Understanding the stages and pathways of travel behavior change induced by technology-based intervention among university students

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We describe how a mobility behavior change support system, Blaze, is able to achieve its effects in changing the travel behavior of university students. We identify a causal pathway linking the effect of the technology intervention to its behavioral outcome through the mediation of a number of variables. Our main findings suggest that Blaze impacts travel behavior via the implementation intention. We discuss the implications of our results on the potential role of technology interventions in inducing permanent sustainable habitual behavior.

Key Words : *Mobility behavior change support system; travel demand management; technology-based intervention; mechanism of change; stage model*

1. INTRODUCTION

With the widespread adoption and pervasive use in society of information and communication technologies (ICT), technology-based interventions (TBI) to modify behavior, notably in the health domain, have undergone rapid development in the last decades. Nonetheless, in the domain of travel behavior modification, less advances have been made (Cohen-Blankshtain and Rotem-Mindali, 2016). Voluntary travel behavior change programs, Sunio and Schmöcker (2017) observed, have not yet fully taken advantage of the ICT platform, which is unfortunate since some empirical evidence suggest that TBIs can produce effects that are comparable to, or better than, approaches delivered through conventional methods (e.g. Jariyasunant et al, 2015; Bamberg et al, 2015).

In technology-based intervention studies, researchers must establish not only the cause of behavior change, but also the mechanism of change (Dallery et al, 2015). That is, they must provide evidence through what processes the intervention, previously demonstrated to be effective, achieved its effects. Often, this requires identifying the variables that mediate the effect of an intervention to the desired outcome. Fortunately, in recent years, integrated theoretical frameworks in travel behavior change – for example, the Stage Model of Self-Regulated Behavior Change (Bamberg, 2013) and Comprehensive Action Determination Model (Klöckner and Blöbaum, 2010) – have been proposed, which can give insights on the possible mediators in the causal chain of travel behavior change.

In this article, we focus on the mechanism of change induced by a technology-based intervention for travel behavior change, called Blaze (Sunio et al, 2017). Research on mechanisms in travel behavior change in non-technological context has been done (e.g. Thøgersen, 2009); but, to the best of our knowledge, there is none yet on the technological context. Dallery et al (2015) and Baraldi et al (2015) argue there may exist significant differences in mechanisms of change between non-technological and technological contexts. This work thus represents one of the first studies on the mechanisms associated with TBIs for travel behavior change. In contrast, studies on the nature of mechanisms of behavior change in the health domain, including reviews, have been extensively carried out (e.g. Schwarzer et al, 2011; Dallery et al, 2015).

The structure of this paper is as follows: after this Introduction, we introduce the mediation model in Part 2. In Part 3, we identify the possible mediating variables drawn from the stage model of self-regulated behavior change. In Part 4, we present the methodology, both the field experiment conducted and the survey instruments used to measure a number of variables. In Part 5, we show the results of our modeling. In Part 6, we discuss the mechanism of change. We summarize and end in Part 7.

2. THE MEDIATION MODEL

In a mediation model, the intervention (X) causes a change in the mediating variable (M), which in turn causes a change in the outcome variable (Y). Two relationships can be distinguished: between X and M, and between M and Y. This corresponds to two important theoretical components in the mediation model: the action theory and the conceptual theory. The first component, action theory, represents a theory about the relationship between the intervention and the mediating variable. The second component, conceptual theory, represents the relation between the mediating variable and the outcome (Baraldi et al, 2015).

Understanding the mechanisms of change between the intervention and the mediators, and between the mediators and the outcome, is essential for designing effective and efficient technology-based interventions. In evaluating the effectiveness of an intervention, generally there must be significant effects on both action and conceptual components. If an intervention fails to produce a desired outcome, this may be because there is failure in either component or both.

3. IDENTIFYING KEY MEDIATORS

Conceptual theory is based on prior research about relationships between a potential mediator and the outcome of interest (Baraldi et al, 2015). Typically, mediators are selected based on established theoretical frameworks. In our work, the Stage Model of Self-Regulated Behavioral Change (SSBC) (Bamberg, 2013) is used to identify all the potential mediators.

The SSBC theory posits that behavioral change is achieved by a transition through a temporal sequence of four stages: (I) predecisional, (II) pre-actional, (III) actional and (IV) post-actional. In this paper, we further distinguish (IV_a) early post-actional and (IV_b) stable post-actional. Those in the former stage have performed the desired behavior, though not yet habitually. The latter includes those whose behavior is already stable. Transition to the next stages is marked by formation of goal, behavioral and implementation intentions. The formation of goal intention marks the individual's transition from pre-decisional to the pre-actional stage. Similarly, the formation of a behavioral (implementation) intention marks the transition to the actional (post-actional) stage of the behavioral change process. SSBC also includes stage-specific affective and socio-cognitive constructs (given below with their measurement). These variables, according to SSBC, influence the formation of the three intention types.

4. METHODOLOGY

(1) Field Experiment

We deploy Blaze, consisting of web and Smartphone application, among students of the Ateneo de Manila University (AdMU) in Metro Manila Philippines. Through the cooperation of 16 teachers, we briefed 20 classes composed of 20-75 students. In total, we were able to invite 1,063 students to participate in the study. However, only 788 students agreed to participate and accomplish the pre-survey. At baseline, we had a total of 414 students in both control and experimental groups. 374 students had to be excluded because they did not meet the inclusion criteria (participants must have access to car) or they gave invalid survey responses. Of the 414 students, 163 (39.37%) are male, 249 (60.15%) are female, and 2 (0.48%) are neither. Ages are 18-26 years old, with mean at 20.09 years (s=1.24). We then assigned the classes into control or experimental groups (199 students in the control group, and 215 students in the experimental group). We asked those in the experimental group to register and use our website or Smartphone application for about 4 weeks (1st-24th day) of February 2017. Incentives were offered in the form of extra credit in class and a chance to be one of the three raffle winners of 10,000 JPY (1 USD = 110 JPY). The incentive is offered for using our system, and not for changing behavior. Each time the student uses our system by performing certain tasks, he earns system points and is included in the raffle. Four weeks after the first contact, we again approached the same classes and administered the post-survey. 700 students answered the post-survey. We then matched the post-survey and the pre-survey for the same users. We were able to match 138 students in the control group, and 163 students in the experimental group. Some students had to be excluded from the experimental group, because they never registered in our website, or used it after registration. In the end, for subsequent analysis, we only considered a further reduced sample size (control=115; experimental=126) because of cases of missing values in some responses. The experiment was approved by the University Research Ethics Committee of the Ateneo de Manila University.

(2) Measurement of Theory-Implied Constructs

Our pre- and post- survey consists of questions asking students of the following: demographics, stage membership, thoughts on car use, and typical main mode used each day of the week both for going to the university and returning home.

The stage membership questionnaire is based on Bamberg (2013). We ask the students to choose one among the 7 statements that best describes their level of car use: (I_a) I often use car to school, either as a student driving alone or as the only passenger being driven. I feel content with this behavior and I do not see any reason to change it. (I_b) I use car frequently to school. I am unsure if I need to change this behavior. (II) I often use car to school, but I am also thinking about taking alternatives like public transport, or sharing rides with others, but I am not sure whether and how I can achieve this goal. (III) I often use car to school but it is my aim to change this behavior. I already know which trips I will make with alternative modes, but, as yet, I have not actually put my plan into practice. (IV_a) I often use car to school but recently, I was able to go to school by other modes. I succeeded in reducing my car use! (IV_b) I mostly share rides or use alternative modes. (V) As I do not own/have access to a car, car use is not an issue for me.

The questionnaire on thoughts on car use consists of 14 questions, measuring on 11-point scale the socio-cognitive constructs in the SSBC model. To ensure construct validity, the questions are derived from Schwarzer (2008), Bamberg (2013), Klöckner (2014) and Klöckner (2017):

Problem awareness: There are problems associated with car use: traffic congestion, traffic accidents, air pollution and global warming.

Personal responsibility: Each of us can contribute in solving problems associated with car use by using car less or ridesharing with others if possible.

Personal norm: Before I make the trip by car, I first consider if I can make the same trip by alternatives. Cars should be seen as mode of last resort.

Social norm: I know some Ateneans who, though have access to cars, go to school by alternatives. They somehow motivate me to travel like them.

Positive emotions: I will feel good about myself if I am able to use alternatives for my trips to school.

Negative Emotions: I will feel bad if I do not use alternative modes.

Perceived behavioral control: It is practical / possible for me to go to the university (more often?) by alternative modes.

Goal intention: I intend to contribute in taking cars off the roads, either by taking alternative means or pooling with others car trips going to same destination.

Attitudes towards alternatives: Among the different mode options to go to the university, there is one option, except driving alone or being the only passenger driven, that is favorable for me.

Behavioral intention: I have decided which mode to use as substitute for my car for some of my trips to the university. I intend to make a plan on how to go to the university using this mode.

Action plan: I have a commute plan on how to go to school by alternatives, and I have already run through my head on how to best carry out this plan.

Coping plan: I have anticipated all the possible problems that can occur and hinder me as I put my commute plan into practice.

Maintenance efficacy: I have already mentally developed ways to overcome problems and obstacles to my commute plan or to be flexible depending on the situation.

Implementation intention: Within the next seven days, I intend to actually use alternatives in going to the university/home.

Recovery efficacy: I will continue to use alternatives to go to school, even though this may be inconvenient.

As can be seen in our questionnaire, we used single-item measures per construct. This is clearly a limitation, since we cannot test the internal consistency using indices such as, for example, Cronbach’s alpha. However, we decided against multiple-item measures per construct in our survey because they are costly and time-consuming in practice (Christophersen and Konradt, 2011). Moreover, the developer of our application advised against having too many questions. Furthermore, single-item measures can be reliable and are preferred especially when respondent burden is primary concern (Bergkvist and Rossiter, 2007; Lucas and Donnellan, 2012). Finally, Klockner (2014), in his study in which some of our survey questions are based, also used one-item measures.

An alternative to reliability testing by examining internal consistency is by using longitudinal data (Lucas and Donnellan, 2012). To test the reliability of our single-item survey, we assess the stability of the responses of the students (in the control condition) at two different time points: at baseline and after four weeks. We use a specific cohort of the control group for our analysis: those students identifying themselves as not having changed their stage membership over four weeks. This is to ensure that their test-retest responses on all the questions are not likely to change over time. Only data from postaction-stable (N=47) are used since this constitutes the largest sample size. Following Thøgersen (2009), we calculate the T-test and correlation at the two time points to find any systematic changes over time in the postaction-stable group. If there is not any systematic change, we can assume that the survey instrument is reliable since the responses to the survey instrument are stable over time in stable subjects (Vaz et al, 2013).

5. RESULTS

(1) Reliability of Measurement

Table 1 Reliability of survey instrument. *significant at 0.05 level **significant at 0.01 level

Construct	Mean (baseline)	Mean (4 weeks)	Paired T-test	Pearson Correlation
Pos Em	2.85	2.57	0.253	0.673*
Neg Em	2.51	0.83	**<0.01****	0.415*
P. Norm	1.25	2.14	0.065	0.408*
S. Norm	1.49	2.18	0.113	0.443*
P. Resp	4.32	4.17	0.302	0.444*
P. Aware	4.53	4.06	0.312	0.312*
PBC	4.06	3.28	0.035*	0.298*
Goal Int	3.77	3.40	0.215	0.611*
Att	3.07	3.32	0.176	0.354*
Beh Int	2.85	3.40	0.089	0.674*
Action Plan	2.91	3.18	0.430	0.669*
Cope Plan	2.60	3.04	0.260	0.536*
M. Eff	2.48	3.22	0.038*	0.528*
Imp Int	3.29	3.13	0.683	0.663*
R. Eff	3.24	3.62	0.238	0.616*

Table 1 above shows the T-test and correlation at the two time points for the postaction-stable cohort group. So far, there is no consensus on the acceptable value of correlation coefficient, although 0.80 and below are considered insufficient in sports and medical sciences, but in sociological and behavioral sciences, lower relative reliability thresholds may be adopted (Vaz et al, 2013). In Thøgersen (2009), the correlation ranges from 0.25-0.69 for test-retest for control group (over 1-month period) for the variables considered. Hence, insofar as the correlations of our variables are concerned, we consider them acceptable. In the table above, the T-test shows that, at 0.01 significance level, questions to all constructs, except negative emotions, are reliable. We thus decide to drop the negative emotions from our subsequent analysis.

(2) Distribution across stages and stage transition

As previously mentioned, we only consider a sample size of N=241 (control=115; experimental=126). At baseline (T0), 31.1% of the students in both control and experimental groups belong to the predecision stage (PreD); 16.6% in the preaction (PreA); 7.5% in the action (A); 7.9% in the early postaction (PostA1); and 36.9% in the stable postaction (PostA2). Four weeks later, the distribution changes: 27.8% are in the predecision; 17.0% in the preaction; 5% each in action and early postaction; and 45.2% in the stable postaction.

Table 2 Stage distribution and transitions. T_0=baseline; T_1=4 weeks later

T_0/T_1	PreD	PreA	A	PostA1	PostA2	N
PreD	53	9	3	2	8	75
PreA	9	20	5	3	3	40
A	2	8	3	2	3	18
PostA1	2	3	0	4	10	19
PostA2	1	1	1	1	85	89
N	67	41	12	12	109	241

(3) Association between car use and stage memberships

We first examine the relationship between car use and stage membership. We consider weekly car use (values from lowest use at 0 to highest use at 10) and the five stages (PreD, PreA, A, PostA1, and PostA2). We check both cross-sectional data at a single time point and longitudinal data over two time points.

In Fig.1(a), which plots the car use at baseline across stages, we observe that the weekly car usage decreases as we progress towards advanced stages (car use: PreD=9.69, PreA=8.25, A=7.39, PostA1=5.16). Nonetheless, considering confidence intervals, there is a significant overlap among the first four stages. In the last stage, we notice a big drop in the car use (PostA2 car use=0.64), indicating that those in the late postaction have adopted the low car-use behavior.

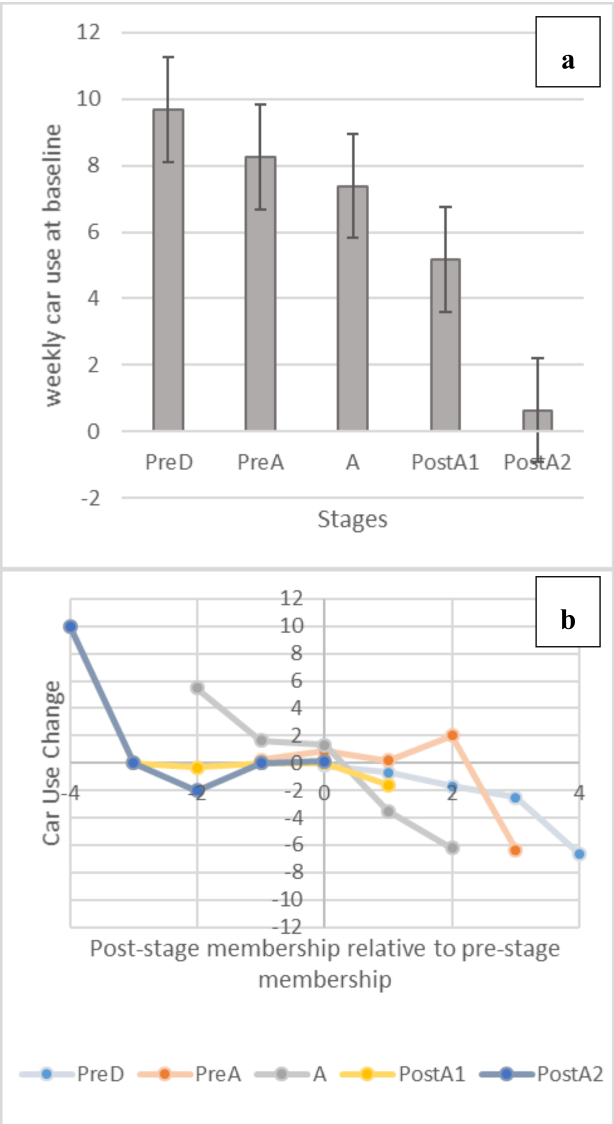
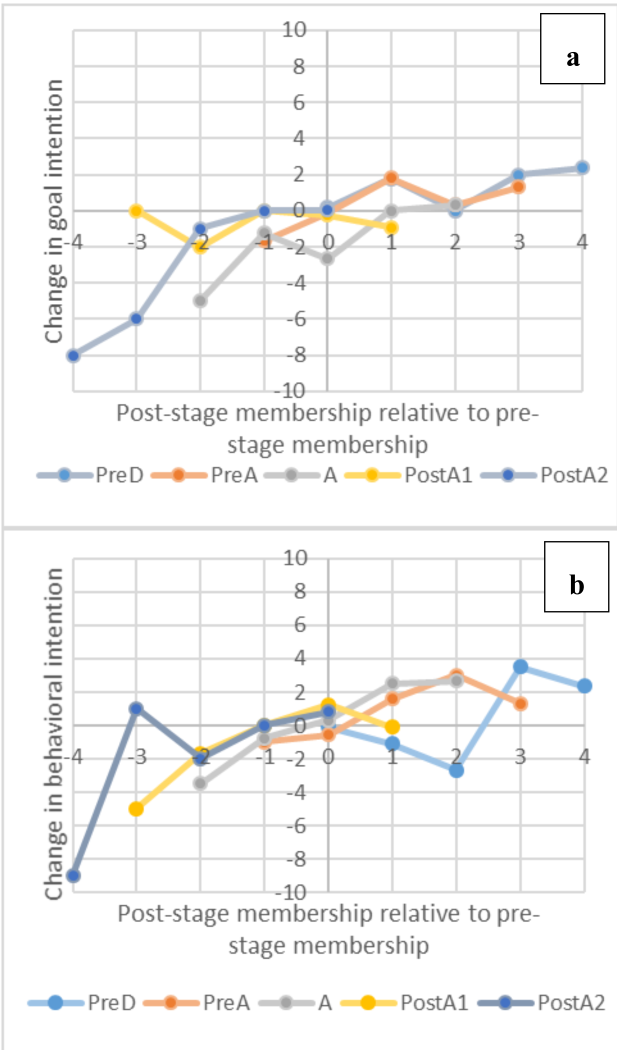


Fig.1 (a) Car use frequency and (b) car use change across stages.

In Fig.1(b), we examine the change in car use with respect to the post-intervention stage membership. The values on the x-axis denote the post-stage taking the pre-stage as reference. As an illustration, consider the points on the line labeled PreD. These points represent the car use change of those belonging in the predecision at T0. After four weeks, some of them remain in the same stage, while others advance to the next stages. We represent stage progression with the integers on the x-axis taking as reference the stage at T_0. Hence, those who remained in the same stage after four weeks have their car use change plotted at x=0. The car use change of those who progress one stage up is plotted at x=1, and of those who regress one stage down is marked at x=-1. Looking at the PreD plot, we see that as the students belonging to the predecision stage progress to more advanced stages over 4 weeks, they also reduce their car usage. In fact, those who transition to PostA2 from PreD have decreased their car use by as much as 6 (this means that they substituted their 6 car trips to school with alternatives). We also observe the same trend in other longitudinal data: progression through the stages is associated with reduction in car use. Calculating the slope of the lines connecting these points (Table 3), we see that the slopes are negative, indicating that as we advance through the stages, the car use is reduced.

(4) Progression in stage membership is associated with formation of three types of intentions

Next we try to check any association between stage progression and intention strengths. In the next three graphs, we see from our longitudinal data that stage progression is associated with increase in intention strengths. The slopes of these lines in the graphs are positive, indicating increase in intention strengths with increasing stages (Table 3). We also later on confirm the same results using ordinal logistic regression model (Table 4).



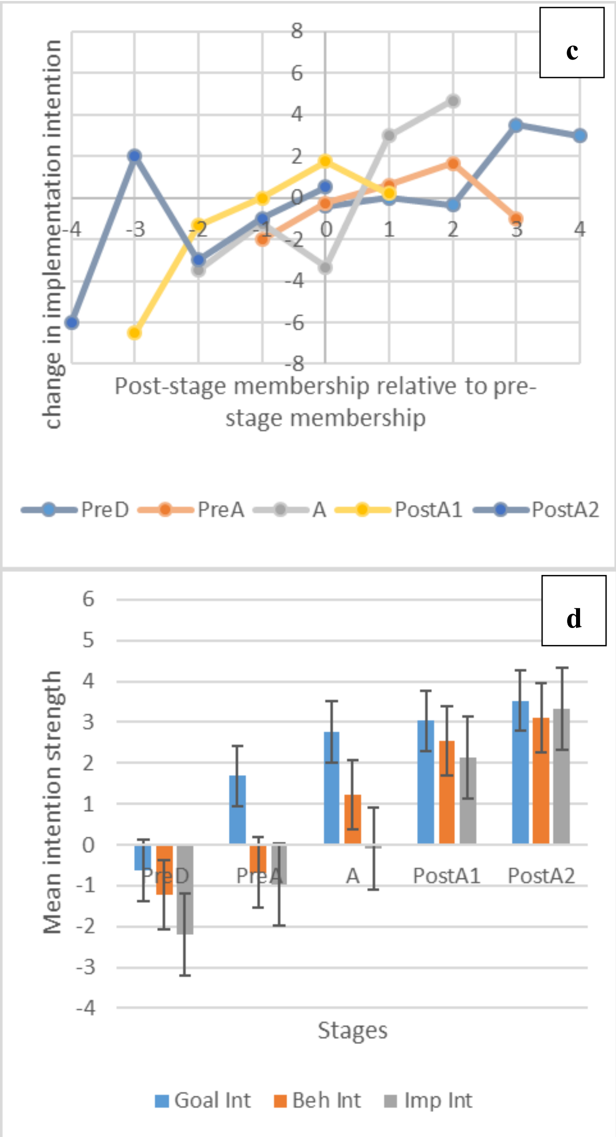


Fig.2 (a) Change in goal intention; (b) change in behavioral intention; (c) change in implementation intention relative to stage progression; and (d) mean intention strengths across stages

Table 3 Slopes of the points in Fig 1(b), and Figs. 2(a)(b)(c)

	PreD	PreA	A	PostA1	PostA2
Car Use	-1.474	-1.200	-2.860	-0.290	-1.980
Goal Int	0.463	0.643	1.192	-0.005	2.212
Beh Int	0.959	0.822	1.558	1.272	1.867
Imp Int	1.029	0.392	2.058	1.648	1.006

Looking at the cross-sectional data produced by combining two cross-sectional data at two time-points (Figure 2d) gives the same insights. All the three intentions (i.e. means) become stronger as stage progresses. Nonetheless, if we examine two consecutive stages, we observe that there is both an overlap and a discontinuity among intentions. For instance, comparing preD to preA, we notice that the behavioral and implementation intentions overlap, but the goal intention does not. Comparing preA and A, however, we see that there is discontinuity on behavioral intention but an overlap in goal and implementation intentions. In A and PostA1, the break is in the implementation intention. We observe overlap among the three intention types in both postaction stages. These discontinuity patterns in variables indicate the existence of stages (Armitage & Arden, 2002).

The results seem to suggest that progression to later stages is associated with an increase in strengths in all three intention types, but transition to a particular stage is especially associated with a specific intention type crossing a certain threshold. The transition from PreD to PreA is significantly correlated with goal intention only, from PreA to A with behavioral intention only, and from A-PostA1 with implementation intention only.

Next we perform an ordinal logistics regression on the ordered categorical variable (the time-ordered sequence of stages) using the three intention types as explanatory variables (Hedeker, Mermelstein, & Weeks, 1999; Bamberg, 2013). We can posit a continuous latent "readiness of change" variable, which is divided at certain thresholds (cut-off points) to make the stages that we observe in our data. In the present case, as we have five stages, we can conceptualize four thresholds that separate these ordered stages. We can then assess the role of the predictors – the three intention types – on crossing these thresholds. Since predictors have differential effects on the thresholds, an assumption by stages of change theories (Hedeker & Mermelstein, 1998; Hedeker, Mermelstein & Weeks, 1999; Lippke, Ziegelmann & Schwarzer, 2005; Bamberg, 2013), we utilize the nonproportional logistics regression. Following Bamberg (2013), we dichotomize the three intention variables using median split prior to the analysis. Table 4 presents the results cumulative and adjacent categories models.

In the cumulative model, the first cumulative logit compares the first stage versus the four next stages combined (i.e. PreD versus PreA-A-PostA1-PostA2 combined). This is to assess the effect of the three intention predictors on the threshold between predecision to preaction. Since the size of the estimate is difficult to interpret (Bamberg, 2013), we only determine which of the intentions are significantly associated with crossing the thresholds. We see that goal and implementation intentions are significant predictors at 99% level, and behavioral intention at 90% level. In the second cumulative logit, we compare the first two stages versus the next three stages (i.e. PreD-PreA versus A-PostA1-PostA2) to evaluate the association of the three intentions on the preaction-action threshold. All three intentions are significant predictors at 99% level on the transition from preaction to action. Similarly, from the third cumulative logit, which compares the three early stages versus the two latter stages (i.e. PreD-PreA-A versus PostA1-PostA2), we find that all three intention types are significant. Finally, in the fourth cumulative logit, comparing the first four stages versus the last stage (PreD-PreA-A-PostA1 versus PostA2), we see that only the goal and implementation intentions are significant. The results confirm our previous observation from the graphs that stage progression is associated with all the intention types.

Next we compare two consecutive stages through adjacent-category ordinal logistic regression. Having been in a particular stage, we want to determine the significant predictor for progression (or regression) to the immediate next stage. We first compare predecision versus preaction, and we find that only goal intention is closely associated with the transition between the two stages. Comparing next preaction versus action, we observe that only behavior intention is a significant predictor. Comparing action and early postaction, we find that only implementation intention is significant. Finally, if we compare the two post-action stages, we see that none of the intentions is significant. This confirms our previous result from the graph using cross-sectional data that transition to a particular stage starting from a stage immediately prior to it is especially associated with a specific intention type crossing a certain threshold. The transition from PreD to PreA is significantly correlated with goal intention only, from PreA to A with behavioral intention only, and from A-PostA1 with implementation intention only.

Table 4 Results of the Ordinal Logistic Regression Using Cumulative and Adjacent Categories. Significance codes: Bold 0 '***' 0.001 '**' 0.01 '*' 0.05 'a' 0.1

	Cumulative		Adjacent	
	Estimate	Standard Error	Estimate	Standard Error
PreD-PreA				
Intercept	**0.4252****	0.1447	**0.8073*****	0.1667
Goal Int	**-2.2061*****	0.4070	**-1.8157*****	0.4736
Beh Int	-0.5399[a]	0.2981	0.2692	0.3871
Imp Int	**-2.4516*****	0.4345	-0.8550	0.5473
PreA-A				
Intercept	**1.8067*****	0.1831	**1.8928*****	0.3452
Goal Int	**-1.6273*****	0.2770	-0.5999	0.4805
Beh Int	**-1.0504*****	0.2791	**-1.2591***	0.5252
Imp Int	**-2.5877*****	0.3143	-0.7829	0.5660
A-PostA1				
Intercept	**2.0972*****	0.1990	0.6895	0.5156
Goal Int	**-1.3036*****	0.2590	0.1802	0.5508
Beh Int	**-0.8275****	0.2823	-0.3720	0.6572
Imp Int	**-2.4749*****	0.2875	**-1.0345**[a]	0.6081
PostA1-PostA2				
Intercept	**2.3010*****	0.2128	**-1.3198****	0.4506
Goal Int	**-1.3264*****	0.2574	-0.6479	0.4168
Beh Int	-0.4619	0.2930	0.5317	0.5390
Imp Int	**-2.2381*****	0.2833	-0.7278	0.4839
Model fit (-2LogL)	975.7266		977.6582	
Model fit (df)	1912		1912	

(5) Determinants of the three intention types: model structure and parameter estimates

So far, from the preceding results, we can make the following observations regarding the mechanism of change in the reduction of car use: decrease in car use is associated with progression through a sequence of temporal stages, which is also associated with an increase in three intention types. In this section, we consider the determinants of each of the three intention types.

As mentioned previously, the determinants are drawn from the stage model of self-regulated behavior change theory (Bamberg, 2013). Nonetheless, we drop three determinants from the original model in our subsequent analyses – namely, negative emotions, personal responsibility, and problem awareness. Negative emotion is dropped because of unreliability of the instrument measuring it. Personal responsibility and problem awareness are dropped because when we compare the responses across stages at both time points, we find that problem awareness and personal responsibility are not a significant predictor of stage membership.

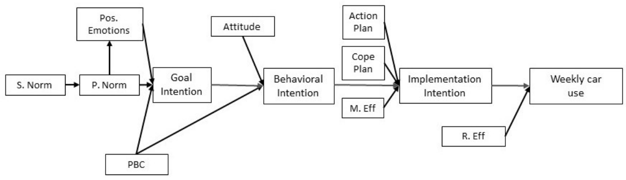


Fig.3. Original model (based from Bamberg (2013))

First, we fit our data to the original model proposed by Bamberg (2013). To assess model fit, we report the Chi-square and degree of freedom ($\chi2$ and df), including the p-value, Tucker-Lewis index (TLI), Comparative fit index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). A $\chi2$/df ratio of 2 is acceptable, with an insignificant p-value ($p>0.05$). However, since $\chi2$ is sample size dependent, we consider other indices. TLI and CFI values greater than 0.95 are acceptable. An RMSEA of <0.07 and and SRMR of <0.08 are considered acceptable (Hooper, Coughlan & Mullen, 2008). We find a very poor fit between our data and the original Bamberg model: $\chi2$ (df = 43, n = 241) = 404.408, p <0.001; RMSEA = 0.187; CFI = 0.714; TLI = 0.621; SRMR = 0.197. We then try to make some modifications to the original model.

Based on previous results, we see that the general path of successive formation of three types of goals leading to the new behavior is supported by our data. Next we specify the determinants of each of the intentions. We hypothesize that goal intention to reduce car use is activated by personal norms and perceived goal feasibility, and that attitudes towards a particular alternative are the main determinant of choosing that alternative over car (behavioral intention). Moreover, we assume that the ability to make a plan of action to implement the new behavior is a significant predictor of the implementation intention, and the ability to recover from relapse is the main factor for the maintenance of the behavior.

After several iterations and checking modification indices, we obtain the following base model. Other constructs from the original model are insignificant so they are dropped. We also estimate the parameters of the path coefficients.

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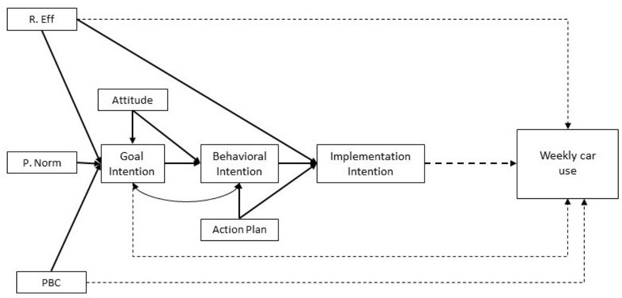

Fig.4. Base model

We explain model structure through path analysis. Path analysis is used to capture influences of (observed) variables among each other and to investigate their pattern of relationships within the overall dataset (Golob, 2003). We note that in our base model, the recovery efficacy construct has a direct path to goal intention, implementation intention and behavior. This means it is an important determinant in the predecision, action and postaction stages. This may come as odd since recovery efficacy is usually associated with recovery from relapse after adopting the new behavior. Nonetheless, since we measure recovery efficacy as "I will continue to use alternatives to go to school, even though this may be inconvenient", we hypothesize that this statement may be interpreted differently by individuals belonging to various stages. For those in the pre-decisional stage, they may interpret this question as: "I am a car user now, but if I am to begin using alternatives, will I be able to continue doing this behavior, even though this may be inconvenient?" In post-actional: "I am an alternative user now. Will I be able to continue with this?" Moreover, we observe in our parameter estimates in Table 5 that a large magnitude of recovery efficacy coefficient is associated with later stages, and a smaller value in the early stage.

Furthermore, attitude predicts goal intention, but it has lower influence on it than on the behavioral intention. The action plan also has a direct influence on the behavioral intention, aside from the implementation, and it has a greater influence on the former than on the latter. We think that when a person considers choosing an alternative over a car, he considers not only his attitudes toward that alternative, but also his ability to make a trip plan using that alternative. Finally, the fact that the goal intention still has direct influence over the behavior (and not simply mediated by other intentions) signifies that the goal or purpose of doing the desired behavior must always be reconsidered. To avoid relapse, people must always maintain the goal they have set.

We test the base model against complete sample using R 3.4.0 software. The maximum likelihood estimation method (ML) was employed. The fit indexes reveal good fit of the model, $\chi2$ (df = 11, n = 482) = 23.487, p =0.015; RMSEA = 0.049; CFI = 0.994; TLI = 0.986; SRMR = 0.014. We also test the same path analysis model against subgroups (i.e. control group only, experimental group only, both groups before/after intervention, etc.), and we see that the model fit is good. This analysis establishes the acceptability of the base model.

(6) Parameter estimates of the base model and multiple group analyses

Subsequently, after establishing the appropriate base model, we try to estimate the parameters. Since there are multiple groups, we also try to establish if the parameters – e.g. regression coefficients, intercepts, variances and co-variances, etc. – can be set to be equal or invariant across the different subgroups. In multi-group approach, we test a sequence of models starting from an unrestricted model with the parameters freely estimated across subgroups, to more parsimonious models whose parameters are constrained at different levels (see, for example, Lippke, Ziegelmann & Schwarzer (2005) for the general strategy in using multi-group invariance test for stage-based models).

In particular, we attempt to establish if the parameters are invariant across treatment groups and across time. For this purpose, multiple group approach using maximum likelihood estimation method (ML) was used to compare subgroups on the base, unconstrained, model. We first consider two groups: control group and experimental group. We want to check whether the relationships among the constructs and their parameter estimates are invariant across experimental conditions.

At the first step of the multiple group approach, a model without any invariance—a configural model (i.e., the same model in all groups, but all parameters to be estimated individually in all groups) was tested. The fit indexes reveal good fit of the model, $\chi2$ (df = 22, n = 482) = 37.424, p =0.021; RMSEA = 0.054; CFI = 0.993; TLI = 0.983; SRMR = 0.016.

In the second step, we set the regression coefficients to be equal across the four groups – the weak invariance model (i.e. the same model with equal regression coefficients in all groups, but all other parameters to be estimated individually in all groups). The fit indices are: $\chi2$ (df = 36, n = 482) = 51.913, p =0.042; RMSEA = 0.043; CFI = 0.992; TLI = 0.989; SRMR = 0.026. A chi square difference test (p=0.4139) showed no significant difference between the configural model and the equal regression model, and so an invariance of regression coefficients across all four groups can be claimed.

The third step is the equal intercept model (regression coefficients and intercepts fixed to be equal across all groups, while other parameters are free. The fit indexes reveal good fit of the model, $\chi2$ (df = 40, n = 482) = 57.477, p =0.036; RMSEA = 0.043; CFI = 0.992; TLI = 0.989; SRMR = 0.028. Chi square difference test (p=0.2341) also showed no difference between the equal regression model and the equal intercept model.

There is parameter invariance across group (experimental vs control). This means regardless of the treatment groups, we can set the regression coefficients and intercepts as equal. Although we do not show the calculations here, but we also performed the same invariance test with a different pair of groups – both control and experimental *before* intervention and both groups *after* intervention – in order to establish invariance across time, and the result is that time invariance of parameters cannot be claimed.

However, we can do partial constraint and repeat the same three steps outlined above. We set some parameters fixed, others free, at both time points (constrained parameters are marked with * in Table 5). Doing so, we then compare the models at both time points. We see that the Chi square difference is not significant (p=0.306 in Step2 and p=0.231 in Step 3). Almost all of the regression coefficients are significant and lie in the expected direction.

Table 5 Parameter estimates of the model structure with partial constraint

Baseline					
Path	**B**	**SE**	**p**	**β**	**R^2**
pnorm → gi *	0.180	0.030	0.000	0.206	
					0.590
pbc → gi	0.443	0.044	0.000	0.512	
att → gi	0.135	0.051	0.008	0.146	
reff → gi	0.043	0.051	0.406	0.048	
gi → bi	0.303	0.079	0.000	0.281	
					0.676
ap → bi *	0.461	0.035	0.000	0.469	
att → bi	0.253	0.053	0.000	0.254	
bi → ii *	0.216	0.037	0.000	0.193	
ap → ii *	0.202	0.038	0.000	0.184	0.729
reff → ii *	0.604	0.034	0.000	0.561	
ii → beh *	-0.245	0.083	0.003	-0.178	
					0.466
reff → beh *	-0.600	0.093	0.000	-0.404	
pbc → beh *	-0.123	0.063	0.050	-0.085	
gi → beh *	-0.172	0.075	0.023	-0.103	
gi ↔ bi	-0.730	0.298	0.014	-0.260	
gi *	0.636	0.098	0.000	0.238	
bi *	-0.445	0.118	0.000	-0.154	
ii *	-0.390	0.073	0.000	-0.121	
beh *	6.813	0.182	0.000	1.529	

4 weeks later					
Path	**B**	**SE**	**p**	**β**	**R^2**
pnorm → gi *	0.180	0.030	0.000	0.196	
pbc → gi	0.044	0.040	0.276	0.054	0.621
att → gi	0.365	0.044	0.000	0.364	
reff → gi	0.270	0.043	0.000	0.345	
gi → bi	0.690	0.124	0.000	0.554	
ap → bi *	0.461	0.035	0.000	0.503	0.628
att → bi	-0.063	0.090	0.487	-0.050	
bi → ii *	0.216	0.037	0.000	0.202	
ap → ii *	0.202	0.038	0.000	0.206	0.845
reff → ii *	0.604	0.034	0.000	0.578	
ii → beh *	-0.245	0.083	0.003	-0.189	
reff → beh *	-0.600	0.093	0.000	-0.443	0.570
pbc → beh *	-0.123	0.063	0.050	-0.088	
gi → beh *	-0.172	0.075	0.023	-0.099	
gi ↔ bi	-1.462	0.379	0.000	-0.476	
gi *	0.636	0.098	0.000	0.248	
bi *	-0.445	0.118	0.000	-0.139	
ii *	-0.390	0.073	0.000	-0.114	
beh *	6.813	0.182	0.000	1.537	

As for the signs, all lie in the expected direction. At T_1, however, the sign of att→bi is negative (but insignificant). At T_0, however, this path is positive and significant. We can say then that we lose the direct path from attitude towards alternatives to behavioral intention at T_1. This holds true even when we separately look at control and experimental groups. In contrast to the results at T_0, the path reff →gi becomes significant at T_1. The path coefficient is greater in the control group (0.334) than in the experimental group (0.201), but the p-value of the difference is not significant (*p*=0.113). The regression coefficient values at T_0 are almost the same for both groups (we also find no significant difference).

(7) Prediction of change in behavior using the model

Finally, we analyzed whether behaviour change is influenced by a change in any of the determinants in the model. That is, we investigate associations between change in the determinants of intentions, and change in intention and behaviour. Fit indices indicate adequate model fit, but the results represent a significant departure from theory. The model also accounted for only 6% of the variance in change in behavior. Personal norm change did not predict change in goal intention, which in turn did not predict behavioral intention change. Implementation intention change, goal intention change and PBC change did not predict change in behavior. Recovery efficacy change predicted change in behavior, but only at 10% significance level.

Table 6 Prediction of change parameter estimates. All variables are now *change variables*.

Path	B	SE	p	β	R^2
pnorm → gi	0.053	0.052	0.316	0.057	
pbc → gi	0.214	0.049	0.000	0.245	0.277
att → gi	0.239	0.047	0.000	0.295	
reff → gi	0.192	0.062	0.002	0.180	
gi → bi	0.193	0.172	0.262	0.182	
ap → bi	0.438	0.051	0.000	0.466	0.388
att → bi	0.195	0.070	0.005	0.227	
bi → ii	0.227	0.053	0.000	0.229	
ap → ii	0.161	0.052	0.002	0.173	0.543
reff → ii	0.574	0.055	0.000	0.512	
ii → beh	-0.089	0.082	0.277	-0.091	
reff → beh	-0.173	0.094	0.066	-0.156	0.060
pbc → beh	0.063	0.061	0.303	0.069	
gi → beh	-0.065	0.072	0.366	-0.063	
gi ↔ bi	-0.802	0.912	0.379	-0.165	
n	241				
χ2	19.859				
df	11				
p-value	0.047				
CFI	0.978				
TLI	0.949				
RMSEA	0.058				
SRMR	0.035				

(8) Pathway of interventions: mediation by implementation intention alone

We construct two models to determine the pathway of intervention. In Model 1, we model the effect of intervention on car use at T_1, using cross-sectional data at T_1 and entering the car use at T_0 as covariate. The fit indices show a good fit: χ2 (df = 13, n = 241) = 20.082, p =0.093; RMSEA = 0.048; CFI = 0.995; TLI = 0.986; SRMR = 0.012. We present the results of our estimates in Table 7.

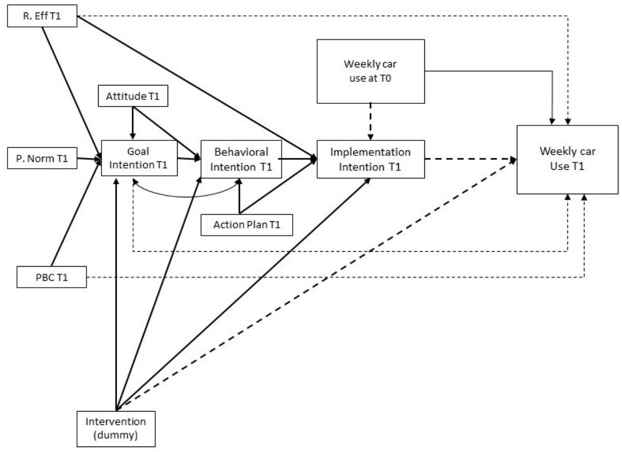

Fig.5. Model 1

Table 7 Parameter estimates for Model 1

Path	B	SE	p	β
int → gi1	0.220	0.204	0.282	0.042
int → bi1	0.035	0.259	0.894	0.005
int → ii1	0.392	0.176	0.026	0.057
beh0 → ii1	-0.026	0.026	0.330	-0.034
beh0 → beh1	0.568	0.045	0.000	0.578
int → beh1	-0.500	0.299	0.094	-0.057
ii1 → beh1	-0.220	0.096	0.022	-0.171
reff1 → beh1	-0.286	0.112	0.011	-0.213
pbc1 → beh1	0.029	0.065	0.661	0.021
gi1 → beh1	-0.001	0.079	0.992	-0.000
R^2				
gi1	0.642			
bi1	0.623			
ii1	0.850			
beh1	0.743			
Model fit indices				
n	241			
χ2	20.082			
df	13			
p-value	0.093			
CFI	0.995			
TLI	0.986			
RMSEA	0.048	0.000 -0.086		
SRMR	0.012			

We find that car use at T_0 is a significant covariate. Past behavior is a stronger predictor of current behavior than any of the previously mentioned antecedents/determinants. At the same time, car use is also a conscious decision or volitional (implementation intention and recovery efficacy are significant predictors of behavior in the model). The intervention has mediated effect (via implementation intention) on car use at T_1 (we also test if the intervention has mediated effect via recovery efficacy but we find it is not significant). It has been suggested in the literature (Thøgersen, 2009) that habits not only influence behavior, but also constrain the mind in what has been called a ''habitual mind-set''. In our model, we note that past behavior has an insignificant effect on implementation intention (hence it does not constrain the mind in what is called habitual mindset). The last statement is important since the intervention influences behavior via the mediation of implementation intention.

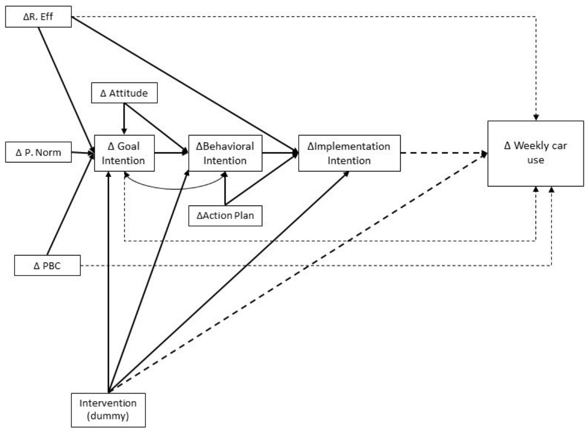

Fig.6. Model 2

Table 8 Parameter estimates for Model 2

Path	B	SE	p	β
int → Δgi	0.117	0.298	0.693	0.022
int → Δbi	0.241	0.289	0.405	0.043
int → Δii	0.709	0.243	0.004	0.128
int → Δbeh	-0.909	0.349	0.009	-0.167
R^2				
Δgi	0.277			
Δbi	0.394			
Δii	0.559			
Δbeh	0.086			
Model fit indices				
n	241			
χ2	20.295			
df	11			
p-value	0.041			
CFI	0.978			
TLI	0.939			
RMSEA	0.059	0.011-0.099		
SRMR	0.031			

In Model 2, we examine if the intervention induces a change in the determinants and in the intentions, which then cause the behavior to change. However, since we have seen in Section 5(7) that the change in implementation intention and change in behavior are not significantly correlated, then we cannot formally test for mediation (Baron & Kenny, 1986). The model fit is acceptable: $\chi 2$ (df = 11, n = 241) = 20.295, p =0.041; RMSEA = 0.059; CFI = 0.978; TLI = 0.939; SRMR = 0.031. We present the parameter estimates in Table 8.

In Model 2, the intervention changes the implementation intention and the car use. The effect in both cases is significant. Combining the insights from Model 2 and Model 1, we can say then that the intervention induces change in implementation intention and car use (cf. Model 2). The intervention makes the habit-driven student (note that habit influences current behavior) stop and conscious about his behavior, which is reflected in the change in implementation intention. The change in implementation intention, however, does not have a significant effect on change in car use (cf. Model 2). This may make sense because, if the student is in the predecision stage for instance, a change in his implementation intention does not necessarily translate to a change in car use (he may transition for example to preaction or action, while maintaining his high car use; here stage progression may mediate the effect of the change in implementation intentions). The intervention has mediated effect (via implementation intention) on car use at T_1.

6. CONCEPTUAL AND ACTION COMPONENTS OF MECHANISM

In this section, we discuss the mechanism of change based on the results we have so far. We discuss the mechanism separately for conceptual and action components. The conceptual component tackles the relationship between the mediating variables and the outcome of interest, while the action component deals with the relationship between the intervention and the mediating variables..

(1) Conceptual Component

In summary, this is what we claim about the mechanism of change in the reduction of car use:

•Decrease in car use is associated with progression through a sequence of temporal stages. We observe that there is a corresponding reduction in car use among those who transition to advanced stages in the behavior change process.

•Transition to later stages is also associated with an increase in three intention types: goal, behavioral and implementation intentions. We also find some evidence that transition to a particular stage is especially associated with a specific intention type, not only increasing, but also crossing a certain threshold.

•Behavior is not only determined by implementation and goal intentions, but also by self-efficacy or ease of behavior (recovery efficacy and perceived behavioral control). Recovery efficacy has the largest influence on behavior, followed by implementation intention.

•Implementation intention is predicted by behavioral intention, action plan and recovery efficacy.

•Behavioral intention is formed by goal intention, action plan and attitude towards alternatives.

•Goal intention is activated by personal nor, attitude and self-efficacy (recovery efficacy and perceived behavioral control).

•Change in behavior due to changes in intentions such as implementation intention is not, however, supported by our data.

(2) Action Component

In brief, this is what we can say about the effect of the intervention, Blaze, on the mediators:

•The intervention is able to induce significant changes in both implementation intention and behavior. However, change in implementation does not have a significant effect on the change in car use.

•The intervention makes the habit-driven student (note that habit influences current behavior) stop and conscious about his behavior, which is reflected in the change in implementation intention.

•The intervention has mediated effect (via implementation intention) on car use at T_1.

7. LIMITATIONS AND IMPLICATIONS

In the present study, we acknowledge a number of weaknesses. First, although we claim our study has a longitudinal character, we are only limited by two data points (before-after the intervention). Our study design is able to capture the immediate effect of the technology intervention, but we fail to understand its (potential) long-term effect. Other studies (e.g. Thøgersen, 2009) conducted data collection in three waves (before and after the intervention, and 6 months later). Thus, he was able to assess the long-term impact (if any) of the intervention. Klöckner (2014) also employed repeated measures for two months. Studies like these, with frequent data collection, are able to capture, not only between-group dynamics, but also the intra-person (within-person) dynamics over time. Second, we used single-item measures only. Multiple-item measures are generally recommended, but caution must be taken on the length of questionnaire so as not to unnecessarily burden the respondents. Perhaps, two-item measures per construct are acceptable. Third, we have a small sample size, especially for some stages. We observe that many of our respondents belong to the predecision and late post-action but very few of them belong to certain stages, such as action and early post-action. This makes it necessary to consider with caution our analysis regarding stage progression. Finally, we employed quasi-experimental design, and not a randomized controlled trial (RCT) as our experimental design, a standard requirement for studying mechanism of effect (Kazdin, 2007). This limits our ability to draw robust inferences between intervention and change. However, as Bamberg and Rees (2017) recently noted, in transportation research, quasi-experimental design counts already as sufficient evidence.

Nonetheless, our results have important implications for intervention development involving technology. We have seen that our technology-based intervention is able to induce changes in the mediating variables and also car use behavior. In particular, the effect of the intervention is on the final stages of the behavior change process (action and post-action). The intervention caused changes in the implementation intention, which may enable progression from action to early post-action. It also caused changes in the actual car use behavior, which indicates its potential role in supporting habit formation and maintenance.

In mobility management, the short-term effect of interventions is easily demonstrable, but persistence of their effects on behavior change is largely unproven. Richter et al (2011) argue that the issue of whether the effects are long-term remains to be addressed by future studies. Some interventions temporarily break habits, but as soon as the interventions are withdrawn, the old behavior reverts back, thus failing to induce a permanent, long-lasting change (Thøgersen & Møller, 2008). In this regard, interventions (e.g. Fujii & Kitamura, 2003) that unfreeze old (undesirable) habits temporarily, while supporting the new (desirable) behavior to form, and sustaining it in the long-term are important. Our work suggests, which Stawarz et al (2015) also corroborate, the potential of technology, such as smartphone applications, in supporting habit formation. More research on the potential role of technology interventions in the formation of sustainable habitual behavior should be done.

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