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Habit formation following routine-based versus time-based cue planning: A randomized controlled trial

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Objectives. Habit formation has been identified as one of the key determinants of behaviour change. To initiate habit formation, self-regulation interventions can support individuals to form a cue-behaviour plan and to repeatedly enact the plan in the same context. This randomized controlled trial aimed to model habit formation of an everyday nutrition behaviour and examined whether habit formation and plan enactment differ when individuals plan to enact their behaviour in response to a routine-based versus time-based cue.

Design. Following a baseline assessment, $N = 192$ adults (aged 18–77 years) were randomly assigned to a routine-based cue or a time-based cue planning intervention, in which they selected an everyday nutrition behaviour and linked it to a daily routine or a time cue.

Methods. Participants responded to daily questionnaires over 84 days assessing plan enactment and the behaviour's automaticity (as an indicator of habit formation). Multilevel models with days nested in participants were fitted.

Results. As indicated by asymptotic curves, it took a median of 59 days for participants who successfully formed habits to reach peak automaticity. Group-level analyses revealed that both routine-based and time-based cue planning led to increases in automaticity and plan enactment, but no between-condition differences were found. Repeated plan enactment was a key predictor for automaticity.

Conclusions. Linking one's nutrition behaviour to a daily routine or a specific time was similarly effective for habit formation. Interventions should encourage persons to repeatedly carry out their planned behaviour in response to the planned cue to facilitate habit formation.

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Statement of contribution

What is already known on this subject?

- Individual habit formation in real-world settings can be described by asymptotic curves.
- Cue-based planning and subsequent plan enactment may facilitate automatic behavioural responses.
- Routine cues are linked to higher behavioural automaticity in cross-sectional research.

What does this study add?

- Linking nutrition behaviour to a daily routine or time was similarly effective for habit formation.
- Participants with successful habit formation needed a median of 59 days to reach peak automaticity.
- Plan enactment at the within- and between-person level was key for habit formation.

Background

Contemporary definitions of habit centre on the mental association between a cue and behaviour, learned through repetition, which generates an impulse to act when the cue is encountered (Fleetwood, 2019; Gardner, 2015). Once habits are formed, control of behaviour is passed to an associative system, which triggers action rapidly and efficiently, compared to a deliberative information-processing system which requires conscious resources to be activated (Strack & Deutsch, 2004). Habit formation has been identified as one of the key determinants of behaviour change (Kwasnicka, Dombrowski, White, & Sniehotta, 2016; Kwasnicka et al., 2019). To help people with forming healthy habits in behaviour change interventions, it is essential to investigate this process in detail (e.g., Fleig, Pomp, Schwarzer, & Lippke, 2013).

Habit research on the group level versus the individual level

A serious impediment to scientific progress is that most habit research is based on group-level data analyses (e.g., Orbell & Verplanken, 2010), which prohibits examination of within-person variability over time in responses to behavioural interventions. Theories of behaviour change are formulated to apply to individuals (Johnston & Johnston, 2013); however, they are mainly used to explain behaviour at the group level. The idiographic method, also known as *single-case method* or *N-of-1*, employs a within-participant design to test predictors of behavioural outcomes over time. Studies applying this method in habit research are scarce (Kwasnicka, Konrad, Kronish, & Davidson, 2018); yet, they have tremendous potential to explore habit formation theory and inform personalized interventions promoting habit development.

Modelling day-by-day individual habit formation in the real world

Lally, Van Jaarsveld, Potts, and Wardle (2010) modelled habit formation within individuals over time in a real-world setting. Participants self-selected a behaviour that they would perform in response to a once-a-day and daily cue for 12 weeks, each day reporting the enactment of the behaviour and its automaticity. This study fitted an asymptotic curve (in which the increase with each day reduces over time until a plateau is reached) to each individual's automaticity data, examining the time when 95% of the asymptote was reached (i.e., how fast does a behaviour become automatic) and the level of the asymptote (i.e., how automatic a behaviour has become). Participants for whom asymptotic models fitted well needed a median of 66 days (range: 18–254 days) to reach stable automaticity (i.e., indicator for habit formation). However, asymptotic curves did not adequately model

the habit formation process for all participants (i.e., low model fit for $n = 43$ out of $N = 82$ participants).

By using asymptotic curves, one assumes that automaticity reaches a stable level after a certain time and is then maintained long-term. This is the shape that would be expected where participants are consistent in performing the behaviour when a cue is encountered (Lally et al., 2010). As many factors such as change in daily routines or change in goals might hinder behavioural performance, consideration of alternative curve shapes could be informative. Statistical models that capture *discontinuous progress in habit formation* such as quadratic curves can also be investigated (e.g., an inverted U shape would reflect initial increases in automaticity, followed by decreases). Figure 1 provides a conceptual overview of potential curves modelling automaticity over time: a null model with a constant, a quadratic, and an asymptotic curve.

Promoting habit formation: Cues, planning, and plan enactment

Key to successful habit formation is behavioural repetition in response to a cue (Gardner, 2015; van der Weiden, Benjamins, Gillebaart, Ybema, & de Ridder, 2020) such as drinking a daily glass of water when watching the news. Planning as the mental simulation of any cue-behaviour contingency is assumed to facilitate behavioural repetition and, thereby, automatic behavioural responses (Gollwitzer, 1999). Previous intervention research has shown that forming cue-behaviour plans promoted habit formation (Fleig et al., 2013; Verplanken & Orbell, 2003). It is important to draw a distinction between the mere occurrence of the desired behaviour (unconditional behaviour; Sniehotta, 2009; e.g., drinking water), and the repetition of the desired behaviour when encountering the specific cue set out in a plan, called *plan enactment* (Fleig et al., 2017; or *conditional planning effect*, Sniehotta, 2009; e.g., drinking water when the news is on). In line with Gollwitzer (1999), forming cue-behaviour plans and subsequent regular plan enactment (as an indicator of cue-specific behavioural repetition) should facilitate the development of automaticity.

Moreover, progress in habit formation may depend on the type of cues people use to link to a chosen behaviour. Fournier et al. (2017) found that the average modelled number of days needed to develop a habit (reach the plateau of an asymptotic curve) was fewer in individuals who engaged in a stretching exercise upon waking up in the morning (106 days) than individuals who performed the stretching exercise before going to bed in

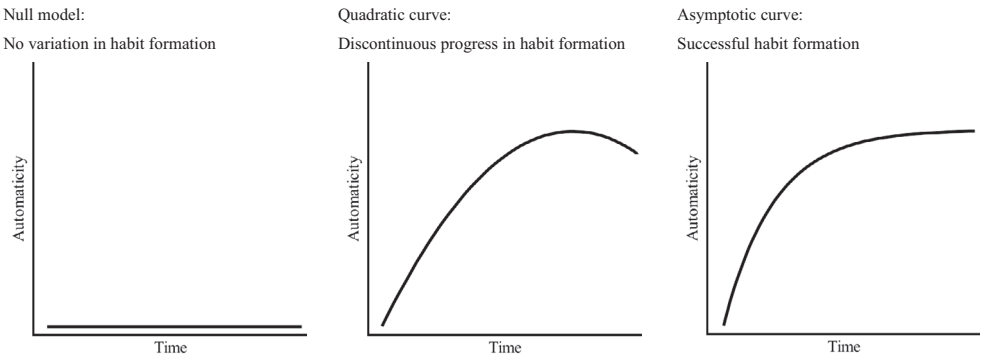


Figure 1. Conceptual curves of habit formation over time.

the evening (154 days). Previous research showed that anchoring new behaviours around personal daily routines (e.g., breakfast) is well accepted and beneficial for behavioural adoption (Fleig et al., 2017; Keller et al., 2017). A cross-sectional study from Pimm et al., 2016 revealed that more consistent routine cues, but not time-based cues, were linked to higher automaticity. Routines may allow for more situational flexibility to execute the planned behaviour and cue detection might be easier as it requires less monitoring, for example, perceiving that breakfast is finished (Judah, Gardner, & Aunger, 2013). However, further causal testing is needed to learn more about differential effects of routine-based and time-based cues on the development of a behaviour's automaticity.

Aims and hypotheses

The first aim of the present study was to model and describe the habit formation process at an individual level (Fournier et al., 2017; Lally et al., 2010). The second aim of this study was to examine – at the group level and by means of an experimental manipulation – whether the process of habit formation varies depending on anchoring the desired behaviour around a self-selected routine cue versus a time cue. Based on previous theory and research, the following was explored and hypothesized:

1. At the individual level, it was explored which type of curve (i.e., asymptotic or quadratic curve) describes the change in automaticity over time for persons attempting to form a habit.
2. At the group level, it was hypothesized that routine-based and time-based cue planning is related to a) increasing rates of plan enactment and b) increases in automaticity over time.
3. Differential effects of changes over time in plan enactment and automaticity between both planning intervention conditions should be explored.

Method

Design and procedure

This study reports primary and secondary analyses of an online-based intensive longitudinal two-condition randomized controlled trial (RCT) with adults from the general population in Germany, conducted between February and June 2019. The aim of this RCT is to investigate habit formation for a self-selected healthy nutrition behaviour in individuals who formed a plan based on a *routine cue* compared to individuals forming a plan based on a *time cue*. The prospective preregistration for the RCT can be accessed at the German Clinical Trials Register https://www.drks.de; registration number: DRKS00016720. After providing informed consent, participants responded to the baseline questionnaire (Day = 'D'; D0), were randomized to the routine-based cue or the time-based cue condition, and received the intervention (D0). Subsequently, participants were asked to respond daily to short end-of-day questionnaires over 12 weeks (i.e., 84 days; D1–D84). This study presents findings on primary and secondary outcomes of the RCT, which were assessed across 85 daily measurement occasions (D0–D84). The institutional review board at the first author's institution granted ethics approval for this study. The CONSORT checklist is provided with Supporting Information S1.

Sample and recruitment

Eligible participants were at least 18 years old and had sufficient visual ability and German language skills to understand and complete the study questions and materials. In February 2019 and after the preregistration of the RCT, the study was advertised to university students of the Freie Universität Berlin and Medical School Berlin, and the general population through email lists, flyers and online postings (e.g., interest group websites). Participants were offered an online shopping voucher of 5EUR and, if applicable, course credits for taking part in the full 12 week study period. A total sample of 192 adults was enrolled with random allocation to each intervention condition (Figure 2). At baseline, participants' (86.5% female) mean age was 24.76 years (SD = 7.50; range: 18–77), their mean body mass index was 22.38 (SD = 3.57), and 8.4% of participants reported having children.

In order to adequately model a habit formation trajectory, it is necessary to have enough data points to adequately fit a curve. Also, previous studies modelling habit formation (e.g., Lally et al., 2010) suggest that the average time to reach a plateau may be higher than the 60-day mark. Thus, data were not retained for analysis when a participant responded to <6 daily assessments (providing insufficient data; Bolger & Laurenceau, 2013) or did not respond beyond D60 (study disengagement). A total of 135 participants were retained for data analyses (routine condition: n = 65; time condition: n = 70).

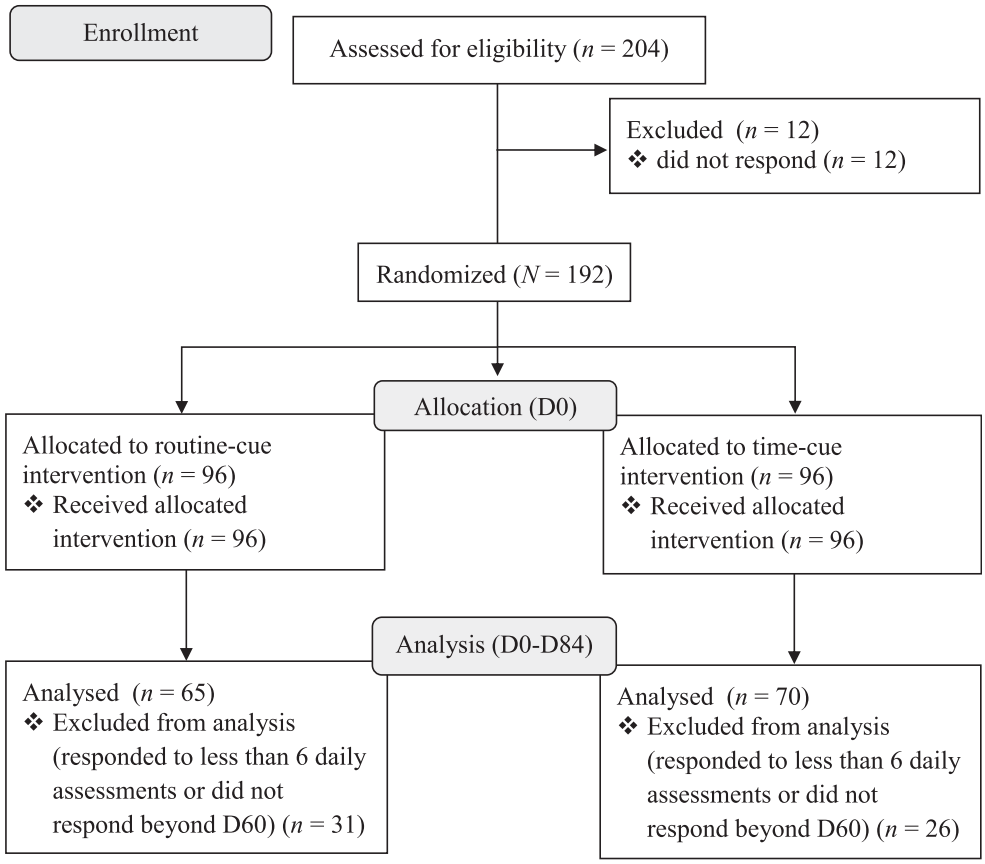


Figure 2. Flow diagram showing participant attrition. *Note*. 'D' refers to day of assessment following baseline.

Randomization and intervention

Using a simple randomization procedure (i.e., 'flipping a coin' resulting in 0 or 1) via the web-based study software, enrolled participants were randomly allocated to the *routine-based cue* planning intervention condition (hereafter described as routine condition) or the *time-based cue* planning intervention condition (hereafter described as time condition). The randomization procedure resulted in equal group allocation ($2 \times n = 96$). No blinding techniques were applied. The online-based intervention applied in this study was a very brief healthy nutrition-related planning intervention developed by health psychologists from the first and senior authors' institution (see Supporting InformationS2 and S3). The intervention took about 5 min for both groups and included the behaviour change techniques action planning, information about health consequences, habit formation, and pros and cons (Michie et al., 2013). Participants in both conditions received general information about healthy nutrition behaviours, and they created their personalized cue-behaviour plan for a healthy nutrition behaviour. In the routine condition, participants were asked to form a plan including a daily routine cue (e.g., after breakfast). In the time condition, participants were prompted to form a plan including a time cue (e.g., at 9 am). To increase comprehension and adherence to the intervention protocol, a cue-behaviour example was provided in both conditions. Participants were asked to select cue-behaviour combinations which they did not currently perform (i.e., 'drinking water' is a usual daily behaviour, but 'drinking water after breakfast' might be a novel plan for a participant). Subsequently, participants were asked to carry out their behaviour in the planned context every day for 12 weeks.

Measures

Participants were asked to enter their behaviour and cue before completing any further items throughout all daily questionnaires, thus, measures from daily questionnaires referred to each participant's chosen behaviour and cue.

Automaticity

The primary outcome was automaticity (as an indicator of habit strength) for the self-selected healthy nutrition behaviour assessed daily between D0 (i.e., baseline assessment) and D84 with the 4-item Self-Report Behavioral Automaticity Index (Gardner, Abraham, Lally, & de Bruijn, 2012). Automaticity items (e.g., 'My self-selected nutrition behavior is something I do automatically') were answered on a 6-point scale (1 = 'does not apply at all' to 6 = 'applies exactly'). The reliability of person-level averages (i.e., between-person) across all automaticity observations (R_{KF}; Cranford et al., 2006) was approximately 1 for both groups. Moreover, within-person reliability coefficients of .89 (routine condition) and .84 (time condition) were found, reflecting high reliability to detect within-person fluctuations across measurement occasions (Scott et al., 2020).

Plan enactment

The secondary outcome was plan enactment, that is, the enactment of the self-selected nutrition plan, assessed daily between D1 and D84. Participants reported whether or not they had enacted their self-selected nutrition behaviour in response to the cue set out in their plan, 'yes' (1) or 'no' (0) answer.

Covariates

Covariates were age, gender, body mass index, and plan-specific self-efficacy (see dropout analyses below) at baseline. Plan-specific self-efficacy was measured daily with one item 'I am confident that I will be able to perform my new behavior exactly as planned' (Scholz, Sniehotta, Schüz, & Oeberst, 2007).

Sample size determination

A priori Monte Carlo simulations (n = 1,000) were used to determine that 100 participants with a missing response rate of 80% across 85 repeated assessments result in > 90% power to detect small between-condition differences (a pseudo-R2 for reductions in between-level variance of .01 in trajectories of automaticity).

Analyses

For all reported data analyses, the R software, Version 3.6.1, was used. The R scripts used for this study are available on https://osf.io/qbk26/.

Preliminary analyses

Attrition and randomization were analysed with chi-square and *t*-tests which were followed by logistic regressions. Both attrition (0 = not retained for analysis, 1 = retained) and intervention condition (0 = time condition, 1 = routine condition) were used as dichotomous outcomes.

At the individual level: Patterns of change in automaticity

To examine individual change patterns of automaticity, automaticity values over time were analysed applying three different regression models for each participant. A *model with a constant* (M1, null model, $\hat{y}(t) = b0$) with t representing the day following the intervention, a *quadratic model* (M2, $\hat{y}(t) = b0 + b1*t + b2*t^2$), and an *asymptotic model*[1] (M3, $\hat{y}(t) = b3 + (b0 - b3)*\exp(-\exp(b4)*t)$, with $b0$ representing the response on day zero, $b3$ representing the horizontal asymptote on the right side, $b4$ representing the natural logarithm of the rate constant, were fit. Based on fit indices (i.e., lowest Bayesian Information Criterion, BIC), a final model type was obtained for each participant. In models M2 and M3, time trend parameters were centred at baseline (D0).

At the group level: Patterns of change for the average participant

In order to test for changes in automaticity and plan enactment across participants from the analysed sample, two-level models with daily assessments (level 1) nested in participants (level 2) using the R *lme4* package (Bates et al., 2015) were computed. To identify patterns of change in automaticity, three different models were fitted, that is, *constant models* (M1), *quadratic models* (M2), and *asymptotic models* (M3). In line with findings from van der Weiden et al. (2020) and based on preliminary analyses showing that

[1] *Asymptotic models were modeled as logarithmic models with an upper bound asymptote (Lally et al., 2010). Preliminary analyses of logistic models with a lower and an upper bound asymptote (Fournier et al., 2017) revealed that these models did not fit the data well.*

model fit always improved when time parameters were allowed to vary between participants (random effects), all possible random effects were modelled (Barr, Levy, Scheepers, & Tily, 2013). Moreover, a condition predictor (0 = time condition, 1 = routine condition) was added and interactions with time parameters were modelled as further predictors of automaticity (see Supporting Information S4 for model equations). To test whether model parameters differed between the two intervention conditions, incremental fit was evaluated using likelihood-ratio tests for nested models (i.e., models without vs. with modelled intervention condition variable). For comparisons across the three model types (M1-M3), Akaike and Bayesian Information Criterion (AIC and BIC), and deviance parameters were evaluated with lower values reflecting a better fit to the data. For sensitivity analyses, covariates were included as predictors in final two-level models.

To examine whether frequent plan enactment facilitates habit formation, plan enactment and time × plan enactment interactions were added as further predictors in best fitting two-level models predicting automaticity. Plan enactment was modelled on the between level (i.e., persons with higher vs. lower plan enactment over 84 days) and the within level (i.e., days on which plans were enacted vs. not enacted).

Results

Preliminary analyses

Retained participants did not differ from participants who dropped out on most study variables, except for plan-specific self-efficacy which was higher in retained participants [$n = 57$ not retained participants: $M = 4.50$, $SD = 0.77$; $n = 135$ retained participants: $M = 4.74$, $SD = 0.73$; $t(101.26) = -2.01$, $p = .047$]. Of retaining $n = 135$ participants, average response rate to the baseline questionnaire and 84 daily questionnaires was 74.90 (out of 85: 88%; $SD = 11.30$) and responses ranged between 19 and 85. In randomization checks, no significant unique between-intervention differences of study variables emerged. A manipulation check revealed that $n = 70$ (100%) participants from the time-based condition entered a valid time in an hh:mm format at the online platform. Of the $n = 65$ participants from the routine-based condition, 6 participants entered a time of the day (e.g., in the afternoon), 4 participants entered an internal state (e.g., when I feel stressed), and 55 (85%) participants entered a routine as their cue (e.g., after getting up in the morning).

The individual level: How many days were needed to reach stable automaticity?

From 135 participants, 18 participants did not adhere to intervention instructions, that is, they planned a nutrition behaviour that was already automatic at baseline (i.e., above the scale mean of 3.5; reflecting a higher degree of automaticity) or planned the avoidance of an undesired or unhealthy nutrition behaviour (e.g., not eating candy anymore). A total of $n = 117$ participants adhered to the intervention protocol and selected drinking water ($n = 58$; 50%), consuming fruit ($n = 28$; 24%), vegetables ($n = 8$; 7%), a mix of fruit and vegetables ($n = 7$; 6%), or another nutrition behaviour ($n = 16$; 13%; e.g., take a tablespoon of linseed oil) as their behaviour to become a habit. Of those $n = 117$ participants, seven participants (6%) did not show any variation (i.e., their automaticity always scored at the same level) or showed a variation around an automaticity constant; thus, the prediction of automaticity change over time by solely a constant showed the best model fit (i.e., lowest BIC). For 66 participants (56%), a quadratic curve showed the best

model fit, and for 44 participants (38%), an asymptotic curve showed the best model fit for automaticity changes. Most participants ($n = 95$ out of 117; 81%) yielded positive automaticity changes over time, that is, quadratic curves with a higher predicted level at D84 (vs. baseline) or positive asymptotic curves (i.e., with an upper bound asymptote). For 15 participants (out of 117; 13%), negative automaticity changes over time were found. Figure 3 provides examples of three participants with negative (Panel 1) or positive (Panel 2, Panel 3) automaticity changes over time.

Successful habit formation was represented by positive asymptotic curves with a modelled end point higher than 3.5, which was true for $n = 27$ participants (out of 117; 23%). The criterion of an asymptotic curve end point higher than 3.5 (above the scale mean) was chosen as it reflects a plateau level at which participants on average responded to automaticity items with 'rather applies', 'applies', or 'applies exactly' indicating an overall agreement that the behaviour was somewhat automatic. Based on model parameters, these participants reached or will reach 95% of the asymptote (i.e., as an indicator for successful habit formation) after a median of 59 days with a range between 4 and 335 days. The number of participants with successful habit formation ($n = 14$ versus $n = 13$) and the number of days when 95% of the asymptote was reached by those participants (after a median of 60 versus 59 days) was similar when comparing the routine condition versus the time condition. In a post-hoc analysis, we tested whether participants with successful habit formation ($n = 27$) differed from the remainder of the sample ($n = 108$) on baseline characteristics. *T*-tests showed that intrinsic reward (Wiedemann, Gardner, Knoll, & Burkert, 2014) and anticipated regret (Abraham & Sheeran, 2003) were significant baseline correlates. Participants with successful habit formation were more likely reporting higher baseline intrinsic reward [scale from 1 to 6; $n = 27$; $M = 4.84$, $SD = 0.72$; $n = 108$: $M = 4.38$, $SD = 0.77$; $t(133) = -2.81$, $p = .006$] and higher baseline anticipated regret [scale from 1 to 6; $n = 27$; $M = 4.48$, $SD = 0.96$; $n = 108$: $M = 4.05$, $SD = 1.03$; $t(133) = -1.99$, $p = .049$]. A logistic regression analysis revealed that intrinsic reward, but not anticipated regret, was a unique predictor of being categorized as having successfully formed a habit.

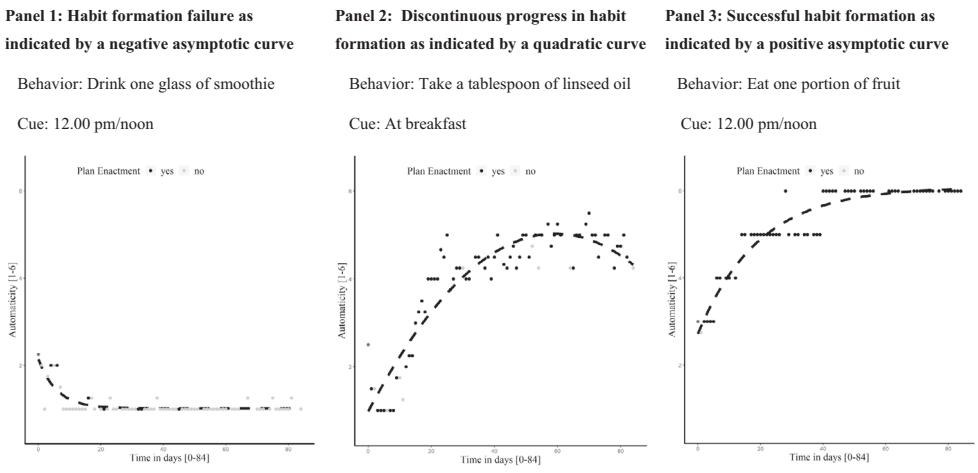


Figure 3. Examples of different types of automaticity time courses from three participants.

Descriptive statistics on automaticity and plan enactment

Table 1 presents descriptive statistics of automaticity and plan enactment at D0 (only automaticity), D1 as well as across D1-D27 (month 1), D28-D56 (month 2), and D57-D84 (month 3) for the retained participants in the routine condition ($n = 65$) and the time condition ($n = 70$). Moreover, descriptive statistics for the subsample of participants for whom individual-level analyses indicated successful habit formation are also presented. Automaticity and plan enactment were moderately correlated between participants ($r = .53$, 95% CI = [0.39; 0.64]), but showed low correlations at the within-level ($r = .17$; 95% CI = [0.15; 0.19]).

The group level: Plan enactment and automaticity by intervention condition

Modelling plan enactment over time

Group-level analysis of two-level logistic regression models predicting dichotomous plan enactment across $n = 135$ participants indicated a significant linear time prediction, that is, the probability of plan enactment increased over time ($B = 0.01$, $SE = .00$, $z = 2.95$, $p = .003$). However, this increase did not differ between intervention conditions ($B = -0.01$, $SE = .01$, $z = -1.26$, $p = .207$).

Modelling automaticity over time

As indicated by lowest AIC, BIC, and deviance parameters, best fit to the data across model types were found for quadratic models (M2), followed by asymptotic models (M3) (Table 2). The quadratic model with the intervention condition variable as a moderator (Model 2b) did not yield a better fit when compared to the basic quadratic model 2a. Thus, time courses in automaticity did not differ between intervention conditions. Results from the quadratic model 2a indicate that automaticity in both conditions showed an initial steep increase (positive linear time trend, Table 3), followed by a less steep automaticity change for later study days (negative quadratic time trend). Sensitivity analyses revealed that this pattern of results did not change when covariates were added.

Automaticity for participants who enacted their plans

Analyses of quadratic models with plan enactment as an additional predictor of automaticity (Model 2c; as an extended model 2a) revealed that plan enactment is a relevant correlate at the within and between level (Table 3). Within-level links between plan enactment and automaticity indicate that, on days when participants reported successful plan enactment (vs. no plan enactment), predicted automaticity was higher. Automaticity links with between-level plan enactment reflect that persons who repeatedly enacted their plans (vs. those who did not) were more likely to show higher automaticity levels. The significant linear time × plan enactment (between) prediction indicates that increases in automaticity at earlier study days were particularly steep when plans were repeatedly enacted. This pattern of effects was also found when controlling for covariates.

Illustrating effects from model 2c, Figure 4 displays different modelled quadratic time courses for participants with low vs. average vs. high plan enactment throughout the 84 study days. The quadratic curve for participants with higher plan enactment (i.e., those who enacted their behaviour each day; Figure 4) reflects particularly steep increases

Table 1. Descriptive statistics of automaticity and plan enactment in two planning intervention conditions

		Analysed sample (n = 135)		Successful habit formation (n = 27)	
		Routine condition (n = 65) *M* (*SD*)	Time condition (n = 70) *M* (*SD*)	Routine condition (n = 14) *M* (*SD*)	Time condition (n = 13) *M* (*SD*)
Automaticity [1–6]	D0, baseline	2.22 (0.91)	2.51 (1.16)	2.02 (0.68)	2.08 (0.83)
	D1	2.38 (0.84)	2.35 (1.00)	2.54 (0.96)	1.96 (0.93)
	Month 1: Daily average, D1-D28	2.89 (1.08)	2.81 (1.02)	3.48 (1.00)	3.46 (1.17)
	Month 2: Daily average, D29-D56	3.48 (1.25)	3.32 (1.14)	4.43 (0.70)	4.26 (0.90)
	Month 3: Daily average, D57-D84	3.74 (1.34)	3.54 (1.23)	4.73 (0.68)	4.57 (0.85)
	ICC [95% CI] across study days	0.69 [0.61; 0.76]	0.69 [0.62; 0.76]		
% of participants' plan enactment	D1	61.67 (49.03)	65.71 (47.81)	69.23 (48.04)	69.23 (48.04)
	Month 1: Daily average, D1-D28	68.92 (46.30)	66.68 (47.15)	80.87 (39.38)	80.12 (39.97)
	Month 2: Daily average, D29-D56	69.93 (45.87)	69.24 (46.16)	85.80 (34.96)	83.60 (37.09)
	Month 3: Daily average, D57-D84	68.31 (46.54)	70.62 (45.57)	82.12 (38.38)	88.57 (31.87)
	ICC [95% CI] across study days	0.31 [0.23; 0.39]	0.36 [0.28; 0.44]		

Note. Based on individual curve analyses, n = 27 participants were classified with successful habit formation. An example curve is displayed by Figure 3, Panel 3.
M = Mean. *SD* = Standard deviation. [1–6] refers to the response scale of the variable. 'D' refers to day of assessment following baseline. Plan enactment assessment started at D1. ICC = Intraclass correlation.

immediately after starting with their behaviour, followed by lower increases for later study days, which looks similar to an asymptotic curve. Post-hoc analyses revealed that this group of participants reached an average maximum automaticity of 4.28 after 83 days, that is, had their highest automaticity score at the end of the study. In contrast, a flat

Table 2. Model comparisons of two-level models predicting automaticity with different time parameters

Models	*df*	*AIC*	*BIC*	*Deviance*	$\Delta\chi^2$	Δdf	$p(\Delta\chi^2)$
Null model: No variation over time (M1)							
M1a: A constant	3	20,996	21,017	20,990	0.07	1	.787
M1b: M1a + Routine (vs. time) condition modelled	4	20,998	21,026	20,990			
Quadratic models (M2)							
M2a: Time parameters of quadratic models	10	11,294	11,366	11,274	0.82	3	.845
M2b: M2a + Routine (vs. time) condition modelled	13	11,300	11,393	11,274			
Asymptotic models (M3)							
M3a: Time parameters of asymptotic models	7	11,907	11,958	11,893	0	2	1.00
M3b: M3a + Routine (vs. time) condition modelled	9	11,922	11,986	11,904			

Note. In models 'b', main effects of condition and interaction effects of condition × time parameters were added. Models M1, M2, and M3 with maximized random effects.
BIC = Bayesian Information Criterion; AIC = Akaike Information Criterion.

quadratic curve for participants with lower plan enactment was found, indicating a lower average maximum automaticity of 3.00 (i.e., lower than the scale mean) after 75 days.

Discussion

This intensive longitudinal two-condition RCT aimed to model habit formation of an everyday nutrition behaviour over 12 weeks. The study examined whether plan enactment and subsequent habit formation differ when the planned behaviour is anchored around a self-selected routine cue compared to a time cue. Modelling of automaticity over time, as an indicator for the habit formation process, showed variation between persons and can be described in three general ways: (1) habit formation failure, (2) discontinuous progress in habit formation, and (c) successful habit formation. Of those participants who successfully formed a habit, as indicated by asymptotic curves, a median of 59 days was needed to reach 95% of the asymptote ('successful habit formation'). This is similar to the median of 66 days found by Lally et al. (2010). Participants with successful habit formation were more likely to have chosen to perform a behaviour which felt intrinsically more rewarding to them. Future interventions addressing habit formation could emphasize the importance of choosing behaviours that have personal value to participants (Gardner & Lally, 2013).

At the group level, mean automaticity and plan enactment increased over time, irrespective of intervention condition (routine-based or time-based cue planning). Plan enactment was confirmed as a predictor of automaticity: Individuals who frequently enacted their behaviour in response to their cue were more likely to increase their automaticity.

How quadratic curves can describe habit formation

Present results showed diverse trajectories of automaticity for different participants, supporting the notion that habit formation attempts are a highly personalized process.

Table 3. Fixed effects estimates for two-level models predicting quadratic time trends of automaticity

Outcome: automaticity	M2a: time parameters of quadratic models			M2b: M2a + condition predictions		
	Fixed effects		Random effects	Fixed effects		Random effects
Predictors	*B* (*SE*)	*T*	*SD*	*B* (*SE*)	*t*	*SD*
Intercept (at first daily assessment D0)	2.47*** (.08)	32.08	0.89	2.51*** (.11)	23.43	0.89
Linear time	1.38*** (.17)	8.18	1.92	1.26*** (.23)	5.36	1.93
Quadratic time	−0.41*** (.08)	−5.01	0.94	−0.37** (.12)	−3.21	0.94
Routine (vs. time) condition				−0.09 (.15)	−0.55	
Linear time × Routine (vs. time) condition	0.26 (.34)	0.76		Quadratic time × Routine (vs. time) condition	−0.09 (.17)	−0.57
Pseudo-R^2	.70	.70				

Predictors	M2c: M2a + Plan enactment predictions		
	B (*SE*)	*t*	*SD*
Intercept (at first daily assessment D0)	2.50*** (.08)	32.48	0.88
Linear time	1.36*** (.16)	8.37	1.85
Quadratic time	−0.40*** (.08)	-4.97	0.92
Plan enactment (within)	0.23*** (.03)	9.05	0.25
Plan enactment (between)	0.77** (.28)	2.77	
Linear time × Plan enactment (between)	1.67** (.59)	2.86	
Quadratic time × Plan enactment (between)	−0.43 (.29)	-1.47	
Pseudo-R^2	.71		

Note. $n = 135$ participants. Time trends were z-standardized and centred at first daily assessment (D0). Main effects of time trends were modelled as random effect predictions. Pseudo-R^2: Reduction of L1-Residual Variance compared to null model. Pattern of results remained unchanged when adjusting models for baseline age, gender, body mass index, and plan-specific self-efficacy.
SE = standard error.
***$p < .001$. **$p < .01$

Extending previous studies on daily habit formation in real-world settings focusing on asymptotic curves (Fournier et al., 2017; Lally et al., 2010), it was tested whether quadratic curves modelling automaticity over time fitted this type of data. A quadratic curve with its maximum at the end of the modelled time frame reflects a participant's continuous automaticity increase with a particularly steep initial increase, which can be similar to the shape of asymptotic curves (cf. Figure 4, upper curve). For another participant, a quadratic curve can reflect a discontinuous automaticity time course, for example, when initial automaticity increases are followed by later decreases (cf. Figure 3, Panel 2). Therefore, fitting a quadratic curve at a group level seems to be a flexible analytical approach as it allows for both types of trajectories to be captured. The proposal that automaticity can decrease over time needs careful consideration. Conceptually, habit research suggests that the mental association underlying habitual impulses will not degrade due to a lack of performance (Gardner, Rebar, & Lally, 2020). However, the perception of automaticity may well do so when a behaviour is not performed (e.g., due to

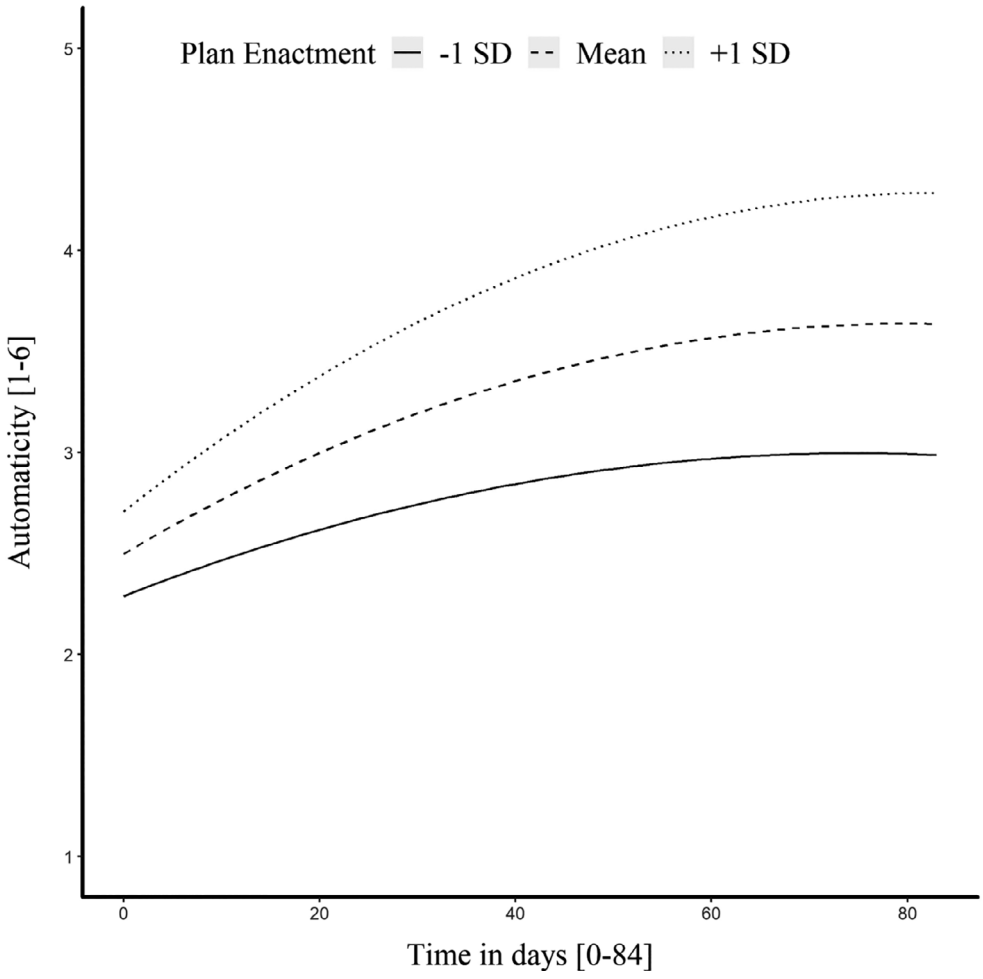


Figure 4. Group-level analysis of quadratic automaticity curves across both intervention conditions by distinct levels of between-person plan enactment (referring to M2c, see Table 3). *Note.n* = 135 participants. Curve for lower plan enactment (Mean – 1*SD* refers to 22.59%): The maximum automaticity of 3.00 was reached after 75 days. Curve for mean plan enactment (refers to 68.89%): The maximum automaticity of 3.64 was reached after 80 days. Curve for higher plan enactment (Mean + 1*SD* refers to 100%): The maximum automaticity of 4.28 was reached after 83 days.

a cue not being encountered or detected). The results presented here show that participants with less frequent behavioural performance were the participants whose curves reduced earlier in the study (Figure 4).

Plan enactment is key to habit formation

Present findings on plan enactment-automaticity relationships confirmed previous evidence that behavioural repetition is key to habit formation and particularly important for automaticity changes at the beginning of the habit formation process (Fournier et al., 2017; Lally et al., 2010; van der Weiden et al., 2020). Extending previous research, present

results indicate that lower between-level plan enactment is linked to flat average automaticity curves with an automaticity maximum lower than the scale mean (Figure 4). This highlights that multiple omissions are impeding the habit formation process. Regarding interventions that may support the habit formation process, future research could apply a just-in-time adaptive intervention (Spruijt-Metz & Nilsen, 2014), once repeated omissions were detected.

Type of cue: Routine-based and time-based cue planning

Although evidence from observational studies highlights that routine cues are flexible, do not require continuous monitoring, and are less challenging for memory than time cues (Judah et al., 2013; McDaniel & Einstein, 2000), no between-condition differences were found (routine vs time-based cue planning). It may be possible that even when participants in the time condition were asked to use time-based cues, they chose a time at which they are usually performing the same behaviours, hence the cue could also be related to a routine. To test this, future work could assess the exact time and situation of behavioural performance, for instance, by using objective measures.

Moreover, the difference for the efficacy of plans with time versus routine cues may be person-specific and better tested within individuals. For instance, when applying a within-person N-of-1 RCT, researchers could vary time blocks when routine and time cues are randomly allocated to answer the question which plans are most suitable for each individual and for each behaviour of interest.

Strengths, limitations, and outlook

This study has several strengths. First, within-person and between-person differences were explored showing that habit formation attempts lead to different and individual-specific trajectories of automaticity change. Second, further evidence was generated that routine-based and time-based cue planning can be used to initialize habit formation. Third, this study helped to answer a topical question: '*how long does it take to form a habit?*'. Results showed that modelled time for successful habit formation (i.e., time when 95% of the asymptote was reached) varied between individuals from 4 to 335 days with a median of 59 days.

The present study also had some limitations. First, the sample consists of a large number of female participants and participants from younger age groups. Thus, the present findings may not generalize to other subgroups. Second, without a control group it was not possible to demonstrate the impact of planning itself; however, this has been robustly demonstrated in the literature (Hagger, & Luszczynska, 2014). It cannot be ruled out that simply responding to daily questionnaires on one's nutrition behaviour has led to behavioural effects. Third, plan enactment and automaticity were solely captured by self-reports. Future studies could additionally assess objective plan enactment using meal photographs and their timestamps. Self-reported automaticity is often the best measure available for tracking habit formation, but more work is needed to assess how people respond to this measure.

Conclusion

To conclude, this study showed that habit formation attempts for a self-selected nutrition behaviour is an individual-specific process and that plan enactment is key for successful

habit formation. Linking one's nutrition behaviour to a daily routine or a specific time of day was similarly effective for habit formation. Future work should seek to investigate this further to understand whether advice around cue choice can aid habit formation.

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Conflict of interest

All authors declare no conflict of interest.

Data availability statement

The data sets generated during this study are not publicly available as we do not have permission from study participants. However, group-level information about the data is available from the corresponding author on reasonable request. An English version of the intervention materials (originally in German) is included in the Supporting Information S2 associated with this article. The R code used for data analysis can be found under https://osf.io/qbk26.

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Supporting Information

The following supporting information may be found in the online edition of the article:

Supplementary Material CONSORT 2010 checklist of information to include when reporting a randomised trial

Supplementary Material Intervention material

Supplementary Material The TIDieR (Template for Intervention Description and Replication) Checklist

Supplementary Material Model equations