The App, the Habit, and the Change: Digital Tools for Multidomain Behavior Change

Research Paper

Felix Reinsch[1], Maren Kählig[1], Maria Neubauer[1], Jeannette Stark[1], Hannes Schlieter[1]
[1] TUD Dresden University of Technology, Research Group Digital Health
{felix.reinsch, maren.kaehlig. maria.neubauer, jeannette.stark, hannes.schlieter}@tu-dresden.de

Abstract. Habits can trigger a ripple effect, driving positive changes across multiple lifestyle domains. Therefore, exploring how digital habit apps integrate and leverage these interconnected behaviors is essential, yet current research on this integration remains unclear. This study analyzes 585 behavior recommendations from 36 contemporary habit apps, classifying them into 20 meta-behaviors. Findings show significant variation, with apps averaging 45 suggested behaviors spanning roughly 13 meta-behaviors. Physical exercise is most prominently represented and interconnected, frequently paired with Nutrition and Leisure Activities. Apps supporting more lifestyle domains generally offer advanced habit-formation functionalities. However, user ratings suggest that functional diversity alone does not guarantee satisfaction. This paper provides users and developers with insights into selecting and designing effective habit apps, emphasizing the potential of interconnected behaviors to foster comprehensive and sustained lifestyle improvements.

Keywords: Digital Behavior Change Application, Habit Formation, Behavior Change Support System, Mobile Application

1 Introduction

A major portion of our daily activities is driven by habits, with approximately 43 % of everyday behavior falling into this category (Wood et al., 2002). Habits are automatic behaviors that develop through repetition in stable contexts and, once established, require minimal cognitive effort for execution (Lally and Gardner, 2013; Verplanken, 2018; Wood and Neal, 2007). A key characteristic of habits is the link of a specific behavior to a recurring context (Wood and Rünger, 2016), leading to automatic execution whenever the context occurs. For example, brushing one's teeth (behavior) before going to bed (context) can typically be described as a habit, as the bedtime routine consistently triggers the action without requiring conscious decision-making.

However, forming habits where behavior occurs automatically is challenging for two reasons (Stark et al., 2023). First, individuals often need an initial push to take action and select a behavior they want to turn into a habit (Fogg, 2009, 2020). Second, habit formation requires consistent repetition over an extended period until the behavior becomes ingrained in the chosen context, necessitating considerable perseverance (Lally et al., 2010). Habit-focused lifestyle applications (hereafter called habit apps) provide structured, consistent, and personalized support to address these challenges. They offer features such as timely reminders, progress tracking, motivational feedback, and various behaviors to choose from for forming a habit. These features help users (a) select a behavior and (b) repeatedly reinforce it within the chosen context. By facilitating this process, habit apps support the transition from intention to sustained behavior change (Stawarz et al., 2015; Stojanovic et al., 2020; Zhu et al., 2024). In the research field of information systems (IS), habit apps are conceptualized as digital infrastructures that enable repeated system use and contribute to the formation of stable behavioral routines (Limayem et al., 2007).

Many of these apps have entered the market in recent years, reflecting increasing interest in their potential to promote positive lifestyle changes (Appfigures, 2020). Driven by this rise in availability, prior research has explored how these apps utilize specific habit-formation techniques, such as personalization, habit stacking (linking new habits to established behaviors), and reminder strategies (Stark et al., 2023). Furthermore, prior research indicates that the effectiveness of these techniques varies across habit formation stages, emphasizing the importance of aligning app features with users' progress (Reinsch et al., 2025; Singh et al., 2024; Stark et al., 2023).

In addition to these targeted functionalities investigated in prior research, many habit apps offer predefined behaviors categorized into lifestyle domains such as fitness, nutrition, and sleep. In some apps, these predefined behaviors are actively recommended to users based on selected goals (e.g., weight loss) or lifestyle domains they want to tackle (e.g., physical exercise, sleep), as seen in apps like (Strides (2025)) and (HabitMinder (2025)). Actively recommending behaviors inspires users to a new habit and, more importantly, nudges them into taking action. This approach has already been associated with increased habit strength, particularly when users can choose the behavior they want to adopt for themselves (Singh et al., 2024; Thaler and Sunstein, 2008).

Beyond facilitating habit formation, behavior recommendation in habit apps also has the potential to support broader lifestyle changes across multiple domains, a phenomenon that aligns with the key-habit theory. Key-habit theory suggests that adopting positive habits in one area can trigger beneficial changes in related areas (Duhigg, 2012). For example, increasing physical activity has been associated with better sleep quality, while improvements in mental health have been shown to enhance physical health and vice versa (Chahine et al., 2022; Fleig et al., 2014; Prince et al., 2007). From the perspective of key-habit theory, habit apps may foster synergies between different habit areas by strategically recommending behaviors that create a reinforcing feedback loop, where positive changes in one behavior amplify beneficial outcomes in related lifestyle areas. However, little is known about whether and how current habit apps actually implement interconnected recommendations. Empirically analyzing these patterns can deepen our understanding of how digital tools translate behavioral theory into design, and how they might leverage cross-domain effects to support more holistic and sustained behavior change. To address this gap, this paper seeks to answer the following research question (RQ):

RQ: Which behaviors do habit apps recommend to users, and what patterns of interconnectedness emerge among them?

We conducted a content analysis of 36 contemporary habit apps to answer this question, documenting each recommended behavior, resulting in 585 distinct instances. Our study highlights a strong emphasis on *Physical Exercise* (measured in the amount of provided habits in the apps), which appears nearly twice as frequently as the next most represented domain, *Nutrition*. Furthermore, we identified areas extensively connected to multiple other domains, which may serve as structural anchors for broader lifestyle routines. This paper translates these patterns into theory-informed reflections, offering users guidance in selecting habit apps with multidomain coverage and providing developers with design-oriented recommendations based on observed behavior combinations.

2 Theoretical Background

A habit is a learned behavior that, through repetition, becomes an automatic response triggered by a specific context, which is associated with that behavior, such as doing a morning exercise (behavior) after getting up (context). The link between behavior and context is reinforced when the behavior is consistently executed in the context, and the habit strengthens (Lally and Gardner, 2013; Verplanken, 2018). Unlike intentional actions, strong habits require minimal cognitive effort and occur automatically, even when motivation fluctuates (Bargh, 1994). This automaticity, driven by the strong mental link between context and behavior, holds enormous potential for lasting behavior change (Rippe, 2018). For example, regular daily exercise within a stable morning routine can culminate in attaining specific health outcomes, such as improved fitness or achieving a desired physique. Thus, context provides stability and consistent cues, behavior represents the targeted action, and the outcomes signify the achievement of broader motivational objectives.

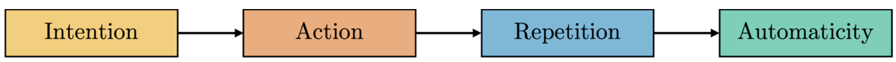

Figure 1. Four Stages of Habit Formation

Habit formation has been categorized into four stages: Intention, Action, Repetition, and Automaticity, as shown in Figure 1 (Gardner et al., 2011; Lally et al., 2010; Lally and Gardner, 2013). The Intention stage marks the beginning of the process, where an individual decides to adopt a new behavior, often motivated by broader health goals or external influences. The Action stage involves the initial execution of the chosen behavior, demanding substantial cognitive effort as no prior mental association between context and behavior exists. Cognitive effort declines during the Repetition stage, as consistent execution strengthens the mental connection. This stage is a critical turning point, as automaticity gradually develops, solidifying the behavior. Eventually, when the habit becomes thoroughly ingrained, it reaches the Automaticity stage, characterized by effortless, automatic execution. The Intention and Action stages are particularly critical due to the high cognitive demands involved, making new habits susceptible to motivational fluctuations. Therefore, ensuring an optimal fit between the individual and the intended habit facilitates quicker and more sustainable habit formation (Wyatt, 2024).

Habit apps increasingly support users in the initial phases of habit formation, often by suggesting specific behaviors to adopt. Many apps categorize their recommendation into lifestyle domains such as physical exercise, mental health, and nutrition. Others tailor suggestions to particular goals, for example, recommending a short walk after meals for weight loss or avoiding digital devices before bedtime for improved sleep (Reinsch et al., 2024). Beyond initiating action, suggesting the proper habits can drive behavioral changes across lifestyle domains (Duhigg, 2012; Thaler and Sunstein, 2008), creating a reinforcing improvement cycle (Prince et al., 2007). Health-promoting behaviors are closely interrelated and can catalyze broader lifestyle changes (Duhigg, 2012). For instance, physical activity has been shown to enhance cognitive control and facilitate healthier dietary choices (Fleig et al., 2014). Table 1 highlights positive associations between different lifestyle domains.

Table 1. Interconnected Behavioral Domains

Primary Domain	**Reinforcing Domain**	**Positive Effects**	**Source**
Physical Activity	Healthy Nutrition	Increased self-control, greater motivation for dietary improvements, weight lost, obesity prevention	(Fleig et al., 2014; Leme et al., 2020; Silva et al., 2024)
Physical Activity	Sleep Quality	Improved hormonal balance, regulated circadian rhythm	(Castelli et al., 2022)
Healthy Nutrition	Mental Health	Reduced risk of depression, improved cognitive function	(Ventriglio et al., 2020)
Morning Activity	Sleep Quality	Improved sleep hygiene, reduced sleep onset latency	(Chahine et al., 2022)
Sleep Quality	Mental Health	Improved cognitive function, reduced depression risk	(Castelli et al., 2022)
Physical Activity	Reducing Sedentary Behavior	Less sitting time leads to increased overall activity	(Martín-Martín et al., 2021)

Integrating structured behavior combinations within digital habit-tracking apps could enhance long-term habit formation and user retention. However, the extent to which habit apps recommend habits across interconnected domains remains largely unexplored. This paper investigates these connections by analyzing behaviors and domains promoted by habit apps and assessing potential synergies that could enhance habit formation. Empirical insights into such design patterns can contribute to theoretical un-

derstanding of how cross-domain behavior change processes are operationalized in digital interventions. Moreover, examining whether and how current apps align with principles of key-habit theory can inform the development of more effective, theory-driven behavior change tools.
Building on these psychological insights, habits from an information systems (IS) perspective are fundamentally conceptualized as a form of implementation and automatic (digital) system use that evolves into stable use over time through repeated interaction (Limayem et al., 2007). This view shows that habitual behavior integrates into IS continuity models, emphasizing that persistent use often bypasses conscious intention. Finally, in this topic area, shows how the temporal dynamics of system use first take shape as intention, which initially drives short-term engagement, but habits sustain long-term use (Lee, 2014). This distinction is particularly relevant for habitual apps that are designed to support user behavior over longer periods of time. Complementing this behavioral perspective, introduce the concept of digital nudging, which understands the design of user interfaces as a form of digital decision architecture that can guide decisions and behavior (Weinmann et al., 2016). Habit apps use such nudging to encourage habit formation. This development in IS research shows how habit research is anchored in IS theory and positions habit apps as digital infrastructures for behavior change that combine psychological mechanisms with IS design principles.

3 Method

We employed a content analysis approach (Krippendorff, 2018) to (a) examine the behaviors contemporary habit apps recommend to users, such as physical exercise, nutrition, and personal hygiene. Furthermore, the approach was used to (b) examine functionalities of habit apps that help implement and strengthen habits. While the functionalities were investigated and published in (Stark et al., 2023), this paper focuses on the behaviors facilitated and recommended by the apps.

We collected the sample using an API-based approach via a custom Python script (Catozzi et al., 2020; Richter et al., 2021). As the Google Play Store did not support API-based data collection at the time of analysis in 2023, we restricted our sample to apps available on the German Apple App Store for iOS devices. Using the search terms *Habit, Habit Tracking, Habit Tracker, Pattern Tracker, Pattern Tracking, Streak Tracker, and Streak Tracking,* we initially identified 320 apps. After removing duplicates, 149 apps remained. To refine the sample and ensure relevance, we excluded all apps with either a mean user review score of zero or a mean number of user ratings of zero, reducing the dataset to 120 apps.
We aimed to focus exclusively on general habit apps rather than targeting a specific habit or outcome. Accordingly, we manually reviewed the 120 apps and excluded those primarily serving a single habit. Apps with a narrow, specialized focus, such as those offering only meal plans or workout guides without broader habit formation features, were removed. Digital well-being apps designed solely to limit device functionality were also excluded. After this filtering process, 64 apps remained eligible for review

and testing. However, three additional apps were removed due to technical issues or bugs, and four were excluded as they required payment without offering a free trial or testing phase, resulting in a final sample of 57 apps. These 57 apps were the sample for our previous analysis published in (Stark et al., 2023) and, to ensure continuity, are also used as the foundation for the present study, allowing us to integrate our findings with prior research. Although we build on the app sample previously analyzed in Stark et al. (2023), this study focuses on a different aspect of habit app design: the analysis of behavior recommendations and their distribution across lifestyle domains.

Among these 57 habit-tracking apps, 21 provided no behavior suggestions to users. In these cases, users were required to manually enter a behavior to form the habit without receiving any feedback or guidance. As these apps did not align with our research focus, they were excluded from the analysis, leaving a final sample of 36 apps for this analysis. To ensure consistency in coding and classification, we employed inductive consensus coding and a split coding approach (O'Connor and Joffe, 2020; Richards and Hemphill, 2018) while also managing time and resource constraints. All coders downloaded and evaluated the first 20 apps to establish a shared analytical framework—the research team agreed on classifying each uniquely suggested behavior separately. For example, if one app suggested *"Do 10 minutes of physical exercise"* and another suggested *"Do 15 minutes of physical exercise"*, these were recorded as distinct instances rather than being merged into a single category. Once a common methodology was established, the remaining apps were analyzed, with each app independently by one coder, who systematically documented the habits suggested by each app. This process resulted in a total of 585 instances. Following data collection and initial coding, the research team conducted a two-step categorization process to classify the behavior based on the individual instances (O'Connor and Joffe, 2020):

- Initial Categorization: 300 behaviors were extracted from the 585 instances. For instance, the behavior *Physical Morning Exercise* was extracted from the instances *"Do 10 minutes of physical exercise after waking up"* and *"Do 15 minutes of physical exercise after waking up"*.
- Final Aggregation: In a second iteration, meta-behaviors were formed by combining the initial categorization into 20 meta-behaviors. Continuing the example, behaviors categorized as *Physical Morning Exercise* were further consolidated with other similar behaviors into the overarching *Physical Exercise* meta-behavior.

Any ambiguities during the classification process were resolved through team discussions, ensuring consistency in definitions and interpretations.
Preliminary descriptive statistics were performed in Microsoft Excel. Subsequently, advanced analyses were executed in Python. Specifically, the scikit-learn library was employed for machine learning tasks, and plotly was used for data visualization.

4 Results

The 585 initially found instances of behavior suggestions have been categorized into the 20 meta-behaviors, as shown in Table 2.

Table 2. Number of behaviors per meta-behavior

Meta-Behavior	Behaviors		Meta-Behavior	Behaviors
Medicine	1		Relaxation	20
Routine	2		Learning	21
Sex	2		Finance	28
Weight	6		Mental Health	32
Screen time control	8		Home Maintenance	36
Behavior Control	9		Social Interactions	43
Spirituality	10		Leisure Activities	55
Substance Control	14		Productivity	65
Sleep	18		Nutrition	77
Hygiene	20		Physical Exercise	118

To understand the distribution and interconnectedness of behaviors in habit apps, we analyzed the frequency of suggested behaviors and their classification into broader lifestyle categories, as seen in Figure 2. This figure provides an overview of the distribution of behaviors across 20 lifestyle domains — hereafter referred to as meta-behaviors — and the number of apps that included at least one suggested behavior from each meta-behavior category. A meta-behavior represents a broad category encompassing multiple related behaviors. We coded behaviors into 20 meta-behaviors, mainly addressing health- and well-being-related goals.

Our analysis reveals that habit apps do not distribute suggested behaviors evenly across meta-behaviors. On average, a typical habit app provided users with 45 suggested behaviors spanning 12.58 meta-behaviors. The highest number of supported meta-behaviors in a single app was 19, covering nearly all identified meta-behaviors, while the lowest was 2. Thus, no habit app supported all meta-behaviors, and no app was limited to just one meta-behavior. While *Physical Exercise* emerged as the most frequently represented meta-behavior, appearing in at least one habit suggestion across 35 of the 36 reviewed apps, a closer examination of individual habit instances revealed a more nuanced distribution. Specifically, the total count of suggested habits categorized under *Physical Exercise* (n = 369) was more than twice as high as that of the second most prevalent meta-behavior, *Nutrition* (n = 168). This substantial discrepancy underscores the prioritization of *Physical Exercise* within habit apps and highlights it as the most differentiated meta-behavior, characterized by a notably more extensive variety of suggested habit instances. However, some outlier behaviors, such as *Home Maintenance* (household chores) and *Hygiene* (personal grooming), stand out. These less common meta-behaviors indicate that certain habit apps focus on specific, non-health-related behaviors.

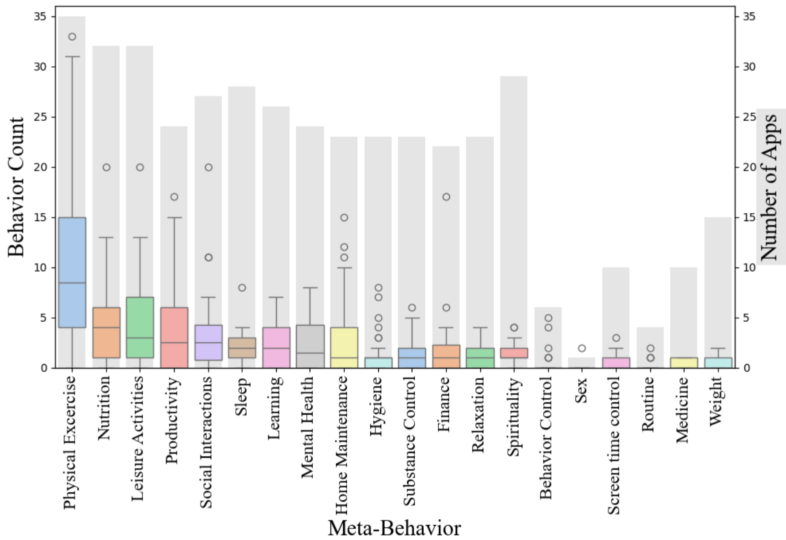

Figure 2. Distribution of Sub-Meta-behavior Counts per Habit App and Number of Habit Apps by Meta-behavior

Figure 3 represents a Jaccard heatmap, providing an overview of the relationships between meta-behaviors in habit apps. The Jaccard Index quantifies the similarity between pairs of meta-behaviors, with higher values indicating stronger overlaps in their co-occurrence across habit apps. This heatmap allows the identification of patterns and interconnections, offering a more nuanced understanding of how habit apps promote holistic behavior change. Our results reveal several notable relationships among the meta-behaviors. *Physical Exercise* emerges as a central anchor for behavior change, with strong associations with *Nutrition* (0.86), *Leisure Activities* (0.91), and *Sleep* (0.80). While this may suggest a central position with current app design, it does not imply causality of effectiveness in promoting behavior change across domains. Nonetheless, the consistent integration of physical activity across multiple behavioral contexts could be seen as a practical starting point for designing habit-based interventions, particularly when aligned with theoretical considerations such as key-habit theory, where adopting one habit triggers a reinforcing cycle of improvements across various aspects of daily life (Duhigg, 2012; Fleig et al., 2015).

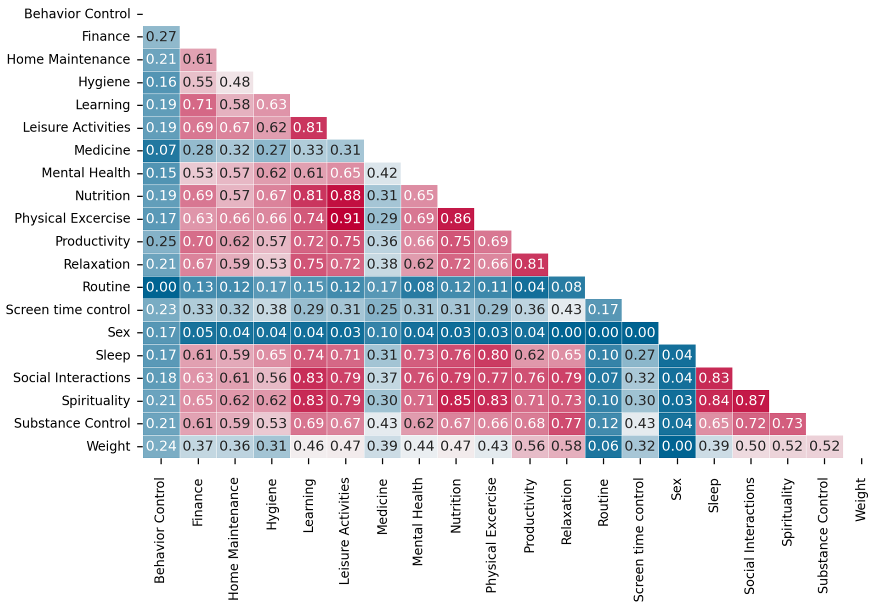

Figure 3. Jaccard Heatmap

However, certain meta-behaviors, such as Sex (average overlap ~0.03), exhibit limited integration with other behaviors. This may reflect their underrepresentation in habit app design or their individualized nature. Similarly, Medicine and Screen Time Control show weaker connections, suggesting that these areas are often treated as isolated domains. Interestingly, *Weight*, often linked to *Physical Exercise* and *Nutrition* in traditional health promotion strategies (Reinsch et al., 2024), shows only moderate associations (0.43 and 0.47, respectively). This counterintuitive finding may indicate that weight management is siloed as a specific goal in habit apps rather than embedded within broader lifestyle behaviors. Lastly, the heatmap highlights the interconnected nature of holistic behaviors, such as *Mental Health*, *Sleep*, and *Social Interactions*, as well as the inclusion of domains like *Finance* and *Spirituality*. These patterns suggest that habit apps are increasingly designed to promote comprehensive lifestyle improvements, leveraging the synergies between behaviors to encourage cascading habit formation. Furthermore, we combined our findings with previous research focusing on habit app functionalities (Stark et al., 2023). Our analysis examined the relationship between the number of suggested behaviors and integrated functionalities. Results show a significant correlation (Pearson's $r = 0.47$, $p = 0.004$), indicating that apps with more functionalities also cover a broader range of lifestyle domains. We applied a PCA-based K-Means clustering approach to explore the relationship between the functionalities, the number of suggested behaviors, and their ratings on the App Store (in terms of number and average score), as shown in Figure 4. We identified the optimal number of clusters by finding the point where the rate of decrease in inertia sharply diminishes, which was k=3. This approach offered a different analytical perspective, revealing that the user rating variable strongly influences PCA component 2. This result indicates that user ratings, reflecting subjective satisfaction, play an essential role in differentiation.

It also suggests that many functionalities or suggested behaviors alone do not necessarily ensure that a habit app is satisfactory to users, as evidenced by similar apps on the horizontal axis but widely dispersed on the vertical one.

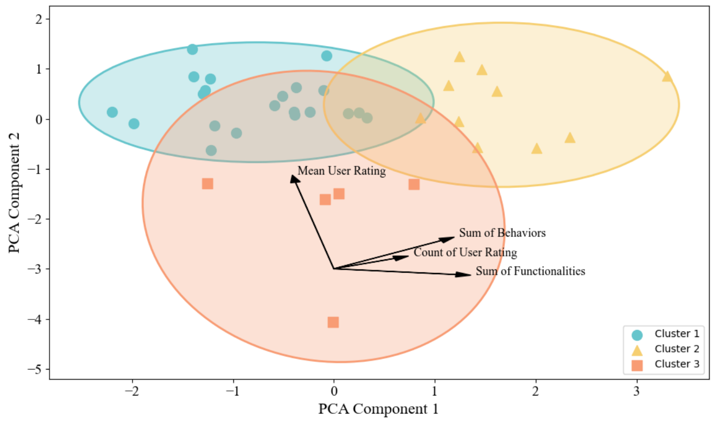

Figure 4. PCA K-Means Clustering

5 Discussion

A central finding of this study is that, on average, habit apps include behaviors from over twelve distinct lifestyle domains (12.58 meta-behaviors per app). While no app covers all 20 meta-behaviors, some come close, with the broadest app including 19. This scope suggests that app designers increasingly adopt a multidomain approach, potentially supporting the development of interconnected habits. Additionally, apps suggest an average of 45 behaviors, indicating a broad and diverse selection, even though most still specialize in certain areas. From the perspective of key-habit theory (Duhigg, 2012), this practical implementation aligns with the idea that changes in one domain may reinforce changes in others. The observed structure of behavior suggestions may therefore reflect an implicit design logic that enables positive spillover effects across domains, even if such interconnections are not explicitly based on behavioral theory. Rather than focusing on isolated co-occurrence indicators or correlations, the structural diversity and cross-domain coverage provide insights into how digital habit apps might translate theoretical principles of habit formation into design practice. Regarding patterns of interconnectedness between meta-behaviors and functionalities, the following points emerge:

The Dominance of Physical Exercise as a Meta-Behavior: Among all identified meta-behaviors, *Physical Exercise* is the most frequently recommended domain and the most commonly selected primary meta-behavior. Additionally, *Physical Exercise* is highly differentiated, meaning that apps provide a variety of habit suggestions within this category, from simple daily movement goals to structured fitness routines. The central role of *Physical Exercise* reflects its frequent occurrence across habit apps and its strong co-occurrence with other behaviors, particularly *Nutrition* and *Leisure Activities*. This prominence may reflect design conventions or user expectations rather than evidence of cross-domain effectiveness. Still, from a design standpoint, and consistent with key-habit theory, emphasizing physical activity may be a strategic starting point, given its visibility, goal orientation, and broad user appeal.

More Supported Behaviors Correlate with More Features: Our findings in cross-comparison with the results of (Stark et al., 2023) also reveal a positive correlation between the number of supported behaviors and the number of integrated functionalities. Apps covering more (meta-)behaviors offer a broader range of habit-forming features, such as reminders, and habit-stacking techniques**.** This suggests that more versatile apps provide users with additional tools to facilitate habit formation.

User Ratings as Exploratory Contextual Insight: While not central to the research question, we included user ratings as an exploratory variable to examine whether the diversity of supported behaviors and functionalities aligns with user satisfaction. Interestingly, our results show that user ratings in app stores do not necessarily correlate with the number of supported meta-behaviors or available functionalities. While some highly rated apps offer extensive behavior recommendations and advanced features, others receive positive ratings despite a narrower scope. These observations underline the importance of user experience in shaping app evaluations.

Habit apps typically recommend behaviors across many lifestyle domains, averaging over twelve meta-behaviors per app. This variety may help users form habits that span multiple areas of life.

Look for Multidomain Structure: Apps that support a greater number of lifestyle areas are often equipped with more habit-forming features. Rather than relying solely on app store ratings or aesthetic impressions, users may benefit from choosing apps that recommend behaviors across multiple domains, which can help initiate or reinforce broader lifestyle changes.

Use Familiar Behaviors as Anchors: The prominence of Physical Exercise in most apps suggests that this domain often serves as an organizing element. For users unsure where to begin, selecting behaviors in this category may offer an intuitive starting point, especially as they often appear alongside habits from related domains, such as sleep or nutrition. This may increase the chances of building routines that span different aspects of daily life, even though such spillover effects were not measured directly in this study.

The structural co-occurrence patterns identified in this study, especially the consistent pairing of certain meta-behaviors – can inform design strategies for digital habit apps.

Design for Cross-Domain Opportunities: Our findings indicate that many habit apps already integrate behavior suggestions across multiple domains. Developers could build on this by intentionally designing user flows that highlight such combinations, thereby encouraging users to recognize and engage with cross-domain routines.
Balance Popularity and Differentiation: While Physical Exercise dominates the behavioral landscape of current apps, this saturation also creates opportunities for differentiation. Developers may consider highlighting less-represented domains that still show meaningful co-occurrence patterns and could support holistic habit development.

6 Limitations

The results should be interpreted with caution, as the coding process affects outcomes. For example, walking-related behaviors were coded under seven different labels (e.g., *walk for 20 minutes outdoors*, *do 5000 steps*). Some behaviors received multiple codes, for instance, a *20-minute outdoor walk* was labeled with two codes. Furthermore, different domains' "natural" characteristics affect the number of possible behaviors within each domain. Only one code (*take your medicine*) was identified in the medicine domain, possibly due to apps avoiding the prescription of more detailed habits in this area. In *physical exercise*, however, 118 distinct behaviors were coded, and 77 behaviors were identified in nutrition.

7 Future Research

Future research may build on this paper in several ways to deepen our understanding of how habit apps influence behavior change and long-term engagement. A longitudinal and experimental approach may be necessary to assess not only the sustained impact of multi–meta-behavior habit apps but also the causal mechanisms through which they influence user behavior and outcomes. While our study highlights the interconnected nature of behaviors within habit apps, it does not allow for conclusions regarding the effectiveness of specific habit combinations. Future studies should investigate whether the adoption of a single, strategically chosen habit can catalyze multidimensional behavior change across lifestyle domains. Such research could involve controlled trials or long-term observational studies that track habit adoption and spillover effects over time, thereby providing stronger evidence for the design of effective, holistic behavior change interventions. Also, user-centered research should explore how individuals engage with habit apps and perceive the value of holistic habit-tracking. Qualitative studies, including interviews and surveys, could offer deeper insights into user preferences, motivation, and potential barriers to adopting interconnected habits.

8 References

Appfigures, 2020. Anzahl der im Apple App-Store verfügbaren mHealth-Apps vom 1. Quartal 2015 bis zum 3. Quartal 2020 [Graph].

Bargh, J.A., 1994. The four horsemen of automaticity: Awareness, intention, efficiency, and control in social cognition, in: Wyer, R.S., Srull, T.K. (Eds.), Handbook of Social Cognition: Applications. Lawrence Erlbaum.

Castelli, L., Galasso, L., Mulè, A., Ciorciari, A., Fornasini, F., Montaruli, A., Roveda, E., Esposito, F., 2022. Sleep and spa therapies: What is the role of balneotherapy associated with exercise? A systematic review. Front. Physiol. 13, 964232. https://doi.org/10.3389/fphys.2022.964232

Catozzi, D., Gualano, M.R., Voglino, G., Corradi, A., Bert, F., Siliquini, R., 2020. Mobile Apps for Vaccination: an in-depth scan of Apple App Store. European Journal of Public Health 30. https://doi.org/10.1093/eurpub/ckaa165.1034

Chahine, K.R., Chahine, N.R., Nader, M., 2022. Morning exercise improves sleep quality in university students. Int J Res Med Sci 10, 1858. https://doi.org/10.18203/2320-6012.ijrms20222259

Duhigg, C., 2012. The power of habit: why we do what we do in life and business. Random House, New York, NY.

Fleig, L., Kerschreiter, R., Schwarzer, R., Pomp, S., Lippke, S., 2014. 'Sticking to a healthy diet is easier for me when I exercise regularly': Cognitive transfer between physical exercise and healthy nutrition. Psychology & Health 29, 1361–1372. https://doi.org/10.1080/08870446.2014.930146

Fleig, L., Küper, C., Lippke, S., Schwarzer, R., Wiedemann, A.U., 2015. Cross-behavior associations and multiple health behavior change: A longitudinal study on physical activity and fruit and vegetable intake. J Health Psychol 20, 525–534. https://doi.org/10.1177/1359105315574951

Fogg, B., 2009. A behavior model for persuasive design, in: Proceedings of the 4th International Conference on Persuasive Technology. Presented at the Persuasive 2009: Persuasive 2009; 4th International Conference on Persuasive Technology, ACM, Claremont California USA, pp. 1–7. https://doi.org/10.1145/1541948.1541999

Fogg, B.J., 2020. Tiny habits: The small changes that change everything. Houghton Mifflin Harcourt, Boston.

Gardner, B., De Bruijn, G.-J., Lally, P., 2011. A Systematic Review and Meta-analysis of Applications of the Self-Report Habit Index to Nutrition and Physical Activity Behaviours. ann. behav. med. 42, 174–187. https://doi.org/10.1007/s12160-011-9282-0

HabitMinder, 2025. HabitMinder - Healthy habit reminder and tracker app [WWW Document]. URL https://habitminder.com/ (accessed 3.13.25).

Krippendorff, K., 2018. Content analysis: An introduction to its methodology. Sage publications.

Lally, P., Gardner, B., 2013. Promoting habit formation. Health Psychology Review 7, S137–S158. https://doi.org/10.1080/17437199.2011.603640

Lally, P., van Jaarsveld, C.H.M., Potts, H.W.W., Wardle, J., 2010. How are habits formed: Modelling habit formation in the real world. European Journal of Social Psychology 40, 998–1009. https://doi.org/10.1002/ejsp.674

Lee, W.-K., 2014. The temporal relationships among habit, intention and IS uses. Computers in Human Behavior 32, 54–60. https://doi.org/10.1016/j.chb.2013.11.010

Leme, A.C.B., Haines, J., Tang, L., Dunker, K.L.L., Philippi, S.T., Fisberg, M., Ferrari, G.L., Fisberg, R.M., 2020. Impact of Strategies for Preventing Obesity and Risk Factors for Eating Disorders among Adolescents: A Systematic Review. Nutrients 12, 3134. https://doi.org/10.3390/nu12103134

Limayem, M., Hirt, S., Cheung, C., 2007. How habit limits the predictive power of intention: The case of information systems continuance. MIS QUARTERLY 31, 705–737. https://doi.org/10.2307/25148817

Martín-Martín, J., Roldán-Jiménez, C., De-Torres, I., Muro-Culebras, A., Escriche-Escuder, A., Gonzalez-Sanchez, M., Ruiz-Muñoz, M., Mayoral-Cleries, F., Biró, A., Tang, W., Nikolova, B., Salvatore, A., Cuesta-Vargas, A.I., 2021. Behavior Change Techniques and the Effects Associated With Digital Behavior Change Interventions in Sedentary Behavior in the Clinical Population: A Systematic Review. Front. Digit. Health 3, 620383. https://doi.org/10.3389/fdgth.2021.620383

O'Connor, C., Joffe, H., 2020. Intercoder Reliability in Qualitative Research: Debates and Practical Guidelines. International Journal of Qualitative Methods 19, 1609406919899220. https://doi.org/10.1177/1609406919899220

Prince, M., Patel, V., Saxena, S., Maj, M., Maselko, J., Phillips, M.R., Rahman, A., 2007. No health without mental health. The Lancet 370, 859–877. https://doi.org/10.1016/S0140-6736(07)61238-0

Reinsch, F., Weimann, T., Stark, J., 2025. From Instant Cues to Fading Views: Piloting Just-in-Time and Fading Strategies in Digital Habit Formation, in: AMCIS 2025 Proceedings.

Reinsch, F., Weimann, T.G., Stark, J., 2024. Tailoring Health: Contextual Variables In Health Recommender Systems. Presented at the Proceedings of the 6th Workshop on Health Recommender Systems co-located with ACM RecSys 2024, CEUR Workshop Proceedings, Bari, Italy.

Richards, K.A.R., Hemphill, M.A., 2018. A Practical Guide to Collaborative Qualitative Data Analysis. Journal of Teaching in Physical Education 37, 225–231. https://doi.org/10.1123/jtpe.2017-0084

Richter, J.G., Chehab, G., Kiltz, U., Becker, A., Von Jan, U., Albrecht, U.-V., Schneider, M., Specker, C., 2021. Identifikation rheumatologischer Gesundheits-Apps im Apple App Store mit der Methode der „semiautomatischen retrospektiven App Store-Analyse“: Eine longitudinale Betrachtung. Z Rheumatol 80, 943–952. https://doi.org/10.1007/s00393-021-01099-9

Rippe, J.M., 2018. Lifestyle Medicine: The Health Promoting Power of Daily Habits and Practices. American Journal of Lifestyle Medicine 12, 499–512. https://doi.org/10.1177/1559827618785554

Silva, C.C., Presseau, J., Van Allen, Z., Schenk, P.M., Moreto, M., Dinsmore, J., Marques, M.M., 2024. Effectiveness of Interventions for Changing More Than One Behavior at a Time to Manage Chronic Conditions: A Systematic Review and Meta-analysis. Annals of Behavioral Medicine 58, 432–444. https://doi.org/10.1093/abm/kaae021

Singh, B., Murphy, A., Maher, C., Smith, A.E., 2024. Time to Form a Habit: A Systematic Review and Meta-Analysis of Health Behaviour Habit Formation and Its Determinants. Healthcare 12, 2488. https://doi.org/10.3390/healthcare12232488

Stark, J., Weimann, T., Reinsch, F., Hickmann, E., Kählig, M., Gißke, C., Richter, P., 2023. Building Habits in the Digital Age: Incorporating Psychological Needs and Knowledge from Practitioners to Inform the Design of Digital Therapeutics. Wirtschaftsinformatik 2023 Proceedings.

Stawarz, K., Cox, A.L., Blandford, A., 2015. Beyond Self-Tracking and Reminders: Designing Smartphone Apps That Support Habit Formation, in: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Chi '15. Presented at the CHI '15: CHI Conference on Human Factors in Computing Systems, ACM, Seoul Republic of Korea, pp. 2653–2662. https://doi.org/10.1145/2702123.2702230

Stojanovic, M., Grund, A., Fries, S., 2020. App-Based Habit Building Reduces Motivational Impairments During Studying – An Event Sampling Study. Front. Psychol. 11, 167. https://doi.org/10.3389/fpsyg.2020.00167

Strides, 2025. Strides: Goal & Habit Tracker + SMART Goal Setting App [WWW Document]. URL https://www.stridesapp.com/ (accessed 3.13.25).

Thaler, R.H., Sunstein, C.R., 2008. Nudge: Improving decisions about health, wealth, and happiness. Yale University Press, New Haven, CT, USA.

Ventriglio, A., Sancassiani, F., Contu, M.P., Latorre, M., Di Slavatore, M., Fornaro, M., Bhugra, D., 2020. Mediterranean Diet and its Benefits on Health and Mental Health: A Literature Review. CPEMH 16, 156–164. https://doi.org/10.2174/1745017902016010156

Verplanken, B. (Ed.), 2018. The psychology of habit: theory, mechanisms, change, and contexts. Springer, Cham.

Weinmann, M., Schneider, C., Brocke, J.V., 2016. Digital Nudging. Bus Inf Syst Eng 58, 433–436. https://doi.org/10.1007/s12599-016-0453-1

Wood, W., Neal, D.T., 2007. A new look at habits and the habit-goal interface. Psychological Review 114, 843–863. https://doi.org/10.1037/0033-295X.114.4.843

Wood, W., Quinn, J.M., Kashy, D.A., 2002. Habits in everyday life: Thought, emotion, and action. Journal of Personality and Social Psychology 83, 1281–1297. https://doi.org/10.1037/0022-3514.83.6.1281

Wood, W., Rünger, D., 2016. Psychology of Habit. Annu. Rev. Psychol. 67, 289–314. https://doi.org/10.1146/annurev-psych-122414-033417

Wyatt, Z., 2024. The neuroscience of habit formation. Neurology and Neuroscience.

Zhu, Y., Long, Y., Wang, H., Lee, K.P., Zhang, L., Wang, S.J., 2024. Digital Behavior Change Intervention Designs for Habit Formation: Systematic Review. J Med Internet Res 26, e54375. https://doi.org/10.2196/54375