RecSys Challenges in achieving sustainable eating habits

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ABSTRACT

Most food recommender systems successfully fit one's current appetite for different food items. However, one's current preferences (e.g. I like high-carb foods) may conflict with a new dietary goal (e.g. I want to minimize my carb intake), which can be detrimental to recommendation quality over time. Moreover, choices in the short-term might not lead to behavioral change in the longer-term. This short position paper outlines a few challenges related to changing habits, and reports a small analysis to show how the Rasch model could complement CF-based approaches in research on sustainable eating habits.

CCS CONCEPTS

• Information Systems → Decision Support Systems
• Human-centered Computing → User Studies

KEYWORDS

Behavioral Change; User Experience; Rasch Model; Sustainability; Eating habits

1 Introduction

Recent data-driven studies have addressed the topic of sustainable eating [1, 13]. Whereas some users employ recommender systems to acquire recipes that fit their appetite or contain certain nutrients [9, 12], 'sustainable eaters' have a dual goal of fine dining at little environmental costs. To date, research has focused on algorithmic development (e.g. using CF-based RecSys), an approach that has proven its merit in domains where there is little difference between items with regard to the behavioral thresholds to adopt or choose them, such as in movie recommender systems. However, we argue that simply presenting items that resonate with one's current habits and preferences might not be effective in the long run [7].

2 Key challenges

A number of recommender domains show that presenting appropriate recommendations is only the first step of adoption [3, 4, 13]. Although food, health, and energy recommender systems present items that should ultimately result in behavioral change [3, 8, 10], there has been little work on how behavioral change can be achieved in the longer run [1, 3]. Most studies are limited to decision-making within an interface, while only few studies monitor users over a longer time period [9]. However, straightforward, one-time web studies cannot tackle questions that concern changing habits, as this involves complex lifestyle aspects as social practices [2, 11]. Moreover, energy intervention studies in a persuasion or HCI context show that treatment effects can diminish quickly and may depend on the type of incentives provided [2], as superficial interface changes and financial rewards only have short-lived effects.

Another challenge is that one's current habits and preferences may differ from one's behavioral goals, such as when taking up a new diet. Traditional algorithms may simply reinforce one's current behaviors (e.g. 'perhaps you want a bag of crisps'), rather than allowing users to discover new items that might have a lower predictive accuracy, since they are at odds with one's current habits (e.g. recommending low-calorie food). Although tags may be able helpful for discovery of novel items [1], recommender systems might need to forgo on their predictive accuracy and focus on listening to users with regard to goal-setting [3]. In addition, how decision psychology, persuasion and interface design can effectively complement such algorithms to spur behavior change is currently an open question [12].

3 Proposed research on changing habits

Recent studies show key differences in the behavioral difficulty between various food items or energy-saving measures and their resulting attractiveness [9, 10]. Whereas it is easy to achieve a small behavioral change (e.g. eating two cookies a day instead of four), moving away from one's current behavior is tricky. In a similar vein, behaviors related to medication adherence seem to vary in their execution difficulty [6], showing that fully sticking to one's prescriptions is too hard for most patients.

To take behavioral difficulty into account, Schäfer and Willemsen [9] and Starke et al. [10] have used the psychometric Rasch model to conceptualize nutrient intake and energy conservation as one-dimensional constructs. They show that one's motivation to perform a behavior (referred to as: ability or attitude [5]) becomes apparent through the behavioral items one already engages in. This results in high adoption probabilities for items that are commonly performed (i.e. have a low behavioral difficulty, 'popular'), while such probabilities are low for obscure items (e.g. installing solar PV or optimizing fiber intake) [9, 10].

The interplay between a user's ability and item difficulty allows a recommender system to sketch the path towards behavioral change, particularly for the dual behavioral goal of

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sustainable eating. The Rasch model suggests that it might be more effective to take small steps over time, that slowly increase in behavioral difficulty and continuously match a user's ability [5, 11]. This would differ from CF-based approaches, as it does not look users that have similar 'bad' habits, but relies on users that can lead the way to habit improvement.

To exemplify the difference between a Rasch-based approach and CF-based approaches, we analyzed 7,551 dichotomous self-reports ('yes' or 'no') of 304 users to 134 energy-saving behaviors, including food measures. We predicted Top-10 recommendation sets for both approaches. Rasch would predict the highest score for measures whose behavioral costs match a user's ability. For the CF-based approach, we trained a Rating Prediction model in MyMediaLite, using matrix factorization and 5-fold cross-validation, noting that the CF model was not very accurate (RMSE = 0.49 under dichotomous data).

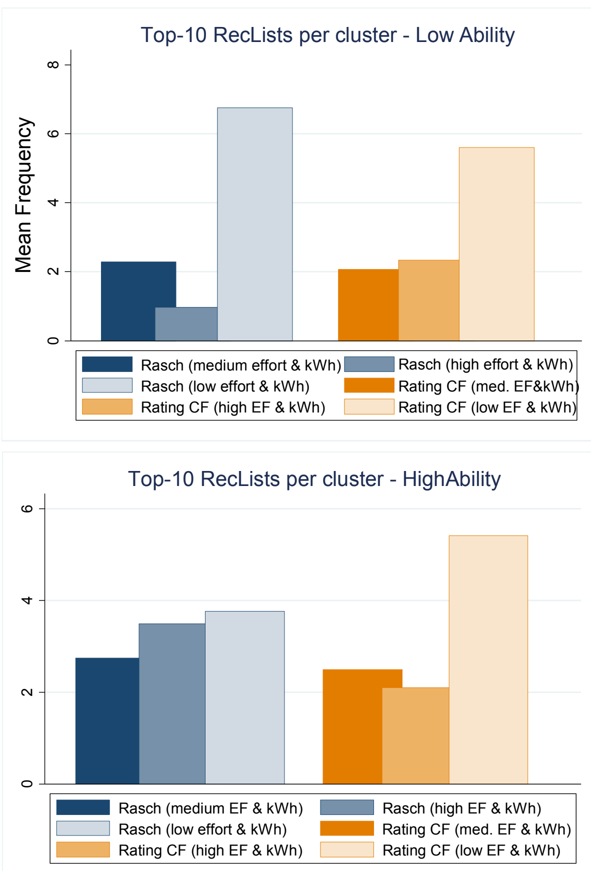

Figure 1. Rasch-based and Rating-based recommendation sets for low-ability (top) and high-ability users (bottom), divided among three clusters of energy-saving measures.

Figure 1 shows the results for users with either a low (at the top) or high ability (at the bottom). Both graphs discern between three measure clusters (a combination of high/low effort and kWh savings). Figure 1 shows that Rating-based CF is not sensitive to changes in a user's ability or motivation to engage in sustainable behavior, as both graphs show similar results. In contrast, the Rasch-based set changes from mostly low-effort measures for low-ability users, to a mixed recommendation set for high-ability users, including high kWh savings.

4 Conclusion

The Rasch model used in Figure 1 is one example of how an algorithm can consider changes in habits over predictive accuracy [cf. 7]. However, it does not address the question how a user can effectively change his or her habits. The recommender community should conduct more intervention studies over a longer-term period, by not only focusing on optimizing the recommender's predictive accuracy, but also by monitoring the user's behavior. For example, while historical data could point out one's current habits, other methods of elicitation should reveal one's behavioral goals. A useful method would be to conduct more studies using mobile devices, as it would allow researchers to have user dialogs at multiple time points.

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