A Goal-Based Approach for Persuasive Health-Behaviour Recommender Systems

Wald Habets[1,*], Karin Coninx[1]

[1]Human-Computer Interaction en eHealth (Hasselt University), Hasselt, Belgium

Abstract

To enhance user acceptance and facilitate behaviour change, this paper introduces a goal-based approach for designing persuasive health-behaviour recommender systems (HRS). Current HRS often fall short in supporting behaviour change, particularly in domains like nutrition and physical activity, due to their failure to integrate behavioural theories or use of ineffective recommendation strategies. To address these challenges, we propose a conceptual design model that aligns recommendations with patients' current behaviour, short-term goals, and long-term health goals. The design model is grounded in established behaviour change theories, including the self-efficacy theory, health behaviour goal model, health belief model, self-determination theory, goal-setting theory, and feedback-intervention theory. Nine propositions are derived from these theories to guide the design of more persuasive HRS. The proposed approach emphasizes the importance of incremental, achievable goals, user autonomy, and intrinsic motivation to foster sustained behaviour change. Future work will focus on validating and refining the design model to provide a robust framework for developing effective health-behaviour recommender systems.

Keywords

Health recommender systems, Persuasive technology, Behaviour change, mHealth

1. Introduction

In current clinical practice, behaviour change is an important component of rehabilitation and prevention. For example, in cardiac rehabilitation, secondary prevention mainly involves modifying lifestyle-related risk-factors, such as stress reduction, smoking cessation, medication adherence, physical activity and dietary management [1]. This is often a multidisciplinary intervention that includes counselling, exercise prescription, dietary prescription, etc. [2]

Such behavioural change can be challenging due to its long-term nature, while limited healthcare resources often don't allow for long-term follow-up. Past research showcases mobile health initiatives and their growing potential [3], and has indicated that they aid the modification of behaviours and risk-factors in the short-term [4]. These applications may support behaviour change by enabling communications with healthcare providers, increasing motivation through persuasive techniques or gamification, providing information and guidance, and supporting dietary or activity management.

In recent years, health recommender systems (HRS) are also making their introduction to the healthcare domain. These systems leverage personalized health data to support patients and caregivers in their decision-making [5].

During the past decade, mobile health initiatives have seen a steady shift towards integrating behavioural science principals [6]. Research indicates that incorporating behaviour change techniques in internet-based interventions tends to produce better outcomes [7]. Similar calls have gone out in the domain of HRS. A scoping review by Hors-Fraile et al. concluded that HRS may be further improved by including behaviour change theories [8]. Tran et al. suggested that food recommender systems should integrate health psychology theories to stimulate users to comply with healthy eating behaviours [9].

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*Corresponding author.

wald.habets@uhasselt.be (W. Habets); karin.coninx@uhasselt.be (K. Coninx)

0000-0001-6161-9198 (W. Habets); 0000-0001-6730-3426 (K. Coninx)

In the past, attempts have been made to create (guidelines for) more persuasive recommendations. Schäfer et al. introduced a goal-based HRS that uses the Rasch-model to tailor nutritional goals to a patient's abilities [10]. Alslaity et al. found that associating persuasive strategies based on Cialdini's principles of influence [11] with recommender systems shows efficacy in impacting users' decisions [12]. However, the research mostly focuses on general recommender systems and Cialdini's principles of influence [11] are not necessarily targeted at health behaviour change. Thus, it focuses mainly on the participants' willingness to accept the recommendation, and not on the long-term effects on behaviour change.

Yet, we observe that limited attempts have been made to align HRSs with behavioural theories. Indeed, in their overview of HRS, Tran et al. list persuasiveness and personalization as open issues [13]. Instead, many HRS employ knowledge-based filtering, with an increased focus on contextual and behavioural data [6, 13, 14].

In this paper, we analyse existing behaviour change theories and introduce nine propositions to make HRS more effective in influencing user behaviour. Additionally, we present a conceptual model for goal-oriented recommendations that aligns with these propositions. The primary objective of this conceptual model is to increase the persuasiveness of recommendations, thereby enhancing users' acceptance and facilitating behaviour change. The conceptual model achieves this by aligning recommendations with patients' current behaviour and their short- and long-term goals.

2. Theoretical Background

In this section, we will outline the key behaviour change theories (BCT) informing our proposal, providing a brief description and only highlighting the aspects most relevant to our research. From these theories, we derive propositions for designing HRS.

Selection of the BCT was generally guided by three key criteria: relevance to health behaviour change, broad applicability, and theoretical foundational value. Theories primarily focused on non health related behaviours (e.g., purchasing or consumption) were excluded, so were theories tailored to highly specific contexts (e.g., smoking cessation or HIV prevention). We prioritized theories that are either foundational (contributing significantly to other BCT, e.g. self-efficacy), or are widely recognized in the design of health applications (e.g. self-determination), particularly those related to goal-setting. Finally, it must be noted that the selection is non-exhaustive, and introducing additional theories may yield additional propositions. However, BCT often overlap (e.g. self-efficacy appears across multiple frameworks [15]), thus many theories may yield similar propositions.

2.1. Self-Efficacy Theory

The self-efficacy theory [16] posits that behaviour change depends on a person's confidence in their ability to enact that change (which is distinct from understanding that certain behaviour will produce the desired outcome). For instance, someone may know that reducing caloric intake promotes weight loss but doubt their capacity to do so.

The theory identifies four sources of information that influence the perception of self-efficacy. The strongest source is (1) performance accomplishments: prior successes in performing the target behaviour strengthen self-efficacy expectations, while prior failures undermine them. Similarly, self-efficacy expectations can be strengthened by (2) vicarious experiences (e.g., observing others successfully perform the behaviour, or attempt to do so without adverse effects). However, this is usually a weaker source than performance accomplishments. (3) Verbal persuasion and suggestion may also strengthen self-efficacy expectations, but are again weaker sources and can easily be offset by unsuccessful coping attempts. Finally, (4) emotional arousal, such as anxiety and stress, could undermine self-efficacy expectations and performance of behaviours.

Proposition 1. *Health recommender systems should recommend items that are within a patient's perceived self-efficacy.*

2.2. Health Belief Model

According to the health belief model [17], people's likelihood of undertaking preventive action for certain health risk behaviours is depended on four factors.

The first two factors are (1) perceived susceptibility to, and (2) severity of the disease. These shape a person's perception of the overall threat. Susceptibility describes the perceived risk of contracting a condition, while severity is judged by the emotional impact and the anticipated difficulties it may cause (relating to health, professional, social... consequences). Both aspects are at least partially dependent on knowledge. For example, a person with cardiovascular disease may be both obese and suffer from severely elevated blood pressure, yet dismiss the latter's seriousness, or believe it to be a consequence of their weight. Recommending strategies or items that target blood pressure may be swiftly rejected by that person.

Proposition 2. *Health recommender systems should primarily focus on recommendations where a person's perceived susceptibility or severity is high.*

The last two factors are a person's (3) perceived benefits of, and (4) barriers to taking action. A person's decision to accept a certain course of action depends on their perceived effectiveness of the action; e.g., do they believe the action will reduce susceptibility or severity. However, when a recommended action is experienced as inconvenient, expensive, unpleasant, painful, etc. these aspects act as barriers. For instance, a patient may skip recommended exercises if they cause pain, require unavailable equipment, or if it is unclear how it will aid their condition.

Proposition 3. *It should be clear to a patient why certain recommendations are provided and how they might benefit them.*

2.3. Health Behaviour Goal Model

The health behaviour goal model [18] generally overlaps with the Health Belief Model (see Section 2.2). However, it adds that behaviour change is more likely to occur if it is compatible with a person's personal goal structure, which is typically separated into abstract higher-order goals and concrete lower-order goals that contribute to attaining the former goals. On the other hand, advancement toward a lower-order goal is more likely if this goal is in line with higher-order goals.

Proposition 4. *Health recommender systems should align their output with a patient's personal goal structure.*

Furthermore, the model distinguishes between approach goals and avoidance goals. It states that when targeted health behaviour involves adoption of a new behaviour (e.g., start exercising), it is more likely to be attained than when it involves cessation.

Proposition 5. *Health recommender systems should aim to recommend items that promote adoption of a new behaviour (or replacement of an old one) rather than avoidance of an existing one.*

It is important to note the distinction between the Health Behaviour Goal Model and the Health Belief Model, as a certain target behaviour might occur in a person's personal goal structure, but may have a low likelihood of undertaking preventive action.

2.4. Self-determination theory

The self-determination theory [19] is a meta-theory consisting of five sub-theories. It identifies three fundamental psychological needs: (1) autonomy, referring to the need to have control over one's actions and decisions; (2) competence, the need to feel effective and capable (i.e., self-efficacy); and (3) relatedness, the need to feel connected to others. The theory states that extrinsically motivated people can still feel autonomous when the external regulation of behaviour is internalized by the person.

Proposition 6. *Health recommender systems should provide mechanisms for patients to influence the recommendations and thus create a perception of autonomy.*

The self-determination theory further distinguishes between three types of motivation: amotivation, extrinsic and intrinsic motivation. The theory suggests that intrinsic motivation is promoted by autonomous factors and is generally more sustainable. Therefore, the more autonomous a person's motivation is, the more likely they initiate and maintain the behaviour. Additionally, when a context satisfies the three psychological needs, it cultivates intrinsic motivation.

Proposition 7. *Health recommender systems should capitalize on intrinsic motivation rather than depending on extrinsic motivation.*

2.5. Goal-setting theory

The goal-setting theory [20, 21] describes the various mechanisms through which goals can influence behaviour. It states that goals can have a directive function, diverting attention and effort towards goal-relevant activities. The theory further describes that goal performance is influenced by the difficulty and specificity of the goal. In particular, difficult and specific goals can trigger better performance. Additionally, commitment to a goal is influenced by the patient's perceived importance of that goal, their self-efficacy and the complexity of the task. Performance may decrease for complex goals, as they may require the acquisition of new skills or knowledge. Proximal goals (that are achievable in the short term, rather than difficult distal goals) may increase performance in complex or dynamic situations.

Proposition 8. *Health recommender systems that recommend goals to patients, should aim to recommend specific and proximal goals that are difficult, but within reasonable bounds of a person's self-efficacy.*

Finally, assigned goals may be influenced by their alignment to personal goals and external incentives may further influence performance.

2.6. The Feedback-Intervention Theory

The feedback-intervention theory [22] describes the impact of feedback on behaviour and future performance. Feedback is obtained by comparing performance to a predefined standard (or goal). It is positive when performance matches or exceeds the standard: leading to reduced effort, since that standard is already met, or, alternatively, indicating opportunities for further self-enhancement, which could trigger an increase in the standard.

Feedback is negative when performance does not meet the standard. In such case, a person may attempt to increase performance, or shift their attention to task learning or meta-task processes. The former consists of forming and testing hypothesis (for improving performance). The later may shift attention to activities that boost the patient's self-image, and potentially lower the standard (to match the current feedback), reject the feedback, or reject the standard altogether (e.g., abandoning the goal).

The core principle behind the feedback intervention theory is that negative feedback signs are more likely to prompt increased effort for the task, and people become motivated to remove the discrepancy.

Proposition 9. *Health recommender systems should recommend items that aid patients in reducing negative discrepancies between performance and the standard.*

3. A Goal-based approach for Persuasive Health-Behaviour Recommender Systems

To align recommendations with the propositions stated above, we propose a goal-based approach for persuasive HRS, drawing inspiration from the health behaviour goal model [18]. Our model posits that specific item recommendations (such as healthy meals, products, or exercises) should consider a

patient's current behaviour, short- and long-term goals. Short-term goals similarly align with current behaviour and long-term goals. The outlines of this conceptual model to guide the design process for persuasive HRS are visualized in Figure 1.

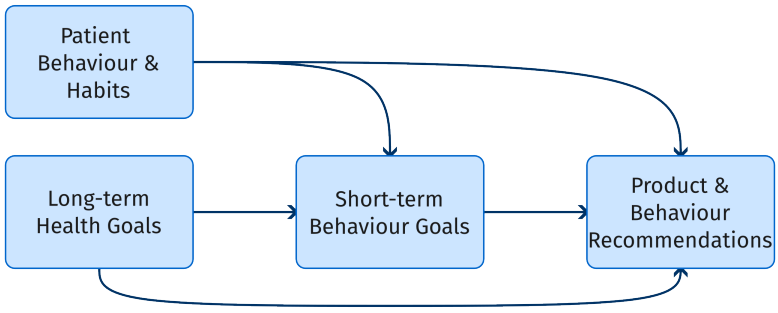

Figure 1: A visual representation of the goal-based approach for recommender systems.

The core idea is that aligning HRS-output with a patient's personal goal structure will yield better acceptance of its recommendations (Proposition 4). In this model, "Product & Behavioural Recommendations" represent traditional recommender items, such as recipes, food products, physical or mindfulness exercises, etc. "Long-term health goals" are goals such as losing weight, lowering blood pressure, stress reduction, etc, which are generally not very actionable on their own. "Short-term behaviour goals" are items such as eating 2 pieces of fruit each day, daily step goals, or getting a minimum daily number of hours of sleep. These goals are more actionable and act as a bridge between long-term goals and specific recommendation items. Letting patients define their long-term health goals enhances their sense of autonomy (Proposition 6) by giving them control over the system's output. Similarly, offering a choice among system-generated short-term goals further supports autonomy.

While Proposition 7 is not specifically addressed, it may be fulfilled by satisfying psychological needs such as autonomy (Proposition 6) and competence (Proposition 1). To support Proposition 5, HRS may focus on promoting new or alternative positive behaviours (akin to implementation intentions [23]), rather than specifically forbid certain behaviour.

3.1. Patient Behaviour and Habits

When a system's input relies solely on patient preferences, and disregards their behaviour, it may risk recommending items for which the patient's behaviour already matches the standard. Therefore, in order to fulfil Proposition 9, we argue that HRS should analyse a patient's behaviour, and thus be, to some degree, context-aware. Indeed, the collecting behavioural data to provide personalized mHealth experiences is not new [13], nor is the concept of context-aware recommender systems [6].

However, to achieve Proposition 1 and 8, HRS must do more than identifying the areas where the user is performing poorly. Since the patient is using external tools, they may have a history of failed attempts, the gap between their current behaviour and the standard may be large, and expectations of self-efficacy are likely low. Therefore, we argue that recommended items should match the patient's self-efficacy rather than the standard, and instead incrementally nudge a patient towards that standard.

3.2. Long-term Health goals

As is stated by Ekstrand et al., eliciting user preferences has potential to enable more empowering experiences, specifically regarding behaviour change. Similarly, we argue that in order to achieve proposition 2, the system needs to have an understanding of the patient's health beliefs (and higher-order goals). While consensus states that using implicit feedback for recommendations is often better

than explicit feedback, these insights were mostly attained in the field of multimedia or e-commerce, rather than long-term health behaviour change. Indeed, a recommendation may be medically sound, but may still be misaligned with a patient's priorities. For example, suggesting low-sodium products to a patient with obesity and high blood pressure that is currently focussed on weight loss, may risk rejection. We thus propose that patients should be able to explicitly indicate their long-term health goals to a HRS.

3.3. Short-term Behaviour goals

Traditional HRS recommendations (e.g., recipes, exercises) may lack clarity in purpose and impact. It may be difficult to infer a clear behavioural standard from them, and they often lack direct feedback when accepted. Aligning recommendations to short-term goals may bridge these gaps in three ways. (1) Short-term goals may make long-term goals more actionable (e.g. maximum weekly caloric consumption VS "weight loss"). (2) Suggested items may be linked to short-term goals, which clarifies their health effects and alignment with the patient's health beliefs (Proposition 3). (3) Short-term goals give a sense of tangible progress and achievement may boost self-efficacy (Proposition 1). Preferably these goals are generated from long-term health goals, focusing only on areas needing improvement (Proposition 9), and designed as incremental steps toward standards (e.g., gradually increasing steps from 1,000 to 10,000/day) to support Propositions 1 and 8.

4. Conclusion

This paper analysed established behaviour change theories and introduced nine propositions for more persuasive health recommender systems. Additionally, it introduced a conceptual model for goal-oriented recommendations that adheres to these propositions. The aim of this model is to increase the persuasiveness of recommendations and consequently users' perceived acceptance of those recommendations with the aim of facilitating behaviour change. The model relies on aligning recommendations with patients' current behaviour, short- and long-term goals. At the time of writing, efforts are ongoing to use the model to guide the design of an application for dietary management. Future work will validate and fine-tune the model.

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Declaration on Generative AI

During the preparation of this work, the author(s) used Mistral in order to: Paraphrase and reword. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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