# Habit Formation Dynamics: Finding Factors Associated with Building Strong Mindfulness Habits

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**Abstract.** Mindfulness is widely recognized as an effective technique for managing mental and physical health. However, a significant challenge remains when attempting to transform its practice into a habit. To understand the individual characteristics and contexts that correlate with habit formation experiences, we conducted a six-week observational study involving 62 participants who planned to adopt a new mindful breathing habit. Overall, 47.4% (N = 1,234) of daily surveys were completed and 41 participants completed the post-study survey. Using a growth curve modeling framework, we confirm the presence of significant overall change in habit automaticity across participants in the first 21 days of habit practice. Furthermore, we identify four factors that are significantly correlated with the gradient of participant habit formation trajectories: how committed a participant is to building the habit before starting the practice period, their prior mindfulness experience, and two dimensions of personality – agreeableness and emotional stability.

**Keywords:** Habit formation · Health behavior change · Well-being · Mindfulness · Growth curve modeling · Observational study

## 1 Introduction

The practice of mindfulness has wide-ranging health benefits [4,9,15]. While even a single session can be advantageous, many of its benefits require regular practice over extended periods of time. *Habit formation* is an effective mechanism through which to achieve such behavioral regularity and is associated with improving long-term health outcomes [7]. Building a habit allows one to transition a behavior from a deliberation that requires motivation into an automatic impulse [8]. By doing so, habit serves as a form of self-control [6], enabling consistent performance of health behaviors even with inevitable motivation lapses.

However, habit formation is not straightforward and attempts to develop new habits often end up unsuccessful. While past work identifies the archetypal shape of successful habit formation and the importance of consistent repetition in the forming process [11,13], little is known about the individual characteristics and contexts that correlate with different outcomes during habit formation attempts.


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Our ongoing work addresses this gap by applying an interpretable quantitative framework to data collected from our observational study on forming mindful breathing habits. We report results on significant factors associated with the observed heterogeneity in participant outcomes, and outline how we will extend this analysis. More broadly, our investigation relates to established challenges in the HCI community, including personalized and context-dependent user modeling, as well as the role technology can play in supporting human well-being and *eudaimonia* [16]. An eventual goal of our work is to design a digital health behavior change system that helps users to form new healthy habits.

## 2 Related Work

Lally et al. [11] analyzed the process of habit formation by fitting nonlinear regression models to self-reported habit strength on a per-individual basis. Their study participants selected a target behavior from categories of healthy eating, drinking or exercise. Items from the Self-Report Habit Index (SRHI [19]), reported by participants daily, were then used to quantify the concept of habit *automaticity* – the extent to which an individual is aware of, intentional about, in control of, or efficient with their practice of the target behavior [1]. The authors regressed automaticity against time using an asymptotic function, and concluded that it took between 18 to 254 days for an individual to reach 95% of the asymptote in their automaticity trajectory, emphasizing the heterogeneity in habit formation experiences. Furthermore, they observed that consistent target behavior repetitions were associated with better model fits.

Our work extends this quantitative understanding of habit formation by using a growth curve modeling framework [2,5]. Growth curve models are used in *repeated measures* data scenarios – such as those that occur in disease progression [3] and developmental psychology [10] – to model the between-person differences in within-person change processes. More specifically, they provide an interpretable lens through which we can scrutinize how both time-invariant factors (such as demographics and personalities) and time-varying factors (such as daily mood and context) correlate with the shape of participant growth trajectories, and thus serve as a way to categorise the observed heterogeneity in habit formation journeys and outcomes.

## 3 The Forming Healthy Habits Study

We conducted a six-week observational study, from November 2020 to January 2021, that involved 62 participants who planned to develop a new daily mindful breathing habit. At study initiation, participants received an overview of the study protocol and the concept of a habit, and were guided to choose a daily cue on which to anchor their mindful breathing practice. They then completed the Self-Report Habit Index (SRHI [19]) for mindful breathing to baseline the strength of any existing habit. Information on personality [12], mindfulness experience, commitment to forming the habit, and well-being [17] was also collected.

**Table 1.** Data collected from our six-week observational study in which 62 participants attempted to develop a new daily mindful breathing habit.

| | |
|---|---|
| **A. Daily survey items** | |
| 1. Completion | Whether or not the participant did the mindful breathing exercise |
| 2. SRHI habit automaticity | 3 questions from the SRHI [19] scale related to habit automaticity. On a 7-point scale from "Extremely Inaccurate" to "Extremely Accurate", participants rate the extent mindful breathing is something that: i) I do automatically, ii) I do without having to consciously remember, iii) I would find hard not to do. Note: on every seventh day, participants complete the full 12-item SRHI |
| 3. Other habit reflections | Participants rate (7-point scale) their i) motivation and ii) confidence for the building the habit. Additionally, if they did the breathing exercise they rate how iii) rewarding and iv) how challenging it felt |
| 4. Mood | For the past 24 h, participants rate (7-point scale) how often they felt in i) a good mood and ii) a bad mood; the extent they felt iii) calm or stressed and iv) lethargic or energetic; and v) their overall rating of mood from extremely unpleasant to extremely pleasant |
| 5. Daily context | Participants rate (7-point scale) i) how busy their day was, ii) how well they slept, iii) how physically active they have been, iv) how well they ate, v) how much they interacted with other people, vi) how much they enjoyed the weather, and vii) how much time they spent away from their home residence. |
| **B. Pre-survey items** | |
| 1. Demographics | Various items of information on how participants identify (for example age, gender and ethnicity) |
| 2. Past experience | Participants rate (7-point scale) how experienced they are at mindfulness |
| 3. Commitment | Participants rate (7-point scale) how committed they are to forming the daily mindful breathing habit during the study |
| 4. Habit strength | Participants complete the 12-item SRHI [19] to survey the strength of their mindful breathing habit at study initiation |
| 5. Well-being | Participants complete The Warwick-Edinburgh Mental Well-being Scale survey (WEMWBS [17]) |
| 6. Personality | Participants complete the Five Factor Personality Model survey [12]. |
| **C. Mid- and post-survey items** | |
| 1. Well-being | Participants complete the WEMWBS survey again [17] |
| 2. Habit formation reflections | Participants are prompted to rate (7-point scale) how i) rewarding, ii) challenging, and iii) frustrating their habit formation experience has been. There is also space for participants to provide open-ended reflections on their experiences. |
| **D. Passive smartphone usage data** | |
| 1. Smartphone usage | The Beiwe *digital phenotyping* platform [18] was also used to passively collect data on participant daily smartphone usage for the duration of the study period. Data includes location, accelerometer, and screen lock/unlock time |

Every day for the next six weeks, participants completed daily surveys, including whether they did the breathing exercise; how rewarding and challenging it felt; their confidence and motivation for building the habit; three SRHI items on perceived habit automaticity; and questions about mood and daily activities. Participants also installed Beiwe [18] on their smartphones for passive smartphone data collection, including streams for location, activity and screen-time. Finally, participants completed a mid- and post-study survey (after 3 and 6 weeks, respectively), that resurveyed their well-being and habit strength. Overall, 47.4% (N = 1,234) of daily surveys were completed and 41 participants completed the post-study survey. Table 1 presents details of the data collected.

## 4 Habit Formation Insights Using Growth Curve Models

### 4.1 Data, Methods and Assumptions

Our initial analysis focuses on the association of *time-invariant covariates* with the shape of habit formation trajectories. To this end, we use a simple average of the three SRHI items collected daily from participants (A2 in Table 1) to define a measure of habit automaticity to use as the target variable in our model. Habit automaticity is a component of habit strength, though it is worth noting that it does not encompass the full concept[1]. We use items B2-B6 from Table 1 as our time-invariant independent variables. Our future work will incorporate further variables from Table 1 as *time-varying covariates* [5].

We use the multilevel modeling paradigm to define the linear growth curve model in Eqs. 1–3. The self-reported automaticity score for participant $i$ on day $t$ of the study is represented by $y_{ti}^{SRHI\_A}$. Equation 1 is a *level-1 equation* (i.e. time-varying and within-person): $b_{1i}$ and $b_{2i}$ are the fitted intercept and gradient for participant $i$, respectively, and $u_{ti}$ is a time-specific residual score. Equations 2–3 are *level-2 equations* (i.e. time-invariant and between-person): $\beta_{01}$-$\beta_{C1}$ and $\beta_{02}$-$\beta_{C2}$ are level-2 regression parameters that represent relations between time-invariant covariates values $X_{1i}$-$X_{Ci}$ for participant $i$ and their individual-level intercept ($b_{1i}$) and gradient ($b_{2i}$), respectively, and $d_{1i}$ and $d_{2i}$ are residual scores that capture the variance at the between-person level not explained by $X_{Ci}$.

$$y_{ti}^{SRHI\_A} = b_{1i} + b_{2i} \cdot t + u_{ti} \tag{1}$$

$$b_{1i} = \beta_{01} + \beta_{11} \cdot X_{1i} + \beta_{21} \cdot X_{2i} + ... + \beta_{C1} \cdot X_{Ci} + d_{1i} \tag{2}$$

$$b_{2i} = \beta_{02} + \beta_{12} \cdot X_{1i} + \beta_{22} \cdot X_{2i} + ... + \beta_{C2} \cdot X_{Ci} + d_{2i} \tag{3}$$

The following further assumptions apply to our analysis:

1. Only participants with 3 or more observations are included in the analysis, which ensures the linear growth curve model is over-identified [2,5]. We also exclude 1 participant who is the only participant to report high well-being in the pre-survey, thus avoiding the use of a covariate value with very low representation in our models
2. Only the first 21 consecutive observation days for each participant are used (including days where surveys were not completed). While participants may have up to 42 days each of data, we make this simplifying assumption as a) a large number of participants reported in the post-survey that the end of

[1] *Behavioral frequency* and *identity* also relate to the notion of habit strength. However, we do not assess these concepts given: i) our study introduces bias on behavioral frequency by asking participants to practice the habit daily, and ii) related work cites disagreements in using identity as a measure of habit strength [11,19].

semester (which occurred after 3 weeks for all participants) disrupted their practice of the habit, thus presenting a bias that may need to be explicitly accounted for, and b) data incompleteness is less severe in our first 3 weeks of observation (58.9% in first 3 weeks vs 38.0% in last 3 weeks). Combined, assumptions (1–2) reduce the observations to 713 days from 52 participants

3. Finally, a participant may be missing a full observation (dependent and all independent variables) at any given time point, however partial observations are not possible. We assume that these full observations are missing at random [2,5], and we do not explicitly handle them when fitting our model[2]

### 4.2 Results

We first assess different growth curve models for how well they fit the empirical data in Table 2. First, we compare an unconditional linear growth model (M2) to a no-growth model (M1). Using a likelihood ratio test, $\chi^2(3) = 169.14$ ($p \ll 0.01$), we conclude that a linear growth process is a significantly better representation of the data than a model in which the dependent variable does not vary with time. Thus, on average, participants' habit automaticity is changing with practice over time.

**Table 2.** Model fit statistics for unconditional (M1 and M2) and conditional (M3) growth curve models.

| | No growth (M1) | Linear (M2) | Linear with TICs (M3) |
|---|---|---|---|
| Observations | 713 | 713 | 713 |
| Participants | 52 | 52 | 52 |
| Degrees of Freedom (DF) | 3 | 6 | 26 |
| Log Likelihood | −880.86 | −796.29 | −764.41 |
| Akaike Inf. Crit | 1,767.71 | 1,604.57 | 1,580.83 |
| Bayesian Inf. Crit | 1,781.42 | 1,631.99 | 1,699.64 |
| Model Comparison | – | M2 vs. M1 | M3 vs. M2 |
| Likelihood Ratio | – | 169.14 | 63.75 |
| $\Delta$DF | – | 3 | 20 |
| p-value | – | $\ll$0.01 | $\ll$0.01 |

No growth model: $y_{ti}^{SRHI\_A} = (\beta_{01} + d_{1i}) + u_{ti}$
Linear model: $y_{ti}^{SRHI\_A} = (\beta_{01} + d_{1i}) + (\beta_{02} + d_{2i}) \cdot t + u_{ti}$
Linear with time-invariant covariates (TICs): Eqs. 1–3.
Data and modeling assumptions are detailed in Sect. 4.1

[2] We use the maximum likelihood (ML) estimation algorithm in R's *nlme* package [14].

**Table 3.** Fixed effect intercept and gradient parameters for conditional linear model with time-invariant covariates.

| Parameters | Intercept | Gradient |
|---|---|---|
| Grand mean | 2.71 (2.44, 2.97) | 0.01 (–0.01, 0.03) |
| Medium Experience | –0.03 (–0.35, 0.28) | 0.03*** (0.01, 0.05) |
| Low Experience | 0.10 (–0.34, 0.55) | –0.03 (–0.06, 0.01) |
| Medium Commitment | 0.12 (–0.14, 0.37) | –0.03***(–0.04, –0.01) |
| Low Wellbeing | 0.30** (0.03, 0.57) | 0.00 (–0.02, 0.02) |
| Pre-Study SRHI Automaticity | 0.61*** (0.37, 0.84) | –0.01 (–0.02, 0.01) |
| Lower Extraversion | –0.01 (–0.27, 0.25) | –0.00 (–0.02, 0.01) |
| Lower Agreeableness | 0.16 (–0.10, 0.42) | –0.02**(–0.04, –0.01) |
| Lower Conscientiousness | –0.07 (–0.31, 0.18) | 0.01 (–0.01, 0.03) |
| Lower Emotional Stability | –0.11 (–0.38, 0.16) | 0.02* (–0.00, 0.04) |
| Lower Openness | -0.09 (–0.37, 0.19) | 0.00 (–0.02, 0.02) |

Parameter values are relative to grand mean with confidence intervals (lower, upper). Categorical variables are effect coded using the highest bucket of each variable as the reference category and continuous variables (only Pre-Study SRHI Automaticity) are group mean centered. Equations 1-3 define the model. Significance: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

We subsequently introduce time-invariant covariates into our linear model (Eqs. 1–3) to begin to associate differences in between-person habit automaticity trajectories with observed participant characteristics. From Table 2, we confirm that this conditional linear model (M3) fits the empirical data significantly better than the unconditional linear model (M2) using a likelihood ratio test, $\chi^2(20) = 63.75$ ($p \ll 0.01$). That this difference is significant suggests that at least some of the variance in habit formation trajectories between participants can be associated with characteristics we know about them before they commence habit building practice.

Having established its superior fit, we then report the coefficients for the time-invariant covariates of the conditional linear model in Table 3, where, as a result of the choice of variable coding, all differences implied by the coefficients are relative to a hypothetical participant with an average value for all covariates (the *grand mean* row). Our first conclusion from these coefficients matches intuition: how strong a participant's mindful breathing habit is before they begin practice - quantified by the pre-study SRHI automaticity score - is significantly correlated with the intercept of their growth trajectory. We also note that participants who report lower initial well-being have, on average, higher intercept values.

More noteworthy from Table 3 are the four significant correlations between participant characteristics and the gradient of their habit strength trajectories during the first 21 days of practice. Pre-study commitment to forming the habit, pre-study mindfulness experience, and two dimensions of personality– agreeableness and emotional stability – all have significant associations with this

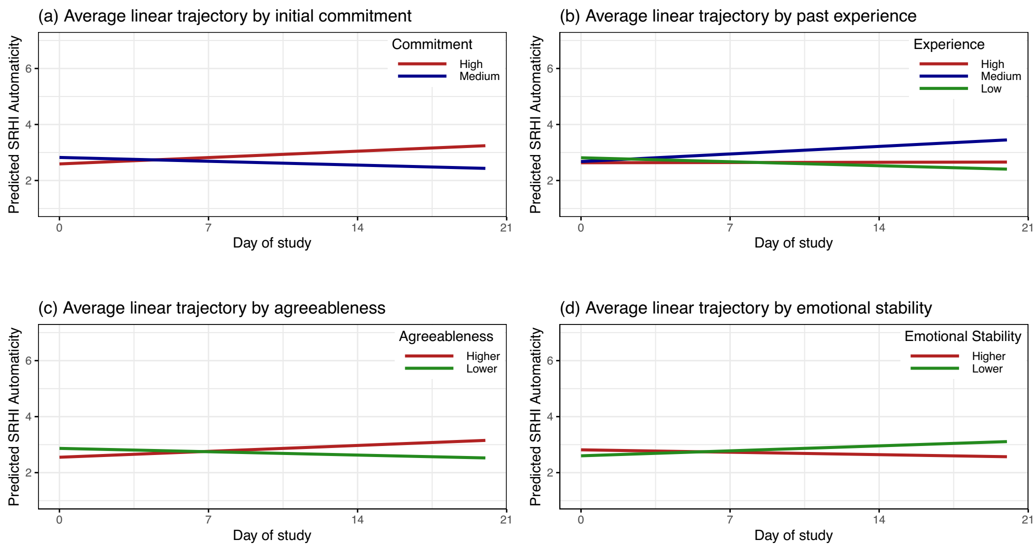


**Fig. 1.** Model-implied average automaticity trajectories for different participant sub-groups identified by time-invariant covariates with significant gradient parameters in Table 3. Sub-group sizes: a) $N_{High} = 27$, $N_{Medium} = 25$; b) $N_{High} = 14$, $N_{Medium} = 27$, $N_{Low} = 11$; c) $N_{Higher} = 26$, $N_{Lower} = 26$; d) $N_{Higher} = 25$, $N_{Lower} = 27$.

parameter. Figure 1 displays the model-implied trajectories for participant sub-groups defined by these significant factors. By discovering the *a priori* covariates that correlate with different habit formation experiences, a system designer – for example, a care professional or behavioral health app developer – might be able to personalize their services to help their clients form stronger habits.

## 5 Conclusion

In this work, we have identified individual characteristics that correlate with significantly different habit formation trajectories. However, there are several limitations to our approach. Firstly, we only assess the fit of linear growth curve models to habit automaticity, which may be an oversimplification of the true dependence of habit strength on days practiced. For example, habit development may be better described by nonlinear trajectories, such as quadratic or piecewise linear. Secondly, our models do not yet incorporate the time-varying covariates collected – practice frequency, mood, daily context, and smartphone usage data – which may enable the explanation of more variance between participants.

Beyond these immediate limitations, future work will also consider participant sub-groupings. For example, we will fit separate models for participants with different outcomes at the mid- and post-study checkpoints (such as those that have significantly increased their habit strength versus those that have not or who have dropped out by this stage). Separate models by sub-group will grant us more flexibility to categorise between participant heterogeneity, for example by varying the functional form (linear or nonlinear) and variance/covariance structures between sub-groups and assessing the impact this has on model fit statistics. Finally, our current framework does not allow us to comment on causality, which is an important area for future investigation.

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