<td>.001</td>
<td>-.11</td>
<td>0.024</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>46.48***</td>
<td>.042</td>
</tr>
</tbody>
</table>

**Note.** Confidence intervals and p-values are based on 1000 bias corrected and accelerated bootstrap samples. \(N = 4166\). a dummy coded 0 and 1 with car/mc as reference; b women = 0, men = 1. *** \(p < .001\).

As hypothesized, car/mc commuters had lower intentions to walk more than public transport users. Though the magnitude of the effect is trivial (Cohen’s \(d = 0.024\)), it is the largest in this model along with gender. Gender was the only variable that predicted intentions to walk beyond usual travel mode, with women scoring almost half a point higher on the intentions to walk more scale.

### Table 5
Multiple Linear Regression Analysis of Intentions to Cycle with all Significant Predictors

<table>
<thead>
<tr>
<th>Item</th>
<th>B</th>
<th>95% Confidence interval</th>
<th>p</th>
<th>β</th>
<th>d/r</th>
<th>F</th>
<th>Adj. R²</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Lower bound</td>
<td>Upper bound</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>constant</td>
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<td>4.39</td>
<td>5.12</td>
<td>.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Usual travel mode a</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bicycle/e-bike</td>
<td>0.71</td>
<td>0.50</td>
<td>0.91</td>
<td>.001</td>
<td>.17</td>
<td>0.051</td>
<td></td>
</tr>
<tr>
<td>Walking</td>
<td>0.16</td>
<td>-0.14</td>
<td>0.46</td>
<td>.306</td>
<td>.02</td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td>Public   t</td>
<td>0.51</td>
<td>0.28</td>
<td>0.76</td>
<td>.001</td>
<td>.10</td>
<td>0.033</td>
<td></td>
</tr>
<tr>
<td>Children (nr.)</td>
<td>0.13</td>
<td>0.05</td>
<td>0.20</td>
<td>.002</td>
<td>.07</td>
<td>0.091</td>
<td></td>
</tr>
<tr>
<td>Age (years)</td>
<td>-0.04</td>
<td>-0.04</td>
<td>-0.03</td>
<td>.001</td>
<td>-.21</td>
<td>-.243</td>
<td></td>
</tr>
<tr>
<td>Physical activity b</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate</td>
<td>0.41</td>
<td>0.22</td>
<td>0.62</td>
<td>.001</td>
<td>.10</td>
<td>0.029</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>0.45</td>
<td>0.17</td>
<td>0.73</td>
<td>.001</td>
<td>.07</td>
<td>0.035</td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>43.60</td>
<td>.096</td>
</tr>
</tbody>
</table>

Note. Confidence intervals and p-values are based on 1000 bias corrected and accelerated bootstrap samples. N =2810. a usual travel mode dummy coded 0 and 1 with car/mc as reference group, b inactive is reference group. *** p < .001.

As hypothesized, public transportation commuters had higher intentions to cycle more than car/motorcycle commuters and the magnitude was slightly larger than the difference in intentions to walk, though the samples were not the same (due to filtering of the physical activity variable) and therefore cannot be directly compared. There was no significant difference between car/motorcycle commuters and walking commuters on their intentions to cycle more. Several explored variables were predictive of intentions to cycle more, with number of children under 18 being positively associated with intentions to cycle and both moderately and highly active people having higher intentions to cycle more than inactive people. Increased age was associated with lower intentions to cycle. While the coefficient for each unit change is quite small, age ranged from 21 to 89 and had the largest standardized coefficient, indicating that it was the variable that contributed most to the model.

**Willingness to Participate**

I hypothesized that intentions to walk and cycle more, usual travel mode, distance from home to work/school and number of children in the household would predict willingness to participate in the web-based intervention to walk/cycle more the next month. In addition to the pre-registered hypotheses, I explored whether other variables could predict willingness to
participate. Following the procedure for exploratory analyses gender was the only explored variable added to the complete model and tested on the full sample. The full overview of explored predictors is shown in Appendix E.

**Full model.** Keeping with the principle of parsimony, the variables were entered hierarchically to ensure that all included variables improved the model significantly. The hierarchical method was preferred over a stepwise method as the former leaves the decision-making with the researcher (Field, 2018). Order of entry was decided by what I expected to have the greatest effect. Intentions to walk/cycle more were added in the first block, trip characteristics (usual mode and distance) were added in the second block, sociodemographic variables (number of children and gender) in the third block and finally interaction terms, separated into blocks in the same order. Of the interaction terms, only the interaction intentions to walk and usual travel mode produced a significant effect and contributed to an improved model. While all other interaction terms were added and tested in the same manner, they are not shown in Table 6 as they demand much space and contribute little information.

Table 6

*Hierarchical Logistic Regression Predicting Willingness to Participate in Intervention*
<table>
<thead>
<tr>
<th>Item</th>
<th>Step 1</th>
<th>Step 2</th>
<th>Step 3</th>
<th>Step 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.43</td>
<td>0.22</td>
<td>0.24</td>
<td>0.25</td>
</tr>
<tr>
<td>Int walk</td>
<td>1.15 [1.10, 1.20] ***</td>
<td>1.17 [1.11, 1.23] ***</td>
<td>1.16 [1.1, 1.22] ***</td>
<td>1.12 [1.02, 1.22] *</td>
</tr>
<tr>
<td>Usual mode</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E-bike/bike</td>
<td>2.17 [1.74, 2.72] ***</td>
<td>2.07 [1.65, 2.60] ***</td>
<td>2.01 [1.60, 2.53] ***</td>
<td></td>
</tr>
<tr>
<td>Distance</td>
<td>1.08 [1.03, 1.14] **</td>
<td>1.08 [1.03, 1.14] **</td>
<td>1.08 [1.03, 1.14] **</td>
<td></td>
</tr>
<tr>
<td>Children (nr.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender^a</td>
<td>1.11 [1.03, 1.20] *</td>
<td>1.11 [1.03, 1.20] *</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Usual mode * int walk</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E-bike/bike * int walk</td>
<td></td>
<td></td>
<td></td>
<td>0.98 [0.87, 1.10]</td>
</tr>
<tr>
<td>Walking * int walk</td>
<td></td>
<td></td>
<td></td>
<td>1.14 [0.95, 1.35]</td>
</tr>
<tr>
<td>Public T * int walk</td>
<td></td>
<td></td>
<td></td>
<td>1.19 [1.03, 1.37] *</td>
</tr>
<tr>
<td>Cox &amp; Snell R^2</td>
<td>.045</td>
<td>.063</td>
<td>.070</td>
<td>.073</td>
</tr>
<tr>
<td>Nagelkerke R^2</td>
<td>.063</td>
<td>.088</td>
<td>.098</td>
<td>.102</td>
</tr>
<tr>
<td>Δ X^2</td>
<td>131.79</td>
<td>52.88</td>
<td>21.35</td>
<td>10.03</td>
</tr>
<tr>
<td>df 2</td>
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<tr>
<td>df 4</td>
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<tr>
<td>df 2</td>
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<tr>
<td>p&lt;.001</td>
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<td></td>
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<tr>
<td>p&lt;.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p=.018</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note.** Results are given as odds ratio [95% confidence interval]. N = 2842. Intentions to walk and cycle are centered around their means. Int = intentions. ^aDummy coded 0 and 1 with women as reference; ^bdummy coded 0 and 1 with car/motorcycle as reference. * = p<.05, ** p<.005, *** p<.001.

Each step shown in Table 6 was a significant improvement to the step before, indicated by the significant increases in X^2 value per step. As hypothesized, higher intentions were associated with increased odds of saying yes to participate in the intervention, both for...
intentions to walk and intentions to cycle. The reference group for usual travel mode was “car/motorcycle” and as predicted, all other travel modes had higher odds of saying yes to participate. Contrary to expectations, distance had a minimal effect (OR = 1.08 [1.03, 1.14]) and was positively associated with willingness to participate, instead of negatively. Inspections with sub-groups revealed that distance was positively related with willingness to participate for people who commuted by car or motorcycle, but not associated with other travel modes. Distance was not a significant predictor of willingness when tested without usual travel mode as a covariate. While number of children was a significant predictor of willingness to participate, the effect went in the opposite direction of what was hypothesized. With each added child in the household, the odds were 1.11(95% CI [1.03, 1.20]) times higher that the person said yes to participate, holding all other variables constant. Gender was also a significant predictor of willingness to participate, with men being less likely (OR = 0.72 [0.61, 0.85]) than women to say yes to the intervention. Of the interaction terms, only the interaction between commuting by public transportation and intentions to walk was significant (OR =1.19 [1.03, 1.37]). This interaction is shown with simple slopes in Figure 2, where low intentions and high intentions represent scores of “2” and “7”, respectively, on intentions to walk more.

Figure 1. Simple slopes for interaction between commuting by car/motorcycle or public transportation and low or high intentions to walk more.

The simple slopes show that while a 5 points difference in intentions to walk more had only a small impact on likelihood of participation for car/motorcycle commuters, such a
difference in intentions to walk more had a dramatic effect on public transport commuters’ likelihood of saying yes to the intervention.

**Physical activity and job status.**

Of the non-hypothesized variables, I was most interested in physical activity, as inactive people represent an important target for the intervention. Physical activity on its own was a significant predictor of willingness to participate (with highly active people being more likely to say yes than inactive people), but this effect became non-significant when it was combined with the pre-registered variable. Physical activity was therefore not tested on the full model. That this effect lost its statistical significance doesn’t mean that there is no difference in activity level for those that participated, but rather that the physical activity variable didn’t add explanatory value to the model. Even though there was no issue of multicollinearity between physical activity and usual travel mode, the share of inactive people varied greatly by travel mode.

![Bar chart of physical activity distribution by usual travel mode.](image)

*Figure 2. Bar chart of physical activity distribution by usual travel mode. N = 2810.*

As Figure 1 shows, cycling and walking commuters had the largest shares of highly active people, and smallest shares of inactive people, a distribution that makes sense as active commuters by definition are physically active. Walking/cycling commuters were more likely to participate than car/motorcycle commuters and this indicates that those who said yes to participate also tended to be more physically active.

Job status was also a significant predictor of willingness to participate but could not be combined in the full model due to the filtering of usual travel mode and distance. Job status was therefore tested in a simple logistic regression on the full sample (N = 3419) with *other* as
the reference group. There was no significant difference between other and those working, but students were significantly more likely to participate (OR = 1.862 95% CI [1.203, 2.883]) compared those in the other group.

**Choice of Active Mode and Choice of Purpose**

Once respondents said yes to participate, they were asked to choose whether they wanted to increase their walking or cycling (choice of active mode) and whether they wanted to be active in their leisure time or as a form of transportation (choice of purpose). For both choices, both alternatives were similarly popular. For choice of purpose, just below half (49%) chose to replace trips made by other travel modes, and for choice of active mode a little more than half (52%) chose cycling over of walking.

**Dependent choices.** As I wanted to explore predictors of the choice between walking or cycling and choice of purpose, I tested the correlation between these variables. I found a moderate-strong correlation with \( r(1091) = .40, p < .001 \) when walking was the reference for active mode choice and leisure the reference for purpose choice. This association is not surprising as cycling is a more effective mode of transportation, but I cannot be certain of the direction of this effect (e.g., if people who want to be active as transportation choose cycling because it is more efficient than walking, or if people who want to cycle choose transportation over leisure to a greater degree than people who want to walk do, as cycling has a greater potential for transportation). In the survey, participants were first asked to choose between walking or cycling and after that to choose leisure or transport, but it is likely they also considered the latter when deciding on the former.

I conducted logistic regressions with active mode choice and purpose choice as the dependent variables to explore whether past behavior and sociodemographic characteristics were associated with the alternative ways of participating in the intervention. As choice of active mode and choice of purpose had a moderate-strong association I included each of them as a predictor of the other when combining variables into models. While it might seem strange to use active mode choice and purpose choice as predictors of each other, this was done to confirm that other variables contributed predictive value beyond that explained by the relationship between choice of active mode and choice of purpose. The interpretative focus should therefore be on the explanatory effects of adding the other predictors to the models, i.e., step two of the models. An overview of all explored associations is showed in Appendix E while the complete models with significant predictors are shown in Table 7, for choice of active mode, and Table 8 for choice of purpose.
Table 7  
*Logistic Regression Predicting Choice of Walking or Cycling as Behavior to Increase*

<table>
<thead>
<tr>
<th>Predictors</th>
<th>B</th>
<th>SE(B)</th>
<th>Wald</th>
<th>df</th>
<th>P</th>
<th>Odds ratio</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Step 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.71</td>
<td>0.11</td>
<td>42.87</td>
<td>1</td>
<td>&lt; .001</td>
<td>0.49</td>
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<td></td>
</tr>
<tr>
<td>Purpose(^a)</td>
<td>1.69</td>
<td>0.16</td>
<td>118.66</td>
<td>1</td>
<td>&lt; .001</td>
<td>5.44</td>
<td>4.01</td>
<td>7.38</td>
</tr>
<tr>
<td>Cox &amp; Snell (R^2)</td>
<td>.15</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Nagelkerke (R^2)</td>
<td>.20</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(X^2)</td>
<td>129.59</td>
<td>df 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>p &lt; .001</td>
<td></td>
</tr>
<tr>
<td><strong>Step 2</strong></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-1.58</td>
<td>0.47</td>
<td>11.31</td>
<td>1</td>
<td>&lt; .001</td>
<td>0.21</td>
<td></td>
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</tr>
<tr>
<td>Purpose(^b)</td>
<td>1.95</td>
<td>0.19</td>
<td>109.57</td>
<td>1</td>
<td>&lt; .001</td>
<td>7.06</td>
<td>4.90</td>
<td>10.18</td>
</tr>
<tr>
<td>Usual mode(^b)</td>
<td></td>
<td></td>
<td>72.32</td>
<td>3</td>
<td>&lt; .001</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>E-bike/bike</td>
<td>1.40</td>
<td>0.24</td>
<td>34.44</td>
<td>1</td>
<td>&lt; .001</td>
<td>4.01</td>
<td>2.54</td>
<td>6.44</td>
</tr>
<tr>
<td>Walking</td>
<td>-0.82</td>
<td>0.33</td>
<td>6.14</td>
<td>1</td>
<td>.013</td>
<td>0.44</td>
<td>0.23</td>
<td>0.84</td>
</tr>
<tr>
<td>Public t</td>
<td>-0.03</td>
<td>0.25</td>
<td>0.01</td>
<td>1</td>
<td>.917</td>
<td>0.97</td>
<td>0.60</td>
<td>1.59</td>
</tr>
<tr>
<td>Gender(^c)</td>
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<td>0.18</td>
<td>38.93</td>
<td>1</td>
<td>&lt; .001</td>
<td>3.14</td>
<td>2.19</td>
<td>4.50</td>
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<td>Children(^d)</td>
<td>0.47</td>
<td>0.18</td>
<td>6.83</td>
<td>1</td>
<td>.009</td>
<td>1.60</td>
<td>1.13</td>
<td>2.27</td>
</tr>
<tr>
<td>Physical activity(^e)</td>
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<td></td>
<td>11.45</td>
<td>2</td>
<td>.003</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Moderate</td>
<td>0.27</td>
<td>0.31</td>
<td>1.40</td>
<td>1</td>
<td>.237</td>
<td>1.31</td>
<td>0.84</td>
<td>2.06</td>
</tr>
<tr>
<td>High</td>
<td>1.01</td>
<td>0.31</td>
<td>10.71</td>
<td>1</td>
<td>.001</td>
<td>2.75</td>
<td>1.50</td>
<td>5.03</td>
</tr>
<tr>
<td>Cox &amp; Snell (R^2)</td>
<td>.32</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nagelkerke (R^2)</td>
<td>.43</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(\Delta X^2)</td>
<td>174.19</td>
<td>df 8</td>
<td></td>
<td></td>
<td>p &lt; .001</td>
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</tr>
</tbody>
</table>

*Note.* \(N = 792.\) \(^a\) Leisure activity = 0, transportation = 1; \(^b\) dummy coded 0 and 1 with car/mc as reference; \(^c\) women = 0, men = 1; \(^d\) no children = 0, have children = 1; \(^e\) dummy coded 0 and 1 with inactive as reference.

Purpose choice was a strong predictor of active mode choice, as expected due to the moderate-strong correlation between these. However, several other variables were also associated with the choice of active mode and the explained variance equivalents more than
doubled when the second step was added. Usual travel mode was a significant predictor of choice of active mode, and this effect was caused by active commuters preferring their own modes (especially cycling commuters who had more than four times the odds of choosing to cycle over walking compared to car/motorcycle commuters). There was no significant difference in active mode choice between public transportation and car/mc commuters, indicating a similar preference for walking/cycling for these groups. Men had more than three times the odds of choosing cycling over walking compared to women (OR = 3.14 95% CI [2.19, 4.50]) and people with children were more likely (OR = 1.60 [1.13, 2.27]) to choose cycling compared to people without children. In addition, people who were highly active had more than twice the odds (OR = 2.75 [1.50, 5.03]) of choosing cycling over walking compared to inactive people.

Table 8
Logistic Regression Predicting Choice between Recreational and Transportation Purpose

<table>
<thead>
<tr>
<th>Predictors</th>
<th>B</th>
<th>SE(B)</th>
<th>Wald</th>
<th>df</th>
<th>P</th>
<th>Odds ratio</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.94</td>
<td>0.10</td>
<td>93.82</td>
<td>1</td>
<td>&lt; .001</td>
<td>0.39</td>
<td>4.19</td>
<td>7.03</td>
</tr>
<tr>
<td>Mode choicea</td>
<td>1.69</td>
<td>0.13</td>
<td>163.37</td>
<td>1</td>
<td>&lt; .001</td>
<td>5.43</td>
<td>4.19</td>
<td>7.03</td>
</tr>
<tr>
<td>Cox &amp; Snell R²</td>
<td>.15</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nagelkerke R²</td>
<td>.20</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>X² 178.50</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>df 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>p &lt; .001</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Step 2
<table>
<thead>
<tr>
<th>Predictors</th>
<th>B</th>
<th>SE(B)</th>
<th>Wald</th>
<th>df</th>
<th>P</th>
<th>Odds ratio</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.65</td>
<td>0.27</td>
<td>5.97</td>
<td>1</td>
<td>.015</td>
<td></td>
<td>3.91</td>
<td>6.64</td>
</tr>
<tr>
<td>Mode choicea</td>
<td>1.63</td>
<td>0.14</td>
<td>145.84</td>
<td>1</td>
<td>&lt; .001</td>
<td>5.10</td>
<td>3.91</td>
<td>6.64</td>
</tr>
<tr>
<td>Age (years)</td>
<td>-0.03</td>
<td>0.01</td>
<td>39.14</td>
<td>1</td>
<td>&lt; .001</td>
<td>0.97</td>
<td>0.96</td>
<td>0.98</td>
</tr>
<tr>
<td>Cox &amp; Snell R²</td>
<td>.18</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nagelkerke R²</td>
<td>.24</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔX² 40.74</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>df 1</td>
<td>p &lt; .001</td>
<td></td>
</tr>
</tbody>
</table>

Note. N = 1092. a Walking is reference.
Age was the only variable that significantly improved the prediction of purpose when controlling for mode choice. While the odds ratio for age was quite close to 1 (OR = .097 95% CI [.096, .098]), age was a continuous variable ranging from 21-89 and there was very little error associated with the coefficient. It is clear that increased age was associated with lower likelihood of choosing transportation over leisure activity.

**Purpose choice for participants with and without children.** I hypothesized that people with children who said yes to participating to a greater degree would choose to be active in their leisure time rather than as a form of transportation. Due to the smaller sample size, and expectation of a small effect size, I transformed the “number of children” variable into a dichotomous variable of whether participants had children or not. The dependent variable was choice of purpose. There was no significant difference between people with and without children on their choice of purpose $X^2(1, N = 1092) = 3.668, p = .055$. Closer inspection of the expected counts versus counts showed a trend in the opposite direction of what was hypothesized (people with children being more likely to choose transportation purpose), but this difference was not significant.

**Distance.** Distance from home to work/school was not a significant predictor of neither purpose choice nor choice between walking or cycling as the behavior to increase. When using only the sub-sample of people who chose transportation as their purpose, distance was a significant predictor of mode choice $X^2(1, N = 477) = 16.215, p < .001$, with explained variance equivalents ranging from 3.3% (Cox & Snell $R^2$) to 4.8% (Nagelkerke’s $R^2$). Increased distance between home and work/school was associated with a higher likelihood of choosing to cycle instead of walking when the purpose of the trip was transportation, with an odds ratio of 1.259 (95% CI [1.121, 1.414]) per level of increased distance.

**Completion of the Intervention**

Of the 1092 who said yes to participating, 346 (32%) completed the intervention. As there was much attrition it was important to examine whether sociodemographic variables and past behavior could predict likelihood of completing the intervention. Physical activity was the only variable associated with completion, with a model $X^2(2, N = 929) = 11.59, p = .003$ that was significant according to the Bonferroni correction adjusted alpha level (.004).

Participants in the moderately active group had 1.80 (95% CI [1.26, 2.58]) times the odds of completing the intervention compared to participants who were categorized as inactive. There was no significant difference between the inactive and the highly active category.

**Discussion**
In line with the aims of this thesis, I confirmed that usual travel mode and sociodemographic characteristics could predict both different intentions and willingness to participate in the intervention. Exploratory analyses also revealed that physical activity at baseline was associated with intentions to cycle more, choice of active mode and completion of the intervention. I discovered many significant relationships between variables, but effect sizes were generally trivial according to suggested rules of thumb for interpretation (Cohen, 1998) and even the complete models had generally low $R^2$s (.042 and .096 for intentions to walk and cycle, respectively, but substantially higher for predicting choice of active mode and purpose). However, models with low $R^2$s are common when predicting individual travel behavior (Ferrer & Ruiz, 2013) and these values are consistent with others found in travel behavior literature (e.g., Bamberg, Ajzen, & Schmidt, 2003; de Bruijn & Gardner, 2011; Ferrer & Ruiz, 2013). In addition, the aim wasn’t to find the largest effect sizes possible, but to identify what easily available information (e.g., usual travel mode, age, gender) that can be useful for future targeted interventions. While models using perceived behavioral control, attitudes and subjective norms to predict intentions explain far more variance in intention than the models in my thesis (e.g., Sutton, 1998) such psychological constructs must be measured before they can be used. The results from my thesis can be used to tailor intervention content to groups based on sociodemographic characteristics and past behavior.

**Persistent Past Behavior**

As walking and cycling commuters are already walking and cycling quite regularly, I hypothesized that they would have lower intentions to walk/cycle more the next month. Conversely, I found that people who already walk/cycle had higher intentions to walk/cycle more than other groups (except that public transportation commuters did not differ significantly on intentions to walk compared to walking commuters). The unexpected result could be because intentions weren’t that high in the first place (median of 4 on a bipolar 7-point scale) so scoring higher doesn’t necessarily mean that they had strong intentions to walk/cycle more. It could also be a real effect that people who are active commuters have higher intentions of walking and cycling more, perhaps because they enjoy it and realize that they have a potential for being more active. A study comparing different travel modes found that satisfaction with the travel mode was greater for those who regularly walk and cycle than those who regularly use a car and, particularly, public transport commuters (Anable & Gatersleben, 2005). Positive experiences with active commuting would increase both their attitudes toward walking/cycling and their perceived behavioral control, both of which are important predictors of intentions (Ajzen, 1991). Implications of this might be that getting
people to use active transportation is a difficult barrier, but once they have started people generally enjoy it and will want to increase their walking/cycling further. A previous study found that active commuters had stronger travel habits than both car and public transport commuters, and speculated that this might be caused by an increased affective value associated with active mobility (Thomas & Walker, 2015).

As expected, people who commuted by a car or motorcycle had lower intentions to walk and cycle more than people who used public transportation. This finding is consistent with previous research on car and public transportation commuters’ inclination to switch to walking/cycling (Ferrer & Ruiz, 2013). We didn’t ask them why their intentions were the way they were, but previous research has found that car-users are more satisfied with their travel mode than public transportation users are, especially concerning important instrumental aspects such as convenience and flexibility (Anable & Gatersleben, 2005). In addition, car trips tends to be rated higher on affective aspects than trips by public transportation and positive driving experiences have been shown to be negatively associated with willingness to switch to more sustainable travel modes (Gatersleben, 2014).

Usual travel mode was also a significant predictor of willingness to participate, even when controlling for intentions. This means that if a car/motorcycle commuter and a public transportation commuter had equal intentions to walk/cycle more, the car/motorcycle commuter would still be less likely to say yes to participate than the public transportation commuter. In addition, there was a significant interaction between intentions to walk and public transportation. Simple slopes revealed that higher intentions to walk more, compared to low intentions, were associated with a dramatic increase in likelihood of saying yes to the intervention for public transportation commuters. For participants commuting by car/motorcycle, however, the difference between low and high intentions to walk more had a minimal effect on willingness to participate. As mentioned above, car trips have been rated considerably higher than public transportation trips on instrumental aspects (Anable & Gatersleben, 2005) and this might affect willingness in addition to intentions. If people believe that instrumental aspects (e.g., convenience, speed, control of the trip) that are essential for their transportation needs won’t be met by active modes, that could reduce their likelihood of participating in the intervention even if their intentions to walk/cycle more are high.

There was no significant interaction between intentions to walk more and walking as the usual travel mode, indicating that people commuting by walking (just as car/motorcycle commuters) had similar odds of saying yes to participating at varying levels of intentions.
Previous research has established that having experience with behavior has an inverted U-shape effect on the strength on the intention-behavior relationship for that behavior (Sheeran, Godin, Conner, & Germain, 2017). Having a little experience with a behavior seems to stabilize intentions and strengthen their association with behavior, while having much experience with the behavior weakens the intention-behavior association as habits take over (Sheeran et al., 2017). As I predicted willingness to participate (and not actual behavior), I didn’t expect habit to have much effect on participants’ responses, but people who already commute by active modes can be assumed to perceive fewer barriers for those behaviors and might therefore be less likely to reject the intervention than people commuting by others modes, regardless of their intentions.

In addition to predicting intentions and willingness to participate, usual travel mode was also associated with whether participants chose walking or cycling as the behavior they wanted to increase. This association was mostly caused by already active commuters being significantly more likely to choose the mode they commute by (particularly cyclists choosing to cycle), while there was no significant difference for choice of active mode between car/motorcycle commuters and public transportation commuters.

Baseline physical activity predicted intentions to cycle, with both moderately and highly active people having higher intentions to cycle than inactive people. There was no such difference for intentions to walk. Previous research into barriers for cycling has found that those who didn’t contemplate cycling to work to a greater degree than other groups experienced that “not being fit enough” was a barrier to cycling (Gatersleben & Appleton, 2007), and the lack of significant differences in intentions to walk in my thesis might indicate that walking is seen as a more accessible activity for inactive people.

Physical activity on its own was a significant predictor of willingness to participate (with highly active people being more likely to participate than inactive people), but this effect became non-significant when it was included in a model with the other predictors, including usual travel mode. The active modes had a larger share of highly active people and smaller share of inactive people compared to both public transportation and car/motorcycle users. As physical activity was no longer a significant predictor when combined with usual travel mode, the trend that more active people were more willing to participate could be disguised by the fact that more active people were also more likely to use active travel modes, and active commuters were more likely to participate.

While not explaining willingness to participate, baseline physical activity was the only variable that was significantly associated with completion of the intervention. People who
were moderately active were more likely to complete the intervention compared to inactive people, but there was no significant difference between inactive people and highly active people. Previous research on attrition in exercise interventions has found that inactive people are more likely to drop out (Arikawa et al., 2012; Jancey et al., 2007) and my results are consistent with those findings. This illustrates the challenge for future interventions to create measures that keep sedentary people from dropping out, as these are the people who would benefit most from completing the intervention.

A study using implementation intentions to increase physical activity found a greater effect for people who were already active at baseline (Armitage & Arden, 2010). Implementation intentions perform better when they are relevant and specific (de Vet, Oenema, & Brug, 2011), and one explanation for lack of effectiveness for sedentary people might be that they chose situational cues and behaviors based on hypothetical situations, while already active participants created plans based on their own experience (Armitage & Arden, 2010). If that was the case for our participants as well, sedentary people might have created less relevant or useful plans and experienced less sense of achievement, thereby being less likely to complete the intervention.

Highly physically active people were also more likely to choose cycling over walking as their targeted behavior compared to inactive people and this is consistent with previous research showing that being physically active increases the likelihood of cycling (Heinen et al., 2010).

**The Effects of Sociodemographic Characteristics**

Of the sociodemographic variables tested, gender, having children in the household, age and job status were significantly associated with any of the outcome variables. No significant effects were found for income or education level, perhaps because most respondents were highly educated and had near or above the average Norwegian income (Statistisk Sentralbyrå, 2018). When predicting intentions to walk and cycle, the sociodemographic characteristics had the largest effect sizes. Particularly the effects of age ($r = -.243$) and being a student ($d = 0.65$) or working ($d = 0.23$) on intention to cycle distinguished themselves with substantial, as well as significant, effects.

Both working and being a student were associated with having higher intentions to cycle. The reason for comparing these groups was that those in the *other* category were assumed to not have a regular commute, and of the regular trips Norwegians make, work and school commute have the highest cycling shares (Ellis et al., 2016). It therefore makes sense that people working from home hold lower intentions to cycle more. Job status was also a
significant predictor of willingness to participate, as students were significantly more likely to say yes (OR = 1.862 [1.203, 2.883]) compared to those in the *other* group. There was no significant difference between *working* and *other* when predicting willingness to participate, indicating that perhaps being a student is more important for willingness than having a commute and students have previously be found to have a larger proportion of both cyclists and utility walkers compared to other groups (Ryley, 2006).

Higher age was associated both with lower intentions to cycle and lower odds of choosing cycling over walking. These findings correspond with previous research from Norway showing that people who cycle for transport are younger (Veisten et al., 2011) and that the cycling percentage is lower for older cohorts (Ellis et al., 2016).

Gender and parenthood were associated with intentions, willingness to participate and the choice between walking or cycling as the target behavior for the intervention. Previous research has found that the presence of children in the household can be expected to be negatively related to active transportation (Hamre & Buehler, 2014) and that not having children is associated with increased cycling (Heinen et al., 2010). Conversely, I found that an increased number of children under 18 in the household was associated with higher intentions to cycle, higher odds of participating in the intervention and higher odds of choosing cycling over walking. That the effect went in the opposite direction of what I expected might be explained by the intention-behavior gap; having intentions and acting on them are two different things. My hypothesis was based on findings that people with children cycle less and my results indicate that they want to cycle more and are interested in programs that will help them do it. It might be that parents experience more barriers to cycling than other groups (e.g., due to more time constraints, transportation needs and trip-linking) and therefore experience a greater discrepancy between how much they want to cycle and how much they do cycle. The higher intentions to cycle more indicate that people with children are likely to be inclined abstainers and that they are promising targets for future cycling interventions with a volitional emphasis.

Previous research has consistently found that men participate less than women and this was also the case for this intervention. A review of workplace health promotion program participation found that this gender difference disappeared for the sub-category “fitness center studies” (Robroek et al., 2009). That the gender varied for different types of health promotion programs could indicate that men are more sensitive to the content of intervention programs and that it might be important to identify what attracts men to interventions. Recruiting men to active travel interventions might be especially important as more car users are men and
switching car travels for active modes has a great potential to both improve local climate and increase physical activity (Delso, Martín Ramos, & Ortega, 2018).

I found no significant difference in intentions to cycle for men and women, but there was a significant difference in intentions to walk, with women having higher intentions to walk than men. Gender was a significant predictor of active mode choice with men having more than twice the odds of choosing cycling over walking compared to women. The fact that women didn’t have lower intentions to cycle, but were less likely to choose cycling, might indicate that the intention-behavior gap was larger for women and cycling than other gender-mode combinations.

Near half (49%) of the respondents in this thesis were from Oslo, and my results correspond to previous research on gender effects on cycling in Oslo. While women in Oslo have been found to have more positive attitudes to cycling in general than men, men rate the standard of cycling facilities higher than women do and are more satisfied with Oslo as a cycling city (Spacescape, 2016). In Oslo in general, trips taken by men were more likely to be cycling trips than trips taken by women, but this difference decreased when level of cycling facilities were included, indicating that women are more sensitive to the degree of cycling facilitation (Ellis et al., 2016).

**Willingness to Participate and Completion of the Intervention**

As expected, higher intentions to walk and cycle more were associated with increased probability of saying yes to participating in the intervention. As the intention scores were designed to capture the discrepancy between intention and behavior (“I want to walk/cycle more the next month than I currently do”) this indicates that inclined abstainers are willing to engage with programs that help them achieve their walking or cycling goal, and more willing the higher their intention scores. The invitation to participate did not include much information about the intervention, and none that would increase motivation to walk and cycle more. It thus makes sense that having an existing motivation would increase likelihood of saying yes to the intervention. Self-regulation interventions are intended to help inclined abstainers act on their intentions and previous research has emphasized the importance of matching interventions to where participants are in the behavior change process (e.g., Lippke et al., 2010). My finding that higher intentions to walk/cycle more were positively associated with likelihood of saying yes to the intervention indicates that the recruitment used in this study was suitable for recruiting inclined abstainers. Consequently, interventions aiming to create an intention in unmotivated people should consider other approaches.
It is not immediately clear where to place “saying yes to an intervention” in the behavior change process. One way to interpret respondents’ answer to the intervention is as somewhere in the intention-behavior gap, closer to expressing an intention than to behavior. While saying yes to an intervention is not the same as walking or cycling, being asked to participate might have triggered a practical consideration of walking or cycling over the next month, beyond what simply asking their intentions did. In this thesis, I view participants’ response to the intervention as an extension of their intentions, but with a bigger emphasis on feasibility and as a step along the way to behavior. According to research on the Theory of Planned Behavior, perceived behavioral control can predict behavior both indirectly, via intentions, and directly (Ajzen, 1991). Perceived behavioral control (PBC) wasn’t measured in the recruitment survey and it could be interesting for future research to investigate whether PBC is associated with willingness to participate beyond its association with intentions.

While saying yes to participating in an intervention to increase walking or cycling could be interpreted as an extension of intentions, completion of the intervention might represent following-through on this intention, or at least actively attempting to do so. While quite a few were lost to attrition along the way this is to be expected for internet interventions (Eysenbach, 2005) and the more important question is whether those who dropped out differed from those who completed the intervention.

Several variables were associated with willingness to participate, but none of these could predict completion of the intervention. Except for baseline physical activity, there were no significant differences between those lost to attrition and those who completed the intervention. Notably, higher intentions to walk/cycle more were not associated with greater odds of completing the intervention. Stage theories of behavior change state that motivation is essential for creating an intention, but that other strategies are necessary for acting on those intentions (Achtziger & Gollwitzer, 2018; Schwarzer & Luszczynska, 2008). That intentions were important for indicating willingness and not for completion supports the distinction between a motivational and volitional phase of behavior change.

The Non-significant Distance

Despite longer distance between home and work being an established barrier for commuting by bicycle (e.g., Heinen et al., 2010; Stinson & Bhat, 2004), I found no effect of distance on neither intentions, completion rates nor choice of purpose. The effect on willingness to participate was minimal and in the opposite direction of expected (longer distances predicting more willingness). Other than that, the only significant association between distance home-work/school and an outcome was when the analyses was conducted
only on the sub-group that wanted to be active as a form of transportation, and in that case increased distance between home and work/school was associated with increased odds of choosing cycling over walking. This was to be expected as cycling is a more efficient mode of transportation than walking.

There could be several reasons for this lack of association between distance and the outcome variables, for example if there’s a critical distance that was hidden by the categorical way of reporting distance. One explanation that seems likely was that the distance measured (home to work/school) didn’t match well enough with the distances people decided to travel.

Instead of changing their commute, people who wanted to be active as a form of transportation might have chosen to cycle to the store, the gym or any other place they regularly visit. In addition, people changing their commute might have decided to walk for transportation part of the way and use public transportation the rest, thus the distance they walked would have little to do with the distance between their home and their work.

While it was surprising to find such little effect of distance it seems likely that this is due to the operationalization of distance and not due to participants being immune to the effects of distance.

Strengths and Limitations

Pre-registered hypotheses and exploratory analyses. There’s a well-established publication bias in psychology where preference is given to novel and statistically significant. This publication bias, combined with hard competition for grants that invokes a ‘publish or perish’ mentality, might lead to problematic research practices, such as p-hacking (Gonzales & Cunningham, 2015) or hypothesizing after results are known (Kerr, 1998). Open science methods require a distinction between pre-planned hypothesis testing and exploratory analyses, and pre-registration represents a way to ensure that the final report accurately reflects what was originally planned (Lindsay, Simons, & Lilienfeld, 2016). Keeping with the ideal of transparency and open science I pre-registered my hypotheses and analyses before looking at the data. Writing a master’s thesis is a learning process and I pre-registered quite early in the process, meaning that I learned much about both research methods and previous research in the months afterward. Thankfully, pre-registration doesn’t preclude exploratory analyses and deviations from the plan aren’t failures, but simply something that should be made explicit when reporting the results (Lindsay et al., 2016).

Being open about confirmatory analyses reduces their evidential status compared to pre-registered hypotheses and this is increasingly viewed as the scientifically correct approach (Allen & Mehler, 2018). As I conducted many exploratory analyses, I developed a procedure
for these to reduce the risk of Type 1 error. Exploratory analyses were tested on half the sample, first alone and then in combined models, and significant models were confirmed on the full sample. The exception was explored predictors of completion of the intervention and these were instead subjected to a Bonferroni correction that reduced the significance cut-off to \( p < .004 \). While it is unfortunate that my pre-registration did not include important variables such as completion of the intervention and physical activity, and one cannot be as confident about exploratory findings, my results do correspond with previous findings and can be used to inform future research on the topics.

**Broad intervention.** A feature of this study is that the intervention had a very broad scope, including both leisure activity and active mobility as well as both walking and cycling. Walking and cycling are often looked at either in separate studies or treated as the same (Ton et al., 2018), but we included them as separate modes and asked participants to choose. This can be considered both a weakness and a strength, depending on the focus. The strength lies in that this provided participants with flexibility and didn’t exclude for example people who wanted to increase their physical activity but were uncomfortable with cycling. The potential weakness lies in confounding of predicting willingness to participate if the dependent variables are differentially associated with walking/cycling and leisure/transportation.

A previous study conducted in the Netherlands found that cycling and walking are influenced by different determinants (Ton et al., 2018) and I found that several characteristics could be used to predict mode choice, including gender, parenthood, usual travel mode and physical activity. This indicates that walking and cycling are distinct behaviors that appeal to different groups of the population. Allowing people to choose their own active mode might therefore be a way for future physical activity/active transportation interventions to recruit more people than if the interventions are limited to one active mode.

Leisure and transport walking/cycling might be considered distinct behaviors with different motivations and including both types of behavior in the intervention could therefore influence whether certain variables predicted willingness to participate. Gatersleben and Appleton (2007) found that the main reasons for wanting to commute by cycling were convenience, increasing fitness and environmental considerations. Similarly, Veisten et al. (2011) found that among irregular cyclists/pedestrians more than half indicated exercise as the most important reason for active transportation. Among regular cyclists, however, about a third indicated exercise as most important, and a similar share chose speed and flexibility as the most important reasons (Veisten et al., 2011).
To address the potential confounding effects of including both leisure and transport walking/cycling, I examined whether choice of purpose could be predicted in the same manner as willingness to participate. My results show that purpose choice was mostly associated with choice of active mode (walking associated with leisure and cycling with transport) and that beyond that only age was a significant predictor of purpose choice. That almost half (49%) of participants chose active transportation over leisure activity implies that there’s an interest in increasing active mobility in the population and a potential for future interventions with this aim.

As only those who said yes to participating were asked to choose a purpose for their trips it’s impossible to say whether different people would have been interested in participating if the intervention had been pitched with a more specific focus on either leisure activity or active transportation.

**Sample and selection to the recruitment survey.** A strength of this thesis is the large sample \(N = 4814\) and the fact that respondents included adults of all ranges, close-to-equal shares of people with and without children, and similar shares of women and men. This differs from the typical psychological research sample consisting of students recruited from university classes (Hanel & Vione, 2016) or typical samples for willingness to participate studies, such as workplaces (Röttger et al., 2017) or patient groups (van Gils et al., 2011). However, improving on other typical study samples doesn’t mean that my sample is free from representativity issues. The purpose of predicting willingness to participate was to identify groups that are unlikely to be reached by volitional interventions to walk/cycle more, and one obvious limitation is the self-selection to answering the recruitment survey.

Many people had the opportunity to answer the survey but chose not to do so, and this might bias the results (Olsen, 2008). While I had much information about people who said no to participating, this group was limited to those who did respond to the recruitment survey. The intervention was shared on social media sites associated with cycling, with a pitch that emphasized an interest in active commuters and was targeted to people living in the biggest cities in Norway. Some examples of the selection to the survey include that the most common travel mode was cycling (when in the actual population this is the next smallest group; Hjorthol et al., 2014), that only 55 respondents lived a place “other” than Oslo, Bergen, Stavanger, Trondheim and surrounding areas, and that nearly half of the participants had 5 or more years of higher education. This lack of representativeness means that one must be careful with generalizing the findings (Davern, 2008), especially to groups that differ substantially (e.g., people in rural areas without any higher education). This selection to the
survey has consequences for both intentions to walk/cycle more and willingness to participate, as those who chose to answer the recruitment survey knowing about the active mobility focus might generally be more positive toward walking/cycling, and might also be more similar to each other than those of each group who chose not to answer. This is especially relevant when considering the proportion of those who said yes to the intervention (32%) as it is likely that those who were uninterested in answering the recruitment survey would also be less interested in participating.

**Self-report data.** All the data used in this thesis are self-report data from an online survey and are therefore subject to issues associated with self-reporting. While most people should be able and willing to answer the demographic questions correctly (e.g., their age, education level, number of children, etc.), there are more issues related to distance, travel behavior, intentions and physical activity. Some of these issues relates to people’s ability to answer correctly; do they know the distance? Can they remember how physically active they were?

Petrunoff, Xu, Rissel, Wen, and van der Ploeg (2013) examined the validity of a self-report travel behavior questionnaire asking about ‘last week’ and found that the weakest associations were for the days six and seven days before (e.g., if participants answered on a Thursday they had most discrepancies for their travel behavior the Thursday and Friday before). My own experience interviewing people using similar questions for another project was that people, when answering questions about their commute, though not about the specific day but rather how “a typical day” was. A similar effect might come into play for the physical activity variable since people were asked to recall the last seven days.

Another issue relates to whether people answer honestly. Some types of behaviors can elicit social desirability bias, where people answer in a way that puts them in a better light, consciously or not (Callegaro, 2008). For instance, people might say that they ‘usually’ travel by bicycle, even though in reality they mostly travel by car or public transportation with only a day on bicycle, or they might overestimate how many minutes they spent on each type of physical activity last week. One study examining whether social desirability bias influenced the self-reporting of physical activity found significant, but minimal effects (Motl, McAuley, & DiStefano, 2005), indicating that it is not much of an issue. A systematic review found that the IPAQ short form has a tendency to overestimate physical activity, though it has shown acceptable correlations for walking and vigorous activity (Lee, Macfarlane, Lam, & Stewart, 2011). Either way I can expect that these influences should be similar across the different groups I am comparing, even if the minutes are somewhat inflated overall.
In addition to ability and willingness to answer honestly, people might differ in how they tend to answer surveys. Response bias can relate to preferring to answer closer to the edge (more extreme) or closer to the middle, or to being more acquiescent and therefore more likely to say ‘yes’ or ‘agree’ rather than disagree (Holbrook, 2008; Villar, 2008). People who are otherwise similar might be different in their tendency to say yes in general and therefore differ on their response to the intervention. If so, this would undermine the effects of other predictor variables, though any such differences between people should be similar in other interventions and not affect the generalizability of the results. In addition, intentions to walk and cycle more were measures on a bipolar agree-disagree scale and it is possible that the results would have been different if they had been measured on a unipolar scale where the middle did not equal “neutral”.

**Implications for Policy and Future Research**

**Future Interventions.** That almost a third of all that were asked wanted to participate indicates that there is an interest in such self-regulation interventions, even if they don’t include financial incentives or other “goodies” to attract people. While two-thirds of the participants were lost to attrition, the initial interest was there even if they didn’t complete the intervention for various reasons (one of which could be that follow-up e-mails might have ended up in the spam folder). Participants were given very little information about the intervention before they said yes (or no) to participate and this indicates that there’s a general interest, and potential, for walking and cycling interventions in the population.

The findings in my thesis indicate which groups in the population that are more likely to participate in a self-regulatory intervention without financial incentives. Future research could identify why, for instance, women are more likely to agree to participate than men, or why people without children are less likely to participate, and use this to create interventions better tailored to these groups. The small amount of variance explained when including all significant independent variables also reveal that there are important factors for willingness to participate that were not measured in the survey used in this thesis.

**Reaching Those Who Benefit Least.** One of the reasons for predicting willingness to participate and completion of the intervention was to see if the intervention would reach those people who would benefit most from it. As the intervention targeted both recreational walking/cycling and active transportation the most relevant groups of people were (1) inactive people and (2) people who commute by car/motorcycle. As mentioned above, past behavior was associated with nearly all outcomes. Car/motorcycle commuters had lower intentions to both walk and cycle more and were less likely to participate in the intervention, while inactive
people had lower intentions to cycle more and were more likely to drop out of the intervention. These findings pose interesting challenges to researches as the groups who would provide the most benefit for the climate or themselves are also the groups least likely to participate in and complete the intervention. Future research should investigate why these groups are harder to include or retain and what can be done to change this.

**Reducing car trips.** A potential interpretation of the lower intentions to walk/cycle more for car/motorcycle commuters is that they might benefit more from measures to increase their motivation and intention to walk or cycle than from interventions with a self-regulation focus. However, the interaction between intentions to walk and travel mode showed that even car/motorcycle commuters with the highest score (7) on intentions to walk were only a little more willing to participate than car/motorcycle commuters with very low (2) intentions to walk. The low impact of higher intentions indicate that other factors are more important for willingness to participate and more that substantial measures might be needed to reach car/motorcycle commuters. The fact that people who commute by public transportation, compared to car users, both have higher intentions to walk and cycle more and are more likely to say yes to an intervention to do so also when controlling for intentions, indicate that public transportation users are promising targets for future campaigns and strategies with volitional content for increasing walking and cycling. However, the interaction between intentions to walk and public transportation shows the importance of increasing intentions for this group.

Reducing trips by car is essential for reaching policy goals such as improving local climate and increasing physical activity (Espeland & Amundsen, 2012; Samferdselsdepartementet, 2016-2017). One way to reduce car trips could be to move public transportation commuters to active modes and car/motorcycle commuters to public transportation. In my results, public transportation users were more similar to active commuters in both intentions and willingness to participate, and a previous study (Anable & Gatersleben, 2005) found that car drivers to a much higher degree rated public transportation as their ‘most likely alternative travel mode’ rather than cycling and walking (76% versus 19% and 6%, respectively). While moving public transportation commuters over to walking or cycling itself wouldn’t have much effect on climate gas emissions, public transportation commuters had a larger share of inactive people compared to both active modes and might therefore benefit from increased physical activity.

**Conclusion**

For my thesis I have used data from a large recruitment survey to predict intentions to walk and cycle more, willingness to participate in an intervention to do so, by what mode and
to what purpose people want to be more active and whether they completed the intervention. My results show that there are group differences in intentions, related to both demographic groups and travel mode groups, and that some groups are more willing than others to participate in an online intervention. Most notably people who drive a car or motorcycle both have lower intentions to walk and cycle and are, also when controlling for intentions, less likely to say yes to participating than other travel mode groups. Public transportation users, on the other hand, are more similar to those who already walk and cycle for their commute and represent a promising group to target for future volitional interventions. My results indicate that people who commute by active modes and enjoy it and want to increase their walking or cycling, which is promising for reaching the ambitious goals of increased cycling shares in Norway (Espeland & Amundsen, 2012). The challenge lies in getting people to start walking or cycling in the first place. The findings in this thesis can be used to further investigate why these groups differ in their intentions, willingness and completion, and then tailor campaigns and interventions to their needs, thereby increasing the effectiveness of future intervention.
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Appendices

Appendix A: Pre-registration

**AS PREDICTED**

CONFIDENTIAL - FOR PEER-REVIEW ONLY

**Intervention to increase walking and cycling (#15882)**

Created: 11/02/2016 08:14 AM (PT)
Shared: 04/26/2019 09:42 AM (PT)

1) Have any data been collected for this study already?
   It's complicated. If we have already collected some data but explain in Question 2 why readers may consider this a valid pre-registration nevertheless.

2) What's the main question being asked or hypothesis being tested in this study?
   For recruitment survey:
   H1: Main transport mode will predict people's intention to walk/cycle more in that
   a) People who mainly travel by car or motorcycle will have less of an intention to walk/cycle more than people who travel by public transportation
   b) People who commute by walking will have less of an intention to walk more, and people who commute by cycling will have less of an intention to cycle more, than people who don't commute by the mode specified in the intention measure
   c) People who work from home will have more of an intention to walk/cycle more than people who commute to work/school
   H2: Willingness to participate is predicted by
   a) Number of children under 18 in the household, with less willingness to participate for people with more children
   b) Distance home-work/school, with less willingness to participate for participants with a longer distance to travel
   c) By main transport mode, with less willingness to participate for people who mainly use personalized motorized vehicles
   d) Intention strength for walking/cycling more, in that people with stronger intentions are more likely to agree to participate than people with weaker intentions.
   e) Intention strength will moderate the effects of a), b), and c) on willingness to participate, in that the effects of a), b), and c) will be stronger for people with weak intentions.
   For intervention specific part of recruitment survey:
   H3: Participants with children who choose to participate in the intervention will to a greater degree choose to walk/cycle as a leisure activity rather than as transportation.
   H4: Higher intention strength increases total number of plans made in the intervention survey.
   H5: The effect of intention strength on number of plans will be more positive for people with strong habits than for those with weak habits.

3) Describe the key dependent variable(s) specifying how they will be measured.
   Recruitment survey:
   H1: dependent variable is intentions on a 7-point Likert scale, the same two items each for bicycling and walking (“I want to cycle more than next month than I currently do” & “I want to cycle more the next month than I did the same time last year”). The mean of the two items will be used provided that the items correlate adequately (minimum r=.4). If they do not, the items will be used separately. For H1a and H1c, the mean of the walking and cycling items will be used as main DV, for H1b, the two will be analyzed separately.
   H2: dependent variable is binary, as participants respond either “yes” or “no” when asked if they want to participate in an intervention to increase their walking or cycling.
   Predictors: how people normally travel to work/school (choose from walking, bicycling, electric bicycle, car, MC, public transportation, working from home and "other"); number of children (0, 1, 2, 3, 4 or more), distance home-work/school, intention strength (options 2 to 7 on a bipolar Likert scale)
   Intervention specific part of recruitment survey:
   H3 dependent variable: Participants are asked whether they want to walk/cycle more by replacing trips by car, trips by public transportation, trips by other forms of transportation or as a leisure activity.
   Predictor (H4): Habit strength (SRIS-4 items) for people who choose to walk/cycle by replacing trips by car or public transportation.
   Intervention survey:
   H4 and H5: participants are given the option of creating up to 6 plans, with the possibility of creating 0 plans if they ignore the instructions. This creates a sum ranging from 0 to 6.
   Predictor (H4) and Moderator (H5): intentions on a 7-point Likert scale, two items for either cycling or walking, specified to number of trips to increase participation have been chosen as a goal (e.g. “I want to walk at least 3 more trips each week” & “I am motivated to walk at least 3 more trips each week”). The two intention strength items will be combined if they correlate sufficiently (r>.40) and analyzed separately if they do not.
   People are also asked how many more trips of walking/cycling they want to do each week (from 1-4), which might also be an indication of intention strength. If the number of trips goal correlates adequately (r>.40) with the intention strength items, this will be combined with the intention strength items. If not, it will be analyzed separately as a predictor (H4) and moderator (H5) of number of plans.
   The predictor habit strength for H5 is taken from the recruitment survey.

4) How many and which conditions will participants be assigned to?

Verify authenticity: http://aspredicted.org/bidlink.php?7k7a6z
The data collected is from a large project with several workgroups, who sent out a shared recruitment survey. Respondents first answered demographic and baseline behavior questions and were then asked to participate in different projects depending on which they qualified for. If they qualified for more than one project, they were randomly assigned to be asked to participate in first one project, and if they declined they were asked about other projects.

Participants who agreed to an intervention using volitional strategies (hereafter referred to as “the intervention”) completed a section of the recruitment survey specific to participants in the intervention. Later they were randomly assigned to either test group or control group and contacted two weeks later to complete the intervention (or control) survey.

H2 sample: All respondents who completed the recruitment survey
H2 sample: All respondents who completed the recruitment survey, qualified for participation in the intervention and answered whether they were interested in participating in the intervention.

H3 sample: People who agreed to participate in the intervention and completed the part of the recruitment survey which was specific to intervention participants.
H4 and H5 sample: People who agreed to participate in the intervention and were randomly assigned to the test group, and who completed the intervention survey. Participants in the control group will not be used for my analyses.

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.

Alpha levels are set at .05.

H1a: Linear regression with intention to walk/cycle more as DV and main transport mode as IV, comparing those who indicated motorized vehicles with those who indicated public transport (binary).

H1b: Some as H1a, separately for walking and cycling intentions. Predictor for walking is commuting by walking vs. all other alternatives, predictor for cycling is commuting by cycling vs. all other alternatives (binary).

H2: Same as H1a, but comparing working from home with all other commuting options (binary).

H2: Logistic regression with willingness to participate as DV and main transport mode, number of children and distance home-work/school as IV. The independent variables will first be examined separately and then together in one model to see if the significance of one IV can be explained by another.

H3: For this hypothesis, the categories for number of children (0, 1, 2, 3, 4 or more) will be combined to make a binary variable (children: yes/no) and with the alternatives for how they wish to walk/cycle in their day (replace trips by car, replace trips by public transportation, replace trips by other forms of transportation or as a leisure activity). I will combine all ”replace transportation trips” alternatives, making this also a binary variable (want to walk/cycle more by: replacing transportation trips/ as a leisure activity). I will then conduct a chi-square test.

H4 and H5: Linear regression with number of plans as DV, and intention strength from intervention survey as IV.

H5: Linear regression with number of plans as DV, habit strength and intention strength from intervention survey as well as their interaction as predictors.

I will check the data for assumptions for parametric tests and apply appropriate corrections. Also, I will calculate the power for each hypothesis, assuming an effect size of f = .15. If the power for any of the hypotheses is below .80 I will drop that hypothesis.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.

For H1, H2 and H3: People who did not complete the recruitment survey or did not give an e-mail address at the end. These will be excluded to ensure that they are not duplicate responses or test responses.

For H4 and H5, I will exclude any who ignored the instructions to create plans (i.e., produced 0 plans).

7) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.

H1: Sample size is determined by how many participants completed the recruitment survey
H2: Sample size 3824, which is how many participants completed the recruitment survey and answered whether they were interested in participating in the intervention or not.
H3: Sample size is 1089, which is how many completed the intervention specific part of the recruitment survey.
H4 and H5: Sample size is 218, which is how many participants in the test group who completed the intervention survey.

8) Anything else you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)

For exploratory analysis I will first use half of the relevant sample and if I find anything I will use the full sample to confirm it. Using the H1 sample: I will explore the relationship between number of children and intention to walk/cycle

Using the H2 sample: Demographic variables including age, gender, income, education level, city of residence, job status have been collected and any relation between these variables and willingness to participate will be explored. As will the relationship between baseline walking/cycling at recruitment survey and general physical activity, and willingness to participate.

Using the H3 sample: I will explore the relationship between distance home-work/school and main transport mode and whether people who agree to participate choose to walk/cycle more as a transport or leisure activity.
The most drastic changes are that I realized that instead of looking at number of plans made in the intervention itself (H4 and H5), it would be more cohesive to examine whether I could predict who would complete the intervention. This is a natural extension of willingness to participate and just as important for the effectiveness of interventions and both their internal and external validity. As the intervention was broader than is usual (including both walking and cycling and both recreational and utilitarian purposes) I also examine what predicts the choices of how to conduct the intervention, as this might illuminate differences that would otherwise be hidden by combining all ways of participating.

Due to the small number of people working from home (N = 29), there wasn’t enough statistical power to test H1c with confidence in the results and this hypothesis was therefore disregarded.

H1a and H1b were conducted with all travel modes rather than made binary as that made more sense for the results, as combining travel modes with very different average intentions into one “other” group could create misleading differences or hide true ones.
Appendix B: Facebook pitch and e-mail for recruiting survey respondents

Figure B1. Example of survey recruitment via Facebook.

The following text was sent in an e-mail to 40 000 NAF members.

**Hvordan reiser du i hverdagen?**

Transportøkonomisk institutt (TØI) skal gjennomføre en studie for å få ny kunnskap om hvordan folk velger å reise i hverdagen, og teste ut gode løsninger for å møte byenes økende transportbehov.


Norges Automobil-Forbund (NAF) som er landets største forbrukerorganisasjon vil gjerne bidra til kunnskapsopplysning og støtte derfor studien. Du har blitt trukket tilfeldig fra NAFs medlemsregister for å delta i undersøkelsen.

Ved å svare på spørreundersøkelsen er du med i trekningen av et **gavekort på 5 000 kr.** Det tar omtrent 10 minutter å svare på skjemaet. **Svarfrist er 31. august.**

**Du svarer på undersøkelsen ved å klikke på lenken:**

http://dc.miprocloud.net/DCWebEngine/panelsurvey.aspx?qif=33c4ddc3-5a04-461b-ae03-c07c206b61e2

**Har du spørsmål** til studien, eller ønsker å benytte deg av dine rettigheter, ta kontakt med prosjektleder Aslak Fyhri (af@toi.no) ved Transportøkonomisk institutt (TØI).

Prosjektet er finansiert av Norges Forskningsråd.
Deltakelse er frivillig, og du kan når som helst trekke deg. Vi behandler opplysninger om deg basert på ditt samtykke. Undersøkelsen er meldt til Personvernombudet for forskning, NSD - Norsk senter for forskningsdata AS.
mvh
Aslak Fyhri,
Prosjektleder, TØI
https://www.toi.no/prosjekt-nudging/category1796.html
Appendix C: Survey questions

**Say**

Takk for at du deltar! Innledningsvis har vi noe utdypende informasjon om studien og personvern.

**Consent**

Hvordan foregår datainnsamlingen?
Dataene samles inn via elektroniske spørreskjema og en mobilapplikasjon (Sense.DAT). Spørsmålene omhandler aktivitetsnivå og transportmiddelbruk. Les mer om appen her: (http://archief.dat.nl/en/products/sensedat/)

Hva skjer med informasjonen om deg?

Frivillig deltakelse.
Så lenge du kan identifiseres i datamaterialet, har du rett til: innsyn i hvilke personopplysninger som er registrert om deg, å få rettet opp personopplysninger om deg, å få slettet personopplysninger om deg, å få utlevert en kopi av dine personopplysninger (dataportabilitet), og å sende klage til personvernombudet eller Datafylkset om behandlingen av dine personopplysninger. Dersom du har spørsmål til studien, eller ønsker å benytte deg av dine rettigheter, ta kontakt med prosjektleder Aslak Fyhri (af@toi.no) ved Transportøkonomisk institutt (TØI). Du kan også kontakte vårt personvernombud NSD – Norsk senter for forskningsdata AS, på epost (personvernombudet@nsd.no) eller telefon: 55 58 21 17. På oppdrag fra TØI har NSD – Norsk senter for forskningsdata AS vurdert at behandlingen av personopplysninger i dette prosjektet er i samsvar med personvernregelverket.

• **range:**

Jeg har lest informasjonen og samtykker til å delta i undersøkelsen

![1](range)

**Place of residence**

Først vil vi vite litt om deg

**Hvor bor du?**

![ ]
<table>
<thead>
<tr>
<th>Range: *</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Oslo og omegn</td>
<td>1</td>
</tr>
<tr>
<td>Bergen og omegn</td>
<td>2</td>
</tr>
<tr>
<td>Stavanger og omegn</td>
<td>3</td>
</tr>
<tr>
<td>Trondheim og omegn</td>
<td>4</td>
</tr>
<tr>
<td>Annet sted</td>
<td>5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Year of Birth</th>
<th>Hvilket år er du født?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range: 1910:1997</td>
<td></td>
</tr>
<tr>
<td>Skriv inn årstall</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Gender</th>
<th>Er du mann eller kvinne?</th>
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</thead>
<tbody>
<tr>
<td>Range: *</td>
<td></td>
</tr>
<tr>
<td>Mann</td>
<td>1</td>
</tr>
<tr>
<td>Kvinne</td>
<td>2</td>
</tr>
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<table>
<thead>
<tr>
<th>Income</th>
<th>Omtrent hva var din bruttoinntekt siste år?</th>
</tr>
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<tbody>
<tr>
<td>Range: *</td>
<td></td>
</tr>
<tr>
<td>Under 100 000</td>
<td>1</td>
</tr>
<tr>
<td>100 000 til 299 000</td>
<td>2</td>
</tr>
<tr>
<td>300 000 til 499 000</td>
<td>3</td>
</tr>
<tr>
<td>500 000 til 699 000</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td><strong>Hva er din høyeste fullførte utdanning?</strong></td>
</tr>
<tr>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>1</td>
<td>Grunnskole (inkl. ungdomsskole/realskole)</td>
</tr>
<tr>
<td>2</td>
<td>Videregående (inkl. gymnas/ yrkesskole/ handelsskole)</td>
</tr>
<tr>
<td>3</td>
<td>Høgskole/universitet, lavere grad (t.o.m 4 år)</td>
</tr>
<tr>
<td>4</td>
<td>Høgskole/universitet, høyere grad (5 eller flere år)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th><strong>Hvor mange barn (under 18 år) bor i husstanden din?</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Ingen</td>
</tr>
<tr>
<td>2</td>
<td>1 barn</td>
</tr>
<tr>
<td>3</td>
<td>2 barn</td>
</tr>
<tr>
<td>4</td>
<td>3 barn</td>
</tr>
<tr>
<td>5</td>
<td>4 eller flere barn</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th><strong>Hva er din hovedaktivitet?</strong></th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>
### Yrkesaktiv

- **1** Går på skole/studerer
- **2** Pensjonist/trygdet
- **3** For tiden ikke i arbeid
- **4** Annet
- **5** Ønsker ikke svare

### Usual travel mode

<table>
<thead>
<tr>
<th>Usual travel mode</th>
<th>Hvordan reiser du vanligvis til arbeid/skole på denne tiden av året?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>filter:</strong> jobbstatus.a=1,2</td>
<td>Velg det transportmiddelet du reiser lengst med</td>
</tr>
</tbody>
</table>

- **range:**

<table>
<thead>
<tr>
<th>Transportmiddelet</th>
</tr>
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<tbody>
<tr>
<td><strong>1</strong> Bil</td>
</tr>
<tr>
<td><strong>2</strong> MC/moped</td>
</tr>
<tr>
<td><strong>3</strong> Sykkel</td>
</tr>
<tr>
<td><strong>4</strong> Elsykkel</td>
</tr>
<tr>
<td><strong>5</strong> Gange</td>
</tr>
<tr>
<td><strong>6</strong> Offentlig transport</td>
</tr>
<tr>
<td><strong>7</strong> Jeg jobber hjemmefra</td>
</tr>
<tr>
<td>Annet</td>
</tr>
</tbody>
</table>
### Intentions

Vennligst ta stilling til følgende påstander

<table>
<thead>
<tr>
<th>• range:*</th>
<th>1: Helt uenig</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7: Helt enig</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jeg har lyst til å sykle mer den neste måneden enn jeg gjør nå</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
<tr>
<td>Jeg har lyst til å sykle mer den neste måneden enn jeg gjorde på samme tid i fjor</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
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<tr>
<td>Jeg har lyst til å gå mer den neste måneden enn jeg gjør nå</td>
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<tr>
<td>Jeg har lyst til å gå mer den neste måneden enn jeg</td>
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<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
<td>○</td>
</tr>
</tbody>
</table>

### Distance

Omtrent hvor lang er reiseveien du vanligvis velger hjemmefra til arbeid/skole?

- **filter:** VanligJobb.a=5
Til fots tar det omtrent 10 minutter å gå 1 km

| • filter:**jobbstatus.a=1;2  
• range:* |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>under 3 km</td>
<td>○</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-5 km</td>
<td>○</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5-7 km</td>
<td>○</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7-10 km</td>
<td>○</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10-15 km</td>
<td>○</td>
<td>5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>15-20 km</td>
<td>○</td>
<td>6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over 20 km</td>
<td>○</td>
<td>7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vet ikke</td>
<td>○</td>
<td>8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Blant personene som svarer på denne undersøkelsen vil noen få tilbud om å bruke et kort, forskningsbasert planleggingsverktøy som kan hjelpe deg med å gå eller sykle mer i hverdagen. Gjennomføringen er på internett, og du kan selv velge om du vil fokusere på å sykle eller gå.

<table>
<thead>
<tr>
<th>Recruitment Intervention</th>
<th>Er dette noe du tenke deg å være med på?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• filter:\aktuell_ii.a=1</td>
</tr>
<tr>
<td></td>
<td>• range:*</td>
</tr>
<tr>
<td></td>
<td>• skip:nextsection</td>
</tr>
<tr>
<td>Ja</td>
<td>[ ] 1</td>
</tr>
<tr>
<td>Nei</td>
<td>[ ] 2</td>
</tr>
</tbody>
</table>

Walking days
I tillegg til hvordan du reiste i går, har vi noen spørsmål om den foregående uken. Hvilke av disse dagene gikk du minst 10 minutter sammenhengende?
Merk av for aktuelle dager, uansett hva som var formålet med gåturen.

<table>
<thead>
<tr>
<th>Walking days</th>
<th>I tillegg til hvordan du reiste i går, har vi noen spørsmål om den foregående uken. Hvilke av disse dagene gikk du minst 10 minutter sammenhengende?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>• filter:\RouteChoice_JA_ia.a=1&amp;\RouteChoice_JA.a=1</td>
</tr>
<tr>
<td></td>
<td>• range:*</td>
</tr>
<tr>
<td>(i går)</td>
<td>☐ 1</td>
</tr>
<tr>
<td>(for 2 dager siden)</td>
<td>☐ 2</td>
</tr>
</tbody>
</table>
### Walking minutes

Du sa du gikk minst 10 minutter sammenhengende på følgende dag(er):

- **filter**: `wlk_days.a=1`
- **filter**: `wlk_days.a=2`
- **filter**: `wlk_days.a=3`
- **filter**: `wlk_days.a=4`
- **filter**: `wlk_days.a=5`
- **filter**: `wlk_days.a=6`
- **filter**: `wlk_days.a=7`

**Hvor mange turer (over 10 minutter) gikk du vanligvis disse dagene, og hvor mye tid (antall minutter) brukte du vanligvis på disse turene per dag?**

Vi er interessert i hvor mye du går en vanlig dag, du kan oppgi gjennomsnittlig antall turer og minutter de dagene du markerte. Eksempel: Hvis du gikk 3 dager, og hver av disse dagene gikk 2 turer på 15 minutter hver, skriver du 2 turer og 30 minutter.
Antall turer per dag

Antall minutter per dag

Cycling days

I tillegg til hvordan du reiste i går, har vi noen spørsmål om den foregående uken.

**Hvilke av disse dagene syklet du minst 10 minutter sammenhengende?**

Merk av for aktuelle dager

- **filter:** RouteChoice_JA.ia.a=1|RouteChoice_JA.a=1
- **range:** *
- **exclusive:** yes

Ingen av disse dagene
Vi er interessert i informasjon om ulike former for fysisk aktivitet som folk driver med i dagliglivet, altså tiden du har brukt på fysisk aktivitet de siste 7 dagene (i dag ikke medregnet). Vennligst svar på spørsmålene uansett hvor fysisk aktiv du selv synes du er.

Tenk på aktiviteter du gjør på jobb, som en del av hus- og hagearbeid, for å komme deg fra et sted til et annet, og aktiviteter på fritiden.

Vi skiller mellom meget anstrengende, og

---

### Cycling minutes

Du sa du syklet på følgende dag(er):

- **filter:** bic_days.a=1

- **filter:** bic_days.a=2

- **filter:** bic_days.a=3

- **filter:** bic_days.a=4

- **filter:** bic_days.a=5

- **filter:** bic_days.a=6

- **filter:** bic_days.a=7

Hvor lenge (antall minutter) og hvor langt (antall km) syklet du disse dagene til sammen? Ta bare med de turene som varte mer enn 10 minutter.

- **filter:** any_bic.a=1

  |Totalt antall minutter| 1
  |Totalt antall km| 2

---

### Say

- **filter:** any_bic.a=2 & any_wlk.a=2

Vi er interessert i informasjon om ulike former for fysisk aktivitet som folk driver med i dagliglivet, altså tiden du har brukt på fysisk aktivitet de siste 7 dagene (i dag ikke medregnet). Vennligst svar på spørsmålene uansett hvor fysisk aktiv du selv synes du er.

Tenk på aktiviteter du gjør på jobb, som en del av hus- og hagearbeid, for å komme deg fra et sted til et annet, og aktiviteter på fritiden.

Vi skiller mellom meget anstrengende, og
middels anstrengende aktivitet.

Say

• filter:\any\_bic.a=1\|\any\_wlk.a=1
Vi er interessert i om du drev med andre typer fysisk aktivitet de siste 7 dagene (i dag ikke medregnet).
Vennligst svar på spørsmålet uansett hvor fysisk aktiv du selv synes du er.
Tenk på aktiviteter du gjør på jobb, som en del av hus- og hagearbeid, og aktiviteter på fritiden.
Vi skiller mellom meget anstrengende og middels anstrengende aktivitet.

Say

Meget anstrengende aktivitet får deg til å puste mye mer enn vanlig.
F.eks. rask/hard løping, aerobics og annen hard trening, og hardt/tungt kroppsarbeid.
Middels anstrengende aktivitet får deg til å puste noe mer enn vanlig.
Eksempler kan være rolig løping, moderat/lettere styrketrening, moderat/lettere kroppsarbeid.

<table>
<thead>
<tr>
<th>Physical activity last week</th>
<th>Har du utført ulike former for middels anstrengende eller svært anstrengende fysisk aktivitet i løpet av de siste 7 dagene?</th>
</tr>
</thead>
<tbody>
<tr>
<td>• filter:\any_bic.a=1|\any_wlk.a=1</td>
<td></td>
</tr>
<tr>
<td>Se bort fra det du allerede har oppgitt om sykling og/eller gange.</td>
<td></td>
</tr>
<tr>
<td>Regn bare med aktiviteter som varte minst 10 minutter sammenhengende. Du kan markere flere alternativer.</td>
<td></td>
</tr>
</tbody>
</table>

• range:*
• skip:nextsection
• exclusive:yes

Nei
Ja, middels anstrengende aktivitet
Ja, meget anstrengende aktivitet

<table>
<thead>
<tr>
<th>Vigorous activity days</th>
<th>Hvilke av de siste 7 dagene drev du med meget anstrengende fysisk aktivitet?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Altså fysisk aktivitet som får deg til å puste mye mer enn vanlig (så mye at det er vanskelig å føre en samtale). Merk av for alle aktuelle dager. Regn bare med aktiviteter som varte minst 10 min sammenhengende, og ikke det du alt har oppgitt om sykling eller gange.</td>
</tr>
</tbody>
</table>

- **filter:** aktivitet\_janei.a=3
- **range:**

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(i går)</td>
<td>1</td>
</tr>
<tr>
<td>(for 2 dager siden)</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>6</td>
</tr>
<tr>
<td>(for 1 uke siden)</td>
<td>7</td>
</tr>
</tbody>
</table>

- **skip:** nextques
- **exclusive:** yes

Ingen dager

<table>
<thead>
<tr>
<th>Vigorous activity minutes</th>
<th>På de dagene du drev med meget anstrengende fysisk aktivitet (</th>
</tr>
</thead>
</table>


Hvor lenge (antall minutter) varte dette til sammen?

- filter:aktivitet_janei.a=3&!meget_IPAQ.a=8
- range:(-)(10:1600)

Totalt 1

Say

- filter:aktivitet_janei.a=2

Tenk på all middels anstrengende aktivitet du har drevet med de siste 7 dagene. Altså fysisk aktivitet som får deg til å puste noe mer enn vanlig (men ikke mer enn at det er mulig å føre en samtale).

Ta bare med aktiviteter som varer minst 10 minutter i strekk.
### Moderate activity days

<table>
<thead>
<tr>
<th>Activity</th>
<th>Reason</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Moderate activity days</strong></td>
<td>Hvilke av de siste 7 dagene har du drevet med middels anstrengende fysisk aktivitet?</td>
<td>Merk av for alle aktuelle døgn. Ta bare med aktiviteter som varte minst 10 minutter sammenhengende, og ikke regne med det du alt har oppgitt om sykling eller gange.</td>
</tr>
</tbody>
</table>

- **filter**:aktivitet_janei.a=2  
- **range**:  
  (i går) □ 1  
  (for 2 dager siden) □ 2  
  □ 3  
  □ 4  
  □ 5  
  □ 6  
  (for 1 uke siden) □ 7  

- **skip**:nextsection  
- **exclusive**:yes  

Ingen dager □ 8

### Moderate activity minutes

På de dagene du drev med middels anstrengende fysisk aktivitet (  

- **filter**:middels_IPAQ.a=1  
- **filter**:middels_IPAQ.a=2  
- **filter**:middels_IPAQ.a=3  
- **filter**:middels_IPAQ.a=4
Hvor lenge (antall minutter) varte dette til sammen?

Totalt

Choice of active mode

Til sist har vi noen spørsmål om hvordan du tenker rundt hverdagsreisene dine. Tidligere svarte du at du kan være interessert i å prøve verktøyet som kan hjelpe deg med å gå eller sykle mer. For at du ikke skal svare på for mange spørsmål, og fordi ingen kan trekkes ut til to tiltak, lurer vi på følgende:

Hva har du mest lyst til - å sykle mer, eller å gå mer?

- Jeg har mest lyst til å gå mer
- Jeg har mest lyst til å sykle mer

mode_c transportmiddel_hidden

- gå
- sykle
<table>
<thead>
<tr>
<th>Choice of purpose</th>
<th>Hvis du skal mer den neste måneden, hva passer best for deg?</th>
</tr>
</thead>
<tbody>
<tr>
<td>• filter:\mode_c.a=2</td>
<td>Jeg vil sykle...</td>
</tr>
<tr>
<td>• filter:\mode_c.a=1</td>
<td>Jeg vil gå...</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>• range:*</th>
</tr>
</thead>
<tbody>
<tr>
<td>.. på turer hvor jeg ellers ville kjørt bil</td>
</tr>
<tr>
<td>.. på turer hvor jeg ellers ville reist kollektivt</td>
</tr>
<tr>
<td>.. på turer hvor jeg ellers ville reist med andre transportmidler</td>
</tr>
<tr>
<td>.. på fritiden</td>
</tr>
</tbody>
</table>
Appendix D: G*Power graphs of sample size for logistic regressions

**Figure D1.** G*Power graph of sample size for logistic regression with binary predictor.

**Figure D2.** G*Power graph of sample size for logistic regression with continuous predictor and covariates.
## Appendix E: Exploratory analyses

### Table E1

**Overview of Explored Associations and Their Results**

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Intentions to walk</th>
<th>Intentions to cycle</th>
<th>Willingness to participate</th>
<th>Completed intervention*</th>
<th>Purpose choice</th>
<th>Walk/cycle choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intentions to walk</td>
<td>N.s.</td>
<td></td>
<td>N.s.</td>
<td>N.s.</td>
<td>Combined full</td>
<td>Single half</td>
</tr>
<tr>
<td>Intentions to cycle</td>
<td>N.s.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>N.s.</td>
<td>Combined full</td>
<td>N.s.</td>
<td>N.s.</td>
<td>Combined full</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>Combined full</td>
<td>N.s.</td>
<td>Combined full</td>
<td>N.s.</td>
<td>N.s.</td>
<td>Combined full</td>
</tr>
<tr>
<td>Children (nr.)</td>
<td>Single half</td>
<td>Combined full</td>
<td>N.s.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Children (yes/no)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Combined full</td>
</tr>
<tr>
<td>Usual travel mode</td>
<td>N.s.</td>
<td>N.s.</td>
<td></td>
<td></td>
<td></td>
<td>Combined full</td>
</tr>
<tr>
<td>Income</td>
<td>Single half</td>
<td>Single half</td>
<td>Single half</td>
<td>N.s.</td>
<td>N.s.</td>
<td>Single half</td>
</tr>
<tr>
<td>Education</td>
<td>Single half</td>
<td>Single half</td>
<td>N.s.</td>
<td>N.s.</td>
<td>N.s.</td>
<td>N.s.</td>
</tr>
<tr>
<td>Job status</td>
<td>Single full</td>
<td>Single full</td>
<td>Single full</td>
<td>N.s.</td>
<td>Single half</td>
<td>N.s.</td>
</tr>
<tr>
<td>Physical activity</td>
<td>Single half</td>
<td>Combined full</td>
<td>Single half</td>
<td>Combined full</td>
<td>N.s.</td>
<td>Combined full</td>
</tr>
<tr>
<td>Distance</td>
<td>N.s.</td>
<td>N.s.</td>
<td></td>
<td>N.s.</td>
<td>N.s.</td>
<td>N.s.</td>
</tr>
<tr>
<td>Place of residence</td>
<td>N.s.</td>
<td>Single half</td>
<td>N.s.</td>
<td>N.s.</td>
<td>N.s.</td>
<td>Single half</td>
</tr>
<tr>
<td>Mode</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>N.s.</td>
<td>Combined full</td>
</tr>
<tr>
<td>Purpose</td>
<td>Single full</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Combined full</td>
</tr>
</tbody>
</table>

*Dependent variables are in columns, independent variables in rows, blank cells either pre-registered or not tested, single half = significant predictor of DV when only predictor on
half of the sample, single full = significant predictor of DV when only predictor on full sample, combined full = significant predictor in combined model on full sample, a tested on full sample due to small sample, b in some cases tested as only predictor on full sample due to other predictors being filtered by job status.