Integrating Behavior Change and Persuasive Design Theories into an Example Mobile Health Recommender System

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ABSTRACT

Behavior change for health promotion is a complex process that requires a high level of personalization, which health recommender systems, as an emerging area, have been trying to address. Despite the advantages of behavior change theories in explaining individuals' behavior and standardizing the behavior change program overall, these theoretical models are either overlooked or unreported for the most part in health promotion systems, a small share of them being related to mental well-being. For a health recommender system to personalize interventions, the interventions should be properly designed, and the behavior change aspects should be adequately integrated into the recommendation process. This paper demonstrates an implementation guideline derived from a practical approach in integrating behavior change theories and persuasive design principles into an example mobile-based health recommender system for mental health promotion. This implementation maps a set of relevant theories for designing the health recommender system into a set of requirements using a functional framework. By realizing these requirements, one can assure that the behavior change theories are at the very least considered. This effort serves as a guideline for future implementations and highlights elements that could perhaps be used for other health or recommendation domains and, particularly, user integration purposes.

CCS CONCEPTS

• **Human-centered computing** → *User centered design*; • **Information systems** → **Recommender systems**.

KEYWORDS

Health recommender systems; Behavior Change; Persuasive Design

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1 INTRODUCTION

By tracking user behaviors over time using sensor-enriched devices, one intends to better understand human behavior and support them where necessary. Modeling, estimation, and prediction of the target behavior or psychological concepts, such as stress and mood, are means to build intelligent systems that help the promotion of health for the general populations, make early diagnosis possible, and support target populations suffering from specific health conditions in recovery and coping. However, these goals are better achieved when the tracking and prediction are followed by machine generated, personalized, or perhaps reactive, recommendation of Behavioral Interventions (BI).

BI are among the principal methods that health professionals use for both preventive and curative health care. It is a combination of advice, activities, services, and support for individuals in order to change an existing behavior or shape a new one. Professionals use various BI for a broad range of purposes, such as education, prevention, monitoring, and support of the subjects, who may require interventions for learning and shaping a healthy lifestyle and behavior. They also use BI for patients suffering from mental or physical illnesses and help them cope with their conditions, particularly for those with a chronic or long-term condition. Behavior change, in general, requires careful consideration of vital elements that are different for every individual, such as the person's initial state, her/his habits, behaviors, health state, mental state, abilities, personal characteristics, goals, risk factors, environment, and personal preferences. The interventions for behavior change also have to be adjusted in time with the person's progress and state during the process. In other words, they should be individualized from the start and get adjusted in the process, and this requires a meticulous consideration of user health information, behavior, and preferences.

A growing field addressing personalization of BI has been health recommender systems [37]. This field yet faces a variety of challenges, including the integration of behavior change models and theories, mostly neglected despite its critical relevance. Namely, a recent scoping review [15] found no evidence with which it can determine the integration level of the behavior change theories due to a lack of discussion and existing information surrounding the creation and design of the interventions. This review [15] also highlighted the importance of integrating proper behavior change theories into the health recommendation process and reporting the details of the intervention design. It should also be noted that behavior change is not just about the intervention platform and personalization, and the underlying theories upon which the interventions should be designed and presented [29], and the user interaction with the interventions as well as their adherence using the platform [17], all play vital roles. However, the majority of the efforts for user persuasion and integration in health recommender systems are not theory-driven. They are, for the most part, limited to isolated implementation techniques, and no comprehensive framework, model, or practical design guidelines have been used or discussed so far in this area to the best of our knowledge. Such a model or framework is particularly critical for the health domain because of its interdisciplinary nature and need for user consistency, persuasion, and adherence.

This paper concentrates on integrating behavior change theories and persuasive design principles into the design of a health recommender system for mental health promotion as a Mobile Health (mhealth) app, with respect to its relationship with users as an interdisciplinary, interactive medium. Here, we demonstrate a conceptual framework for this purpose through a set of requirements (a total of 50), briefly explaining how the underlying behavior change theories and persuasive design principles can be adapted or utilized. These requirements were then realized with a system prototype in three stages: First, the intervention (i.e. recommendation item) design; second, the app design; and third, the algorithm design for personalization. This, in particular, shows that the integration effort is a broad effort involving various aspects of the health recommender system development. The requirements and examples presented in this paper can be considered as a guideline for design decisions for future implementations. They also highlight elements derived from behavioral theories and persuasive design principles, which could be used for user integration in other recommendation and health application domains.

2 BACKGROUND

Classic BI-related methods highly relied on face-to-face interactions between the subjects and health professionals. To resolve the limitations of these approaches, particularly in personalization, costs, and accessibility of the interventions, the potentials of the digital world were utilized, and computer-delivered (or tailored) interventions were used [4, 22, 26]. Nowadays, electronic devices are used for tracking, data collection, generation, personalization, or delivering of the interventions, e.g., [3, 20, 22, 44, 46]. These interventions are generally categorized into three health domains: self-management and chronic conditions; health promotion; and mental health categories [22]. When these electronic mediums are mobile devices, it is commonly called *mobile health (mHealth) interventions*, e.g., [21, 45]. mhealth interventions are effective in improving well-being and reducing stress and its negative consequences, such as stress-related health problems, especially for non-clinical population [45].

The interventions, their goals, and constructs, sometimes as part of a behavior change program, are designed and developed based on the respective behavior change theory (or theories). These theories try to model and explain elements of human behavior change and often present a framework and set of tools to determine its success. Commonly used theories are namely, theory of reasoned action / planned behavior (TBP) [1, 2], Social Cognitive Theory (SCT) [6], Health belief model (HBM) [32, 33], I-change model [9], Goal Setting Theory (GST) [19], Self-Determination Theory (SDT) [34, 35], and Fogg's behavior model (Fogg) [10]. Most of the health behavior models that are frequently discussed in the literature have common components [24, 25]. For example, the HBM discusses benefits and threats and can be considered as a form of outcome expectations [6]. Bandura [6] argued that attitude toward behavior and norms from TPB [1, 2] are also forms of outcomes.

Although several of these theories and models may have overlapping components, they describe health behavior change from their specific perspective and are, therefore, limited to that perspective. Behavior change, in general, is a complex process, and depending on the study, a particular theory per se might be insufficient. Riley et al. [31] highlighted the shortcomings of behavioral change theories in mhealth interventions and argued that these theories are not entirely suitable for addressing interactive and adaptive characteristics of mhealth interventions, such as just-in-time interventions and within-person personalization. Nahum-Shani et al. [23] further called for the development of advanced health behavior theories for mobile interventions focusing on adherence and just-in-time interventions. For these reasons, scholars have discussed combining and integrating appropriate theories and components with one another [9]. Regardless of the chosen behavior change theory (or theories), their use is encouraged in designing and delivering interventions and for having more effective solutions [12, 25]. Despite their advantages in understanding, modeling, and explaining individuals' behavior and standardizing the behavior change process, behavior change theories are still overlooked or unreported in a large share of the related studies [8, 15, 20]. This lack of attention, discussion, or even presence is severe in health recommender systems [15]. Similar to Hors-Fraile et al. [15], we also did not find any proper integration of any behavior change theories into the health recommendation process for mental health promotion or stress.

It should be noted that looking beyond the domain of health recommender systems, behavior change theory-driven approaches have been discussed in Human-computer interaction (HCI). Specifically, pointing out the existing interdisciplinary gap in using behavior change theories, Hekler et al. [13] highlighted the limitations of these theories and categorized the existing works into the use of theories for informing design, guiding evaluation, and describing target users. Accordingly, the following framework (section 3) concentrates on making system design decisions, i.e. having an informed design for a practical system. Scholars, namely [7, 28, 38, 39], have tried to bridge the gap between theory and design. However, they primarily rely on one theory, or even a few constructs of a theory, to present strategies and practices for motivation and well-being-based design through satisfying basic psychological needs.

The structure of a health recommender system, in general, is more complex than any other typical health promotion system because of having or combining several tracking, interacting, and personalization components. A pervasive health recommender system tracks user behavior, e.g., mood [42, 43], and stress, on top of capturing user preferences for personalization. In addition, it has to nudge users and keep them engaged with the frontend app to increase their adherence to interventions. Users, therefore, may need to follow several tasks, such as questionnaires and interventional tasks, for a successful behavior change and in order for the system to have a holistic perspective of the user and provide personalizations. Particularly in health promotion use cases where users are not faced with a direct health threat, their intrinsic motivation and persuasion play an essential role in determining their commitments, perhaps more than any other type of ehealth-related system.

3 A FRAMEWORK FOR USER AND SYSTEM

In order to integrate the behavior change theories and persuasive design principles into the design of a health recommender system, one first needs a functional framework. This section describes a conceptual framework and its elements, and explains how they are mapped into the system requirements. The health recommender system under discussion in this paper, as an example, is a mhealth platform for reducing the negative effects of stress in daily life and increasing one's stress-coping capabilities. The recommendations are mood and stress-aware and are generated using health recommender system algorithms. Although this use case is specific to the application that we have developed, it is flexible and versatile enough to be used as an inspiration for a wide range of health promotion and mental health applications. As mentioned before, several of the commonly used health behavior change theories have overlapping components [24, 25]. Nevertheless, there is still no universally applicable model [9, 23, 31]. For this reason, we looked into commonly used health behavior change theories and integrated several of their shared components. Our goal was to benefit from the strengths and appropriate perspectives of each theory or model in our mhealth recommender system. Figure 1 summarizes the behavior change model concept on an abstract level. It also lists all constructs and elements that were mapped at least to a requirement.

The included elements in our framework were primarily inspired from the SCT [6]. However, we used constructs also from these theories: HBM [32, 33], TPB [1, 2], stages of change or transtheoretical model (TTM) [18], GST [19], and Implementation Intentions (ImIn) [30]. In addition, we used the following theoretical frameworks, particularly for user engagement and persuasive design: SDT [34, 35, 38, 39], Fogg [10, 11], the Persuasive Systems Design (PSD) framework [27], and user satisfaction with health recommendations (USHR) [40, 41]. The framework here is divided into **user** and **system** components. While the user aspects are more about user beliefs, perceptions, status, goals, and intention, the system aspects are about the content of the health recommendations and persuasive elements of a system. The overall idea is that for a successful mhealth recommender system for behavior change, particularly for mental health promotion and stress reduction as our use case, addressing the elements of both aspects is necessary.

On the abstract level, we have individual factors, beliefs, outcome expectations, and social factors on the user side, all of which are critical in determining the users' goals, incentives, and intentions. **Outcome expectations** is an abstract concept in our framework, taken from the SCT. We considered elements of perceived threats and benefits from the HBM for this element as concrete elements. Threats [32, 33] accordingly refers to the perception of seriousness of the health condition and its possible consequences. Benefits is then about the user perception of the positive consequences of changing an existing behavior [32, 33]. The corresponding requirements were then translated as the following. *Users should receive information about the health risks and the seriousness of the threats. Users should receive the information about the health benefits.* Perceived threat and benefits elements in our system design have been realized with the intervention items. For example, when writing the interventions, we added several interventions specifically explaining the threats from stressful experiences and improper coping and the benefits of following the interventions and the respective coping skill in general. Outcome expectations according to the SCT can be physical, i.e. personal benefits and losses, social, i.e. social (environmental) approval or disapproval, and self-evaluation, i.e. behavior. Accordingly, we additionally considered the emotional gain or effect as discussed in [40, 41] as the outcome expectations and the result of following the recommended intervention. The resulting requirement was: *user emotional gain or effectiveness of a recommendation should be considered as a goal for both personalizations and eliciting explicit preferences.*

Beliefs in our combined framework represents the user's ability and attitude. User attitude, taken from the TPB, is close to the concept of the personal or behavioral outcome. It is about the extent to which users favor a task or prefer it. *Directly capturing user preferences of the recommendation items, and accordingly automatically personalizing the recommendations* as requirements of our system would most likely satisfy this element. Users' belief is also about their ability which is addressed by most behavior change theories, e.g., TTM; TPB; SCT; Fogg; GST; HBM. In some other theories, e.g., SCT, it has been referred to as self-efficacy. This concept is about the users' ability, or belief in their ability, to perform or follow a certain task or behavior within the limitation of their available resources and capacities that lead to an outcome. As a relevant requirement for the system design, *the difficulty of the recommendation items should increase automatically and step by step so that it enhances self-efficacy and users' ability.* When an individual perceives a specific recommendation, i.e. intervention, as either easy or difficult, the system should adjust the task's difficulty to engage users to follow the recommendation. This process should be adaptive and personalized based on the determined users' ability and items' difficulty level. Depending on the users' self-efficacy level, various reactions may be required. For example, users with lower self-efficacy may require more persuasion, interactive elements, and guidance.

Social factors impact the fulfillment of behavior or task. The first element of this construct is social support group or helping relationships. For example, having a positive social network and a feeling of social cooperation may encourage behavior change and increase the adherence to the behavior change program (inferred from SCT, TTM, and PSD). Accordingly, social support aspect as requirements were realized by first, *defining social engagement as one family of intervention types specific to stress interventions*, second, *including seeking social support as one of the stress coping strategies*, and third, *facilitating social support via design elements, such as sharing options and user involvement in the intervention creation process.* Specifically, the real-world social network size and its quality are influential at the algorithm level on the output of the recommendations. Users can also feel a sense of community through at least the ability to consume group-generated and selected content, write new items, and give ratings to the recommendations and the application. The generated items for validity and credibility reasons are only added to the item set after an admin confirmation.

Reinforcement, the second element, is about either social or tangible rewards or punishments for making progress, and is taken from SCT, TTM, HBM, Fogg, and PSD. Conditioning technology in Fogg's model is an example of this element. Reinforcement is often accompanied by reward dialogues and praises. As a requirement,

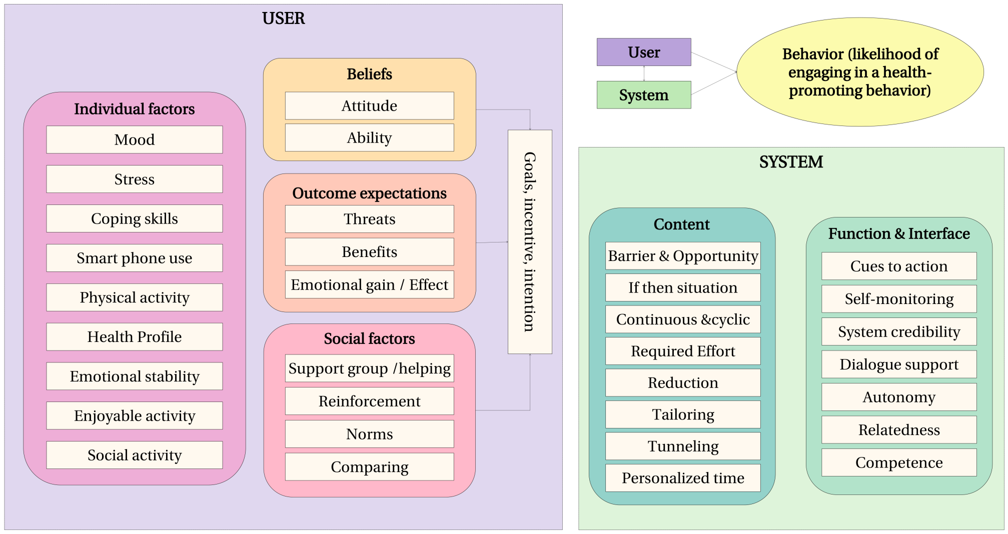

Figure 1: Theory-driven integration of behavior change techniques in health recommender system design. A box shows a construct or its elements derived from the respective theories.

users should receive feedback, incentives, and rewards for making progress. The system should keep track of the users' progress and quantify it. Achievements badges should be defined and presented to the users. There should be a carefully designed top-score table to function as "cue to action" where necessary. Comparing with others as the next element is inspired by Social comparison theory and PSD. It is about providing the opportunity to evaluate one's standing in comparison to others. *Giving a balanced view of progress to the users and comparing it with other users in an overview* are requirements to realize this element. *The comparison overview should be privacy-preserving and constrained to prevent any discouragement*, e.g., requiring too much scroll to see the user's name at the end of the list or unrealistic overconfidence, e.g., feeling good just because the user stands better than many other users.

The next element, norms taken from TPB, is about cultural norms, social appropriateness, and social acceptability and refers to the users' perception of others' approval or disapproval of the behavior. This element has been mapped to the requirement that *recommendations should be socially appropriate for the user*, which can be realized, for example, by having at least a property or contextual attribute for social acceptability and accordingly personalizing the recommendations concerning the users' preferences, e.g., using a context-aware recommender system. Such an attribute specifies if the recommendations can be followed when alone, in public locations, in the presence of others, etc.

Goals, incentives, and intention is an element of SCT and TTM. Accordingly, intentions are considered as attainable goals, and every new intention as a self-incentive. Individual factors, beliefs, outcome expectations, and social factors influence users' goals, incentives, and intentions. Accordingly, we mapped this element to the requirement of *defining progressive, adaptive, and achievable goals for users via a gamified setup with badges and unlocking new functionalities, such as quizzes and recommendation batches to rate.* Each badge contains a verbal description explaining how to achieve a specific, concrete, and actionable goal linked to the batch and has a visual icon. Achieving each badge, visualized on the screen with animation, most likely would impact users' self-efficacy and give them new incentives to follow in addition to their own goals. Considering the discussion surrounding gamification [5, 16, 36], particularly their possible adverse impacts on motivation which occurs at times depending on the design, we linked the badges to concrete and actionable goals. Another requirement was defined as the following: *Recommendations should be personalized to the user's goals based on their preferences and the determined health profiles.*

All elements mentioned so far were categorized as user-inspired constructs. In addition, we considered several elements for persuasive design and categorized them as system-inspired elements in figure 1. Here we have two abstract components: Content and function, and interface. **Content** concentrates on the intervention content, its characteristics, and personalization. When collecting, designing, and writing the interventions, i.e. the recommendation items, several items — corresponding to the elements shown in figure 1 — may be modified or adjusted. For example, the wording of the intervention text may be written or presented as if-then scenarios according to ImIn where possible. For any modification, one should carefully consider the sensitivity of the health domain and its resilience for such changes, and consult with health experts as necessary. For example, preventive interventions for well-being might be generally more resilient to changes than curative ones.

The elements of content impact the functionality of the recommendation algorithm. For instance, the element continuous and cyclic — originated in TTM — holds that change does not occur suddenly, but it rather is a cyclic and progressive process. An essential requirement is mapped from this element, stating that *the relevant recommendation items (i.e. interventions) should be repeated and practiced in order to make it a natural habit for stressful situations.* This requirement makes the health recommender system different from typical recommender systems of other domains where a consumed recommendation is not usually repeated. We addressed this requirement at the algorithm level. As another element, barriers and opportunities, such as time or place or any other barrier on the path of behavior change, can difficult the change process or facilitate it. *One should therefore minimize the barriers of following the recommendation.* This element is inspired from SCT and TPB. According to USHR, we defined two attribute sets for every recommendation item (i.e. an intervention): effort attributes and context attributes. Effort attributes describe how difficult an item is, how long it takes, and when is the most appropriate time for following it. Context attributes specify the proper user context for following the recommendation. As requirements, *Context and ability attributes should be monitored and, as necessary, defined for recommendations and used as an asset, such as for context-aware or effort-aware recommendations.* Users additionally can manipulate these attributes and adjust the characteristics of an item to their liking using our health recommender system platform. These attributes also are considered as part of the personalization algorithms.

Required effort, taken from GST, TPB, and Fogg, is related to the user's ability described earlier. Accordingly, the engagement with a task is defined by users' ability and task difficulty level, which both should be balanced with regard to each other. In particular, GST considers a positive linear relationship between task difficulty and performance. Therefore, *recommendation items should have a property specifying their difficulty or required effort level. The system should be able to determine the task's difficulty automatically.*

Other content-related elements include reduction, tunneling, tailoring, and personalized time, all taken from Fogg. Reduction is about simplifying the process by reducing the steps. As a requirement, *the tasks, i.e. recommendation items, should be simplified and presented as small steps to follow.* Tunneling is about a step-by-step and guided process and is mapped to this requirement: *the system should have a sequence of activities and guide users through them.* Tailoring is about tailoring messages, interfaces, and options. Accordingly, *the system should provide customized information and feedback.* Finally, personalized time emphasizes on finding the right time or opportune moment for suggesting. Based on this element, *the system should give users control over the timing of the recommendations, and where possible automates and finds opportune moments.*

Function and interface elements represent persuasive design principles and are taken from HBM, PSD, and Fogg. According to the first element of this component, cues to action, a trigger, functioning as a reminder, is applied when motivation and ability levels are appropriate. Correspondingly, *the system at least should provide signals or cues to action for users as a reminder to follow a task.* The next element, self-monitoring, is about giving the users the option to self-monitor their states, behaviors, and progresses, which was translated to this requirement: *the system should enable users to track their own behaviors and observe the outcomes.*

System credibility and dialogue support both are inferred from PSD. The first one is about a set of criteria describing how the system can be more credible and, as a result, more persuasive, containing criteria such as trustworthiness, expertise, credibility, etc. The second one is about using dialogue support techniques to bring higher persuasion, such as liking, i.e. visual appeal, and suggestions, i.e. fitting suggestion. Accordingly, derived from system credibility, *the system should provide the source of each recommendation and explain the reason of its effectiveness. It should also provide supporting and source information, such as an accessible link to additional information concerning the credibility and trustworthiness of the items. Users should be able to access the source easily.* The dialogue support is mapped to the requirement that *the system should use attractive and pleasing visualizations.*

Finally, design for autonomy, relatedness, and competence are three elements of SDT realized through personalization, navigability, and dialogue-based communications [34, 35, 38, 39]. Accordingly, for autonomy, a high level of personalization is required; therefore, *users should have various options for customizations, such as changing the app's color, setup, schedules, and behavior. The app should actively involve users, capture their preferences, and personalize interface elements, such as avatars, nicknames, etc., and let them add and modify features. The system should personalize the content and service. The recommendations should be properly personalized. The system elements should all be customizable.*

For relatedness, which states that supporting the feeling of connectedness would enhance relatedness [39], and is about supporting interactivity [38], the requirements are defined as *the app should allow sharing recommendations and have dialogue-based communication with users with first-person basis phrases. Avatar should be used to represent users.* Competence has been considered as supporting proper navigability in the system [38]. Use of intuitive tasks within the range of the user's ability would also support competence [39]. Accordingly, *the app should be easy to explore. A proper navigation map should be provided. Working with the app and its tasks should be easy and feasible for the users and provide a feeling of competence.*

In addition to the elements listed and discussed above, several individual factors were also considered, which is shown in figure 1. These factors represent characteristics of the user that are necessary to provide a holistic representation of her (or him), her (or his) states, and needs. Therefore, our health recommender system platform needs to track or estimate these values and use them for building the user profiles and, subsequently, a holistic recommender system.

4 SYSTEM PROTOTYPE AND DISCUSSION

Based on this framework, we addressed the mentioned requirements with our platform prototype in three stages: First, the intervention (i.e. recommendation item) design; second, the app design; and third, the algorithm design for personalization.

Recommendation items. Since our platform was about stress interventions, we collected and built a set ourselves as there was no established item set for stress coping interventions purposed for well-being. In this process, the relevant requirements explained above, e.g., *content* and *outcome expectations*, were fulfilled. Designed based on stress coping strategies, we categorized these interventions into eight main coping strategies and five types of interventions: physical activity; mindfulness; positive thinking; social engagement; and enjoyable activity. Each item in this set had a wide range of attributes, specifying its context-related attributes as mentioned briefly before, such as social presence, preferred time, location, and age group, effort-related attributes, such as time required and difficultness, and content-related attributes, such as its title, description, supporting materials, being either video, audio, or

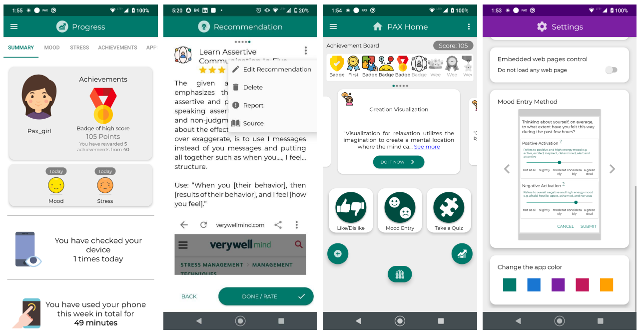

Figure 2: Screenshot of the application frontend

webpages, sources, and additional information. The item set in total contains 447 intervention items, many being micro-interventions.

The mHealth recommender system platform. Our platform is an Android-based application. The app design is where the majority of *function and interface* elements are realized in addition to some elements of *social factors*. Additionally, other requirements related to beliefs, social factors, goals, and content were realized on the app. Figure 2 provides a few screenshots of the app showing on the left, various reports that the user receives, next, the recommendation window, followed by the home screen, and the settings on the right. The platform has several functionalities and is versatile and modular enough to be used for various intervention types and health domains. It was also used for capturing individual factors of our framework listed in figure 1. In addition to the recommendation module, it has a mood and stress tracker and supports a wide range of questionnaires and self-reported instruments for building user profiles and running studies. Most such functionalities are currently schedule-based, flexible to be adjusted by users within the predefined time window by the researchers. The app also is sensor-enriched, and together with experience sampling-based functionalities, provide a comprehensive platform for holistic health recommender systems. Various user-centered design techniques, patterns, and user experience evaluations were utilized in the app design using longitudinal studies.

Recommendation Engine. Our recommendation engine has two components, one on the phone side and the main components on the server. The phone-side recommendation engine supports random presentation and post-filtering functionality for mood-aware and/or context-aware recommendations. With an already developed user profile, it also can run some algorithms purely on the phone side. For further advanced personalization and building user profiles from scratch, namely using collaborative filtering, hybrid methods, or other newly developed recommendation algorithms, we relied mainly on the recommendation engine on the server. Our modular system supports a variety of algorithms which we used to investigate proper technical approaches for building health recommender systems, in particular, and so far for mental health promotion. At the algorithm level in the recommendation engine, the requirements related to the *content* elements of our framework and *social factors* were addressed by specific algorithms and considerations. The recommendation algorithms personalize the interventions according to various inputs, such as users' input, behavior, and health profiles.

Building a health recommender system for behavior change may seem complex at first. Possibly because of this complexity, behavior change theories have been, for the most part, neglected and not mentioned in the design and development of the health recommender systems. However, the underlying theories and processes of user persuasion are critical for success and effectiveness of these systems. User persuasion in health recommender systems particularly plays an essential role in user adherence to both behavior change and system usage, which is necessary for collecting data and user preferences for personalization. The limitation of behavior change theories per se — for instance, in addressing user persuasion and personalization aspects of a mhealth recommender system — encouraged us to integrate selected components of several behavior change theories and persuasive design guidelines, into a functional framework for our purpose of building a health recommender system for mental health promotion, specifically, for coping with daily stress. We then mapped the elements of this framework into several requirements, which were subsequently realized in the platform.

The presented conceptual framework, exemplary requirements, and application based on it are offered as a use case to demonstrate the feasibility of integrating the discussed theories and principles. Such integration requires a broad effort involving the three above-mentioned stages, in addition to tracking and predicting users' states. Despite the broadness and involvement of various aspects in the health recommender system design, the integration can be minimally achieved by taking a few steps to address the relevant requirements. Being only an example use case, we don't claim this framework to be complete. Depending on the requirement of the health domain, other constructs or elements may be necessary for having a high-quality health app. We, however, consider this framework an adequate solution for stress coping and mood-aware interventions for healthy populations. This conceptual framework and the resulting requirements may also be used as a preliminary guideline for researchers and practitioners of health recommender systems. One should also note that the requirements listed here are only those derived directly for integrating behavior change theories and persuasive design principles. Therefore, other requirements, such as those related to user integration in the whole process of decision support system or recommender system design [14], user-centered design, building a research platform, and health platform, among many other aspects, are not discussed in this paper, despite being considered and implemented in the platform.

5 CONCLUSION

Integration of behavior change theories has been overlooked in health recommender systems. In this paper, using the use case of a health recommender system for mental health promotion, we explained how behavior change theories and persuasive design principles could be integrated together in the system design. Proposing a combined conceptual framework for this integration, we then mapped the elements of this framework to a set of high-level requirements. Realizing these requirements with a holistic system prototype demonstrated the realization of the proposed requirements. This conceptual framework and the resulting requirements can be used as an example and guideline for building health recommender systems in the future.

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