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The Effect of Social Support Features via Buddies in App-Based Habit Building

Daniel Biedermann, DIPF Leibniz Institute for Research and Information in Education, Germany

Patrick Oliver Schwarz, DIPF Leibniz Institute for Research and Information in Education, Germany

Jane Yau, DIPF Leibniz Institute for Research and Information in Education, Germany*

Hendrik Drachsler, DIPF Leibniz Institute for Research and Information in Education, Germany

ABSTRACT

App-based habit building has been shown to be a good tool for forming desired habits; however, it is unclear how much individual features that are present in many apps contribute to the success of habit building. In this paper, the authors consider the influence of social support features by developing an app in which habit progress was shared with peers – 'buddies' in the app. In the study, 38 participants created habits and monitored their progress regularly with the app over three weeks. The participants were divided into a control group without a 'buddy' and a treatment group cohort in which they were assigned to buddies based on their desired habits. With each habit repetition, the app gave feedback on the number of repetitions and the automaticity of the user's habit. The results obtained show that the reproduction of app-based intentional habit building is effective and that automaticity could be predicted by habit repetition.

KEYWORDS

Habit Forming, Self-Determination Theory, Social Support Features

INTRODUCTION

There is a considerable number of people who struggle with the technique of forming habits that could improve their learning processes, thereby making them more effective and efficient. Especially in the context of technology-enhanced learning, and due to the increased number of technology-related distractions (e.g., advertisements, temptations to browse other websites), the act of forming desirable or undesirable habits significantly influences the learning process and study success (Fiorella, 2020). Habits can influence learning in a positive way by ensuring regular and consistent learning efforts. At the same time, habits can also have a negative impact, for example when habitual excessive media consumption leads to continual distractions (Lee, 2014). Habits are behavioral patterns that are triggered by a particular context, often outside of conscious awareness (Pinder & Cowan, 2018). A student might have the habit of regularly checking their mobile phone, even when studying. However,

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*Corresponding Author

even though habits are mostly triggered automatically, they can still be actively, consciously, and intentionally learned. Lally *et al*. (2010) showed in their study that participants were able to build up habits over a period of several weeks in their natural environment. They found that the growth of habit strength, which they called *automaticity*, can be described by a quadratic function that first increases sharply and then stagnates once the asymptote / tangent is reached. This means that the initial repetitions cause a high growth of automaticity, which then decreases with each repetition until the behavior reaches its limit of automaticity.

The possibility of helping users to form habits has been taken advantage of by the designers and developers of over 100,000 mobile apps in recent years, particularly for health reasons such as exercise, diet, and weight management (Edwards *et al*., 2016). With the ubiquitous use of smartphones today, hundreds of millions of people use such apps for improving their lifestyle, health, study, and work successes etc. (Ibid). A number of individual features are used by these apps, such as paying the user a (virtual) reward for completing the target activity, or providing accurate feedback about the user's progress and performance towards the goal. In many situations, a social feature component (such as sharing the progress with family or friends) has been found particularly effective for individuals to achieve their goals (Villalobos-Zuniga & Cherubini, 2020). Additionally, features utilized by such apps have been designed based on behavioral theories that focus on observable behavior, such as *Self-Regulation Theory* (Bandura, 1986), *Social Cognitive Theory* (Bandura, 1986), *Theory of Planned Behaviour* (Ajzen, 1985), *Trans-Theoretical Model* (Prochaska & Di Clemente, 1983), *Health Belief Model* (Rosenstock, 1974), and *Goal-Setting Theory* (Locke and Latham, 2002). These theories are typically used to explain the reasons for people undertaking (or not undertaking) a certain activity and the different stages of progressing through it. Villalobos-Zuniga and Cherubini (2020) identified a major common role / indicator, namely a person's motivation for doing the task, as a decisive factor for whether the task will be completed or not. They selected the *Self-Determination Theory* (SDT) (Deci and Ryan, 2008) as the foundation of app features upon which their taxonomy was built, which relates to different aspects of motivation. Broadly speaking, SDT can be classified into intrinsic / internal motivation (e.g., studying for one's own interests) and extrinsic / external motivation (e.g., studying because my family wants me to, or to get a good job). Note that we are often both intrinsically and extrinsically motivated to carry out different tasks. Recently, many apps have utilized additional internal or external incentives to help users to succeed more with completing an activity or reaching a goal or making an activity becoming habitual. In spite of the prevalence of these apps and their large number of users there is a lack of professional guidelines for designers, or industry standards, and lacking knowledge on the long-term effects of such interventions means there are concerns that such apps could even lead people to adopt the opposite of the target behavior, in the worst scenarios (Edwards *et al*., 2016).

Building desirable habits, and getting rid of undesirable ones, has also become a major topic in the digital behavior change literature (Pinder & Cowan, 2018). Habit building via self-monitoring on smartphone apps over longer durations has been successfully demonstrated by Stojanovic *et al*. (2020). The self-monitoring itself is only one feature of digital behavior change apps, and they often utilize a wide range of other motivational features, such as reminders, gamification, or social support (Villalobos-Zuniga & Cherubini, 2020). Despite these features being used often, there is a lack of research regarding the contribution of these individual and/or social features for habit building (Hermsen *et al*., 2016). Especially for social features, which are central to many (commercially successful) apps, research is still in its infancy (Elaheebocus *et al*., 2018; Oinas-Kukkonen *et al*., 2009). With this study, the authors aim to address this gap by exploring and examining the impact of social support features in app-based habit building. For this investigation, the authors created an app called *Habit Buddy* that allows habit creation and self-monitoring with additional social support features. Users of the app can have a peer (henceforth called *buddy*) with whom they can communicate and share their habit tracking progress, which is stored and analyzed. The authors then investigated the effect of these social support features. The objective of this research is guided by the following research question:

1. Does habit automaticity increase with habit repetitions?

    a. Is there a correlation between social support features and higher habit automaticity?
    b. Is the effect of habit repetitions on automaticity stronger when accompanied by social support features?

BACKGROUND

In this section, the authors provide a background literature review on habit forming and its relationship with two different theories – *Self-Regulation* and *Self-Determination* (Bandura, 1986) - *different persuasive app features* identified by Villalobos-Zuniga and Cherubini (2020), and the extension of the authors' previous work on *digital self-control tools* (Biedermann et al., 2021).

Relationship between habit forming and Self-Regulation Theory

The use of habits can be a way for a learner to increase their self-regulation skills in relation to undergoing and continuing with their learning processes and tasks. In a study by Breitwieser *et al.* (2022), it was found that psychological interventions did not typically function as a one-off event, but rather when these become repeated or regular motivational prompts, one can expect a higher rate of achievement of learning goals. Habit forming can be seen as a way of helping a person to become more self-regulated and self-directed within the context of the activity (e.g., to exercise, keep a diary), if this activity is something that the person intentionally wants to form a habit of (Bailey *et al.*, 2020). In this sense, prompts to support repetition in the habit-forming process are more likely to reinforce the behavior. There have been several studies showing that self-regulation skills are a strong predictor of achievement, and therefore Breitwieser *et al.*'s (2022) experiment aimed to show that repeated interventions, similar to those found in habit forming, can improve students' use of self-regulated learning strategies to achieve their goals.

Relationship between habit forming and Self-Determination Theory

In a study by Villalobos-Zuniga and Cherubini (2020), 208 apps were analyzed, which were identified to contain 12 design features that could support users with behavioral adjustment (e.g., exercise more, meditate more, quit smoking, lose weight). The authors classified these design features according to the *Self-Determination Theory*. They identified a number of research gaps including whether the use of such apps a) *actually nurture or thwart intrinsic motivation*, b) *provide support to the three basic needs – growth, well-being and integrity*, and c) *provide optimal challenge*. Cooperation has the possibility to influence habit forming by affecting each individual's intrinsic motivation by focusing and aiming to achieve the same/similar goals together. In particular, one app feature showed the support of close contacts in achieving goals and this led to the individuals feeling a greater relatedness and sense of belonging, which helped them sustain their self-determined motivation. The taxonomy was constructed to help relevant stakeholders such as researchers to test and evaluate their app and includes features / interventions or how a combination of these can be utilized to motivate users to achieve their habit goals (Ibid).

Different persuasive app features identified by Villalobos-Zuniga & Cherubini (2020)

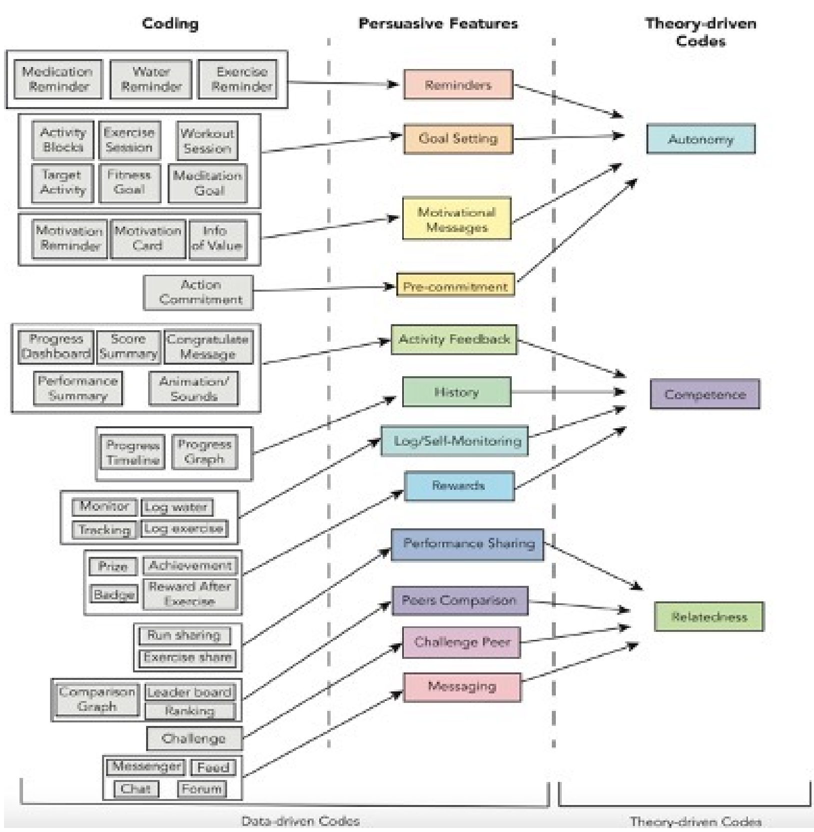
Figure 1 below shows the process by which Villalobos-Zuniga and Cherubini (2020) created their taxonomy from the reviewed apps and interventions, which were then categorized into three sets of categories with different persuasive features. The first set is the **Autonomy** category, which consists of *Reminders, Goal Setting, Motivational Messages,* and *Pre-commitment*. The second set is **Competence,** which consists of *Activity Feedback, History, Log/Self-Monitoring,* and *Rewards*. The third set is **Relatedness**, which consists of *Performance Sharing, Peers Comparison, Challenge Peer,* and *Messaging*.

Extension of the work on digital self-control interventions

Habits play a big role in how learners deal with digital distractions. Beneficial habits, such as turning off the smartphone before starting to learn, can help reduce distractions and improve learning outcomes (Galla & Duckworth, 2015). Building of "good" habits also helps in the interplay with other tools. Common tools for reducing digital distractions include website blockers or visualizations of one's own behavior (c.f. Biedermann *et al*., 2021). Habits often prevent these tools from having their desired effect. A visualization of one's own usage behavior can only work if it leads to better habits. A website blocker does not work if a user gets into the habit of always skipping it. When looking at the success factors of such tools, one finds that intrinsic motivation to use them is a critical success factor.

Extending from this previous work, the research being addressed in this paper examines the perspective of forming habits so that this becomes an intrinsic / internal motivated habit, whether consciously or unconsciously. Thus, the authors' research in this study is focused on whether social support features could enhance habit forming potential and automaticity. In particular, the authors' app has been developed mostly with the Relatedness category in mind because the authors were most interested in the effects of peer and social influence on how habits could be potentially formed and strengthened (Villalobos-Zuniga & Cherubini, 2020). This is also directly related to two theories /

Figure 1. Taken directly and permission given from Villalobos-Zuniga and Cherubini's (2020) taxonomy creation process



concepts – 1) *Social Cognitive Theory* (Bandura, 1986) which states that people often copy / replicate the behavior of others as a social phenomenon, and peers could benefit from motivating one another to achieve a common goal, and 2) the need to belong, which increases motivation (Baumeister & Leary, 1995). The authors are specifically interested in how feedback and self-monitoring (individual feature) as well as sharing of this progress with a peer (social feature) could help form habits more effectively, and how intrinsic and extrinsic motivation can be increased as a result of the individual and social features. From these app features for influencing the processes of forming beneficial habits, and the research gaps mentioned above, the authors identified the potential of an app-based habit formation approach in which users can cooperate and positively influence each other to work toward achieving their goal.

MAIN FOCUS OF THE PAPER

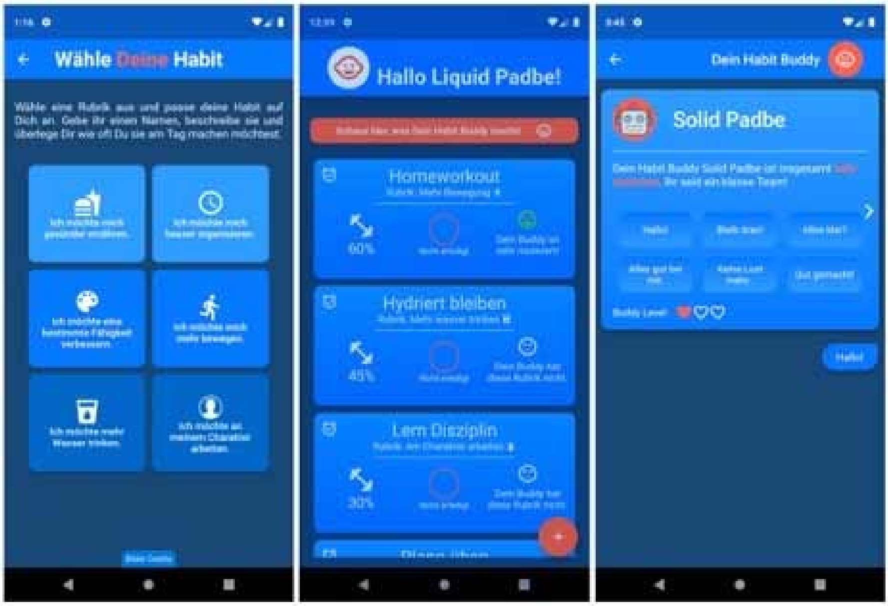
Research Methodology

The authors' study was conducted in a between-subjects design with the dependent variable *habit automaticity*, using an app ***with and without*** social support features for the participants to use in an experimental setting. In order to prove that the app would be suitable for habit building in general, the authors aimed to replicate the results central to app-based habit building in general, thereby proving or disproving the hypothesis H1a. Thereafter, the authors examine whether the use of the additional social support features correlates with higher habit automaticity (hypothesis H1b), and whether the effect of habit repetitions on automaticity is stronger when accompanied by social support structures (hypothesis H1c).

H1a: Habit automaticity increases with habit repetitions.
H1b: The enabling of social support features leads to higher habit automaticity.
H1c: The effect of habit repetitions on automaticity is stronger when accompanied by social support features.

The authors conducted a three-week experiment with 38 participants, where half of the participants used a variant of the app with the social support features being enabled, and the other half used the app **without** these features. The study participants were required to be at least 18 years old in order to give their own consent for taking part. They were recruited through open calls via emails to university students as well as via social media networks. Additionally, there was an incentive given to participants in the advertisement that a fixed number of vouchers would be raffled among the participants. $N = 38$ people (21 female, 17 male) participated, and they were divided into a *Buddy* cohort and a *Non-Buddy* cohort. It was important that participants in the buddy cohort did not know each other personally, as this would influence the effects of social interaction within the app. For this reason, the group division resulted in a *Buddy* cohort of $N_0 = 18$ subjects and a *Non-Buddy* cohort of $N_1 = 20$ subjects. Prior to the experiment, all participants were asked to fill in two questionnaires (1) *Self-Report Habit Index* (SRHI) (Verplanken & Orbell, 2003) with the eight most relevant items for the authors' study (1, 2, 3, 4, 5, 6, 8, 9 from catalogue 4) in order to measure their habit strength and automaticity, and a Self-Regulation Questionnaire (SRQ) by Brown *et al*. (1999). Each time that a participant completed a habit repetition, he/she was required to answer two randomly selected items from the SRHI in order to provide us with more insights into how or if their habits were forming as a result of the habit repetition intervention on the mobile app. The SRHI was used because currently there are no other tools available to assess more broadly how individuals form habits in daily life and for seeking their own perception of this process (Ersche *et al*., 2017). The tool has also been frequently utilized and highly cited by researchers indicating its usefulness and impact. Note that the questions from the SRHI are built within the app on the habit repetition screen for the users to answer. The SRQ was distributed prior to the start of the study.

Figure 2. Screenshots that show screens of the Habit Buddy app (the authors' own adaptation)



(a) The habit categories that the participants could choose from (b) The 'home' view with overview of created habits (c) Communication with the habit buddy

The app was implemented using the *Flutter* framework so that it would be available on both iOS and Android platforms. The app allowed free creation and selection of new / existing habits, but required those to be in specific categories such as the desire to be healthier, to be more organized, to improve certain skills, to exercise more, to drink more water, or to improve one's character (Figure 2a). The purpose of this was so that participants with similar aspirations could be matched to each other without having the exact same habit (e.g., placing the smartphone in a different room and turning the smartphone app off could both be placed in the same category). The authors did not enforce specific habits because the authors wanted to make sure that the participants picked something that they truly cared about. In the authors' app, the authors provided several categories and subcategories so that every *buddy* pair in the authors' experiment would have a larger selection of aspirations to work from and in order to match them with others. In the habit creation screen (Figure 2a), participants could give a name and a description to their aspiration that they wanted to form a habit routine of, and decide whether they wanted to set a reminder in case they forgot this task. A small text box at the bottom of the screen on the app appeared to remind the user of their habit-forming repetition routine (Elaheebocus *et al*., 2018). Participants' active habits were listed with an overview of the status of the habit-forming routine, including the habit strength and whether the action was already performed on that day (Figure 2b). In the app variant with social support features, the *buddy's* motivation was shown next to the habit repetition indicator. The motivation level was translated into a message if a buddy had aspirations to form a habit of the same category. In Figure 2b, the topmost habit (Home workout) is shared with a buddy. In the *Habit Buddy*-view (Figure 2c), the user can send messages to their buddy (Figure 2b). They can furthermore view the history of their buddy's habit repetitions.

Participants received weekly reminders in the three-week experiment to remind them to continue using the app. They also received instructions via email, which were different depending on whether they were in the *Buddy* or *Non-Buddy* cohort. Instructions to both cohorts differed in the section where the function of the *buddy* was explained, which was missing for the *Non-Buddy* cohort. All participants were instructed to read the instructions carefully and were invited to ask questions at any time, if anything was unclear. The instructions for habit creation stated that these categories should be named or labelled as meaningfully as possible. There was no limit to the number of times that a habit could be repeated in a day, with the aim of achieving automaticity.

In the course of the study, six of the participants became inactive and were subsequently removed from the analysis. Since three female and three male participants were removed, this ratio did not change. Note that the gender distribution is not used in the authors' data analysis, but the authors collected the gender information just as a reassurance to show that the gender distribution in the study would be similar to a real-life situation. The 32 participants created a total of $N = 93$ habits ($N_0 = 44$, $N_1 = 49$). The average number of habits created per participant was $M = 2.45$ ($M_0 = 2.44$ and $M_1 = 2.45$). The habits were separated into "Eating healthier" (11.82%), "Organize better" (16.13%), "Improve ability" (12.9%), "More exercise" (for example, take the stairs instead of the lift, or doing more sports, with 23.66%), "Drink more water" (22.58%) and "Work on yourself" (For example, discipline, hygiene or emotions, with 12.9%). The 32 participants generated a total of $N = 609$ habit repetitions with an average of $M = 22.71$ ($SD = 26.92$) habit repetitions. There were 15 participants in the Habit Buddy cohort with a total of $N_0 = 288$ habit repetitions with an average of $M_0 = 19.20$ ($SD_0 = 8.02$). There were 17 participants in the Non-Buddy cohort with a total of $N_1 = 321$ habit repetitions and an average of $M_{12} = 17.2$ ($SD_{12} = 7.74$). Note that five participants continued to use the app even after the end of the study.

DATA ANALYSIS AND HYPOTHESIS TESTING

H1a: Habit automaticity increases with habit repetitions.
H1b: The enabling of social support features leads to higher habit automaticity.
H1c: The effect of habit repetitions on automaticity is stronger when accompanied by social support features.

In order to prove or disprove these hypotheses, all growth curves for the dependent variable automaticity were examined with maximum likelihood parameter estimation. For each of the three hypotheses, three different models were applied using random intercepts ($\tau 0$) and random slopes ($\tau 1$). In all three models, time was also represented as the number of repetitions, similar to the work in Stojanovic et *al.* (2020). For instance, at time t=10, a participant has completed a habit repetition for the tenth time. All statistical calculations were carried out in Py*thon a*nd R.

Model 1 (H1a) consisted of the intercept-only model and was extended by the fixed-effect predictor habit repetitions to a model that could predict the automaticity of a participant p at a time t (Equation 1). The random intercept $\beta 0,_{p}$ (Equation 2) consisted of the average intercept $\gamma 0,0$ and the individual deviation $\tau 0,p$ from that intercept. The average slope $\beta 1,p$ (Equation 3), which is the slope for the moderation effect of habit repetition, is given by $\gamma 1,0$ and $\tau_{1},_{p}$. Here, $\gamma_{1,}0$ is the average slope of the whole sample and $\tau 1,p$ is the deviation from that slope.

Automaticity$t, p = \beta \mathbf{0}, p + _{\beta 1},p$ Habit Repetitions $+ \varepsilon t, p$ (1) $\beta 0,p = \gamma 0,0 + \tau 0_{,p}$ (2) $\beta 1 p = \gamma 1,0 + _{\tau} 1,p$ (3)

For Model 2 (H1$_b$, Equation 4), the presence of a buddy was added as a level 2 fi*xed e*ffect — (Equation 5). In this context, $\gamma 0,1$ is the effect of a buddy and is multiplied by the p*resen*ce of a buddy. If a user had a Habit Bud*dy, t*his was coded with a 1. If there was no buddy, this was coded with a 0. *The o*ther parameters in this regression remain the same as in Equation 1.

Automaticity$t$, $p = \beta 0,p + \beta 1,p$ H**abit Repetit**ions $+ \varepsilon t$, p (4) $\beta 0,_{p} = \gamma 0,0 + \gamma 0,1$ Has buddy$1,_{p} + \tau_{0,}p$ (5)
$\beta_{1},_{p} = \gamma 1,_{0} + \tau 1,p$ (6)

In Model 3 (H1c), a cross-level interaction was added (Equation 7). For the slope $\beta 1,p$ the effect of a Habit Buddy was taken into account. This made it possible to investigate whether there were relationships between the two predictors at level 1 and level 2. This was implemented by adding to $\gamma 1,0$ and $\tau 1,p$ the moderation effect of a Habit Buddy multiplied by the presence of a Habit Buddy (Equation 9).

$$Automaticity_{t,p} = \beta 0,p + \beta 1,p \text{ Habit Repetitions} + \varepsilon_{t,p} \quad (7)$$
$$\beta 0,p = \gamma 0,0 + \gamma 0,1 \text{ Has buddy}_{1,p} + \tau 0,p \quad (8)$$
$$\beta 1,p = \gamma 1,0 + \gamma 1,1 \text{ Has buddy}_{1,p} + \tau 1,p \quad (9)$$

An overview in the form of a table is shown in Figure 3 below. In order to check the distribution across all milestones, a Shapiro-Wilk test was applied, which suggested a left-skewed normal distribution (t(620) = 0.969, p = 0.392). Based on the normal distribution assumption, a one-*sample Welch's t-test o*n both milestone datasets of the Buddy and Non-Buddy cohort showed that the milestones of the Non-Buddy cohort *had* the s*ame mean* as the mean of habit repetitions ((t1(19) = *-2.758,* p = 0.015), (t0(17) = -1.7, p = 0.112)). In order to investig*ate the hypotheses H1a, H1*b *and H1c, the nature of the* automaticity datasets was examined. To ensure that there was actual space for automaticity to grow, only habits with at least five repetitions were considered (N = 58). The tests showed that the automaticity values per habit of the Non-B*uddy g*roup (t1(29) = 0.971, p = 0.557) and the Buddy group (t0(27) = 0.9*53, p = 0.*242) w*ere normally distributed. H*owever, t*he di*stributi*on of the Non-Buddy group* was skewed to the right and the Buddy group to the left. An u*npaired W*elch's t-test showed that both samples *have* identical means (t(56) = 0.296, p = 0.769). The same result occurred when comparing the mean *values with that of the to*tal quantity (t0(84) = -0.218, p = 0.829), (t1(86) = 0.200, p = 0.843). An Intraclass Correl*ation Coefficient analysi*s sho*wed that over 47% of the* variance of the automaticity data could be explained by the person level (level 2) variance. This suggests that sufficient clustering takes place in the inter-individual datasets to make the use of multilevel modelling of the data meaningful. To examine whether the number of habit repetitions would predict automaticity (H1a, Figure 3), a model was built with random intercepts. Habit repetition was then added as a fixed effect and random slopes were used to ensure variation in the habit repetitions to make the model even more flexible. The result was that habit repetition significantly predicted automaticity with a $\beta 1 = 0.027$ (SE = 0.028) and t(24.7) = 4.163, p = 0.000332. Furthermore, the inte*rcept showed a signifi*cant *variance ($\tau 00 = 0.024$), which* suggests that the initial value of automaticity sometimes dif*fered str*ongly within the users.

Figure 3. Multilevel regressions of automaticity on habit repetition & has-habit-buddy attribute (the authors' own adaptation)

Automaticity

	Model 1 (H1a)			Model 2 (H1b)			Model 3 (H1c)		
Predictors	**Estimates**	**SE**	**97.5% CI**	**Estimates**	**SE**	**97.5% CI**	**Estimates**	**SE**	**97.5% CI**
Intercept	0.294	0.028	0.231 – 0.358	0.273	0.038	0.188 – 0.358	0.267	0.039	0.181 – 0.354
Habit Repetition	0.027	0.006	0.012 – 0.041	0.027	0.006	0.012 – 0.041	0.031	0.009	0.012 – 0.051
Has Habit Buddy				0.044	0.053	-0.074 – 0.163	0.057	0.056	-0.068 – 0.182
Habit Repetitions * Has Habit Buddy							-0.010	0.013	-0.038 – 0.019
Random Effects									
σ^2	0.020			0.020			0.020		
τ_{00}	0.024 $_{userId}$			0.023 $_{userId}$			0.023 $_{userId}$		
τ_{11}	0.001 $_{userId.repetitions}$			0.001 $_{userId.repetitions}$			0.001 $_{userId.repetitions}$		
ρ_{01}	-0.197 $_{userId}$			-0.177 $_{userId}$			-0.175 $_{userId}$		
Observations	784			784			784		
Marginal R^2 / Conditional R^2	0.265 / 0.951			0.258 / 0.951			0.330 / 0.955		

In hypothesis H1b (Model 2, Figure 3), the existence of a Habit Buddy was added as a fixed parameter to the model. The aim was to find out whether a Habit Buddy has a positive effect on his partner. The extension of the model showed that having a Habit Buddy positively predicted the automaticity with a $\beta 0 = 0.0441$ (SE = 0.053). This value was over 64.5% higher than $\beta 1$ nevertheless *the habit buddy param*eter had a very high p-value (t(35.14) = 0.833, p = 0.4103), which opens up the likelihood that the predicted *value of the automaticity m*ight have been just as high without the Habit Buddy. The habit repetition was significant as well in this model (t(24.74) = 4.166, p = 0.00329). The effects of random effects remained almost u*nchanged.*

*To investigate hyp*othesis H1c, Model 2 was extended to include a cross-level interaction. By adding this fixed effect, a level 2 predictor was also taken into account for the slope of the regression line. With the resulting Model 3 (Model 3, Figure 3), it was thus possible to examine whether the presence of a Habit Buddy had a different effect on the slope of the level 1 predictor. This cross-level interaction made the model much more flexible in dealing with the hierarchical data. Again, habit repetition significantly predicted automaticity (t(24.35) = 3.54, p = 0.00164). Once again, habit repetition and having a habit *buddy predicted automaticit*y, and both betas actually increased ($\beta 1$ = 0.0314, SE = 0.00887 and ($\beta 0$ = 0.0572, SE = 0.0557). However, only habit repe*tition continued to sh*ow signifi*cance (t(24.353) = 3.*54, p = 0.00164). It is interesting that the p-value of the Habit *Buddy parameter fell sharply* and the t-value increased to over 1 (t(33.38) = 1.027, p = 0.31166). Unfortunately, the direct cross-level effect was *very small, regardless of wh*ether a habit buddy was present, the influence on the slope of the regression line was very negligible (Habit Repetitions * Has Habit Buddy = -0.010, SE = 0.013). A t-test of this inte*raction yielded a t-value below zero and a very high p-v*alue (t(24.78) = 3.54, p = 0.454). Thus, as in Model 2, these values could also have a*risen by chance.*

*To deter*mine the correlation between the participant's self-regulation trait and the number of habit repetitions, the Pearson product-moment correlation coefficient was used. The correlation was low and not significant (r = 0.069, t (30) = 0.383, p = 0.704). A possible explanation for this was that the participants were motivated to take part in this study, which might have caused the saturation effect on habit automaticity by the high number of repetitions, and therefore leveling the effect of the social support features.

CONCLUSION

Situations such as the COVID-19 pandemic have highlighted the need for students to have adequate self-regulation (Daumiller & Dresel, 2019). Therefore, the forming of good habits and eliminating bad ones can make one more resilient to distractions and help to achieve one's goal. In this paper, the authors presented the motivation, research question, hypotheses and data analysis to the research problem relating to whether social support features in an app could help users in forming beneficial habits. In both participant groups, the app demonstrated that it was possible to form habits using a habit-forming mobile app, and habit automaticity increased predictably with habit repetitions. While the habit building in general worked, the addition of social support (features) through having a Habit Buddy did not lead to any additional improvements. The number of comple*ted habit r*epetitions and the automaticity of the participants showed no significant difference between the groups, where one had social support features enabled in their app, and the other that did not have this feature. Although there was a trend that indicated that a Habit Buddy had a positive influence on app-based habit building, the results obtained in this study were not significant.

Potential reasons (and limitations for this research) include (1) participants were assigned their buddies whom were not their mutually-close or trusted friend. In reality, the effect of habits-forming may strengthen by carrying out this process together with a close friend with the same / similar aspirations. This could possibly have led to the fact that they may not have been keen doing this process with a stranger; (2) there was a ceiling effect in the sense that participants had already formed their habit through a sufficient number of habit repetitions and therefore did not repeat this behavior any more, or, conversely (3) due to the time constraints of the three-week experiment, some habits may not have had enough time to be formed and developed at all, (4) the experiment took place during a COVID-19 lockdown, which certainly affected participants' everyday lives and may have prevented the realization and formation of certain desired habits to be formed, for example, going to the gym or indoor areas to do exercise, and (5) similarly, the negative effects of the COVID-19 lockdown may have affected participants' motivation to work on themselves and improving their study- or work-related skills.

The authors' future work includes suggesting and incorporating questions that ask participants how much their behavior deviated from the intended behavior to gain an insight into the deeper process of habit-forming and particularly how these directly as well as indirectly affect individual learning processes. As mentioned by Villalobos-Zuniga and Cherubini (2020), more research is required into how individual learning processes can be facilitated by design features in apps. Another research direction would be to look at the individual differences in habit forming with the recent self-report measure instrument, namely the Creature of Habit Scale, which is a 27-item questionnaire to measure how individuals differ in habitual responding in everyday life taking into account two aspects of habits, namely routine behavior and automatic responses (Ersche et al., 2017). This instrument also combined 20 questions relating to anxie*ty su*ch as worry, tension, apprehension, and nervousness. For the authors' current study, these aspects were beyond the scope of the authors' research, however, it would be interesting to examine how individual differences, personality and various factors affect people's concerns and anxiety, in the development of habits with a larger sample size and also in a longitudinal study.

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Daniel Biedermann is a doctoral researcher at the Educational Technologies group at the DIPF, Leibniz Institute for Research and Information in Education.