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Habit substitution toward more active commuting

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Abstract

Commuting to work is often a highly habitual behavior that people perform automatically over a long period of time. Substituting an inactive with a more active commuting habit might thus support long-term behavior change. This study investigated habit substitution processes in commuting behavior and related psychological determinants. We report primary analyses of an online planning intervention study conducted in Germany with a one-arm pre-post design over 14 weeks including multiple-a-day workday assessments across a baseline week followed by five post-intervention measurement weeks. Forty-two participants (60% female, M_{age} = 32.3 years) reported daily automaticity, experienced reward and regret, and weekly plan enactment for new and old commuting behaviors. Multilevel models were fit. In this one-arm study, automaticity of the old commuting behavior declined linearly, whereas the increase in automaticity of the new commuting behavior was more pronounced in earlier than later study weeks. Within-person plan enactment and experienced reward were positively linked with automaticity of the new commuting behavior. Between-person plan enactment was negatively linked with automaticity of the old commuting behavior. Weekly plan enactment and outcome experiences were associated with increases of new habits and decay of old habits in this study. Results warrant replication using an experimental design.

KEYWORDS

active commuting, ecological momentary assessment, experienced regret, experienced reward, habit substitution

INTRODUCTION

Insufficient physical activity constitutes a significant risk factor for noncommunicable diseases, leading to poor quality of life and premature mortality (Lee et al., 2012; Wardoku et al., 2019). Increasing physical activity rates (World Health Organization, 2018) can also involve the change of individuals' active commuting behavior. Actively commuting to work, that is, walking or cycling to work, can be a promising alternative to enhance daily physical activity levels and comes with the co-benefit of acting in a healthy and environmentally friendly way (Walsh et al., 2021; Woodcock et al., 2009). Next to walking and cycling to work, the use of public transport was demonstrated to significantly increase physical activity levels, through more time spent standing up or walking (Rissel et al., 2012).

Accumulating evidence demonstrates positive links of active commuting with mental and physical health, such as reduced stress and improved well-being (Schmied et al., 2020) as well as reduced risk for cardiovascular diseases (i.e., coronary heart disease, stroke, heart failure) and all-cause mortality (Hamer & Chida, 2008). In Germany, work-related mobility accounts for two thirds of employees' total transportation activity (Nobis et al., 2018). However, despite significant advantages of active commuting for health and environment, inactive mobility (e.g., commuting by car) persists as the predominant way of commuting to work in Germany (Keller, 2022).

Habits in the context of commuting behavior

How people commute to work is often a highly habitual behavior, meaning the behavior is being triggered automatically in response to context cues (Wood et al., 2022). Context cues can refer to any contextual element that coincides with a behavior. For instance, passing through the apartment corridor might prompt the urge to go to the backyard and unlock the bike; the presence of one's partner in the morning could automatically trigger the decision to take public transport to work; the time of day (e.g. 8 a.m.) might initiate the impulse to walk to the bus station; or preceding actions, such as having breakfast, could initiate the impulse to prepare for a bike ride to work (Wood et al., 2022). These context–response associations, commonly referred to as "habits", strengthen through repeated performance of a behavior in stable contexts (Wood et al., 2022). Once a habit is formed, habitual behavior is guided by context cues rather than motivational efforts (Di Maio et al., 2021), yielding its execution efficient, effortless, and automatic (Gardner et al., 2012).

Habitual behaviors are characterized by high resistance to change, making it desirable to cultivate active commuting habits (Verplanken & Whitmarsh, 2021) but challenging to alter unwanted commuting habits (Lattarulo et al., 2019). Individuals with an active commuting routine (i.e., cycling), for example, persisted in actively commuting to work, independent of their intentions to do so (Gardner, 2009) and despite barriers (e.g., bad weather, physical effort, or darkness; van Bekkum et al., 2011). In a similar vein, individuals with an inactive commuting routine, such as car use, were shown to continue their car use in spite of conflicting attitudes toward their inactive commuting behavior (Verplanken et al., 2008) and despite incentives for alternative modes of transport and increased barriers to use the car (Lattarulo et al., 2019).

When old habits (i.e. old context–response associations) persist, individuals attempting to initiate a new behavior are at higher risk of lapsing into the old behavior (Gardner et al., 2021). However, the mere disruption or discontinuity of a habitual commuting behavior (i.e. individuals are no longer exposed to the contexts that previously prompted the behavior) does not necessarily resolve old context–response associations (Walker et al., 2015). In their study, Walker et al. (2015) examined the habit strength of old and new commuting behaviors after old commuting habits were disrupted due to relocation of the workplace (Walker et al., 2015). While habit strength of the new commuting behavior increased, habit strength of the old commuting behavior diminished gradually over the remaining 4 weeks of the study period (Walker et al., 2015). By the end of the study, the new commuting habit was not yet fully established, and the old commuting habit had not entirely faded. Consequently, participants might have returned to their old commuting behaviors when encountering old habit contexts. Note, however, that the observation period of 4 weeks would not have allowed conclusions about longer term trajectories of old and new commuting habit strengths after old commuting habits were disrupted (Walker et al., 2015).

Substituting an old commuting habit with a new commuting habit

For successful long-term behavior change, old commuting habits should be substituted by new, desired commuting habits. Habit substitution refers to the formation of a new, competing context–response link that should become relatively stronger than the old context–response link upon context-dependent repetition of the new alternative response (Gardner et al., 2021). Consequently, the new response (i.e. new commuting behavior) should be triggered more rapidly compared with the old response (i.e. old commuting behavior), making the new response more likely to be executed (Lally & Gardner, 2013). For example, someone who used to automatically grab their car keys and drive to the office (i.e. habitual response) after breakfast (i.e. context) might form a new habit where finishing breakfast cues them to put on their helmet and cycle to work. Previous research has demonstrated successful reduction of habitual behaviors, such as waste disposal (Holland et al., 2006) or unhealthy snacking (Adriaanse et al., 2009), when replaced by a new behavioral alternative. However, little is known about the change trajectories of habit strength when individuals attempt to substitute a commuting habit. When forming a new habit, automaticity levels were demonstrated to increase more rapidly in earlier stages, followed by a slowed increase in later stages of the habit formation process (Keller et al., 2021; Lally et al., 2010; van der Weiden et al., 2020).

As of yet, there is limited understanding of the change trajectories of old habit strengths when a new habitual behavior is formed in response to the same context. Whereas some researchers predicted old habits to persist in the long term (Adriaanse & Verhoeven, 2018), others proposed the habit strength of "old" behaviors to decay when the old habitual behavior is not performed or consistently replaced by a new behavioral response (Keller et al., 2021; Mercuur et al., 2021; Tobias, 2009). Computational simulation studies demonstrated the decay of old habit strength when participants consistently enacted a new commuting behavior (Mercuur et al., 2021) or recycling behavior (Tobias, 2009) in the same situational context. However, longer term, real-life assessments of change in old habit strength are still scarce (Gardner et al., 2021).

To address this gap, the present study examined changes in the habit strength (i.e. behavioral automaticity) of both new and old commuting behaviors over time with an intervention that instructed participants to plan and repeatedly engage in a new, more active commuting behavior in the same context (i.e. before commuting to work). Moreover, the role of weekly plan enactment (i.e. self-reported weekly adherence to the action plans for the new commuting behavior) in replacing old with new commuting behaviors was investigated (Fleig et al., 2017; Keller et al., 2021).

Behavioral determinants of habit substitution processes

In their framework of habit formation, Gardner and Lally (2018) proposed determinants of habit formation depending on the stage of behavioral adoption. These include motivational determinants (i.e. Stage 1, variables influencing the decision to act), volitional determinants (i.e. Stage 2, variables supporting self-regulation), determinants of behavior maintenance (i.e. Stage 3a, variables supporting repetition), and determinants that directly strengthen context–response associations (i.e. Stage 3b). Thus, behavior change techniques (Michie et al., 2013) that support the adoption and maintenance of a behavior should support the formation of a new habit (i.e. Stages 1–3a; Gardner & Lally, 2018).

For habit substitution specifically, recommended behavior change techniques include behavioral prompts (e.g. placing a bike helmet on the doorknob) to encourage context-dependent repetition of the alternative behavior (Gardner et al., 2021) and action plans that aim to establish new mental associations between contexts (e.g. defining behavioral prompts, i.e. where, when or upon detection of a specific cue) and the alternative behavioral responses (i.e. defining how or what; Gardner et al., 2021).

Determinants, such as outcome experiences, that directly reinforce the learning of context–behavior associations beyond behavioral repetition (i.e. Stage 3b of the habit formation framework, Gardner & Lally, 2018) are also considered in the present study.

Outcome experiences in the context of habit substitution

Outcome experiences are proposed determinants of automaticity not only by increasing the frequency of behavioral repetition (Stages 1–3a) but also by directly strengthening the context–response link with each repetition (Stage 3b; Di Maio et al., 2022; Gardner & Lally, 2018). As one form of positive outcome experience, experienced reward following the execution of a behavior (e.g. experiencing pleasure) is largely recognized as a key determinant of habit formation (Wood et al., 2022). Experienced reward can also play a role when substituting a habit. The present study examined whether experiencing a new commuting behavior as rewarding might facilitate the formation of a new, desired commuting habit beyond behavioral repetition (i.e. Stage 3b of the habit formation framework, Gardner & Lally, 2018) while replacing an old commuting habit.

The role of experienced reward in habit formation corresponds with positive reinforcement in classical and operant learning where a positive experience becomes conditioned on the situational cue itself and increases the probability of the repetition of the reinforced behavior (Skinner, 1938; Wood & Rünger, 2016). In classical and operant learning processes, the counterpart to reward is the experience of aversive consequences of behavioral performance during behavioral extinction (Bouton et al., 2021). That is, when a behavior fails to yield the desired outcome or results in negative consequences or discomfort, the behavior is expected to diminish over time. When substituting an unwanted habit, negative outcome experiences as a result of engaging in the unwanted behavior (e.g. experience of regret when executing the unwanted behavior) could facilitate this process of "behavioral extinction." Previous research indicated that negative emotional outcome experiences resulting from unwanted habitual behaviors might stimulate increased deliberative processing of such behaviors (Lee, 2016). Enhanced deliberative processing, in turn, was assumed to modify unwanted cue–response associations (Wood & Neal, 2007), ultimately aiding the process of tapering old, unwanted habits. The present study aims to examine whether experiencing regret of an old, habitual commuting behavior facilitates the decline of the automaticity of the old commuting behavior upon behavioral repetition of the old commuting behavior (i.e. proposed determinant at Stage 3b of the habit formation framework; Gardner & Lally, 2018).

Capturing changes in habit substitution using ecological momentary assessment

Change in behavioral automaticity over time is assumed to be a highly individual phenomenon (Keller et al., 2021). Therefore, systematic gains and losses of automaticity levels when aiming to substitute a habit should be assessed for each individual over a longer time period. Behavioral repetition (i.e. weekly plan enactment of the new commuting behavior) is proposed to strengthen the mental representations of habits (i.e. automaticity of the new commuting behavior) and concurrently reduce the accessibility of alternative responses (i.e. automaticity of the old commuting behavior; Lally et al., 2010). Therefore, the present study examined links of fluctuations in weekly plan enactment with automaticity of the old and new commuting behaviors.

Moreover, as reviewed above, outcome experiences (i.e. reward and regret) are assumed to play an important role when substituting an old commuting habit with a new one, when the latter is repeatedly enacted. However, prior research lacks assessments with a high time resolution that capture the proximal outcome experience in response to a behavior (Di Maio et al., 2022).

The present study employed an ecological momentary assessment (EMA) design, wherein participants provided multiple daily self-reports on behaviors and experiences from the respective day (Doherty et al., 2020), facilitating the analysis of intraindividual fluctuations (i.e. within-person) and interindividual differences (i.e. between-person differences) in behavioral automaticity and its theoretical determinants (i.e. weekly plan enactment, outcome experiences) using a multilevel approach. Moreover, multilevel models provide insights into the heterogeneity of change within a given sample (i.e. estimation of random effects; Singer & Willett, 2003).

Objectives and hypotheses

Studies examining habit substitution processes are needed in order to prevent relapse into unwanted behavior and support long-term behavioral maintenance of wanted behavior (Gardner et al., 2021). The present study aimed to model the trajectories of the automaticity levels of old and new commuting behaviors over time as a function of weekly plan enactment and outcome experiences (i.e. reward and regret) at the within- and between-person levels. In line with theoretical propositions (Gardner & Lally, 2018) and empirical findings outlined above, we assumed the automaticity levels of the old commuting behavior to decay over time (H1) and the automaticity levels of the new commuting behavior to show a rapid increase in earlier study periods that is less pronounced in later study periods (H2). Regarding the determinants of habit decay, we expected negative within-person associations between automaticity of the old commuting behavior and weekly plan enactment of the new commuting behavior (H1a) as well as experienced regret of the old commuting behavior (H1b). With regard to determinants of habit formation, we assumed positive within-person associations between automaticity of the new commuting behavior and weekly plan enactment of the new commuting behavior (H2a) as well as experienced reward of the new commuting behavior (H2b). Furthermore, changes over time of weekly plan enactment, experienced regret, and experienced reward were explored.

METHOD

Study design

The present study reports analyses of an online planning intervention study with a pre-post design using EMA for the primary outcome automaticity. The study was conducted between June 2022 and September 2023 with a convenience sample of adults from the general population in Germany who had the intention to change their commuting behavior for health or environmental reasons. The preregistration for the study can be accessed at the German Clinical Trial Register (DRKS00028479, https://drks.de/search/en/). The study included six measurement weeks, spanning 14 weeks (i.e. baseline Week 0 followed by Weeks 1, 4, 7, 10, and 13; Figure 1). Each measurement week consisted of five consecutive workdays (i.e. Mondays to Fridays) with three EMA surveys per day (duration per survey: 1–2 min) that were prompted (1) before commuting to work, (2) after commuting to work, and (3) at the end of the day. The

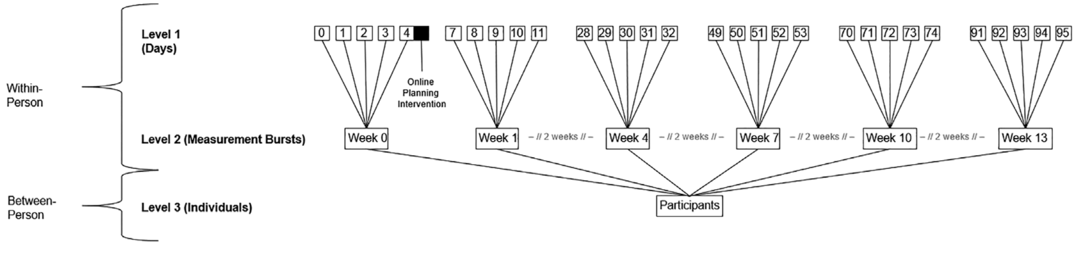

FIGURE 1 Study design. Access links for the online planning intervention were sent out at the end of Day 4 (Friday, Week 0).

online planning intervention took place at the end of the baseline week on a Friday. The ethics committee of the first author's institution granted approval for this study (approval number: 004/2022).

Procedure

An online registration website offered interested persons, who had an intention to change their commuting behaviors for health and/or environmental reasons, to receive more information on the study, check their eligibility, and give informed consent in case they were interested to take part. After providing informed consent, each participant attended an online onboarding session with one trained Master's-level student research assistant of the study team to discuss the details of the study procedure, download the study app, and fill out the baseline questionnaire. At the end of the last day of the baseline week (i.e. Friday), participants received an online planning intervention (approximately 15 min) to create an action plan for their self-selected, more active and/or environment-friendly commuting behavior. Participants were instructed to enact their new commuting-to-work behavior in the planned context throughout the entire study period. Informed consent, the initial baseline questionnaire, and the online planning intervention were delivered via the survey software Unipark (Tivian). EMA surveys were conducted via the study app m-Path (https://m-path.io; Katholieke Universiteit Leuven, Belgium), that participants downloaded on their private smartphones. EMA prompts were event-based (i.e. participants initiated the EMA survey upon arrival at work), and reminders followed individualized sampling schemes. Participants received 25€ for completing 40–79 per cent of all EMA surveys and 50€ for completing at least 80 per cent of all EMA surveys.

Recruitment, eligibility, and power

Recruitment strategies included social media posts, posters, email distribution lists, posts at the intranets of companies, and personal presentations of the study in lectures and seminars for psychology students. Moreover, paper flyers were distributed at various events, in mailboxes of households, and in health care institutions. Recruitment strategies that were not online-based were carried out in Berlin, Germany.

Participants were eligible if they (1) intended to change their commuting behavior to work toward a more active and sustainable behavior and wanted to form a new commuting habit; (2) commuted to work at least on three days a week; (3) had Monday-to-Friday workweeks; (4) usually commuted to work by car, scooter, or public transport, asserting the ability to transition toward a more active commuting behavior; (5) owned a smartphone; (6) were at least 18 years old; and (6) expected to have the same employment throughout the entire study period (14 weeks).

An a priori power analysis for two-level models was conducted using PowerAnalysesIL implemented by the R Shiny app package (Lafit et al., 2021) assuming a small to medium effect size in the level 1 outcome (i.e. automaticity of the new commuting behavior). To detect these effects, a sample size of 60 participants was estimated. With an anticipated dropout rate of 15 per cent, the target sample size was set at 80 participants for the current study. Analyses conducted in the present study deviated (i.e. three-level instead of two-level models; see below) from the planned approach. That is, we found three-level models to be a more appropriate statistical method for modeling the nested structure of the data as well as for examining the relationships of variables within and across bursts (Nestler, 2021; Sliwinski, 2008). However, as the power to detect anticipated effects in within-person analyses should be more dependent on the number of participating persons than on the number of nested lower levels in the data (Bolger & Laurenceau, 2013), the estimated sample size should also be applicable to the three-level multilevel models used in the current study (see below). More seriously, however, due to practical restrictions, the estimated sample goal was not met, likely causing the present analyses to be underpowered. Thus, findings should be interpreted with caution.

Online planning intervention

Participants received links to the online planning intervention via the study app and email. Designed for scalability, the intervention was conducted remotely without interaction with the study team. Fictional personas, Steffi and Tom, illustrated each component of the planning intervention, demonstrating how to replace old commuting habits with new ones. Participants learned about the health and environmental benefits of active commuting and about facilitators regarding the formation of a new commuting habit, such as behavioral repetition in the same context or situation. Participants were prompted to indicate their motivation to change their commuting behavior and to set a goal defining the mode of transport they want to use in the future. Participants were then informed about the benefits of forming a commuting habit, such as effortless behavioral maintenance, and about the facilitators of forming a commuting habit, such as context-dependent repetition. Then, participants were instructed to create action plans in an if–then format (Gollwitzer, 1999). That is, participants defined a daily routine, situation, context, or cue to initiate their new commuting behavior (i.e. if-part) as well as the type of the new commuting behavior participants planned to perform (i.e. then-part). Participants envisioned themselves carrying out the action plan and identified potential barriers, ensuring its feasibility. Participants had the chance to adjust their action plans based on ratings of suitability, effectiveness in achieving their commuting goals, and feasibility behavioral performance (Fleig et al., 2017; Fuchs et al., 2011). Moreover, participants were instructed to define prompts, such as placing a bicycle helmet on top of their shoes, to prompt the new commuting behavior. Participants were instructed to enact their action plan throughout the study period, starting the Monday following the online planning intervention. Please see supplementary file for a comprehensive description as well as supporting information on the online planning intervention.

Measures

Unless otherwise noted, participants responded to items on a 6-point Likert scale ranging from "*does not apply at all*" (1) to "*applies exactly*" (6).

Habit strength (hereafter "automaticity")

Automaticity levels indicated habit strength and were assessed in daily evening questionnaires of the old and, starting post-intervention, of the new commuting behavior using the self-reported behavioral automaticity index (SRBAI; Gardner et al., 2012). During the pre-intervention phase, the scale to assess automaticity of the old commuting behavior was introduced with the item stem "Commuting to work, as I usually do, is something, …." During the post-intervention phase, the item stems "Commuting to work, as I did before the study, is something, …" and "Commuting to work, as I have planned, is something, …" were used to assess the automaticity of the old and new commuting behaviors, respectively. Item stems were followed by four statements (e.g., "I do automatically," "that I do without having to consciously remind myself of it"). Thus, in line with Walker et al. (2015), the automaticity of the old and new commuting behaviors was assessed regardless of whether the respective commuting behavior was performed on that same day.

Weekly plan enactment

Context-dependent behavioral repetition of the new and planned commuting behavior is hereafter described as weekly plan enactment (cf. Fleig et al., 2017; Fuchs et al., 2011). During the post-intervention period, participants reported in daily evening surveys whether or not (i.e. response format yes/no) they had commuted to work as planned ("Today, I commuted to work as planned"). Weekly plan enactment reflected the percentage of the total frequency of times that participants commuted to work as planned per week (i.e. self-reported weekly adherence to the action plans).

Experienced reward and regret

Outcome experiences were assessed in daily surveys upon arrival at work. One item was used to assess experienced reward (i.e. "I experienced the way I commuted to work today as something that felt good," adapted from Fuchs et al., 2011) and one item for experienced regret (i.e. "I regret the way I commuted to work today," adapted from Abraham and Sheeran, 2004). Reports on weekly plan enactment of the new behavior (yes/no) on a specific day were used to define whether reports of experienced reward and regret referred to the new or the old commuting behavior. When a participant did not commute on a given day, a missing value was coded for both outcome experiences. Reports of outcome experiences that had implausible completion times were excluded during the data cleaning process.

Modes of transport

In daily surveys upon arrival at work, participants selected one or more means of transport they used to get to work from a list (i.e. *bicycle*, *walking*, *public transport*, *car*, *motorcycle*, *scooter*, *e-bike*, *other*).

Covariates

Gender (1 = *women*, 0 = *men*), age, and self-reported body mass index (BMI) served as covariates and were assessed at baseline.

Data analyses

Data were analyzed in R (R Core Team, 2024). Intra-class correlations (ICCs) and Pearson correlations as well as within-person correlations were calculated (Bakdash & Marusich, 2017). Multilevel models were fit using the R lme4 package (Bates et al., 2015) to account for the three-level measurement design with commuting days (level 1) nested in weeks (level 2) nested in persons (level 3).

To examine change in outcomes during the post-intervention phase, time was coded linearly from the first day of the post-intervention phase, and a quadratic time slope was tested and retained if significant. In accordance with Keller et al. (2021), quadratic time trends were considered a flexible approach for capturing various types of time trajectories. Specifically, quadratic time trends can model different rates of initial increase as well as varying peak heights of the curve. Moreover, quadratic time trends require fewer data points, making them well suited for modeling data in a measurement burst study design (Bolger & Laurenceau, 2013).

Time of the post-intervention phase was counted in days at level 1 (0, 1, 2, 3, 4, ..., 88) and and in weeks at level 2 (0, 3, 6, 0, 12), both nested in persons (level 3), starting on the-first day or week of the post-intervention phase. In all three-level models, time variables were rescaled to a range of 0–1 to improve model convergence. To examine change in outcomes during the pre-intervention phase, additional time slopes, starting on the first day of the pre-intervention phase, counted days at level 1 (0, 1, 2, 3, 4, ..., 95) and weeks at level 2 (0, 1, 4, 7, 10, 13). Moreover, a dummy-coded phase variable (0 = *pre-intervention*; 1 = *post-intervention*) modeled changes (i.e. jumps) from the pre- to post-intervention phases.

For the analyses at the group level, time-varying predictors at level 1 (day level; i.e. outcome experiences) and time-varying predictors at level 2 (week level; i.e. weekly averaged plan enactment) were centered around their respective person-means (i.e. within-person predictors). Their grand-mean centered person-means (person level, i.e. time-invariant) were included as level 3 predictors. Age and BMI were grand-mean centered person-level covariates.

In a first set of three-level models, we examined day-by-day changes over time in the outcomes automaticity and outcome experiences (i.e. regret and reward) of the old and new commuting behaviors. Change over time in week-by-week plan enactment of the new commuting behavior was estimated using a two-level model with weeks (level 1) nested in persons (level 2). In a second set of three-level models, the automaticity of the old commuting behavior was estimated as a function of weekly plan enactment and experienced regret of the old commuting behavior in two separate models. The automaticity of the new commuting behavior was estimated as a function of weekly plan enactment and experienced reward of the new commuting behavior in two separate models. Models included a random intercept and random slopes for time and within-person predictors. If models did not converge or had a singular fit, the random effects for time slopes and/or within-person variables were removed stepwise (Barr et al., 2013). In order to include as much data as possible, age and BMI were retained only if their inclusion significantly improved model fit or rendered significance in the analyses. This procedure was chosen because some participants had missing data on BMI and age and the lme4 package excludes observations from a participant if any missing values are detected in an exogenous variable.

In accordance with Shrout et al. (2017), we excluded the first 2 days of measurement of the automaticity of the old commuting behavior, because visual inspection of the data indicated an initial elevation bias, that is, systematically higher values at the very beginning of the study (Shrout et al., 2017).

RESULTS

Descriptive information for baseline data and the planning intervention

$N = 45$ participants living in Germany participated in the online onboarding session and in the online planning intervention. Two participants dropped out before and one participant right after the online planning intervention, leaving $n = 42$ participants (60% female) for analyses (see Figure S3 for a detailed participant flow). Participants were on average 32.3 years old (range: 18–63), had a BMI of 24.8 (range: 17–39), worked 33 hours per week ($SD = 12.4$), had lived for 6.3 years at their current home ($SD = 7.9$), had worked for 3.9 years ($SD = 4.3$) at their current workplace, and commuted on average 11.9 km ($SD = 6.9$) to work. Among the 42 participants, 90 per cent ($n = 38$) held a high school diploma, 64 per cent ($n = 27$) reported to live in a relationship, 86 per cent ($n = 36$) reported to have no children, and 36 per cent ($n = 15$) were psychology students.

During the baseline week, participants reported that they did not commute to work on 17 per cent of the potential working days (35 out of 210 days across 42 participants). Given missing values for 15 working days, participants reported a total of 160 commuting trips to work. Of the 160 commuting trips, 72 per cent were undertaken by using public transport, 13 per cent by bike, 9 per cent by using a motorized vehicle (car or motorcycle), 4 per cent by a combination of public transportation and bike, and 2 per cent by walking only.

On average, participants spent 16 min ($SD = 11.1$) to complete the online planning intervention. About half of the participants planned to commute solely by walking or cycling ($n = 20$), whereas the other half planned a combination of public transport and walking and/or cycling for their commute ($n = 22$). See Table S3 in the supplement for descriptives of study variables.

Table S4 depicts the mean percentage of weekly plan enactment (i.e. self-reported weekly adherence to the action plan for the new commuting behavior) as well as weekly mean levels for the automaticity of the old and new commuting behaviors. Whereas plan enactment remained stable across the study period, the automaticity of the new commuting behavior increased, reaching its highest point during the last week of study participation. The automaticity of the old commuting behavior continuously decreased throughout the study period, reaching its lowest point in the last measurement week. See also Figure 2 for the mean average levels of the automaticity of the old and new commuting behaviors.

Trajectories of automaticity of the old and new commuting behaviors over time

The automaticity of the old commuting behavior remained stable during the pre-intervention phase ($b = -4.08$, $p = .469$) as well as from pre- to post-intervention (no jump: $b = 0.11$, $p = .673$; Table S6). In line with our hypothesis (H1), the automaticity of the old commuting behavior decreased linearly across the post-intervention period ($b = -0.59$, $p = .013$; Table S7).

The increase in the automaticity of the new commuting behavior was more pronounced within the first weeks of the study and gradually slowed down in later weeks of the study, as indicated by a quadratic time trend (linear time $b = 2.14$, $p < .001$; quadratic time $b = -1.01$, $p = .012$; Table S8), which was in line with our hypothesis (H2) Figure 2.

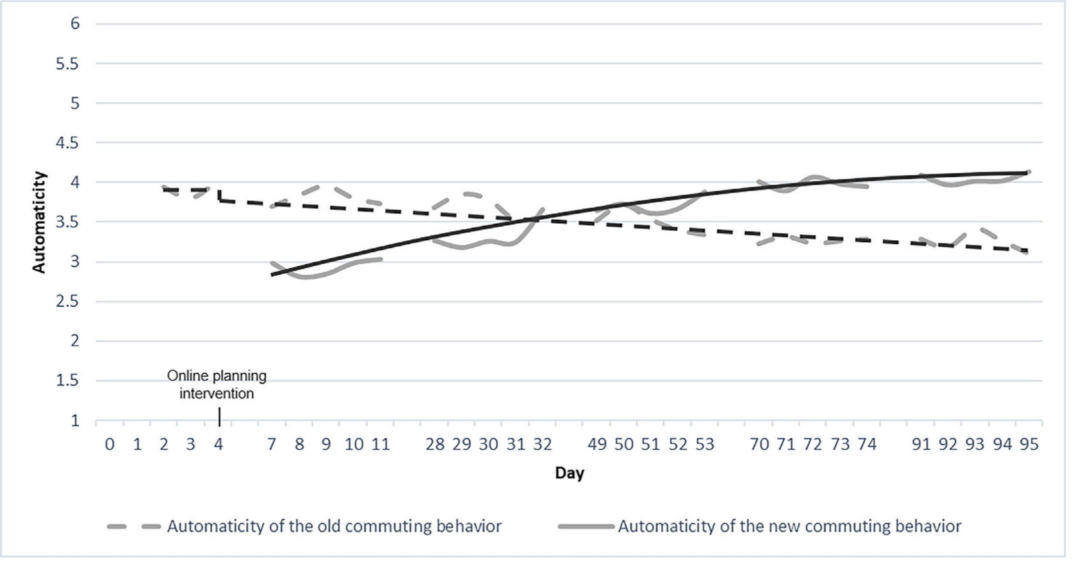

FIGURE 2 Daily average automaticity levels of the old and new commuting behaviors over time. Grey lines represent daily mean levels across participants, black lines represent model-estimated curves. Dashed lines represent the automaticity of the old commuting behavior; solid lines represent the automaticity of the new commuting behavior. Data of the first 2 days of measurement of the automaticity of the old commuting behavior were excluded, because visual inspection of data indicated initial elevation bias, that is, systematically higher values at the very beginning of the study (Shrout et al., 2017). The online planning intervention was conducted on Day 4 of the study.

Trajectories of weekly plan enactment, experienced regret, and experienced reward over time

Weekly plan enactment post-intervention

On average, participants enacted their new commuting behavior on 86 per cent of their total commutes to work per week during the post-intervention phase. Plan enactment remained stable until the end of the study ($b = -0.01$, $p = .176$; Table S5, Figure S4).

Change in experienced reward over time (Figure S5)

No change was detected for experienced reward of the old commuting behavior from pre- to post-intervention ($b = -0.28$, $p = .490$; Table S6) or during the post-intervention period ($b = 0.30$, $p = .457$; Table S7). Experienced reward of the new commuting behavior increased linearly over time ($b = 1.00$, $p = .010$; Table S8).

Change in experienced regret over time (Figure S6)

Experienced regret of the old commuting behavior changed from the pre- to the post-intervention phase, although this change was significant only at a level of $p < .10$ ($b = 0.76$, $p = .077$; Table S6). Experienced regret of the old commuting behavior did not change during the post-intervention phase ($b = -0.12$, $p = .751$; Table S7). Experienced regret of the new commuting behavior remained stable across the post-intervention period ($b = 0.13$, $p = .511$; Table S8).

Automaticity of the old commuting behaviors as a function of weekly plan enactment and experienced regret

Not in line with our hypothesis (H1a), higher between-person weekly plan enactment ($b = -1.67$, $p = .043$), but not within-person weekly plan enactment ($b = 0.04$, $p = .802$), was linked to lower automaticity of the old commuting behavior (see Table 1). That is, participants who enacted their new commuting behavior more often than the sample average, also reported lower automaticity of the old commuting behavior (i.e., significant between-person prediction). Performing the new commuting behavior more frequently than usual, was unrelated to automaticity of the old commuting behavior (i.e. nonsignificant within-person prediction).

As expected (H1b), higher within-person experienced regret of the old commuting behavior was linked to lower automaticity of the old commuting behavior, however only at a significance level of $p < .10$ ($b = -0.29$, $p = .052$). Between-person experienced regret was unrelated to the automaticity of the old commuting behavior ($b = 0.31$, $p = .266$; see Table 1).

Automaticity of the new commuting behaviors as a function of weekly plan enactment and experienced reward

In line with our hypothesis (H2a), higher within-person weekly plan enactment was linked to higher automaticity of the new commuting behavior ($b = 0.35$, $p = .045$; see Table 2). That is, participants who enacted their new commuting behavior more often than they usually did also reported higher automaticity of the new commuting behavior (i.e. significant within-person prediction). No links emerged between the automaticity of the new commuting behavior and between-person weekly plan enactment ($b = 0.92$, $p = .221$). That is, higher average levels of plan enactment compared with the sample mean was unrelated to the automaticity of the new commuting behavior (i.e. nonsignificant between-person prediction).

As hypothesised (H2b), higher within-person experienced reward of the new commuting behavior was positively linked with the automaticity of the new commuting behavior ($b = 0.08$, $p = .006$; see Table 2). On days on which participants experienced the new commuting behavior as more rewarding than usual, they also reported higher automaticity levels of the new commuting behavior. No links of between-person experienced reward of the new commuting behavior and its automaticity emerged ($b = 0.03$, $p = .879$; see Table 2).

DISCUSSION

The present study investigated habit substitution processes when transitioning from an old to a new, more active and sustainable commuting habit in a recurring situational context. We examined changes in the automaticity levels of old and new commuting behaviors over time. We also investigated within-person associations of these outcomes with weekly plan enactment and outcome experiences (i.e. reward and regret) of old and new commuting behaviors. In line with our hypotheses, the automaticity of the old commuting behavior gradually declined over time (H1), whereas the automaticity of the new commuting behavior increased, following a quadratic time trend (H2). Unexpectedly, we found no associations of within-person weekly plan enactment with the automaticity of the old commuting behavior (H1a). In line with our hypothesis (H1b), within-person experienced regret was linked to a lower automaticity of the old commuting behavior. As hypothesised (H2a), within-person weekly plan enactment was linked to a higher automaticity of the new commuting behavior. As expected (H2b), within-person experienced reward of the new commuting behavior was linked to a higher automaticity of the new commuting behavior.

When substituting habits, behavioral responses are supposed to compete with each other, so that the behavior with the stronger mental cue–response association should prevail (Lally &

TABLE 1 Three-level multilevel models: links of plan enactment and experienced regret with the automaticity of the old commuting behavior.

Outcome: automaticity of the old commuting behavior	Predictor: weekly plan enactment of the new commuting behavior			Predictor: experienced regret of the old commuting behavior		
Fixed effects	***b* (*SE*)**	**95% CI**	***p***	***b* (*SE*)**	**95% CI**	***p***
Intercept	3.75 (0.25)	3.26 to 4.24	**<.001**	4.37 (0.39)	3.62 to 5.11	**<.001**
Linear time post-intervention	−0.59 (0.24)	−1.07 to −0.11	**.020**	−0.82 (0.22)	−1.28 to −0.39	**.002**
Gender	0.09 (0.32)	−0.53 to 0.72	.773	−0.66 (0.48)	−1.55 to 0.27	.184
Within-person predictor	0.04 (0.16)	−0.28 to 0.37	.802	−0.29 (0.13)	−0.57 to −0.03	.052
Between-person predictor	−1.67 (0.80)	−3.23 to −0.12	**.043**	0.31 (0.27)	−0.19 to 0.80	.266
Random effects		**Var (*SE*)**			**Var (*SE*)**	
Level 2 intercept		0.13 (0.36)			0.00 (0.05)	
Level 3 intercept		1.03 (1.02)			1.00 (1.00)	
Level 3 linear time post-intervention		2.09 (1.45)				
Level 3 within-person experienced regret					0.14 (0.38)	
Residual		0.25 (0.50)			0.27 (0.52)	
ICC		.86			.82	
Marginal R^2/conditional R^2		.075/.871			.173/.849	

Note: $n = 42$ participants, 30 diary days spanned across 95 days, 76–880 diary days. Time trends were centered at the first day of the pre-intervention as well as the post-intervention phase. Time slope was coded in days and normalized to improve model convergence, ranging from 0 to 1. Age and body mass index (BMI) were excluded as predictors due to missing data and the lme4 package's exclusion of observations with missing exogenous variable values.

Abbreviations: CI, confidence interval; ICC, intra-class correlation.

$p < .05$ are depicted in bold.

Gardner, 2013). At the end of study participation, the average automaticity of the new commuting behavior was relatively higher than the automaticity of the old commuting behavior, suggesting a successful habit substitution process within the study period.

Changes in the automaticity levels of the old commuting behavior over time and as a function of weekly plan enactment

On the first 2 days of the pre-intervention period, we detected very high levels of automaticity of the old commuting behavior, which reflected an initial elevation bias due to measurement effects (Shrout et al., 2017). After correcting for this bias as recommended by Shrout et al. (2017), the automaticity of the old commuting behavior remained stable during the pre-

TABLE 2 Three-level multilevel models: links of within-person and between-person weekly plan enactment and experienced reward with automaticity of the new commuting behavior.

Outcome: automaticity of the new commuting behavior	**Predictor: weekly plan enactment of the new commuting behavior**			**Predictor: experienced reward of the new commuting behavior**		
Fixed effects	***b* (*SE*)**	**95% CI**	***p***	***b* (*SE*)**	**95% CI**	***p***
Intercept	2.92 (0.23)	2.45 to 3.38	**<.001**	2.95 (0.25)	2.46 to 3.43	**<.001**
Linear time post-intervention	2.18 (0.34)	1.52 to 2.84	**<.001**	2.09 (0.35)	1.42 to 2.78	**<.001**
Quadratic time post-intervention	−1.03 (0.28)	−1.59 to −0.48	**<.001**	−0.99 (0.30)	−1.59 to −0.40	**.001**
Gender	−0.14 (0.30)	−0.74 to 0.45	.634	−0.13 (0.31)	−0.75 to 0.48	.668
Within-person predictor	0.35 (0.16)	0.02 to 0.68	**.045**	0.08 (0.02)	0.03 to 0.13	**.006**
Between-person predictor	0.92 (0.74)	−0.59 to 2.40	.221	0.03 (0.18)	−0.34 to 0.40	.879
Random effects	**Var (*SE*)**			**Var (*SE*)**		
Level 2 intercept	0.10 (0.31)			0.09 (0.30)		
Level 3 intercept	0.86 (0.93)			0.90 (0.95)		
Level 3 linear time post-intervention	1.30 (1.14)			1.18 (1.09)		
Level 3 within-person predictor	0.13 (0.36)			0.00 (0.06)		
Residual	0.19 (0.44)			0.17 (0.41)		
ICC	.88			.89		
Marginal R^2/conditional R^2	.117/.893			.103/.899		

Note: $n = 42$ participants, 30 diary days spanned across 95 days, 644–880 diary days. Time trends were centered at the first day of the pre-intervention as well as the post-intervention phase. Time slopes were coded in days and normalized to improve model convergence, ranging from 0 to 1. Age and body mass index (BMI) were excluded due to missing data and the lme4 package's exclusion of observations with missing exogenous variable values.

Abbreviations: CI, confidence interval; ICC, intra-class correlation.

$p < .05$ are depicted in bold.

intervention period as well as from pre- to post-intervention. This was expected, given that the automaticity of established habits is not expected to fluctuate without significant change in context or behavior (Lally et al., 2010).

The linear decrease in the automaticity of the old commuting behavior during the post-intervention period indicated that—at least in part—old habit strength may decay when an old behavior is replaced with a new behavior, which is in line with prior findings (Mercuur et al., 2021; Tobias, 2009; Walker et al., 2015). Moreover, results suggested that the automaticity of the old commuting behavior was lower for participants who performed the new commuting behavior overall more consistently (i.e. negative between-person plan enactment prediction). In contrast, temporary fluctuations were in the performance of the new commuting behavior was unrelated to the automaticity of the old commuting behavior (i.e. nonsignificant within-person plan enactment prediction). It should be considered that the overall decrease in the automaticity of the old behavior was modest at best. This aligns with findings by Walker et al. (2015), who observed a significant, yet small decrease in old commuting habit strength over 4 weeks after old habits were disrupted due to relocation of the workplace (Walker et al., 2015). In their simulation study, however, Mercuur et al. (2021) demonstrated a substantial decline of old habit strength when a single new commuting behavior was consistently enacted in the same context (Mercuur et al., 2021).

Ideally, when substituting habits, the alternative response (i.e. the new commuting behavior) should be linked to the critical cue that was used to trigger the old commuting behavior (Adriaanse et al., 2009), which is most likely the cue that triggered the decision to act (i.e. instigation habit; Gardner et al., 2016). However, given that habits are performed with little conscious awareness, individuals exhibit difficulties in identifying their habit cues (Adriaanse & Verhoeven, 2018; Mazar & Wood, 2022). More recent habit definitions refer to contexts rather than single cues as behavioral trigger (Gardner & Lally, 2022) and therefore consider more prominently that habitual behavior is likely conditioned on multiple cues that covary with the behavior. When individuals begin to perform an alternative behavior in a stable context (i.e. before commuting to work), there should be a significant overlap of cues for the old and new behaviors, such as morning routines, family members, places, or objects in the apartment.

In the present study, participants who habitually commuted to work by public transport prior to the study and then planned a combination of public transport and walking/cycling as their new commuting behavior (approximately 50% of the participants) might have "piggybacked" the new commuting habit onto the old commuting habit. That is, in some cases, new commuting habits might not have altered habitual instigation of the old commuting behavior (e.g. automatically deciding to walk to the train station) but were incorporated into the existing habitually executed commuting behavior (e.g. getting off the bus one station earlier and walking the rest; Gardner et al., 2016). "Piggybacking" habits (i.e. using an existing behavior with a high habit strength as a critical cue for the new behavior) is assumed to be a fruitful strategy for successful habit change (Fleig et al., 2016; Judah et al., 2013).

Changes in the automaticity levels of the new commuting behavior over time and as a function of weekly plan enactment

The increase in the automaticity of the new commuting behavior followed a quadratic time slope, which mirrors findings from earlier studies on habit formation (Keller et al., 2021; van der Weiden et al., 2020). The increase in the automaticity of the new commuting behavior was more pronounced within earlier weeks of the study, followed by a lowered increase in later study weeks. However, we cannot draw conclusions about whether the automaticity of the new commuting behavior would have continued to increase, plateau, or decline beyond the measurement period.

Results also confirmed previous propositions and empirical findings on habits forming upon behavioral repetition (Gardner & Lally, 2018; Keller et al., 2021; Lally et al., 2010). Participants who enacted the new commuting behavior more often than they usually did also reported higher automaticity of the new commuting behavior (i.e. higher within-person weekly plan enactment). The results suggest that every single opportunity to successfully replace the old behavior with the new commuting behavior seemed to be crucial for substituting a commuting habit.

Changes in weekly plan enactment of the new commuting behavior over time

Weekly plan enactment remained high throughout the 12-week long post-intervention phase, which provides evidence for the assumption of habit formation to be supported by frequent behavioral repetition (Gardner & Lally, 2018). Given the positive findings of sustained weekly plan enactment during the post-intervention period, alongside the intervention's minimal resource demands, the planning intervention used in the present study might thus indicate scalability for future research. However, it has to be noted that the absence of a control group does not allow for any causal inferences regarding the effectiveness of intervention components. Regular EMA surveys could have, for example, acted as reminders or behavioral prompts, potentially influencing participants' motivation to achieve their commuting goals (Doherty et al., 2020). To address these limitations, the current study warrants replication using an experimental design.

The role of outcome experiences for habit substitution

The finding that higher than usual experienced regret of the old commuting behavior tended to be linked to automaticity (i.e. Stage 3b, habit formation framework; Lally & Gardner, 2013) contradicts the predictions of the devaluation paradigm, which posits that habits are independent of experienced outcomes (Watson et al., 2023). Yet, results of the current study corroborate previous findings where participants demonstrated sensitivity to behavioral outcomes despite undergoing extensive retraining of cue–response associations within experimental tasks (de Wit et al., 2018). The authors hypothesised that the persistence of outcome sensitivity was due to behaviors not becoming fully habitual (de Wit et al., 2018). More complex health behaviors are likely guided by an interaction of both goal-directed and cue-directed systems (for a definition of behavioral complexity, see Mullan & Novoradovskaya, 2018; Wood et al., 2022), thus likely remaining at least partially influenced by outcome experiences associated with those behaviors. Furthermore, participants exhibited heightened regret regarding their old commuting behavior subsequent to formulating their new commuting plan, likely because the old commuting behavior was now counter-intentional. Given the infrequent performance of the old commuting behavior in the current study during the post-intervention phase, analyses examining experienced regret and reward of the old commuting behavior were notably underpowered. Future research is warranted to replicate these findings. As expected, experienced reward of the new commuting behavior—when it was enacted—seemed to facilitate habit formation behavior (Stage 3b, habit formation framework; Lally & Gardner, 2013), which is in line with theoretical assumptions and prior empirical findings (Di Maio et al., 2022; Lally et al., 2010). Over time, participants perceived the new behavior as increasingly rewarding. A number of factors might play a role here, such as newly detected rewarding features of the behavior including higher well-being (Schmied et al., 2020) and increasing ease in performing it (Gardner et al., 2012).

Strengths, limitations, and future directions

The present study had several strengths. It was among the first studies to measure the automaticity of both new and old commuting behaviors. These measurements were conducted over an extended period of 14 weeks, which was assumed to be an appropriate time period to monitor changes in automaticity (Lally et al., 2010), although the study likely did not capture the entire process of habit substitution. Moreover, an EMA design captured participants' daily behaviors and momentary experiences.

Several limitations of the current study need to be considered when interpreting the results. First, due to the very small sample size, analyses were underpowered, and present results should be interpreted with caution (Hox & McNeish, 2020). Future studies should recruit and enroll a larger sample. Second, automaticity was reported for both old and new commuting behaviors, even if the behaviors were rarely or no longer performed. In particular, the reports on the automaticity of the old commuting behaviors—behaviors that had been rarely performed after the intervention—could only serve as an approximation of habit decay processes and may have been influenced by participants' lay theories about changes in automaticity (Mazar & Wood, 2022). Yet, it is conceivable that participants can experience a decrease in habit strength for an established behavior without performing the behavior, for instance, when exerting self-regulatory effort to suppress or redirect impulses from the old habitual response. Future studies could include a measure that better captures this suppression process (i.e. a decrease in the experienced urge to perform the old behavior in response the cue), which may be distinct from the processes involved in habit formation. Third, the present study conducted analyses separately for old and new commuting habit strength. Ideally, the strength of the automaticity of old and new habitual behaviors should be measured directly within a given situation to determine which habitual behavior is more strongly triggered. Future research should aim to address this by utilizing objective measurement techniques, which could be particularly feasible in the context of smartphone usage (e.g. objectively assessed reaction time to a cue). Nevertheless, this study provides an initial approach to operationalize habit substitution by examining two distinct processes—habit formation and habit decay—within the same situational context.

Conclusion

The present study examined changes in the automaticity of old and new commuting behaviors and related theoretical determinants (i.e. weekly plan enactment and outcome experiences) in the process of substituting a commuting habit toward more active commuting in a one-arm pre-post design. Results suggested that the automaticity of an old, less active and less sustainable commuting habit was reduced—at least in part—when it was replaced by a more active and sustainable commuting habit. Experienced reward of the new commuting behavior was positively linked with habit strength of the new commuting behavior. Future research is warranted to investigate determinants of habit substitution processes that yield long-term behavior change using an experimental design.

CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare.

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DATA AVAILABILITY STATEMENT

Data analysis scripts can be obtained from the authors upon request. The data sets generated during this study cannot be made publicly available as we do not have permission from study participants. However, group-level information about the data is available from the corresponding authors on reasonable request.

ETHICS STATEMENT

The ethics committee of Freie Universität Berlin, Germany, granted ethics approval for this study (approval number: 004/2022).

CLINICAL TRIAL REGISTRATION

The preregistration for the study can be accessed at the German Clinical Trials Register (DRKS00028479, https://drks.de/search/en/).

INFORMED CONSENT

All participants gave informed consent (as mentioned in Section 2.2).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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