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Research directions in recommender systems for health and well-being

A Preface to the Special Issue

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Abstract
Recommender systems have been put to use in the entertainment and e-commerce domains for decades, and in these decades, recommender systems have grown and matured into reliable and ubiquitous systems in today's digital landscape. Relying on this maturity, the application of recommender systems for health and well-being has seen a rise in recent years, paving the way for tailored and personalized systems that support caretakers, caregivers, and other users in the health domain. In this introduction, we give a brief overview of the stakes, the requirements, and the possibilities that recommender systems for health and well-being bring.

Keywords Health recommender system · Health-aware computing · Health-aware information systems · Recommender systems · Well-being

1 Introduction

Information systems developed with the purpose of keeping us healthy and increasing our general well-being have grown in popularity and adoption in the last few years. Recommender systems have an integral part in these systems attempting to improve

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our awareness, understanding, and behavior regarding our own health and general well-being. Popular as they are, these application areas bring new challenges into the recommender systems community, e.g., recommendations that influence the health status of a patient may have legal consequences and, as such, often need to involve a human in the loop to make sure the recommendations provided are sound. Aspects focusing on liability, user trust, as well as privacy are key factors in these systems as well.

This special issue is a follow-up on the series of Workshops on Health Recommender Systems (HealthRecSys) co-located with ACM RecSys (2016–2020). The HealthRecSys workshop has been discussing various domains in which recommender systems can improve well-being, healthcare, and self-awareness (Said et al. 2020; Elsweiler et al. 2019, 2018, 2017, 2016). Recommender systems for health can play a significant role in assisting professionals and individuals in clinical and non-clinical applications. The use of recommender systems in the health domain also gives a new dimension to the current discussions and challenges of the recommender system, such as involving users in the recommendation process and the need to account for the essential aspects of trust and privacy (Schäfer et al. 2017).

2 History and trends

Recommender systems were defined in the current, modern context in 1990 (Karlgren 1990). According to the ACM Digital Library, the first "health recommender systems" papers appeared within a few years (Yount et al. 1991; Goldberg et al. 1992). These early studies were pioneering the way for the recommender systems in the health domain to come. In these early days of the Web and online information systems, research focused on the exploration and development of Web technologies rather than on specific application domains. However, as the Web 2.0 and beyond (Anderson 2007) came into being, recommender systems became ever more so present in online systems and began to appear in health-related systems (Mankoff et al. 2002; Cawsey et al. 2007; Turoff and Hiltz 2008). As the Web has matured and developed, so have recommender systems, and specifically recommender system applications in health (Alhijawi et al. 2022). Recent applications include drug recommendation (Zheng et al. 2022), diabetes treatment recommendation (Oh et al. 2022), cancer drug response prediction (Wang et al. 2022), and recommendations for cancer patients and caregivers (Rahdari et al. 2022), to name a few.

Considering how the recommender systems field has changed over the years, attempting to identify trends specifically in health is not an easy task. However, given the recent literature, it seems health recommenders have entered into more complex and critical domains where the stakes are higher, and the stakeholders are different. Health recommender systems are no longer provisional attempts to bring recommendations into a new research field. They are firmly embedded in the research in disciplines where health and well-being are fundamental parts. In 2017, Schäfer et al. (2017) lined out a "vision of the future" [of health recommender systems], where ethics, domain modeling, user interaction, and privacy were listed as key challenges that needed to be overcome before health recommender could become viable. Given the recent literature, it appears as if the vision is no longer a future—it is our present.

3 Papers in this issue

This special issue contains seven research papers ranging from lifestyle advice like physical activity and nutrition to medical advice like hearing aids, drug interactions, or therapy decisions. Below we summarize the contributions of each accepted paper in this special issue:

Recommendations for marathon runners: on the application of recommender systems and machine learning to support recreational marathon runners In this paper, Smyth et al. give an overview of different studies concerning the use of recommender systems to help runners train for a marathon, including guidance on the run itself and recovery times (Smyth et al. 2021). The studies are based on data collected by mobile and wearable fitness trackers. The presented application is mainly targeted at recreational runners that want to improve their activities by training more effectively and more safely. The paper captures different use cases based on large-scale, real-world datasets, such as determining the runner's fitness level, recommending training activities, predicting the risk for injuries, and helping to improve the pacing during the run.

Fair performance-based user recommendation in eCoaching systems In this paper, Boratto et al. study a system that supports coaches in keeping track of their coachees by applying fair recommendations on where to invest their time at the moment (Boratto et al. 2022). This support should be prioritized by potential health implications and the need for support on the coachee side. The use case of this recommender system is an eCoach for runners. In addition to providing accurate coachee recommendations, the paper focuses on guaranteeing fair exposure in the ranking to secure equal opportunities for all coachees. This fairness is provided by a re-ranking algorithm on top of the one assessing recent low performances in running activities. The algorithms are tested on data from an eCoach platform and provide good standard metrics while still providing fair exposure to users in different groups.

EvoRecSys: evolutionary framework for health and well-being recommender systems In this paper, Alcaraz-Herrera et al. use an evolutionary algorithm to generate personalized bundles combining meal and exercise advice as a multi-objective optimization problem (Alcaraz-Herrera et al. 2022). Their system is based on a proposed framework architecture that captures the relationship between multiple well-being dimensions in bundled items with dynamic properties. These bundles are then recommended based on a combination of the dimensions of user preferences, needs, and well-being goals. Their proposed framework supports models where activity and nutritional needs go hand in hand, such as for chronic diseases or for athletes. Their study shows the first evidence of using genetic algorithms as the core technique of a health recommender system.

Effects and challenges of using a nutrition assistance system: results of a long-term mixed-method study In this paper, Hauptmann et al. study a personalized nutrition recommender system embedded in a mobile nutrition application over the course of 2–3 months with 34 participants (Hauptmann et al. 2021). Besides recommendations based on individual dietary behavior, phenotype, and preferences, the application offers visual feedback and explanations to give the user a better understanding of the underlying system. They report positive results for changes in nutrition behavior but also observe dropout in the system interactions and a preference for visual feedback over recommendations. They interview participants about their system perception and detect limitations of the recommendations due to a lack of diversity over time, trust, and operationalizability in daily life.

Measuring and modeling context-dependent preferences for hearing aid settings In this paper, Pasta et al. study the feasibility of user-adaptive hearing aids considering both individual and contextual differences (Pasta et al. 2022). They use objective (sound pressure level, signal-to-noise ratio) and subjective (listening environment, listening intention) contextual data to optimize recommendations of the most relevant parameters and intervention levels of three audiological parameters (noise reduction, brightness, soft gain). Their results highlight that contextual data significantly improved predictions of participants' explicit and implicit level preferences and their listening experience. Their work on the proposed mixed-effects model for individual users could also be expanded to predictions on a group level by including relevant user features.

Safe, effective, and explainable drug recommendation based on medical data integration In this paper, Symeonidis et al. combine both synergistic and adverse drug–drug interaction (DDI) knowledge graphs to recommend safe and explainable medications (Symeonidis et al. 2022). They combine electronic health record (EHR) graph data containing patient, disease, therapy, and drug information with these DDI graphs to improve the efficacy of the patient's therapy and/or minimize the toxicity and side effects. Besides providing medication candidates or substitutes, the authors used meta-paths in the graph to provide the physicians with robust explanations alongside each drug recommendation. Finally, they run experiments with three real-life medical data sets and show their achieved improvement over the baseline algorithm for the MIMIC III data set.

A pharmaceutical therapy recommender system enabling shared decision-making In this paper, Gräßer et al. study a clinical decision support systems (CDSSs) providing individualized pharmaceutical therapy recommendations to physicians and patients (Gräßer et al. 2021). The authors propose a neighborhood-based collaborative filter (CF) algorithm using similarity measures, which automatically adapt to attribute weights and data distribution in the patient data. This is achieved using the two supervised methods RBA and LMNN metric learning. The paper additionally showcases a user-friendly prototype intended to graphically facilitate explainable recommendations and provide evidence-based information tailored to a target patient, which in turn facilitates a shared decision-making process between physicians and patients.

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