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Chapter 35
Do Habits Fade Out? Discerning Between Two Theories Using Agent-Based Simulation

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Abstract Inducing behavioural change requires a good understanding of how habits break. We identified two theories in the psychological literature on this process: the decrease theory and persist theory. Both theories are used to explain behavioural change, but one states the original habit fades out, while the other theory states the habit persists. We use agent-based simulation to show that the two theories lead to different behaviour when the agents are motivated to do *multiple* alternative actions (e.g., take the bike or take the train), instead of *one* alternative action (e.g., take the bike). This finding is relevant for the social scientific field, because (1) it shows a scenario where it matters if habits persist and (2) it enables an empirical experiment to discern the two theories.

Introduction

There is an increasing interest in considering the influence of habits on behaviour [8–10, 18]. Habitability refers to the principle that behaviour persists because it has become an automatic response to a particular, regularly encountered, context [10]. Habits have been shown to be an important driver of behaviour (e.g., in transport choices [8], food choices [18] or recycling [9]). To change behaviour it is thus important to understand how habits break [10].

Breaking habits is studied on a behaviouristic level and a cognitive level [5]. On a behaviouristic level, a habit breaks if an agent portrays different behaviour given the same context. On a cognitive level, a habit breaks if the mental connection between

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the context and an action is gone. On a cognitive level, a habits can thus persist even when the observable behaviour changes [21]. We will refer to a habit breaking on the behaviouristic level as 'the suspension of habitual behaviour' and to a habit breaking on the cognitive level as 'the decrease of the habitual connection'.

This paper aims to compare two theories on breaking habits focusing only on their long-term dynamics. We study a scenario where an agent is first motivated to do one action (e.g., take the car) and then motivated to do another action (e.g., to take the bike). In case of a successful intervention (e.g., [1]), most agents will change their behaviour (i.e., suspend their habitual behaviour). We identify two theories in the psychological literature that can explain this dynamic on a cognitive level: the decrease theory and persist theory [1, 4, 12, 13]. The decrease theory states that a new habitual connection (i.e., the bike-habit) emerges and the original habitual connection (i.e., the car-habit) *fades out* [12, 13]. The behaviour change is a consequence of the agent enacting the new habit. The persist theory states that a new habitual connection emerges, but the original habitual connection *persists* [1, 4]. The behaviour change is a consequence of the agent intentionally choosing the new action between two (now equally strong) habits. We construct two models to compare the theories and verify these models accurately represent these theories by using simulation.

This paper shows that the two theories lead to different behaviour when the agents are motivated to do *multiple* alternative actions (e.g., take the bike or take the train), instead of *one* alternative action (e.g., take the bike). In the decrease model, the alternative action is taken up and replaces the old habit. In the persist model, the original action persists and no new habit emerges. We explain this difference using the simulation: if the original habit does not decrease, then doing multiple alternatives does not lead to the development of a strong enough habit to replace the original one. This finding is relevant for the social scientific field, because (1) it shows a scenario where it matters if habits persist (i.e., the persistence influences behaviour change) (2) it enables an empirical experiment to discern the two theories.

The remainder of the paper is structured as follows. Section "Psychological Literature on Habits" summarizes literature on habits (in particular the decrease theory and the persist theory) into properties. Section "Model" uses these properties to construct two models: a persist model and a decrease model. Section "Verifying the Models Represent the Theories" verifies that the models accurately describe the theories by using simulation. Section "Finding a Scenario to Discern the Theories" describes the simulation experiment that shows the two theories are discernible when the agents are motivated to do multiple alternatives.

Psychological Literature on Habits

Habitual decisions are fast automatic decision that contrast with a slow intentional decisions [6, 20, 21]. Habits moderate the intention-behaviour relationship [6, 20]: the stronger the habit, the weaker the intention-behaviour relationship. For example, a strong 'car habit' weakens the influence of a 'bike intention' on behaviour. Habits predict behaviour without mediation by intentions [21]. Thus even in the absence of intention a habit continues to predict behaviour. For example, even when one does not intend to use the car anymore one can be 'stuck' in the habit of using a car. We require our habit models to separate between habits and intentions, include the moderating effect of habits on the intention-behaviour relationship and that intentions do not mediate the habit-behaviour relationship.

When a habitual decision is triggered depends on the strength of the habit and the current performance context (i.e., the context in which the agent acts) [21]. Habitual decisions are triggered by specific context-elements [21]. For example, the context-element 'home' can trigger the habit of taking the car (whereas the context-element 'work' might not). Furthermore, context-elements trigger a habitual decision only when they are nearby (i.e., part of same context as the agent). Thus, it is not so much of the habit *in general* that triggers the habitual decision, but the strength of multiple mental habitual connections specific to an activity, agent and nearby context-elements. We require our models to take into account which context-elements are part of the performance-context and with which habitual connections they are related to the deciding agent and the activity under consideration.

The amount of attention attributed to the action influences the decision to act out of habit [16]. The more attention attributed to the decision the lower the chance the action is done out of habit. The literature on the regulation of attention is extensive [2, 19]. Furthermore, to model attention one needs to take into account how different activities interact. When different activities run in parallel, conflicting or cooperating actions can influence which actions gain attention and therefore to what extent an action is done habitually [16]. Given the focus on this paper on the persist theory and decrease theory, we simplify attention and interaction with other activities to a normally distributed variable that lowers the chance the action is done out of habit.

This paper identifies two theories that can both explain the suspension of habitual behaviour, but differ in how a habitual connection updates over time: the decrease theory and the persist theory.

Decrease Theory The decrease theory states a new habitual connection (i.e., the bike-habit) emerges and the original habitual connection *fades out* [12, 13]. The suspension of habitual behaviour is thus a consequence of the agent enacting the new habit. [12] showed that the automaticity individuals report decreased by an average of 0.29 (on a 7-point scale) after missing an opportunity to enact the action. This decrease is small and had no long-term effect. However, this implies habits might lose strength over time. On the individual level, the Machado's model of conditioning [13] studies how mental connection between context-elements and actions update. In the model, an association loses strength when the context-element is presented, but the action is not. The context-element activates a corresponding mental node, which in turn starts a period of 'extinction' where the association at first loses strength quickly, but then decelerates until the strength loss comes to a halt. These authors thus theorize that a habitual connection loses strength when a context-element is presented, but the activity is not enacted.

Persist Theory The persist theory states a new habitual connection emerges, but the original habitual connection *persists* [1, 4]. The suspension of habitual behaviour is a consequence of the agent intentionally choosing the new action between two (now equally strong) habits. [4] argued for this theory when he advised that automatic elicitation of an unwanted habitual response will likely require that the associated cue is linked with a new alternative response, rather than a non-response. [1] showed that, at least in the short-term, performing an alternative action does not immediately replace the automatic activation of the original action with the alternative. However, once again, this leaves open the effect in the long-term. These authors thus theorize that a habitual connection does *not* lose strength when a context-element is presented, but the activity not enacted.

Both theories agree that a habitual connection gains strength when an agent performs an action in the setting of a context-element [21]. [11] empirically studied this strength gain in an experiment where subjects were asked to do the same action daily in the same context and report on automaticity. The subjects reported a gain in habit strength that followed an asymptotic curve and converged at a different maximum habit strength per subject. Similar results have been found when strength gain is studied on the individual level. For example, [3] uses Hebbian learning to capture the strength gain of habits. Hebbian learning is based on neurology and states if two or more neurons are co-activated, the connection between these neurons strengthen [7]. In our case, this implies the habitual connection strengthens each time the action is done in presence of the context-element. The habitual connection thus gains strength when an action is done in presence of the context-element and this strength gain follows a different asymptotic curve per human.

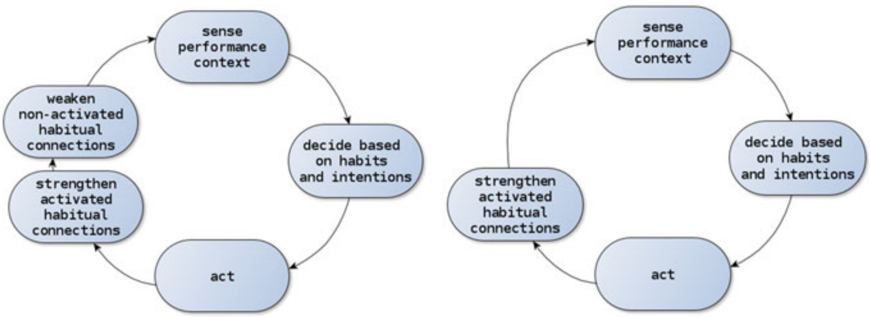
The following properties summarize the literature on habits and will be used to construct two models to compare the theories:

1. Habits and intentions are both predictors of behaviour and interact:
   (a) habits moderate the intention-behaviour relationship
   (b) intentions do not mediate the habit-behaviour relationship
2. The decision to act out of habit is influenced by strength of a habitual connection and the current performance context.
3. Agents increase the chance to break out of a habit when they focus their attention on the decision.
4. Habits gain strength:
   (a) when an action is done in presence of a context-element
   (b) following a different asymptotic curve per agent
5. When an alternative action is performed in the same context, the original habit of the agent:
   (a) **decrease theory:** decreases
   (b) **persist theory:** does not decrease.

Model

This section uses the properties from the last section to construct models that represent the persist theory and the decrease theory. Figure 35.1 presents a decision-making cycle for both the decrease model and the persist model. Both models follow a traditional agent cycle by sensing, deciding, acting and updating. The models differ only in one aspect: the decrease model weakens non-activated habitual connections while the persist model does not. The remainder of this section describes the models in more detail: the concepts necessary for both models and the different modules that form the decision-making cycle.

Concepts To model the dynamics of habits we need to have a conceptual static model the agent uses to decide, act, learn and update. We construct a simplified version of the SoPrA model [14, 15] that focuses on habits (SoPrA-habits) in



(a) The Decrease Model (b) The Persist Model

Fig. 35.1 The decision-making cycle of both the decrease model as well as the persist model

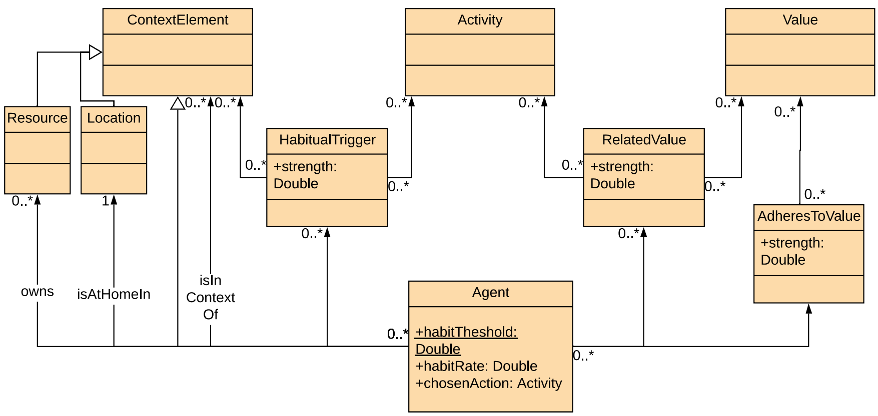


Fig. 35.2 A UML Class Diagram that provides the basic concepts to model habits

UML (Fig. 35.2). We first describe the main classes in the model (i.e., `Activity`, `ContextElement`, `Resource`, `Location` and `Agent`) and then classes with a strength attribute that connect the main classes (i.e., `HabitualTrigger`, `RelatedValue`, `AdheredToValue`).

The `Activity` class models represent things an agent can do. For example, taking the bike, taking the train, taking the car or walking. The `ContextElement` class represents different entities in the environment. There are three different classes that specify (denoted with the white arrowhead) the `ContextElement` class: the `Location` class (e.g., work), the `Resource` class (e.g., a car) and the `Agent` class (e.g., a colleague). The `Value` class represents what one finds important in life. For example, environmentalism or efficiency. Lastly, the `Agent` class represents a decision-maker that chooses between the activities based on how strong it associates these activities with other classes.

The agent associates the `Activity` class with context-elements and values. First, it associates activities with context-elements by keeping track of `HabitualTriggers`. The `HabitualTrigger` represents to what extent a context-element can habitually trigger an activity. For example, it can capture that there is a strong habitual connection between being at home and taking the car. (Thus from now one we will use the SoPrA term `HabitualTrigger` instead of habitual connection to refer to the habitual connection between an action and a context-element.) Second, an agent associates activities with values by keeping track of `RelatedValue` instances. The `RelatedValue` class represents to what extent values are promoted or demoted by the activity. For example, it can capture that taking the car strongly promotes efficiency. The `AdheresToValue` class keeps track of which values the agent finds important. The agent uses these associations to habitually (based on triggers) or intentionally (based on values) choose between activities. The remaining association will be explained in the relevant decision-making modules.

Sense Performance Context To sense the current performance context an agents retrieves a list of context-elements (e.g., locations, resources, other agents) with which it shares the `isInContextOf`-association. When the model initializes the agent uses the `owns` association to determine resources it initially shares a context with and the `atHomeIn` association to determines the other agents it originally shares a context with.

Decide Based On Habits And Intentions We separate between habitual decisions and intentional decisions (see Algorithm 1). First, the agent retrieves for each activity how strongly it is habitually attached to the current context. Second, the agent compares this habit strength of these candidate activities against a threshold (the `habitThreshold` attribute in Fig. 35.2). If the habit strength is lower then the threshold the agent filters the activity out. Third, based on how many activities remain the agent uses one of the following three options to make a decision. If zero candidates remain, habits have no influence and intention is used to make a decision. If one candidate remains, this decision is chosen habitually. If more than one candidates remain, intention is used to choose between these options. Note that the more attention attributed to the action the lower the chance the action is done out of habit. We model this by multiplying an attention variable with the threshold variable. Thus when attention is high (above 1) a higher habit-strength is needed to habitually trigger the action, lowering the chance an action is done out of habit. Recall, attention regulation is postponed to future work and in this model captured by the normal distribution N(1,0.25). Algorithm 1 summarizes this decision process based on habits, intention and attention. Two methods in the algorithm are explained in more detail:

calculateHabitStrength() To calculate the habit strength of each activity given the performance context and an agent we retrieve the `HabitualTrigger.strength` double for each context-element, in that performance context. We have a choice in how we combine these individual strengths into a total. For example, we can average or sum. In contrast to averaging, when summing a habit is triggered even if there are other context cue's distracting you from the triggering ones. Based on the intuition that—even in an abundance of context cue's—relevant context cue's will capture your attention and trigger habits, we choose a summation model.

intentionalDecision() Although we do not have detailed properties regarding the intentional decision, we do need an intentional model to contrast with the habitual model. To make an intentional choice we compare the activities based on a rating. To rate the activities we use the variables related to the `Value` class that SoPrA-habits provides. We calculate a `candidateRating` for each candidate activity based on how strongly an agent adheres to a value (`AdheredValue.strength`) and how strongly an agent relates an activity to the same value (`RelatedValue.strength`). The higher these two variables the higher the rating. The chance an agent chooses an action is based on this rating. For example, if the rating for walking and taking the car have a 5:1 ratio there is a 5:1 chance the agent will walk. Instead of deterministicly choosing the highest rated candidate, we choose a chance model based on the intuition that a human intentionally varies in its actions to satisfy multiple values.

Algorithm 1: The decision influenced by habits and intentions

Data: Candidates - a list of activities, Agent - the agent making the decision, attention - random variable drawn from N(1,0.25)

```
List possibleCandidates;
foreach Activity AC in Candidates do
    habitStrength = calculateHabitStrength(Ac);
    if habitStrength > attention * threshold then
        possibleCandidates.add(A)
if possibleCandidates.length == 0 then
    chosenAction = intentionalDecision(Candidates)
if possibleCandidates.length == 1 then
    agent.chosenAction = candidate
if possibleCandidates.length > 1 then
    chosenAction = intentionalDecision(possibleCandidates)
```

Act Given the focus of the paper the agent does not need to effect the environment with its actions. Acting thus retains to updating the `chosenAction` variable as described in Algorithm 1.

Strengthen Activated Habit Associations The strength of a `Habitual Trigger` class increases when an agent performs the related action in the presence of the related context-element. We use the `habitRate` variable in the `Agent` class to decide the speed with which the strength updates. The model uses a Hebbian learning-rule to increase the strength [7]:

$$newHabitStrength = (1 - habitRate) * oldHabitStrength + habitRate * 1.$$

Weaken Non-Activated Habit Associations (Decrease Model Only) In the decrease model, the strength of a `HabitualTrigger` class decreases when an agent performs the relevant action, but the relevant context-element is not present. We use a similar Hebbian learning-rule to decrease the strength [7]:

$$newHabitStrength = (1 - habitRate) * oldHabitStrength + habitRate * 0.$$

Verifying the Models Represent the Theories

This section verifies that the models portray the properties described in section "Psychological Literature on Habits" and thus reflect the persist theory and decrease theory. Property 1–3 are verified analytically (i.e., without simulation). Property 4 and 5 are verified in a simulation experiment performed on a use case model presented in Table 35.1.[1] In this experiment, the agents are initially motivated to take the car, but after tick 100 are motivated to take the train ($|alt| = 1$). We model 'motivating the agent' as doubling the rating of activities based on intentions. In addition, the amount of attention an agent focuses on the decision is temporarily increased by att_{extra} and discounted each timestep by att_{disc} until it returns to normal. We used Repast Simphony [17] to run the experiment and averaged over 50 individual runs.

Property 1a Habits moderate the intention-behaviour relationship as (1) strong habits prevent intention from influencing behaviour (see line 8–9 of Algorithm 1) and (2) weaker habits influence the intention-behaviour relation. The latter is shown by Algorithm 1 (line 10–11): weak habits will act as an initial filter on actions, but intentions still influence the final decision.

Property 1b Intentions do not mediate the habit-behaviour relationship as strong habits independently trigger action (see line 8–9 of Algorithm 1).

[1] A full description of the computational model and initialization is available on https://github.com/rmercuur/HabitsTraffic.

Table 35.1 The classes and attributes of the use case model used in the verification and simulation experiment. The underlined attributes are parameters that are varied in the simulation experiment

Class/Attribute	Instances	Class/Attribute	Instances
Resource	Car, Bike	Agent.habitRate	N(hr_{μ},0.25hr_{μ})
Location	Home, Work	<u>Mean Habit Rate</u>	hr_{μ}
Activity	takeCar, rideBike, etc.	AdheresToValue.Strength	N(v_{μ},0.25v_{μ})
Value	efficiency, environment	<u>Mean of Value Adherence</u>	v_{μ}
Agent	1–15	<u>Attention Discount Rate</u>	att_{disc}
RelatedValue.Strength	N(1,0.25)	<u>Amount Of Alternatives</u>	$\|alt\|$
HabitualTrigger. Strength (initiation)	0.0	<u>Temporary Extra Attention</u>	att_{extra}

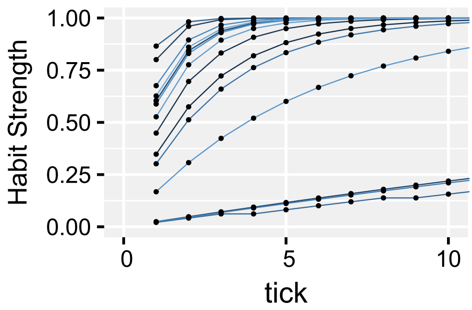


Fig. 35.3 The habit-strength of 15 agents for taking the car at the onset of the simulation (tick 0–10). Each line depicts one agent

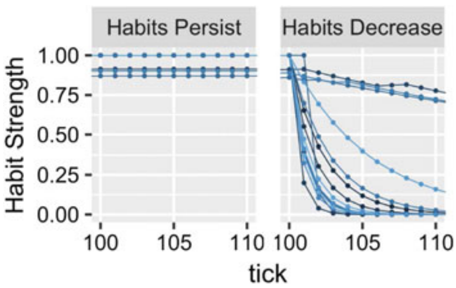
Property 2 As explained in the paragraph Sense Performance Context, the performance context influences the decision by triggering only relevant habitual connections (`HabitualTrigger` classes) and the strength of these habitual connections influences the decision.

Property 3 As explained in the paragraph Decide Based On Habits and Intentions, attention influences the habit threshold and consequently can increase the chance the agent break out of a habit.

Property 4 Fig. 35.3 depicts the habit strength to take the car for each agent between tick 0 and 10. This shows that the habit strength of the agents follows a different asymptotic curve per agent.

Property 5 Fig. 35.4 depicts the habit strength to take the car for each agent between tick 100 and 110; right after the agents are motivated to take the train instead of the car. This shows that in the persist model the strength of the habit persists and in the decrease model the strength of the habit decreases.

Fig. 35.4 The habit-strength of 15 agents for taking the car after an intervention (tick 100–110) in the persist model and the decrease model. Each line depicts one agent.



Finding a Scenario to Discern the Theories

By simulation a range of scenarios, we aim to find a case where the two theories show a different result. Based on a more course-grained initial exploration study we explore the following parameter settings: $|alt| \in [1, 5]$, $att_{extra} \in [2, 5]$, $att_{disc} \in [0.95, 0.99]$, $hr_{\mu} \in [0.01, 0.16]$ and $v_{\mu} \in [0.1, 0.5]$. We used Repast Simphony [17] to simulate these experiments and averaged over 50 individual runs. For each run, we calculate the difference between the number of agents that use a transport mode in the persist model and in the decrease model (e.g., 12 agents use a car in the persist model but only 3 agents use a car in the decrease model). Next, to obtain the total difference ($\Delta_{d,p}$) between the decrease model d and the persist model p we sum over the different transport modes. This results in a performance measure $\Delta_{d,p}$ that represents the difference between the two theories for each parameter setting.

We found that for $|alt| = 2, att_{extra} = 4, att_{disc} = 0.95, hr_{\mu} = 0.01$ and $v_{\mu} = 0.4$ the distance between the two models ($\Delta_{d,p}$) is maximal. This represents a scenario where agents are at first motivated to take the car, but after tick 100 are motivated to do multiple alternatives: take the train or take the bike. The results are depicted in Fig. 35.5. The figure shows that in the persist model agents predominantly take the car and in the decrease model the agents switch their behaviour to taking the bike or train. We explain this result by obtaining the mean habit strengths for the different transport modes from the simulation run. In the persist model, the car habit does not decline and the newly motivated behaviours (i.e., taking the train or taking the bike) do not lead to a strong enough habit to surpass the car habit. Therefore the agent habitually decides to go by car. In the decrease model, the car habit declines and the new bike or train habit surpasses the car habit. Therefore the agents adopt the new behaviour and go by car or bike. In short, in a scenario where agents are motivated to do multiple alternatives the two models show a different result: the agents adopt the new behaviour or not. We interpret this as that the decrease theory and persist theory can be discerned in an empirical experiment where humans are motivated to do *multiple* alternatives.

Using sensitivity analysis we fond that the difference between the two theories in this scenario ($\Delta_{d,p}$) is depended on the mean of the habit rate (corr(hr_{μ},$\Delta_{d,p}$ = -0.69) and the amount of attention given to the decision after the intervention

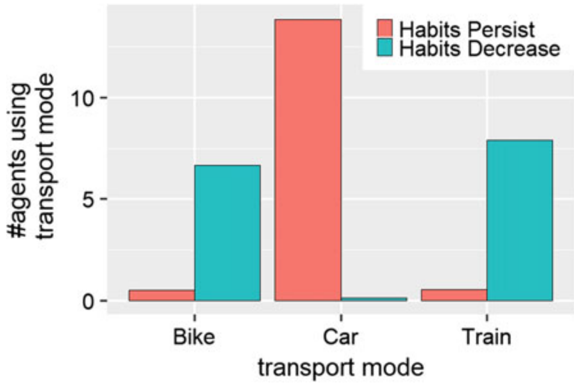


Fig. 35.5 The amount of agents choosing a transport mode in the scenario where the difference between the two models is maximal

(corr(att_{extra},$\Delta_{d,p}$) = −0.17). The mean habit rate and the amount of intervention given to the decision are variables of a different character than the number of alternatives that are motivated. The $|alt|$ is a factor that is easy to manipulate in an experiment: one treatment group is motivated to take the train whereas the other treatment group is motivated to take the train or bike. The hr_{μ} and att_{extra} are factors that are hard or impossible to manipulate in an experiment. Although the sensitivity to these variables cannot be used as a treatment factor it gives insights relevant so selecting the sample (e.g., selecting people that learn habits fast). The sensitivity analysis thus shows that a sample is needed with subjects that learn habits fast and pay extra attention to a decision after an intervention.

Conclusion

This paper aimed to compare two theories on habits focusing only on the implications of the long-term dynamics of updating habits. We showed that the two theories lead to different behaviour when the agents are motivated to do *multiple* alternative actions (e.g., take the bike or take the train), instead of *one* alternative action (e.g., take the bike). Our finding is relevant for the social scientific field, because (1) it shows a scenario where it matters if habits persist and (2) it enables an empirical experiment to discern the two theories.

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