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# User Models for Recommendation Systems

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## ABSTRACT

Currently, a user model or a representation of the user is used to recommend, personalize, predict, and manage inference in different recommender systems. Now, all the necessary user information is scattered. This document presents a systematic study to identify all the user information that recommendation systems use, represented or not by means of a model. This searching is important because it identifies the different data sources where user models are analyzed, and attributes and forms of user interaction are identified. The results presented are very useful for structuring a generalized user model.

**Keywords:** User model, User modeling, User's model

## INTRODUCTION

Systematic review of the literature means identifying, evaluating, and interpreting all the relevant research available for a particular research question, topic area, or phenomenon of interest (Keele, 2007). A systematic literature review system is summarized in three main phases: planning the review, conducting the review, and reporting the review (Campoverde-Molina et al., 2020).

## SYSTEMATIC REVIEW PROCESS

The main research question is: **what are the characteristics and structure for the user model?**

### Sources Selection

The search is carried out in four databases of research publications: a) SCOPUS, Scopus is the largest database of citations and abstracts of peer-reviewed literature. It offers a comprehensive overview of global research output. b) ACM Digital Library ACM (DL) is the world's most comprehensive Library of full-text articles and bibliographic literature covering computing and information technology. c) IEEE Xplore It is a digital research library for the discovery and access to journal articles, conference proceedings, technical standards and related materials in computer science, electrical and electronic engineering, and related fields. d) Web of Science (WOS) platform with bibliographic information databases and information analysis resources that

 

allow evaluation and analysis of research performance. Its content is multidisciplinary and provides information of a high academic and scientific level.

### Parameter Definition

The search parameters represent:

- *Definition of used terms*.
  - Chain1: (User model OR user modeling OR user modelling)
  - Chain2: (User model OR User modeling) AND (Recommender system OR Recommendation system)
- *Place in the document where the terms are searched:* To find the most items. Terms are searched for anywhere in the document.
- *The years of publication:* The period from the year 2010 to the year 2020 has been restricted.
- *Types of articles:* Articles in conferences and journals are considered. Books, technical reports, or any other type of publication are not considered.
- *Language:* English strings have been specified to specifically search for documents in this language.

### Relevance Determination

For the presentation of results, the articles in each source are summarized for each year. If the publications are included or indexed in more than one source, duplications will be eliminated, therefore, the number of articles reviewed per year may be less than the number of articles reported. The content analysis is carried out manually to observe the required topics and their contribution to the context. Articles not important to the object of the investigation are discarded.

## SYSTEMATIC REVIEW RESULTS

Applying the steps established for the systematic review process, the following results are obtained. Table 1 shows the articles found with the search string 1, and Table 2 shows the articles found with the search string 2. Articles are included that describe the different ways of generating user models, either considering the description of their attributes or techniques that are important for the definition of the model. The articles selected for each year are found in the Table 3.

## FOUND TRENDS

For Bakalov (Bakalov et al., 2013) the user model is represented by interests that are represented in a concept model, stores the exact value of the degree of interest in a scientific topic. Inzunza (Inzunza and Licea, 2018), Musto (Musto et al., 2018) Biamino (Biamino and Cena, 2011) Wang (Wang et al., 2010), (JIn et al., 2017) Coleho (Coleho et al., 2010) apply, Demographic characteristics: personal information such as name, nickname, height, weight.

**Table 1.** Number of items found when applying string 1.

| Source | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **ACM** | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | **3** |
| **SCOPUS** | 3 | 3 | 2 | 2 | 4 | 0 | 5 | 5 | 4 | 3 | 0 | **31** |
| **WOS** | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | **5** |
| **IEEE** | 1 | 0 | 0 | 0 | 1 | 2 | 1 | 1 | 1 | 0 | 0 | **7** |
| **Total** | **4** | **3** | **2** | **2** | **6** | **4** | **7** | **7** | **6** | **4** | **1** | **46** |

**Table 2.** Number of items found when applying string 2.

| Source | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **ACM** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **0** |
| **SCOPUS** | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | **5** |
| **WOS** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **0** |
| **IEEE** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **0** |
| **Total** | **1** | **1** | **0** | **0** | **1** | **1** | **0** | **0** | **1** | **0** | **0** | **5** |

**Table 3.** Selected articles by year.

| Año | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Number of articles** | 5 | 4 | 2 | 2 | 7 | 5 | 7 | 7 | 8 | 4 | 1 | 52 |

Physical states: o physiological data of the person, such as heart assessment, sleep quality, keywords, stereotypes, and other information requested from the user etc., disabilities. Psychological aspects, such as the user's personality or empathy. Interests and preferences. Affects: mood, emotions. Knowledge and objectives: What the user know and the objectives. User Connections and Relationships. Contacts (address, social network), Context information, Computing (software, hardware, networks), resources, location (physical - coordinates and address- and digital), time (season, time of day, type of day of the week), physical condition (weather, noise, brightness), and social relationships. Activity Information and Item Information: (Video, book, audio etc.). Dong (Dong et al., 2017), compare demographic user profiles, determine that young people are more active than older people. Normally people interact with people and similar age. That is, they analyze and compare demographic profiles of users on social networks.

Bogina (Bogina, 2017), studies temporal aspects of the user model. The goal is for the user model to continually adapt to new information available from the user. It proposes to detect and analyze the change of your interests, eliminate the included noise and memory usage.

Cena (Cena et al., 2016), performs an analysis of the data sources for the user model that contains data from the daily life of a person, where the view of the user's context becomes relevant. They raise the user model not only from digital data, but from the use of ubiquitous technologies. Among the sensors proposed for the observation of user behavior are GPS, sensors,

smart vision, smartphones, smart devices. Ubiquitous technology will help to observe user behavior and actions in the real world, such as movements, tasks, recurring and repetitive habits. They could help determine sleeping patterns, eating patterns, levels of sedentary lifestyle, activity levels, use of media, etc. Likewise, the physical and mental states of the user, obtain them by tracking the user. From mobile devices, for example, blood pressure, temperature, glucose level, heart rate, etc. as well as persistent characteristics such as chronic diseases, relevant problems, hearing, movement, etc. The social relationships that the user has daily, obtained from the so-called daily, weekly meetings. The psychological record can be recorded from biosensors embedded in smart devices. The demographic characteristics of the user will be obtained by analyzing purchase invoices. Physical characteristics of the environment such as noise, congestion, climate, temperature; all this information is obtained from sensors.

Janowski (Janowski and Pinson, 2014), proposes a user model for rating behavior based on subject bias and error. Differences between subjects are important when analyzing and comparing people because bias can alter the results. The bias acts as a random variable within the ratings (For example, a bias is given, if one person is homophobic, it may turn out that everyone is homophobic)

Lakiotaki and Tran (Lakiotaki et al., 2011, Tran et al., 2019), Sarukkai (Sarukkai, 2013) Sang (Sang et al., 2015), Yang (Yan et al., 2016), Piao (Piao and Breslin, 2018), Ha (Ha et al., 2015), Musto (Musto et al., 2018), Sang (Sang et al., 2015). Yang (Yang et al., 2014), Ha (Ha et al., 2015), Sarukkai (Sarukkai, 2013), Musto (Musto et al., 2018) Piao (Piao and Breslin, 2018), Lai (Lai et al., 2018) considers the social networks Twitter, Facebook, and LinkedIn, YouTube Twitter, Google+. They analyze intentions and preferences influenced by intrinsic interests from user behaviors in social networks considering rankings. Alnahhas (Alnahhas and Alkhatib, 2020), Barros (Barros et al., 2012, Lai et al., 2018), analyze emotions, writing styles and tendencies, variation in texts and variation of emotions on written texts, they propose to build a user model based on the conceptual analysis of texts, to include contextual information of concepts to identify the user's interests: the analysis include common sense in words and phrases analyzing semantic relationships in the knowledge. Guo (Guo et al., 2016), show a computational model that considers social influence in recommender systems. People, directly or indirectly, are influenced by the feelings and actions of others. Social factors such as personality, expertise, interpersonal relationships, and similar preferences amplify the effect of social influence. Wu (Wu, 2012), user preference is driven by two now dynamic relationships 1) user-item relationship, and 2) social network structure reflected by user-user behavior. They generate a user model, considering the historical behaviors in the two types of relationships. They consider hemophilia (love for equals), closeness and social influence.

Madureira (Madureira et al., 2014), to know the decisions and restrictions of the user, from user actions on the system. Sheng (Sheng and Liu, 2010), wants to know the needs of the user, basing his work on the user's search history. Abdar (Abdar and Yen, 2017), identifies the user's context, relating

internal and external factors of the user, internal are considered: priority, preference, attitude and alternatives and external are considered searches, messages, GPS, sensors, city data and date.

Similarly, Paolino (Paolino et al., 2010), Takama (Takama et al., 2018), Kompan (Kompan et al., 2019), and Berger (Berger and Kompan, 2019) base their analysis on stable user characteristics or favorite items called long-term and the latest content delivered called short term or user actions. short-term user. The most common are the short term to model context and behavior. Kompan (Kompan et al., 2019) and Berger (Berger and Kompan, 2019) discuss session abandonment. Takama (Takama et al., 2018) recommends less popular but important items for a small number of people. Guntuku (Guntuku et al., 2016), their goal is to identify a) personality recognition and b) personality perception. based on the inference from the likes of images and/or request a self-assessment from the user.

People with special needs are also considered in the exhibition of user models to represent them. Thus, Kurschl (Kurschl et al., 2014), expose a user model for people with special needs. They look for patterns of interaction based on touch and without touch. They present a user model (stores information about the user experience and interaction concepts), an input model (contains all the information about the input methods and their configuration). They describe the way to control the application, an adaptation model (describes how the content can be adapted to optimize the presentation to the user), and a domain model (describes the content and organization of the domain). They propose the user interface with special needs. Also, Arbelaitz (Arbelaitz et al., 2016), create a social network for people with cognitive disabilities.

## CONCLUSION

As it has been observed, there is a lot of research on attributes that are necessary to represent the user, the different sources and the possible characteristics that represent the user are described. As you can see the information is scattered, many researchers focus their attention on specific aspects without looking at a specific model. This opens the way to gather all the information generated and observe gaps and in a next step represent a general model that represents the user, which will mean a contribution to current recommendation systems.

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