Preface: Opportunities and Issues of Persuasive Recommender Systems*

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Abstract

This volume includes the papers presented at BehavRec '23 International Workshop held in Singapore in conjunction with ACM RecSys '23 International Conference. The workshop aimed to discuss open problems, challenges, and innovative research approaches in the area of persuasive and behavior change recommender systems.

Keywords

Behavior change, persuasive technologies, recommender systems, self-tracking

1. Introduction

Behavior change systems, also known as persuasive technologies, are interactive tools intentionally designed to encourage people to modify their own behaviors and habits. They can be used in a variety of domains, such as health [1], environmental sustainability [2, 3], and education [4]. In the last few years, this research line has increasingly attracted interest from both practitioners and researchers due to the increasing availability of users' personal data [5].

According to a recent claim by IBM, 90 percent of the data available today have been created in the last two years. This exponential growth of digital information has given new life to research on persuasive technologies, allowing designers to deliver extremely personalized behavioral interventions, potentially based on a variety of users' psychological, physiological, and behavioral data [6, 7].

It therefore comes as no surprise that the interest in behavior change recommender systems, which provide users with personalized recommendations on how to modify their behavior, has

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considerably increased in recent years [8, 9, 1, 10]. In fact, in this landscape, novel opportunities for providing "persuasive" recommendations arise [11, 12]. Recommender systems can now exploit data about eating habits, medical records, physiological parameters, mental states, etc. [13, 14, 15], which can be collected by ubiquitous computing technologies, to deliver suggestions anywhere at any time through different communication channels (e.g., leveraging natural language processing) and different devices (e.g., wearable and mobile devices).

However, behavior change is a complex research field, as modifying behavior is extremely difficult and often the intervention fails for lack of engagement or simply because people relapse into previous habits. Moreover, behavior change requires consideration of extremely idiosyncratic factors that are peculiar for a specific individual, such as her objectives, motivations, risk factors, and preferences [16]: in this sense, recommender systems exploiting the user's personal data could provide tailored suggestions that may increase the likelihood of the effectiveness of the intervention [17]. On the other hand, behavior change recommender systems are more complex than other kinds of recommenders, since they have to consider multiple contextual factors and incorporate components for monitoring user behavior, considering her preferences to tailor recommendations, and keeping her engaged to encourage adherence to the intervention [17].

For this, many new challenges and open issues arise: for example, we still do not know what kind of theories we should use to ground the design of persuasive recommendations [6, 9, 16], what kind of communication channels or methods are more effective in delivering them (e.g., boosting vs nudging [18, 19]), what contextual and "life" aspects should be taken into account in designing the intervention [20, 16], and how the system can sustain the person's motivation to keep her pursue her behavior change attempts [21]. Moreover, persuasive use of personalization and recommendations yield ethical concerns about behavior engineering, which may hinder human autonomy and well-being [22, 21]. Therefore, in addition to the many opportunities that the current technological landscape provides for the design of novel behavior change recommender systems, it becomes urgent to discuss the many challenges that they will soon face.

Some questions that still need to be answered are: What kind of personal data should be used to design recommendations? How such recommendations should be delivered? What kind of theory is more suitable to inform their design? How can we support the users' motivation and help them sustain the desired behavior in the long term? What contextual factors may affect the effectiveness of the recommendations and should be considered in design?

To this aim, topics of interests that need for further exploration are: 1) Different types of behavior change recommender systems and their peculiarities, like for health, wellness, safety, sustainability, etc. 2) User Interfaces for behavior change recommender systems, like visual interfaces, context-aware interfaces, ubiquitous, wearable and mobile interfaces, as well as conversational interfaces 3) New approaches to designing and delivering behavior change recommendations: Controllability, transparency, and explainability, argumentation-aware recommendation, culture-aware recommendation, context-aware recommendation 4) How to balance the cost and benefit of behavior change recommender systems, as well as challenges and limitations of implementing them 4) Ethics, Privacy, and theories: Frameworks and models for developing personalized persuasive technology, as well as models for developing ethical and privacy-sensitive behavior change recommender systems - 5) Evaluation: Long-term evaluation and evidence of long-term effects of behavior change recommender systems.

2. Papers presented at the workshop

The workshop addressed the aforementioned topics of interest. The organizing committee received eight papers, and six papers were accepted into the workshop proceedings. A short summary of each contribution is described below.

In “Towards an adaptive Behavior Change Game based on user-tailored and context-aware interventions”, Villata et al. propose to go beyond the one-size-fits-all approach often adopted in persuasive technologies, as well as to consider the meanings that users may attribute to the process of behavior change in the design process. They present a mobile-based adaptive Behavior Change Game that promotes positive habits by personalizing its gameplay on the basis of a comprehensive user model, containing information about the user’s habits, behavior and context collected through smart devices. The adaptation is performed for both the game content and interface, mainly changing, hiding or showing specific game design elements.

In “FitNExT: Leveraging Transformers with Context-Augmented Start Tokens to Generate Recommendations for New Users in Connected Fitness at Peloton”, Yoshida and Meetei introduce the Fitness New user Experience Transformer (FitNExT) model, which combines the strength of transformer architecture in understanding sequential data with an innovative approach for contextualizing the start of a member’s fitness journey. Then, they use the outputs of this model to display rows of recommendations to ease new users into their fitness routine.

In “Contextual Bandits for Hyper-Personalization based on User Behavior in Local Domain”, Kim et al. propose an empirical hyper-personalization problem reflecting user behavior in local domain, that is considered as contextual bandit problem with well-configured recommender system ensemble. The authors empirically introduce how to deal with insufficient user feedback in service by using feedback of other interfaces, how to define user contexts and user features in local domain, and how to ensemble contextual bandits for optimization.

In “Towards Adaptive and Personalised Recommendation for Healthy Food Promotion”, Nurbakova et al. present an adaptive persuasive system that exploits and extends the idea of a constrained question answering (QA) system over a knowledge graph proposed by Chen et al. They introduce the way to model personalised challenges and additional constraints allowing to handle meal plans.

In “Understanding How News Recommender Systems Influence Selective Exposure”, Seddik et al. attempt to ask the following research question: To what extent can News recommender systems influence the selective exposure behavior of news users? The authors present a preregistered online experiment to empirically test the impact of structural factors on selective exposure, by tracking users’ behavior on a news website equipped with two different versions of custom-made NRSs that are designed to nudge users towards increased or decreased selective exposure to like-minded or cross-cutting news.

Finally, in “Using persuasive strategies inside app distribution platforms to warn users about manipulative design used by applications” Babaei and Vassileva investigate the impact of employing persuasive strategies in mobile app distribution platforms to inform users about the manipulative design used by mobile applications. They present the design of a study with three groups, where they aim to measure the attitudes and intentions of the participants toward manipulative design using a questionnaire before and after the participants have been presented with an intervention.

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