USER MODELING AND USER PROFILING: A COMPREHENSIVE SURVEY

A PREPRINT

Erasmo Purificato*
Otto von Guericke University Magdeburg
Magdeburg, Germany
erasmo.purificato@acm.org

Ludovico Boratto
University of Cagliari
Cagliari, Italy
ludovico.boratto@acm.org

Ernesto William De Luca
Otto von Guericke University Magdeburg
Magdeburg, Germany
ernesto.deluca@ovgu.de

February 21, 2024

ABSTRACT

The integration of artificial intelligence (AI) into daily life, particularly through information retrieval and recommender systems, has necessitated advanced user modeling and profiling techniques to deliver personalized experiences. These techniques aim to construct accurate user representations based on the rich amounts of data generated through interactions with these systems. This paper presents a comprehensive survey of the current state, evolution, and future directions of user modeling and profiling research. We provide a historical overview, tracing the development from early stereotype models to the latest deep learning techniques, and propose a novel taxonomy that encompasses all active topics in this research area, including recent trends. Our survey highlights the paradigm shifts towards more sophisticated user profiling methods, emphasizing implicit data collection, multi-behavior modeling, and the integration of graph data structures. We also address the critical need for privacy-preserving techniques and the push towards explainability and fairness in user modeling approaches. By examining the definitions of core terminology, we aim to clarify ambiguities and foster a clearer understanding of the field by proposing two novel encyclopedic definitions of the main terms. Furthermore, we explore the application of user modeling in various domains, such as fake news detection, cybersecurity, and personalized education. This survey serves as a comprehensive resource for researchers and practitioners, offering insights into the evolution of user modeling and profiling and guiding the development of more personalized, ethical, and effective AI systems.

Keywords User Modeling · User Profiling · User Behavior · User Preferences · User Interests · User Representation

1 Introduction

In the pervasive era of artificial intelligence (AI) systems, the integration of such technologies into daily life is inevitable, whether embraced consciously or not. Specifically, within the realm of widely adopted tools, information retrieval (IR) and recommender systems (RSs) proficiently supply pertinent information to users in accordance with their information requirements, personality traits, and contextual cues. Within a context where the interaction with such systems yields a voluminous amount of personal data on a daily basis, the imperative to discern individuals' interests, characteristics, and behaviors is fulfilled by *user modeling* and *profiling* techniques [Eke et al., 2019]. These techniques primarily aim

*Corresponding author.

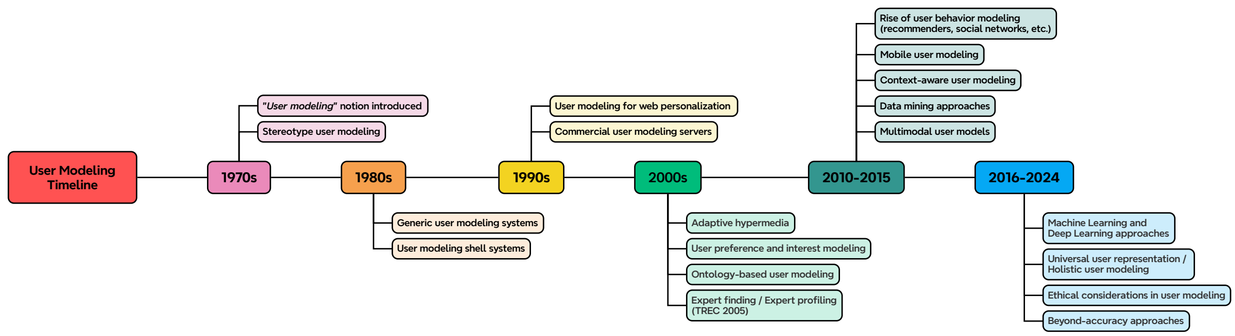

Figure 1: Timeline reporting the major events of the user modeling and profiling history.

to construct a reliable user representation (i.e., a *user model* or *user profile*) commencing from generated data [Kanoje et al., 2015]. User modeling and user profiling are pivotal in understanding user behavior and providing personalized experiences. Organizations can gain valuable insights into individual preferences and interests by analyzing user data, such as browsing history, purchase patterns, and social interactions. This, in turn, enables the delivery of tailored content, products, and services, enhancing user satisfaction and engagement.

In this introduction, we will first illustrate the historical background of user modeling and user profiling research areas. Then, we will present an extensive overview of surveys and literature reviews on user modeling and profiling published over time, followed by a description of the novel contributions presented in this article. Finally, the outline of the paper concludes the introductory section.

1.1 Historical overview

Throughout the history of scientific literature on personalization, user modeling, and user profiling fields have constantly witnessed significant advancements, as described by Kobsa [2001], Cena et al. [2019], and Eke et al. [2019], among others.

Traditionally, the initial steps in this research area can be dated back to the late 1970s when the notions of *"user model"* and *"user modeling"* were introduced by the contributions of Allen, Cohen, Perrault, and Rich (i.e., [Perrault et al., 1978; Cohen and Perrault, 1979; Rich, 1979]). Their pioneering work set the stage for the following decade's research in this field. It led to the creation of numerous application systems that gathered different types of user information with varying adaptive capabilities (e.g., [Sleeman, 1985; Allgayer et al., 1989; Wahlster and Kobsa, 1989]). In these early models, there was no distinct separation between the components used for user modeling and those used for other functions. Specifically, Perrault et al. [1978] proposed a form of modeling that aimed at understanding the beliefs and goals of a user so that they could communicate. Interestingly, dialogues were exploited to understand these goals. The paper's approach to understanding a user's intentions using a model of the speaker's beliefs aligns with user modeling, where a system infers a user's needs and preferences from their interactions. This implies that user modeling systems should tailor their responses based on the user's profile to ensure effective communication. Cohen and Perrault [1979] highlighted the need for a nuanced representation of an agent's mental state, including beliefs, goals, and actions, to predict and influence behavior through communication. This approach was crucial for developing the idea of conversant computers capable of recognizing and generating appropriate speech acts in interaction with users. Rich [1979] introduced one of the earliest successful user modeling techniques by exploring the vision of using *stereotypes* in computer systems to create models of individual users. Stereotypes, in this context, are predefined sets of characteristics that are commonly associated with certain types of users. The author discussed how these stereotypes could infer user preferences and behaviors, allowing the system to make personalized recommendations. The popular system *Grundy* was developed as a result of this research. It acts like a librarian, suggesting novels to users based on the stereotypes assigned to them. Based on user interactions, the system was designed to learn and adapt its stereotypes over time to improve its recommendations. *Stereotype user modeling* constituted the first attempt to differentiate a user from other users [Schiaffino and Amandi, 2009] and inspired several future works (e.g., [Ardissono and Sestero, 1995; Krulwich, 1997; Zimmerman and Kurapati, 2002]).

Since the late 1980s, it became apparent that the user modeling component needed to be reusable in creating user-adaptive systems. The initial move in this direction involved the creation of *generic user modeling systems*. Also defined as *user modeling shell systems* by Kobsa [1990], a generic user modeling system (GUMS) operates as an independent component within a system during runtime, requiring developers to input it with application-specific user modeling knowledge [Kobsa, 2001]. Introduced by Finin and Drager [1986], the primary GUMS was never utilized with an application system, but it established the framework for the fundamental functionality of future *general* (i.e., *application-independent*) user modeling systems, namely providing selected user modeling services that can be configured during development. A few instances of these systems are: UMT [Brajnik and Tasso, 1994], TAGUS [Paiva and Self, 1994], BGP-MS [Kobsa and Pohl, 1994], Doppelänger [Orwant, 1994], and the um toolkit [Kay, 1995]. User modeling shells were anticipated to support intricate assumptions and sophisticated reasoning about the user, particularly in the domains where these characteristics were identified. Furthermore, they were expected to be adaptable for use in a broad spectrum of other domains.

The significance of web personalization gained increasing recognition within the domain of electronic commerce at the end of the 1990s [Hof et al., 1998; Allen et al., 1998]. It involved tailoring product offerings, sales promotions, product news, and ad banners to individual users based on their navigation data, purchase history, and past interactions with the electronic merchant. From a broader perspective, personalization facilitated the transition from anonymous mass marketing and sales to a more individualized *one-to-one* marketing approach on the Internet [Peppers and Rogers, 1993, 1997]. In this context, the involvement of user modeling was deemed crucial [Fink and Kobsa, 2000]. Dozens of systems for web personalization, each boasting diverse capabilities, were developed and published in that period (e.g., [Caglayan et al., 1997; Konstan et al., 1997; Kay et al., 2002; Brusilovsky, 2004; Kobsa and Fink, 2006]).

User profiling and user modeling research saw significant advancements in the 2000s, focusing on improving personalization and adaptability in various systems, including *adaptive hypermedia* [Brusilovsky et al., 1998; Brusilovsky, 2001], a research topic emerged at the intersection of hypermedia systems [Kobsa et al., 2001] and adaptive user interfaces [Langley, 1999]. Unlike regular hypermedia, where all users were offered the same set of hyperlinks, adaptive hypermedia tailored what the user was offered based on a model of the user's goals, preferences, and knowledge. This resulted in providing links or content that were most appropriate to the current user [De Bra et al., 1999]. An adaptive hypermedia system tracks the user's browsing behavior and can change the link to a different web page or document that is more tailored to the user. It is used in various fields such as educational hypermedia, online information and help systems, and institutional information systems [Brusilovsky and Maybury, 2002]. The growing interest in personalization in online systems, seen in the mid- and end-2000s, led researchers to start exploring ways to model user preferences to provide more tailored and relevant content [Zhang and Koren, 2007; Berkovsky et al., 2008], such as personalized recommendations for e-commerce websites [Braynov, 2004; Semeraro et al., 2008] or TV shows [Zimmerman and Kurapati, 2002; Zimmerman et al., 2004; Martinez et al., 2009]. In the same period, research also focused on creating user profiles that accurately captured interests based on observations of user behavior on the web (e.g., [Godoy and Amandi, 2005; Castellano et al., 2007; Li et al., 2007, 2009; Calegari and Pasi, 2010; Gao et al., 2010; Plumbaum et al., 2011]). The advent of the *semantic web* prompted investigations into representing and modeling user preferences through *ontologies* [Middleton et al., 2004; Mehta et al., 2005; Sieg et al., 2007; De Luca et al., 2010; Sosnovsky and Dicheva, 2010; Elallioui and El Beqqali, 2012]. These ontologies were employed to semantically organize and connect user profiles, thereby enhancing the comprehension of user preferences and relationships.

A significant turning point in user modeling and profiling research was characterized by the introduction of the *expert finding* and *expert profiling* tasks within the Enterprise Track at the Text REtrieval Conference (TREC) 2005 [Craswell et al., 2005]. This was when the field started gaining considerable attention [Eke et al., 2019]. The TREC Enterprise Track's acknowledgment of the necessity to delve into and comprehend *expertise retrieval* emphasized the significance of these tasks [Balog et al., 2007]. This, in turn, paved the way for a more profound investigation and comprehension of user profiling within the realm of expert finding and expert profiling [Pavan et al., 2015; Liang and De Rijke, 2016]. *Expert finding* [Balog et al., 2012] is about identifying individuals who possess knowledge or expertise in a specific area within a given dataset. The aim is to find the best matches for a user's specific request for expertise on a topic. For instance, a user might be looking for an expert who has knowledge in a particular field, and the task would involve searching through the dataset to find individuals who have demonstrated expertise in that area. The challenge lies in accurately determining a person's expertise based on the available data and ranking these individuals based on their relevance to the given topic. *Expert profiling* [Balog et al., 2012], on the other hand, is about creating a comprehensive profile of an individual's expertise. It involves gathering all relevant information about a person's skills and knowledge from their documents. This could include their educational background, areas of specialization, projects they have worked on, their contributions to their field, and so on. The aim is to provide a detailed overview of what the person knows and what they are capable of.

The 2010s marked a significant transformation in focus toward more sophisticated user profiling methods, with a growing emphasis on personalization in various digital services, particularly in RSs, where researchers developed advanced algorithms to analyze user behavior and preferences for improved content recommendations [Abel et al., 2011; Lakiotaki et al., 2011; Masthoff, 2011; Konstan and Riedl, 2012]. Innovative approaches involved the use of personality-based user adaptation, where automated methods were developed for recognizing personality traits from user behaviors [Gao et al., 2013; Gou et al., 2014; Barnett et al., 2015] and conversations [Mairesse and Walker, 2010; Ivanov et al., 2011; Wei et al., 2017]. A notable surge in academic literature was due to *semantic user modeling* techniques, which concern the creation of computational models to understand and predict user preferences, behaviors, and intentions based on semantic information derived from various data sources [Aroyo and Houben, 2010; Bakalov et al., 2010; Plumbaum et al., 2011; Cena et al., 2012; Plumbaum et al., 2012; Piao and Breslin, 2016]. This period also saw the proliferation of mobile devices, which led to research on user modeling in mobile and location-based contexts [Ouanaim et al., 2010; Kuflik et al., 2012]. The integration of location data was explored to provide context-aware strategies and recommendations. *Context-aware user modeling* gained traction as researchers aimed to understand how user preferences and behaviors change in different contexts. This included factors such as location, time, and device, leading to more adaptive and responsive systems [Adomavicius and Tuzhilin, 2011; Skillen et al., 2012; Verbert et al., 2012; Said et al., 2013; Codina et al., 2015]. Concurrently, the rise of social media platforms spurred an increased interest in understanding and modeling user behavior within these online social environments [Zafarani and Liu, 2013; Gou et al., 2014; Gilbert et al., 2023]. Researchers began exploring ways to incorporate social network data into user models, applying social network analysis to understand the influence of social connections on user preferences and behaviors [Vassileva, 2012; Zhong et al., 2012; Zhou et al., 2012]. This included integrating social network data and user-generated content to create more accurate and context-aware user profiles [Piao and Breslin, 2018; Kaushal et al., 2019].

During the same period, the ascent of *big data* drove the investigation of advanced *data mining* techniques for user modeling [Romero and Ventura, 2013; D'Oca and Hong, 2014; van Dam and van de Velden, 2015]. Large datasets have witnessed the application of *machine learning* (ML) algorithms, encompassing clustering and classification methods, to unveil meaningful patterns and insights into user behavior [Qi, 2010; Zghal Rebaï et al., 2013; Krishnan and Kamath, 2017]. As users began engaging with services across diverse platforms and devices, the emphasis turned towards formulating cross-platform user models [Deng et al., 2013; Mercado et al., 2016; Shin, 2016; Lin et al., 2019]. Researchers explored methods to construct cohesive user profiles that could encompass user preferences and behaviors across different digital environments. The proliferation of varied data types, including text, images, and audio, spurred efforts in developing *multimodal user models* [Saevanee et al., 2012, 2015; Farseev et al., 2015; Guo et al., 2018b]. These models aimed to attain a more comprehensive understanding of user preferences and behaviors by integrating information from various modalities. Subsequent advances in ML, particularly *neural networks*, began to deeply influence this research area in the latter half of the 2010s. From this period onwards, almost all relevant works in this user modeling and profiling focused on the use of deep neural networks for modeling complex user behaviors and enabling more accurate predictions and personalized experiences [Tang et al., 2015; Żołna and Romański, 2017; Ge et al., 2018; Ni et al., 2018; An et al., 2019; Chen et al., 2019b; Hu et al., 2020; Wanda and Jie, 2020; Chen et al., 2021b; Fazil et al., 2021; Yan et al., 2021; Li et al., 2022b; Yan et al., 2022; Zhao et al., 2022; Xuan et al., 2023]. *Deep learning* (DL) models were also adopted to automatically learn hierarchical representations of user preferences from raw data, leading to improvements in recommendation accuracy [Gu et al., 2020; Wen et al., 2021; Li et al., 2022a; Wei et al., 2022; Xue et al., 2022].

As the collection of user data became more pervasive, in recent years, there was a growing awareness of *privacy* concerns, even though security and privacy approaches for user modeling and profiling have already been proposed in the past [Kobsa and Schreck, 2003; Schreck, 2003]. Researchers and practitioners began exploring ways to balance the need for personalized services with user privacy, leading to the development of privacy-preserving techniques [Aghasian et al., 2017; Isaak and Hanna, 2018; Raber and Krüger, 2022], such as *federated user modeling* [Wu et al., 2021b; Chu et al., 2022; Luo et al., 2022; Liu et al., 2023c]. Furthermore, the increasing need for transparency and interpretability in AI systems has resulted in a widespread surge of scientific contributions focused on *explainable AI* (XAI), including its application in user modeling [Balog et al., 2019; Huang et al., 2019; Guesmi et al., 2022]. Efforts were directed towards enhancing the understandability and interpretability of ML models, enabling users to gain a clearer understanding of the construction of user models and the rationale behind recommendations and predictions [Wang et al., 2019a; Hase and Bansal, 2020; Xian et al., 2021; Liu et al., 2023a].

In the past few years, ethical concerns related to user modeling, particularly focusing on *bias* and *fairness* issues, have gained significant prominence. Addressing these ethical considerations in user profiling has become a priority, with a commitment to fostering transparency, accountability, and fairness in algorithmic decision-making [Balog et al., 2019; Dai and Wang, 2021; Shen et al., 2021b; Purificato et al., 2022; Zheng et al., 2022b; Abdelrazek et al., 2023; Zhang et al., 2023b]. This transition towards a more human-centric design and inclusive approach to user modeling underscores the importance of recognizing diverse user demographics and preventing biases in the modeling process. Active exploration of methods is underway to ensure that user models maintain representativeness and fairness across different user groups [Purificato and De Luca, 2023]. Moreover, the evolving landscape includes a growing emphasis on fostering effective human-AI collaboration to enhance the ethical and inclusive dimensions of user modeling [Çelikok et al., 2023].

1.2 Existing surveys on User Modeling and User Profiling

Over the years, several surveys and literature reviews have been published on user modeling and user profiling. Plenty of them targeted a specific application domain or feature. Only a few general, comprehensive, and exhaustive reviews and surveys have been presented.

Soft computing and personal information agents (2005) Frias-Martinez et al. [2005] investigated the application of *soft computing* methodologies, such as fuzzy logic, neural networks, genetic algorithms, fuzzy clustering, and neuro-fuzzy systems, in user modeling from 1999 to 2004. The research explores the utilization of these techniques either independently or in conjunction with other machine learning methods. Each technique is analyzed for its primary applications, constraints, and prospective avenues for user modeling. Additionally, the study offers guidance on selecting appropriate soft computing techniques based on the specific task implemented by the application. Godoy and Amandi [2005] provided a survey of user profiling techniques within *personal information agents*, exploring a range of algorithms and methods that are pivotal for personalization and recommender systems. It delves into collaborative filtering, text classification, user modeling, and the application of machine learning techniques such as Naïve Bayes classifiers, genetic algorithms, and artificial neural networks. The effectiveness of these methods is compared, particularly in their ability to model and adapt to user interests and preferences, with specific applications in news filtering and email classification. The paper also examines the use of feature selection, stemming, and various supervised learning approaches in text classification, discussing their pros and cons and comparing different methods like decision trees and rule-based classifiers.

Data mining approaches for adaptive hypermedia systems and their applications (2006 - 2007) Frias-Martinez et al. [2006] presented a comprehensive review of *data mining* techniques applied to user modeling within the context of adaptive hypermedia systems. It addresses the challenges involved in selecting the most suitable data mining approach and offers guidelines for the design of user models that leverage these techniques. The paper underscores the importance of hybrid systems and the necessity for standardization in the field of user modeling. Each method is thoroughly described, detailing its fundamental algorithms, applications in user modeling, and inherent limitations. The paper provides practical examples and explores the potential of each technique in crafting user models for adaptive systems. Brusilovsky and Millán [2007] provided a comprehensive overview of adaptive hypermedia and user modeling, with a focus on *personalized information access* and *adaptive educational systems*. The study discusses various aspects of user modeling, including the representation of user knowledge, interests, goals, background, and individual traits, as well as the context of the user's work. It emphasizes the use of Bayesian Networks (BNs) for creating dynamic and qualitative student models that integrate expert knowledge with learning techniques, allowing for real-time improvements in adaptive web applications.

Online Social Networks and Mobile Social Networks (2009 - 2013) Benevenuto et al. [2009] published a broad analysis of user behaviors on *online social networks* (OSNs) by examining detailed clickstream data from a social network aggregator website. The study identifies two types of user activities: "publicly visible" actions and "silent" actions, such as browsing profiles or viewing photos, which are not immediately apparent to others. The authors highlight the dominance of browsing activities, which constitute 92% of all user actions, and note that including silent interactions significantly increases the observed level of user engagement. The research extends to multiple social networks and finds considerable variation in user behaviors and session lengths across different platforms. Mezghani et al. [2012] delved into the complexities of utilizing *social annotations*, particularly *tags*, for modeling user profiles within social networks. The paper underlines the importance of considering both static and dynamic elements when representing user profiles to ensure they remain up-to-date and reflective of users' evolving interests. In the context of recommendations, the paper discusses the use of vector representations and the FOAF ("Friend of a Friend") ontology as methods for describing users and their interests. Remaining in the sphere of social networks, Jin et al. [2013] provided an in-depth analysis of user behavior modeling methods within OSNs, examining aspects such as social connectivity, interaction patterns, traffic activity, and the dynamics of *mobile social networks* (MSNs). The survey underscores the significance of clickstream data as a tool for understanding these behaviors and acknowledges the challenges associated with its use. A key focus of the paper is on the security and privacy concerns prevalent in OSNs. It reviews existing strategies to counter these threats and identifies areas where further research is needed to develop more effective solutions.

Human-Computer Interaction, multi-application environments and interoperability (2010 - 2011) Biswas and Robinson [2010] presented a brief survey of different user modeling techniques used in *Human-Computer Interaction* (HCI). After a discussion of the historical context of user modeling, the paper delves into various approaches, including the *GOMS* family of models (which stands for "Goals, Operators, Method and Selection"), cognitive architectures, grammar-based models, and application-specific models. Each modeling technique is examined for its strengths and weaknesses. Additionally, the authors underscore the significance of understanding the variety of user modeling paradigms available to system analysts. Viviani et al. [2010] analyzed the challenges and current research in user modeling within *multi-application environments*. The study focuses on the concept of user modeling *interoperability*, which is essential for cross-system personalization, and identifies two primary approaches to achieving interoperability: *standardization-based* user modeling, to create common standards for user models that can be used across different systems; *mediation-based* user modeling, to translate and adapt user models between systems that use different representations and formats by means of a mediator. The authors emphasize the importance of developing effective user modeling systems that can operate in a multi-application context. They acknowledge the difficulties in achieving interoperability and suggest that hybrid solutions, which combine elements of both standardization and mediation, may be necessary to overcome these challenges. Another review of user model interoperability was presented by Carmagnola et al. [2011]. The authors explored the motivations behind interoperability and the evolution from centralized to decentralized user model architectures. The study also addresses the challenges associated with this research topic, including privacy concerns, access control, encryption, and the management of conflicting data models and values. Solutions like pseudonymous personalization, perturbation techniques, and scrutable user models are discussed as ways to handle these challenges.

Demographic recommenders, learning environments, and intrusion detection and prevention systems (2016) Al-Shamri [2016] delivered a thorough review of various techniques and approaches utilized in recommender systems, with a focus on demographic data, fuzzy profiling, and similarity measures. The core of the paper is an analysis of different user profiling methods for *demographic recommender systems* (DRS). It highlights the significance of profiling in improving the performance of these systems, noting that certain methods can lead to substantial enhancements. The study's findings are intended to inform the design and implementation of DRS. Medina-Medina and García-Cabrera [2016] presented a comprehensive examination of user modeling approaches within the context of *learning environments*, particularly focusing on natural language systems, intelligent tutoring systems, web personalization, and adaptive educational hypermedia. The core contribution of the paper is the development of a taxonomy for classifying user models. This taxonomy is based on criteria related to the structure and management of user models, such as initialization, update methods, inference techniques, and the types of information they store. Peng et al. [2016] analyzed the role of user profiling in *intrusion detection and prevention systems* (IDPS). The review delves into the concept of behavioral profiling, which encompasses both system and user behaviors. It discusses the use of behavioral biometrics, such as keystroke dynamics and eye movement patterns, and psychometrics, which involve the analysis of a user's psychological attributes like intelligence, decision-making patterns, and preferences. These profiling methods aim to create a detailed user profile that can be used to detect unauthorized access or malicious activities.

Entity profiling and modeling (2017) Barforoush et al. [2017] introduced a classification framework designed to evaluate *entity profiling* (EP) systems on the web, summarizing advancements in the field from 2000 to 2015. The survey provides a set of criteria to compare and classify EP systems, aiming to assist researchers in developing or selecting robust systems tailored to their specific needs. EP is defined as the process of collecting and compiling descriptive information about a specific entity, which could be a person, organization, or location. This information is gathered from various web sources and is used to create a comprehensive profile that represents the entity's characteristics, behaviors, or relationships. *Entity modeling* (EM), on the other hand, refers to the creation of abstract representations of entities, often using formal models that define the types of entities and the possible relationships between them. EM is crucial for understanding and organizing the information collected during the profiling process.

Microblogging social networks and updated Human-Computer Interaction models (2018) Piao and Breslin [2018] presented a comprehensive review of user modeling strategies for inferring user interests in *microblogging social networks*. It aims to provide an overview of the state-of-the-art techniques and methodologies used to construct and evaluate user interest profiles, which are essential for delivering personalized content and recommendations. Similar to previous works, Sajib Al Seraj [2018] examined user modeling approaches within the field of HCI. The author provided an updated review of various models, such as the GOMS family, cognitive architectures, grammar-based models, and application-specific techniques. Among the discussed future challenges, the paper highlights the significance of user control in intelligent systems and raises concerns about privacy and security in relation to user models.

Wearable, ubiquitous and mobile computing technologies (2019) Cena et al. [2019] provided an in-depth analysis of the evolution of user modeling, particularly with the advent of *wearable* and *ubiquitous computing technologies*. The authors introduce the concept of *Real World User Model* (RWUM), which integrates data from a person's everyday life, significantly expanding the scope and depth of traditional user models. Zhao et al. [2019b] presented a survey on user profiling through the analysis of *smartphone application usage*, including the types of data that can be collected, the methods employed for profiling, and the potential applications and implications of this practice. The paper discusses how personal information such as demographic attributes, personality traits, psychological status, personal interests, and lifestyles can be inferred from smartphone app data. It also examines the use of other data sources, such as online social networks and call detail records (CDRs), for effective user profiling.

Representation learning and review-based user profiling (2020 - 2021) Li and Zhao [2020] published a detailed analysis of the latest developments in user modeling, with a particular focus on *representation learning* techniques. The study categorizes the methods into two main types: *static* and *sequential* representation learning. Static representation learning methods include matrix factorization and deep collaborative filtering, which are used to capture user preferences and item characteristics in a static context. These methods are foundational to many recommender systems and are crucial for understanding user behavior. Sequential representation learning methods, such as recurrent neural networks, are discussed as they pertain to capturing the dynamic nature of user preferences over time. These methods are particularly relevant for applications that require understanding the temporal aspects of user behavior. Dong et al. [2021] presented a systematic mapping study on *review-based user profiling* (RBUP), an area of research that utilizes user-generated reviews to create detailed user profiles. The study aims to provide an overview of the current state of the field, its evolution, publication trends, application areas, and co-authorship patterns. The research process for RBUP involves formulating research questions, conducting systematic literature searches using keywords, "snowball" searching, and applying inclusion and exclusion criteria to select relevant papers. The analysis of the selected papers includes bibliometric analysis, examining the time distribution of publications, identifying paper venues, and exploring co-author networks.

Recommender systems (2022) Tenemaza [2022] highlighted the critical role of user modeling in the development of *recommender systems*. The work delves into the various characteristics and structures that constitute user models, examining the diverse range of data sources and attributes that are employed to represent and understand users. It also points out a significant gap in the current research landscape: the lack of a *generalized user model*, conveying that existing studies tend to focus on specific components of user modeling rather than adopting a holistic approach that integrates all relevant aspects.

User behavior modeling with Deep Learning, Long Short-Term Memory networks, and Large Language Models (2022 - 2023) In the same context of recommender systems, He et al. [2023] presented a survey of user behavior modeling. The paper discusses the deep network structures and techniques used to capture behavior dependencies, including the handling of long user behavior sequences and the incorporation of different behavior types. It also explores the challenges and advancements in user behavior modeling, such as the use of long-term behavior histories, multi-type behaviors, and side information. Sudhakar et al. [2022] offered a thorough study on the application of *Long Short-Term Memory* (LSTM) networks for generating and analyzing web user profiles. The primary objective is to create detailed and personalized user profiles that can enhance the customization of applications. The research encompasses several stages, including data collection, preprocessing, feature extraction, and the classification process, all of which are critical for the effective implementation of LSTM in user profiling. A significant portion of the paper is dedicated to comparing the LSTM-based method with existing user profiling techniques, concluding by underscoring the potential of LSTM networks in revolutionizing the field of user profiling and providing a pathway for more personalized and effective web experiences. Tan and Jiang [2023] provided an overview of the use of *Large Language Models* (LLMs) in the field of user modeling and recommender systems. The article highlights the potential of LLMs in understanding user behavior and generating personalized recommendations. It also delves into the challenges associated with LLM-based User Modeling, such as detecting suspicious behavior like fraud and misinformation and addressing privacy and security concerns. It emphasizes the need for comprehensive benchmarks, evaluation criteria, trustworthy user modeling, fairness, and efficient domain adaptation.

General comprehensive surveys (2009 - 2022) Schiaffino and Amandi [2009] discussed the key components of user profiles adopted in that period for intelligent agents, adaptive systems, intelligent tutoring systems, recommender systems, e-commerce applications, and knowledge management systems. The paper also discusses several intelligent user profiling techniques, including stereotypes, Bayesian networks, association rules, and case-based reasoning. Cufoglu [2014] examined the advantages and disadvantages of existing user profiling methods and explored the potential of these methods for enhancing service personalization. A key part of the paper is the analysis of classification and clustering algorithms, which are pivotal in the construction of user profiles. The author conducts simulations using real-world user profile data to evaluate the performance of various algorithms in this context. The survey presented by Kanoje et al. [2015] delves into the significance of user profiling and examines the progression, methodologies, and practical applications across various sectors, including academic literature recommendations, e-tourism, energy conservation, and employment matchmaking. The article outlines a range of user profiling techniques, such as implicit profiling, perceptual preference questionnaires, social profiling, weakly supervised extraction, ontological approaches, and the use of implicit feedback. Farid et al. [2018] explored the essential information required for constructing diverse user models, the methods employed for collecting this information, the representation and maintenance of the user model, and, ultimately, the utilization of the user model to provide personalized services. A classification schema for user profiling research is proposed, and the paper also looks at how user profiling is applied in areas like personalized web search, recommender systems, adaptive learning, visualization, and personalized services in online social networks. The most recent general and comprehensive survey on user modeling and user profiling has been provided by Eke et al. [2019]. This research paper presents an extensive review that focuses on the methodologies, models, and processes involved in constructing accurate user profiles for service personalization. The authors aim to fill a gap in the existing literature by examining user profiling from the perspectives of data acquisition, feature extraction, modeling techniques, and performance evaluation. The paper discusses both static and dynamic user profiles, the process of user modeling, and the construction and updating of user profiles. It delves into the methods of user information collection, data preprocessing, and feature extraction, providing examples of studies that have utilized these techniques in user profiling. Various approaches to user profiling are explored, including collaborative and hybrid filtering, statistical models, neighborhood-based techniques, machine learning, user ontology, and filtering methods. For the sake of completeness, in chronological order, it is worth mentioning two other articles, published, however, with slightly different purposes than to provide a complete overview of user modeling and profiling features. Abri et al. [2021] proposed a classification of the major dimensions of user models. The paper briefly explores the user profiling process, detailing the methods for collecting user information, such as browsing history, search queries, and user feedback. It examines learning techniques for constructing user profiles, including rule induction and predictive statistical models. Recently, Tchuente [2022] conducted a bibliometric analysis of the field of user modeling and user profiling within information systems, utilizing a dataset of 52 027 publications. The study aims to map out the landscape of research in this area by identifying key authors, publication sources, institutions, and countries, as well as examining their collaborative efforts. The article also analyzes the main research topics and their respective subtopics, outlining the evolution of the field and identifying current trends. It further discusses potential future research directions and highlights existing gaps in the literature. This provides valuable insights for academics, researchers, and industry professionals interested in user modeling and profiling.

1.3 Scope and novel contributions of the survey

The scientific literature has long devoted considerable attention to the research areas of user modeling and user profiling, as illustrated in the previous sections. Across the years, tons of papers and numerous surveys on these topics have been published. Our survey stems primarily from a number of key issues that emerged from the study of the literature: (1) the absence of an article including a wide historical overview and general taxonomy; (2) the ambiguous use of basic core terminology (i.e., "user modeling", "user model", "user profiling", and "user profile"); and (3) the lack of a comprehensive and up-to-date overview of this research area since 2019, to fill the gap due to the publication date of the most recent exhaustive survey (i.e., [Eke et al., 2019]).

Specifically, the novel contributions presented by our survey are listed and briefly described below, with the indication of the section including the related content:

- We provide a complete outline of the large, long-standing, and ever-growing research fields of user modeling and user profiling (Section 1), by offering a detailed historical overview (Section 1.1) and an inspection of the literature reviews published across the decades (Section 1.2). After retracing the most significant milestones of the literature, starting from the *stereotype user modeling*, introduced in 1979, to the recent studies on *beyond-accuracy* perspectives, a formal taxonomy is proposed (Section 4), taking into account all the currently active topics in the research area, including the trends that emerged in the last few years.
- We examine the definitions associated with each key term in this research domain (i.e., "user modeling", "user model", "user profiling", and "user profile"), aiming to eliminate ambiguity and confusion in their usage and proposing new, encyclopedic, and easily understandable definitions (Section 2).
- We present in-depth the paradigm shifts that have occurred in recent years, especially due to technological evolution, as well as the current research directions and novel trends in the field (Section 3). In particular, we illustrate and discuss the advances in the following research topics:
  - *Implicit vs. explicit user profiling* (Section 3.1): in recent years, studies have adopted almost solely implicit (or hybrid) approaches for data collection. True explicit profiling (i.e., user data retrieved from surveys or questionnaires) is replaced by a sort of *pseudo-explicit* profiling, where the explicit information is taken from public data already shared by the users for different purposes (e.g., social network accounts).
  - *User preferences and interests* (Section 3.2): the rise and daily use of digital platforms, such as e-commerce services and RSs of all kinds, have inevitably led to a steady increase in information about users' preferences and interests. This phenomenon is obviously reflected in the context of user modeling and profiling research.

- *User behavior modeling* (Section 3.3): the examination of user behaviors has evolved over time, bringing forth novel concepts, such as *micro* and *macro behavior modeling* (i.e., respectively, the immediate actions that a user takes reflecting short-term preferences, and large-scale actions that reflect a user's long-term commitment), *multi-behavior modeling* (i.e., the practice of integrating diverse forms of user interactions with items, as opposed to depending on a single type), *sequential behavior modeling* (i.e., considering the temporal sequences of behaviors influencing user interests), *hierarchical user profiling* (i.e., a technique used in personalized recommender systems, particularly in e-commerce, to model users' real-time interests at different levels of granularity), and *mobile user profiling* (i.e., the effort of discerning users' interests and behavioral patterns from their mobile activities).
- *User representation* (Section 3.4): several works have underlined the absence of a generalized user model, suggesting that current research tends only to concentrate on particular facets of user modeling. This led to the advent and diffusion of the concepts of *universal user representation* and *holistic user modeling*.
- *Evaluation* (Section 3.5): currently, there are two main lines for evaluating the performance of a standalone user profiling approach, i.e., assess the proposed model or method based on the effectiveness of a *classification task* at predicting a user's personal characteristics, or generate *simulated data* to aid in minimizing the volume of gathered user data while maintaining profiling efficiency and safeguarding the privacy and confidentiality of users' personal information.
- *Graph data structures* (Section 3.6): as in many other domains, also in user modeling and profiling, extensive attention has been given to exploring and adopting *graph structures* (including *knowledge graphs*), particularly in the context of online social media.
- *Deep learning* (Section 3.7): the advent of *deep neural network-based models* has ushered in a transformative era across various domains, and user modeling and profiling have not been exceptions. We discuss contributions that employed different deep learning architectures and models, i.e., *differentiable user models*, *attention mechanism*, *graph neural networks*, *convolutional neural networks*, *autoencoders*, *recurrent neural networks*, *long-short term memory*, and *transformers*.
- *Beyond-accuracy perspectives* (Section 3.8): as for deep learning architectures, the adoption of *"beyond-accuracy"* techniques signifies a pivotal transition in every domain, including user modeling and profiling. These approaches go beyond predictive precision, prioritizing values like *privacy*, *fairness*, and *explainability*. In user modeling, it ensures accurate predictions while safeguarding user privacy, addressing biases, and promoting transparency.
- *Application domains* (Section 3.9): user modeling and profiling are finding novel applications in critical domains, addressing contemporary challenges. In the realm of *fake news detection*, these techniques analyze user behavior and content interactions to identify and combat misinformation. In *social networks*, even if not an unexplored domain, user profiling enhances community engagement and content recommender systems by understanding individual preferences. *Cybersecurity* benefits from user modeling through anomaly detection, providing a proactive approach to identifying potential threats. In *Massive Open Online Course* (MOOC) platforms, user modeling tailors educational content, ensuring a personalized learning experience for each student.

• We discuss the findings of our survey, underlining the concepts that hold over time in the field, along with the emerging future research directions (Section 5).

2 Analysis of the Terminology

In this section, we examine the interpretations tied to each significant term related to the research fields studied, with the intention of removing any uncertainty or misinterpretation in their use. Furthermore, we put forth a novel, general, and easily comprehensible set of definitions. Particularly, after selecting specific contributions where precise characterizations were provided, we methodically offer a series of definitions for the terms *"user profile"*, *"user model"*, *"user profiling"*, and *"user modeling"*. Our consideration encompasses both widely accepted and recently formulated definitions, with a focus on capturing the most contemporary meaning of each term in question.

User profile, the first term to get a formal and precise definition together with *user model*, has been described as:

- a representation of the preferences of any individual user; roughly, it is a structured representation of the user's needs through which a retrieval system should, e.g., act upon one or more goals based on that profile and autonomously, pursuing the goals posed by the user [Amato and Straccia, 1999].
- the narration of a user's behavior, interests, characteristics, and preferences obtained through interviews and questionnaires or dynamically with the aid of machine learning algorithms and data mining techniques [Godoy and Amandi, 2005].

- the application of ontology for the systematic representation of the user's interest; it enables the conceptual representation of the knowledge that constitutes user preference and context [Calegari and Pasi, 2010].
- the information that offers insight into a user's need and predicts his future intention; this information depends on similarities, trace handling, and prediction through ML [Alaoui et al., 2015].
- the procedure for gathering information on the user's interest; the system utilizes such information to tailor services and improve the user's satisfaction [Kanoje et al., 2015].
- a set of information that describes a user; it consists of demographic information, such as the user's name, age, country, and level of education, which represents user preferences or interests in either a single or group of users [Ouaftouh et al., 2015].
- a pattern that consists of user behavioral tendencies and preferences; the user profile knowledge acquired provides an idea of the user's behavior knowledge and can predict his/her intentions [Lashkari et al., 2019].
- a collection of user interests, characteristics, behaviors, and preferences, and also a system for collecting, organizing, and guessing user information [Sudhakar et al., 2022].

User model has been defined as:

- a representation of information about an individual user that is essential for an adaptive system to provide the adaptation effect [Brusilovski et al., 2007].
- user's information for effective adaptation in an adaptive system; for instance, it facilitates prioritizing an adaptive selection of important/relevant items for users when searching for relevant data [Gao et al., 2010].
- a data structure that is used to capture specific characteristics about an individual user [Piao and Breslin, 2018].
- a representation of the knowledge and preferences of users; it is not a mandatory part of the software, but it helps to get the system to serve the user better. Any information stored about the user or usage pattern is not a user model unless it can be used to get some explicit assumption about the user [Sajib Al Seraj, 2018].
- a summary of the user's interests, characteristics, behaviors, or preferences [Tchuente, 2022].

Moving to the operations, the definitions provided for ***user profiling*** depict it as:

- the process of acquiring, extracting, and representing the features of users [Zhou et al., 2012].
- the process to produce an accurate user information representation, usually stored in the user profile [De Campos et al., 2014].
- a means of determining the user's interest data that is built upon the knowledge of the user and the accurate system's retrieval of user satisfaction [Kanoje et al., 2015].
- the task of inferring user personality traits from user-generated data [Chen et al., 2019b].
- the process of inferring an individual's interests, personality traits, or behaviors from generated data to create an efficient user representation, i.e., a user model, which is exploited by adaptive and personalized systems [Eke et al., 2019].
- the efforts of extracting a user's interest and behavioral patterns from users' activities [Wang et al., 2019b].
- the process of automatically converting user information into a predefined and interpretable format that reflects the most important aspects of the user's profile, which are useful for further decision-making in practical applications [Vo et al., 2021].

User modeling has been defined as:

- the process of gathering information about a user's interests, constructing, maintaining, and using user profiles [Farid et al., 2018].
- the practice of capturing the latent interests of the user and deriving the adaptive representation for each user [Ren et al., 2019].
- the process of building up and modifying a conceptual understanding of the user. Its task is to learn a latent representation for each user, with the help of items, item features, and/or user-item response matrix, with applications to response prediction, recommendation, and others [Li and Zhao, 2020].
- the process of capturing, recording, and managing user needs and interests by creating a user profile [Abri et al., 2021].

- the process of obtaining the user profile, which is a conceptual understanding of the user for personalized recommender systems. The key idea is to learn the representation for each user by leveraging the user's interacted items or the features of the items, and the obtained representations are used for a wide range of applications such as response prediction and recommendation [Kim et al., 2023].

Originally, another term was also used in research papers (not for long time), i.e., ***user profile modeling***, which has been described as:

- the process that constitutes the methodology for building a user profile; it requires two steps to describe: "what" has to be represented, and "how" this information is effectively represented [Amato and Straccia, 1999].

Upon examining the provided definitions, it becomes apparent that in the literature, particularly when considering articles from the last decade, the terms "user model" and "user profile" (along with "user modeling", "user profiling", and "user profile modeling") exhibit conceptually overlapping descriptions. Consequently, we can assert definitively that these two terms can be utilized interchangeably, and within the scientific literature reviewed, they can be regarded as synonymous. Hereinafter, in our survey, we will use just one term directly, without explicitly specifying the other. In this scenario, bringing together the peculiarities of the provided characterization, we propose two novel, comprehensive, encyclopedic definitions:

- *A **user model** (or **user profile**) is a structured representation of an individual user's preferences, needs, behaviors, and demographic details to personalize system interactions. It is derived from direct user feedback or inferred through machine learning and data mining techniques. It supports the predictions of future user intentions and the refinement of systems response to enhance user satisfaction. User models are often instrumental in optimizing the relevance and efficiency of adaptive systems, ensuring that user interactions are aligned with individual needs and preferences.*
- ***User modeling** (or **user profiling**) is the process of acquiring, extracting, and representing user features and personal characteristics to build accurate user models (or user profiles). It encompasses inferring personality traits and behaviors from user-generated data. This dynamic practice includes automatically converting user information into interpretable formats, capturing latent interests, and learning conceptual user representations. Essentially, user modeling constitutes the methodology for building and modifying user models, determining "what" to represent and "how" to effectively represent this information for adaptive and personalized systems.*

3 Paradigm Shifts and New Trends

As explained in Section 1.3, one of the driving factors behind the creation of this survey is the absence of a thorough and contemporary literature review on the subject of user modeling. The most recent general survey in this research field is dated back to 2019 (i.e., [Eke et al., 2019]), and considers scientific contributions up until December 2018[1]. To be accurate, a few articles on the subject were published after that date, but they cannot be regarded as complete surveys. They offer a bibliometric analysis [Tchuente, 2022] and a concise, non-exhaustive categorization of user model dimensions [Abri et al., 2021].

In this section, we offer a thorough exploration of the recent paradigm shifts, particularly influenced by technological advancements, along with the current research orientations and emerging trends in the field.

3.1 Implicit and explicit user profiling

Traditionally, early profiling methods focused solely on examining static attributes. *Explicit user profiling* (also referred to as *static profiling* or *factual profiling*) required direct input from the user, such as filling out a questionnaire, completing an online form, providing ratings, or explicitly stating preferences (e.g., [Raghu et al., 2001; Poo et al., 2003; Zigoris and Zhang, 2006; Brusilovski et al., 2007]). Relying exclusively on explicit profiling quickly became problematic as users were reluctant to disclose their information due to privacy concerns, or found the form-filling process to be cumbersome and avoided it. Consequently, the accuracy of this type of profiling diminished over time [Kanoje et al., 2015; Kasper et al., 2017].

In this context, although the two approaches were used simultaneously even in the past years, contemporary systems shifted their view by placing greater emphasis on *implicit user profiling* (also known as *behavioral* or *adaptive profiling*) [Kanoje et al., 2015; Eke et al., 2019], which entails the passive collection and analysis of dynamic user data,

[1] The paper by Lashkari et al. [2019] cited within the survey is dated 2019, but it was officially published on September 22, 2018, as reported on the publisher website (`https://journals.riverpublishers.com/index.php/JCSANDM/article/view/5321`).

such as observing user behavior, interactions, and preferences without requiring direct user input (e.g., [Kulkarni et al., 2019; El-Ansari et al., 2020; Qian et al., 2021; Ma et al., 2021; Gu et al., 2021c; Bedi et al., 2022; Han et al., 2022; Yan et al., 2022]).

However, at the same time, the use of static data for user profiling has turned into gathering explicit information derived from public data that users have previously shared for different purposes, such as the creation of social network accounts (e.g., [Shu et al., 2018, 2019]) or the usage of travel platforms (e.g., [Zhang et al., 2020]). For this emerged category, we introduce the term ***pseudo-explicit user profiling***.

3.2 User preferences and interests

In the realm of user modeling, the evolution in exploring user preferences and interests has closely mirrored the advancements in implicit and explicit profiling. Initially, user preferences and interests have been modeled using explicit and direct feedback (e.g., [Amatriain et al., 2009; Lakiotaki et al., 2011; Kellner and Berthold, 2012; Fu et al., 2013]).

In recent times, the increasing prevalence and everyday utilization of digital platforms, including e-commerce services and various recommender systems, as well as the hesitancy of users in providing direct feedback, led to an abundance of user-generated data, such as social interactions and opinionated text content, and to a subsequent growing emphasis of research studies on capturing user interests and preferences hidden in users' historical behaviors (e.g., [Guo et al., 2018a; Cami et al., 2019; Kulkarni et al., 2019; Logesh et al., 2019; Majumder et al., 2019; Greco and Polli, 2020; Hassan et al., 2021; Kostric et al., 2021; Lu et al., 2021; Olaleke et al., 2021; Vo et al., 2021; Yilma et al., 2021; Zhang and Challis, 2021; Curmei et al., 2022; Fan et al., 2022; Gomez Bruballa et al., 2022; Ma et al., 2022a; Ariannezhad et al., 2023; Sguerra et al., 2023; Wang et al., 2023]).

Also worth mentioning, in the area of preference modeling, is the concomitant increase in specific studies pertaining to *short-* and *long-term preference modeling* (e.g., [An et al., 2019; Guo et al., 2019; Wu et al., 2019b; Yu et al., 2019; Hu et al., 2020; Sun et al., 2020; Fazelnia et al., 2022; Liu et al., 2023b]).

3.3 User behavioral modeling

The examination of user behaviors has significantly evolved to include a variety of sophisticated modeling techniques that provide a deeper understanding of user behavior in various contexts.

Micro and macro behavior modeling *Micro behavior modeling* refers to the analysis of immediate actions taken by a user, which reflect their short-term preferences. These actions might include clicks, views, or interactions with specific components on a webpage or app. *Macro behavior modeling*, on the other hand, looks at large-scale actions that indicate a user's long-term commitment or patterns, such as purchase history or subscription renewals. Examples of contributions on these topics are provided by Gu et al. [2020] and Wen et al. [2021].

Multi-behavior modeling This approach integrates various forms of user interactions with items, rather than relying on a single type of interaction. *Multi-behavior modeling* acknowledges that users often engage with platforms in multiple ways (such as clicking, favoriting, reviewing, and purchasing), and each of these behaviors can provide valuable insights into their preferences and intentions, and improve the performance of personalized recommender systems (e.g., [Jin et al., 2020; Xia et al., 2021a,b; Zhang et al., 2022; Cheng et al., 2023; Cho et al., 2023; Xuan et al., 2023]).

Sequential behavior modeling *Sequential behavior modeling* takes into account the order and timing of user actions, recognizing that the sequence of behaviors can influence a user's interests. This temporal aspect is crucial for services like online shopping, news feeds, and advertising, where the sequence of user interactions can reveal evolving preferences and help in predicting future actions (e.g., [Ren et al., 2019; Yuan et al., 2020a; Bian et al., 2021; Cao et al., 2022; Chen et al., 2022a]).

Hierarchical user profiling *Hierarchical user profiling*, integral to personalized recommender systems in e-commerce, models users' real-time interests at various levels of granularity. This approach enables a comprehensive understanding of both immediate and long-term user preferences, crucial for accurate recommendations. Examining user behaviors hierarchically provides nuanced insights, particularly beneficial for predicting conversion rates in e-commerce platforms. This method enhances the precision of recommendations by delving into user preferences and behaviors, contributing to a tailored and effective user experience in the dynamic e-commerce landscape. Examples of works presenting hierarchical user profiling approaches can be found in Gu et al. [2020], Wen et al. [2021], Li et al. [2022a], Wei et al. [2022], and Xue et al. [2022].

Mobile user profiling *Mobile user profiling* involves discerning users' interests and behavioral patterns based on their activities on mobile devices. Given the ubiquity of smartphones and the wealth of data they generate, mobile user profiling is increasingly important for delivering personalized content and services that align with users' on-the-go lifestyles. Contributions in this topic are provided by Bhogi et al. [2019], Wang et al. [2019b, 2020b, 2021b], and Zhao et al. [2022].

3.4 User representation

Different studies have highlighted the scarcity of studies on generalized user model representation (e.g., [Tenemaza, 2022]), pointing out that current research tends to focus on specific aspects of user modeling rather than a holistic approach. This observation has led to the development and widespread adoption of concepts such as *universal user representation* and *holistic user modeling*. The shift towards these inclusive modeling approaches allows researchers and practitioners to better understand and cater to the complex and multifaceted nature of users in digital environments.

Universal user representation *Universal user representation* is an emerging concept that aims to create a unified and generalized profile of a user by encapsulating a broad spectrum of user behaviors and preferences without bias towards any specific task. This approach is designed to be applicable across various domains and applications, providing a more complete understanding of users that can be leveraged for multiple purposes, such as user profiling and preference prediction (e.g., [Ni et al., 2018; Yuan et al., 2020a; Gu et al., 2021b; Yuan et al., 2021; Kim et al., 2023]).

Holistic user modeling *Holistic user modeling* takes this idea further by integrating diverse and heterogeneous personal data sources, such as social networks and personal devices, to construct a comprehensive representation of the user. This model seeks to capture the full range of user characteristics and behaviors, providing a more nuanced and complete picture of the user that can be used to personalize experiences and interactions across different platforms and services (e.g., [Gong and Wang, 2018; Musto et al., 2018, 2020a,b,c, 2021; Gong et al., 2020]).

3.5 Evaluation

There are currently two primary strategies for evaluating the performance of standalone user profiling methods.

The first approach involves assessing the proposed model or method based on its effectiveness in a *classification task*, which aims to predict a user's personal characteristics. This method often involves using machine learning techniques to classify user profiles as genuine or not (e.g., [Costanzo et al., 2019; Chen et al., 2021b; Dai and Wang, 2021; Yan et al., 2021]).

The second approach involves generating *simulated data* to help reduce the amount of user data collected while maintaining the efficiency of profiling and protecting the privacy and confidentiality of users' personal information (e.g., [Zerhoudi et al., 2022; Balog and Zhai, 2023]).

3.6 Graph data structures

In the field of user modeling, much like in many other domains, there has been a significant focus on the exploration and implementation of *graph structures*, including *knowledge graphs*. This is particularly evident in the context of online social media.

Graph structures are powerful data representations that capture relationships among data objects, making them ubiquitous in real-world applications. In the context of user modeling, graph structures can be used to represent and analyze user behavior, preferences, and interactions (e.g., [Guo et al., 2018a; Wang et al., 2019b; Wanda and Jie, 2020; Wang et al., 2021b; Chen et al., 2022b; Guan et al., 2022; Yang et al., 2022; Liu et al., 2023a; Yang et al., 2023]).

Knowledge graphs, a specific type of graph structure, have been recognized for their ability to effectively represent complex information, thereby gaining the attention of both academia and industry. They accumulate and convey knowledge of the real world, making them particularly useful in the context of social media, where they can be used to analyze critical information from people's activities and posts. For example, knowledge graphs can be used to recommend accurate content that interests users and to connect users with persons of interest. Examples of contributions leveraging knowledge graphs for user modeling can be found in Huang et al. [2019], Wang et al. [2020b], Anelli et al. [2021], Wang et al. [2021a], and Xuan et al. [2023].

3.7 Deep learning

The advent of deep neural network-based models has sparked a revolutionary shift across various fields, including user modeling. These models have significantly contributed to advancements in this field, enabling more accurate and comprehensive user profiling and prediction of user behavior. Different deep learning approaches and architectures have been employed in user modeling. In particular, *differentiable user models* (e.g., [Hämäläinen et al., 2023]), *attention mechanism* (e.g., [Wang et al., 2020c, 2022a; Fazil et al., 2021; Qi et al., 2021, 2022b; Chu et al., 2022]), *graph neural networks* (e.g., [Chen et al., 2019b, 2021b; Dai and Wang, 2021; Wu et al., 2021a; Yan et al., 2021, 2022; Han et al., 2022; Zhao et al., 2022; Cheng et al., 2023]), *convolutional neural networks* (e.g., [Wang et al., 2019b; Wanda and Jie, 2020; Fazil et al., 2021; Qi et al., 2022b]), *autoencoders* (e.g., [Abu Sulayman and Ouda, 2019; Wang et al., 2019b; Fazelnia et al., 2022; Liu et al., 2023c]), *recurrent neural networks* (e.g., [Ge et al., 2018; Ni et al., 2018; Yu et al., 2019; Gu et al., 2020; Chu et al., 2022; Li et al., 2022b]), *long-short term memory* (e.g., [Żołna and Romański, 2017; Ma et al., 2020; Fazil et al., 2021; Sahoo and Gupta, 2021; Nkambou et al., 2023]), and *transformers* (e.g., [Gu et al., 2021a; Kota et al., 2021; Zhu et al., 2021; Avny Brosh et al., 2022; Wu et al., 2022; Zheng et al., 2022a]).

3.8 Beyond-accuracy perspectives

Similar to the transformation observed in deep learning, the incorporation of advanced techniques extending beyond mere accuracy marks a significant shift in various domains, with a particular impact on user modeling and profiling. These approaches transcend the conventional pursuit of predictive precision and instead prioritize fundamental values such as *privacy*, *fairness*, and *explainability*. In our domain, these methods ensure not only precise predictions but also the protection of user privacy (especially through *federated learning* approaches, e.g., [Wu et al., 2021b; Chu et al., 2022; Luo et al., 2022; Liu et al., 2023c; Zhang et al., 2023a]), the detection and mitigation of biases (e.g., [Dai and Wang, 2021; Shen et al., 2021b; Purificato et al., 2022; Zheng et al., 2022b; Abdelrazek et al., 2023; Purificato and De Luca, 2023; Zhang et al., 2023b]), and the promotion of transparency and interpretability (e.g., [Balog et al., 2019; Huang et al., 2019; Hase and Bansal, 2020; Xian et al., 2021; De Pauw et al., 2022; Guesmi et al., 2022; Minn et al., 2022; Ding et al., 2023]).

3.9 Application domains

User modeling is being innovatively applied in various important research fields to tackle contemporary challenges.

In the context of *fake news detection*, user modeling techniques are employed to scrutinize user behavior and their interactions with content. This analysis aids in the identification and mitigation of misinformation, thereby enhancing the credibility of the information ecosystem. Examples can be found in Shu et al. [2018, 2019], Monti et al. [2019], Sahoo and Gupta [2021], and Allein et al. [2023].

Social networks, although their domain is not entirely unexplored for user modeling, greatly benefit from it by comprehending individual preferences for enriching community engagement and refining content recommender systems (e.g., [Kaushal et al., 2019; Gilbert et al., 2023]), or detecting fake profiles and bots (e.g., [Wanda and Jie, 2020; Fazil et al., 2021]).

In the field of *cybersecurity*, user modeling contributes significantly through anomaly detection. It offers a proactive strategy to spot potential threats by identifying unusual patterns in user behavior, thereby bolstering security measures (e.g., [Lashkari et al., 2019; Kwon et al., 2021]).

Lastly, in the education sector, particularly on *massive open online course* (MOOC) platforms, user modeling is used to customize educational content. It ensures that each student receives a learning experience tailored to their unique needs and learning style, thereby enhancing the effectiveness of online education. Examples are seen in Sunar et al. [2020], Sanchez-Gordon et al. [2021], and Jin [2023].

4 Current Taxonomy

The taxonomy presented in this section arises from the necessity to offer a renewed and contemporary reference in user modeling research. This aims to benefit present researchers and serve as a valuable resource for individuals who will engage in the study of this subject in the upcoming times. The categorization proposed in our survey takes inspiration from the similar contributions published over the years and described in Section 1.2 (especially [Schiaffino and Amandi, 2009; Kanoje et al., 2015; Farid et al., 2018; Eke et al., 2019]), to make sure to maintain continuity in the literature. Figure 2 shows the formal taxonomy we put forth. It considers all presently active topics within the research area and incorporates the trends that have surfaced in recent years.

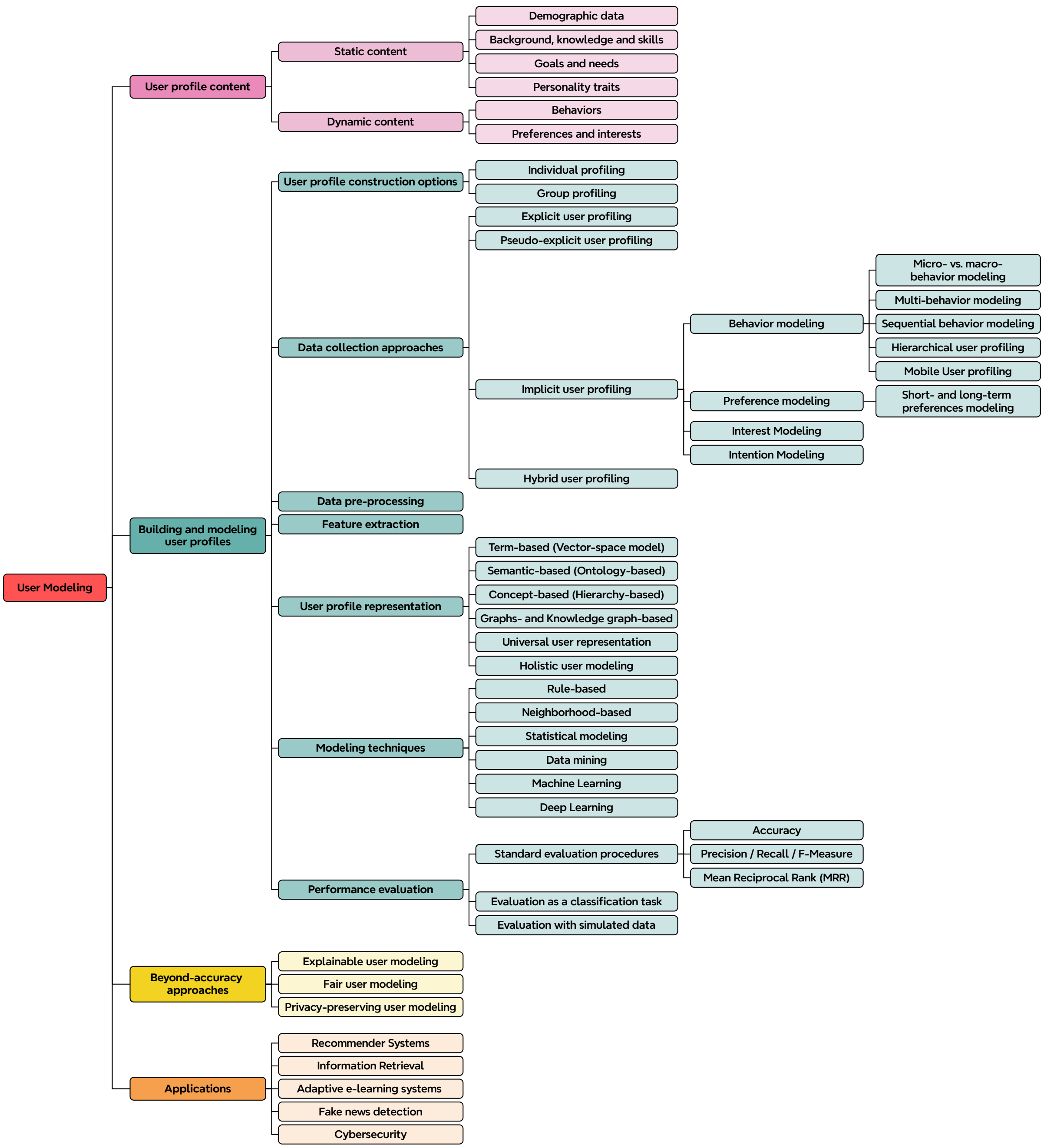

Figure 2: Taxonomy of the reviewed literature and trends for user modeling. The *Modeling techniques* tree is detailed in Figure 3.

4.1 User profile content

User profiles typically hold details about an individual in a specific system or application, incorporating diverse content to shape and personalize the user experience. This content usually falls into two categories: *static*, which provides foundational information, and *dynamic*, offering real-time updates and interactivity. This distinction highlights how content behaves and its frequency of change, creating a complete user representation.

4.1.1 Static content

Static content refers to information that does not change frequently or automatically [Poo et al., 2003]. It is consistent across user sessions and does not adapt in real-time to user interactions [Eke et al., 2019]. Static content is typically set by the user during account creation or through profile settings and remains the same until the user decides to update it manually [Schiaffino and Amandi, 2009]. Examples of static content in a user profile include: *demographic data*, *background*, *knowledge*, *skills*, *goals*, *needs*, and *personality traits*.

Demographic data The demographic characteristics of a user include basic features such as name, country, gender, age, native language, education, family members, and more. Dong et al. [2017] presented a study on user demographic and profile modeling within the context of large-scale mobile communication networks. It focuses on the prediction of demographic attributes such as gender and age by analyzing users' online behaviors, including browsing, gaming, and search activities, as well as their social decisions and communication patterns. Solomon et al. [2018] proposed an approach for predicting demographic attributes of cellphone users by analyzing their GPS data. The authors focus on extracting mobility profiles and location traces to infer characteristics such as age, gender, marital status, and academic affiliation. Zhang et al. [2020] introduced a method for simulating the daily electric vehicle (EV) charging load profiles by incorporating the demographics and social characteristics of vehicle users, such as gender, age, and education level. The study emphasizes that these user attributes significantly influence the magnitude and peak times of EV charging loads. Rozen et al. [2021] presented an approach to predicting the demographic characteristics of online users by analyzing their comments on news articles.

Background, knowledge, and skills Background data, containing information about a user's educational, professional, and personal background, including their field of study, work experience, and cultural background, is crucial for creating wide user profiles. Knowledge data refers to a user's expertise, domain knowledge, or specific knowledge related to a system or platform, and may include details about their educational qualifications, certifications, or areas of expertise. Additionally, skills data pertains to a user's competencies and abilities, covering both technical and soft skills such as communication, problem-solving, and leadership abilities. This diverse set of background, knowledge, and skills data is instrumental in personalizing user experiences, enabling adaptive interactions, and informing the development of tailored training and educational applications (e.g., [Brusilovsky and Millán, 2007; Schiaffino and Amandi, 2009; Guo et al., 2018a; Li and Zhao, 2020]). To provide some specific and recent cases, Minn et al. [2022] presented a method for student modeling called Interpretable Knowledge Tracing (IKT). This approach is designed to predict student performance by leveraging three meaningful latent features: individual skill mastery, ability profile, and problem difficulty. The motivation behind IKT is to address the shortcomings of existing knowledge tracing models, such as Bayesian Knowledge Tracing (BKT), which struggle with capturing learning transfer across different skills. Nkambou et al. [2023] developed an advanced learner model within an Intelligent Tutoring System (ITS) aimed at enhancing logical reasoning skills. This learner model is a composite of several components, and it is designed to provide a personalized learning experience by adapting to the individual needs of each student.

Goals and needs Recognizing a user's goals is a fundamental aspect of user modeling, focusing on understanding the specific objectives users intend to achieve within the application they are utilizing. On the other hand, comprehending information needs is centered around the essential requirement of obtaining pertinent information while, for instance, navigating the web. Modeling users' goals and needs has been a practice applied in every period of the history of user profiling research. Horvitz et al. [1998] presented an in-depth exploration of Bayesian user modeling with the primary goal of inferring the goals and needs of users by analyzing their backgrounds, actions, and queries, thereby providing tailored assistance. The paper by Zhou and Conati [2003] discusses the development and evaluation of a causal model designed to infer user emotions during interactions with an educational game. The model utilizes nodes and links to deduce user goals based on personality traits and interaction patterns. Barua et al. [2014] focused on the development and evaluation of a user model designed to assist individuals in setting and achieving personal long-term health-related goals. Drawing from psychological theories, the authors created a Goal Model representation and a user interface to facilitate goal setting and self-reflection. Recently, a few studies explored user needs as a dynamic feature. For instance, Ma et al. [2022a] designed and implemented the NEST (Need Evolution Simulation Testbed) framework to model the *dynamic* nature of user preferences and needs, particularly during extraordinary events that cause significant shifts in user behavior.

Personality traits In the context of user modeling, personality (or individual) traits are defined as stable and enduring internal characteristics that change only over a long period of time, and can be considered static. These traits, which include learning and cognitive styles, reflect people's characteristic patterns of thoughts, feelings, behaviors, and habits, implying consistency and stability. These features define a user as an individual and are used to create the user model. This allows for different users interacting with the same system to have unique experiences based on their individual traits. The most widely used system of traits in psychology is the Five-Factor Model [McCrae and John, 1992], and even though many works in user modeling have referred to them (e.g., [Barnett et al., 2015]), contributions like that presented by Cena et al. [2022] studied the impact of different specific traits (i.e. need for recognition, locus of control, mindset and self-efficacy) on the development of user models. In general, predicting users' personality traits has seen applications in various contexts. Gao et al. [2013] presented a method for deducing personality traits from social media content, specifically targeting the Chinese language environment. By employing machine learning techniques, the researchers developed a model capable of predicting personality traits with a reasonable degree of accuracy. The findings indicate that there is a significant correlation between the content posted on social media and the personality dimensions of the users. Kim et al. [2013] explored the impact of personality traits on the effectiveness of e-learning systems. It presents the idea that understanding and integrating personality traits into the design of e-learning platforms can lead to more personalized and efficient learning experiences. Gou et al. [2014] examined the idea of deriving personality traits from social media activity, specifically Twitter, and analyzed user attitudes towards sharing these traits in professional settings. The study aimed to determine the feasibility of automatically extracting personality traits from social media and to understand the factors influencing users' willingness to share these traits at work. Berkovsky et al. [2019] introduced a framework aimed at user modeling by detecting personality traits through physiological responses to external stimuli. The study specifically explores the use of affective image and video stimuli alongside eye-tracking data to model user personality. Shen et al. [2021a] presented a user profiling system designed to infer gender and personality traits from non-linguistic audio data during conversations. The system leverages conversational features such as turn-taking and interruption patterns to identify user attributes effectively.

4.1.2 Dynamic content

Dynamic content refers to information that frequently and automatically changes in response to user actions or system updates. This type of content is generated in real-time or on a regular basis, often driven by algorithms that analyze user behavior, preferences, and interactions with the system [Farid et al., 2018]. A dynamic profile is autogenerated by the system, leading to changes in user attributes and contents over time [Eke et al., 2019]. Despite the recent surge of studies also considering the dynamicity of static attributes, as mentioned in the previous section, common dynamic features in user profiles are: *behaviors*, *interests*, and *preferences*.

Behaviors User *behaviors* refer to the actions that users take while interacting with a platform. This can include things like the pages they visit, the links they click on, the amount of time they spend on certain tasks, and the frequency of their visits [Farid et al., 2018; Eke et al., 2019]. By analyzing these behaviors, platforms can gain insights into what users are interested in and how they use the services [Kanoje et al., 2015]. Frequent actions on websites or social networks are exploited to infer a user's intentions (e.g., [Zhong et al., 2012; Jiamthapthaksin and Aung, 2017]). Traditional methods rely on user behavior and labeled data for modeling users, such as Covington et al. [2016], who proposed a YouTubeNet model for video recommendation to model users by leveraging their watched videos and search tokens. Other similar examples can be found in Zhou et al. [2018] and Ouyang et al. [2019]. These techniques may not be optimal when labeled data are scarce. To address this limitation, Wu et al. [2020b] introduced a pre-trained user model (PTUM) approach, inspired by the success of pre-trained language models in natural language processing tasks, to capture the relatedness between past and future behaviors. However, for modern systems in general, the domains where user behaviors are most studied are *e-commerce* (e.g., [Gu et al., 2020, 2021c; Fan et al., 2022; Ma et al., 2022b]) and general *recommender systems* (e.g., [Jin et al., 2020; Shen et al., 2021b; Zhao et al., 2021; Qian et al., 2022; Xuan et al., 2023]).

Preferences and interests *Preferences* and *interests* of users are fundamental aspects of personalization [Farid et al., 2018]. They are related concepts, but they refer to different aspects of an individual's inclinations or likes. Preference is more about choosing or favoring one option over another, often based on user personal tastes or judgments (e.g., [Jiamthapthaksin and Aung, 2017; Cami et al., 2019; Kostric et al., 2021; Zhang and Challis, 2021; Yang et al., 2022; Zheng et al., 2022a]). To provide some specific examples, Kellner and Berthold [2012] developed a tool to assess individual perceptual preferences in the context of information processing, knowledge acquisition, and learning. The primary goal of their contribution is to facilitate user profiling by identifying cognitive preferences, which can then be used to tailor information presentation to enhance user experience. Guo et al. [2018b] presented a personalized product search model that leverages both visual and textual information to capture user preferences. Majumder et al. [2019] introduced a method for personalized recipe generation, which aims to assist users who have incomplete knowledge about ingredients for specific dishes. The core of this study is the adoption of historical user preferences to create tailored recipes based on partial input specifications. Curmei et al. [2022] proposed a methodology that integrates psychological principles into the development of dynamic user preference models. The focus is on capturing the nuances of user behavior by formalizing three classic psychological effects.

On the other hand, interest is about the level of curiosity or engagement a user has in a particular subject or activity, which may or may not translate into making choices or decisions (examples of general approaches employing user interests, see Piao and Breslin [2018], Zhou et al. [2018], and Wang et al. [2021a]). Wang et al. [2022b] presented an approach for enhancing user profiling in the context of personalized point-of-interest recommendations by leveraging a knowledge graph with temporal information to capture the dynamic and evolving preferences of users with respect to various locations. Xuan et al. [2023] introduced a framework designed to enhance user modeling in recommender systems by leveraging multi-behavior information. This approach acknowledges that different behaviors can reflect varying levels of user preference and intent, providing a richer and more nuanced understanding of user interests.

Dynamic profile that considers time may distinguish between *short-term* and *long-term interests*. In user modeling research, short-term interests refer to immediate preferences, subject to quick changes. In contrast, long-term interests are enduring preferences that remain relatively stable over an extended period, offering insights into consistent user likes and engagement areas. Early approaches are dated to mid-2000s (e.g., [Díaz and Gervás, 2004; Li et al., 2007; Liu et al., 2007]), but numerous significant contributions have been published in recent years (e.g., [An et al., 2019; Guo et al., 2019; Wu et al., 2019b; Yu et al., 2019; Xu et al., 2022; Liu et al., 2023b]). Hu et al. [2020] implemented a graph-based model designed to capture both long-term and short-term user interests to enhance the accuracy of news recommendations. The model achieves this by constructing a heterogeneous graph that interlinks users, news articles, and topics, thereby encapsulating the complex relationships within the data. Sun et al. [2020] introduced an approach for the next point of interest (POI) recommendation by incorporating both long-term and short-term user preferences, as well as considering the spatial and temporal contexts of user visits. Fazelnia et al. [2022] proposed a user modeling model designed for music recommender systems that is distinctive in its ability to capture both stable, long-term user interests and dynamic, short-term preferences. The model differentiates between "slow features", which represent historical interactions indicative of enduring interests, and "fast features", which capture recent interactions reflecting immediate preferences.

Take-home messages from user profile content.

- ***Combination of static and dynamic content****: User profiles blend static content (like demographics and skills, which are stable) with dynamic content (such as behaviors and preferences, which evolve over time) to create a full picture of the user.*
- ***Detailed user data for personalization****: In-depth static data covering a user's background, skills, and goals are key for personalized experiences, especially in educational and adaptive systems.*
- ***Adaptive profiles with dynamic content****: Dynamic content, reflecting real-time user behaviors and preferences, allows systems to adapt and personalize experiences, catering to both immediate and long-term user interests.*

4.2 Building and modeling user profiles

The process of building and modeling a user profile, which aims to capture, record, and manage user needs, interests, and any kind of information described in Section 4.1, incorporates several elements, from profile construction and data collection techniques to their evaluation. In this section, we discuss every component of the process.

4.2.1 User profile construction options

A crucial facet of user modeling revolves around profile construction, which can be classified into *individual* and *group profile modeling* (or simply *individual/group profiling*). Individual profiling relies on information linked to a single user, such as enclosing aspects like demographic details, and it refers to the standard and almost the entirety of the studies published in the research area; On the other hand, group profiling involves a collective of users who share common interests, goals, or preferences. In group profiling, a partially complete profile is generated by overlapping information across users.

Group profile modeling Masthoff [2004] investigated the complexities of group modeling in the context of adaptive television viewing, where the goal is to accommodate the preferences of multiple viewers simultaneously. The research delves into how individuals within a group make collective decisions about what to watch and how satisfied they are with those decisions. Experiments conducted as part of the study reveal that individuals consider factors like fairness, avoiding individual misery, and overall group approval when making selections. Generally, the contributions on group modeling are strictly related to the topic of *group recommender systems*. Masthoff [2011] provided an in-depth analysis of group recommender systems, focusing on the methodologies for aggregating individual preferences to cater to a collective audience. The article emphasizes the importance of understanding and modeling the affective states of users to enhance the recommendation process for groups. Boratto and Carta [2014] focused on the evaluation of various group modeling strategies within group recommenders. The paper underlines the importance of accurately combining individual preferences to generate group recommendations and highlights the influence of group size and the diversity of individual preferences on recommendation accuracy. The same authors implemented the Automatic Recommendation Technologies (ART) framework [Boratto and Carta, 2015], which employs clustering algorithms to automatically detect groups of users based on their preferences. The study identifies the Additive Utilitarian strategy as the best approach for modeling group preferences. More lately, Logesh et al. [2019] introduced an intelligent travel recommender system designed to generate personalized recommendations for both individual and group users. Central to this system is a user profiling module that leverages a broad set of user-specific data. This data includes social, contextual, behavioral, geographical, and categorical information. Zhou et al. [2021a] presented a group-based personalized search model that leverages both search behavior and friend networks to enhance search results for users, particularly those with sparse historical data. Group profiles are created by identifying friend circles through the user's social connections and shared search behaviors.

4.2.2 Data collection approaches

A central phase of user modeling involves *collecting data* about the user, which can be obtained either through the user's input or automatically collected by an intelligent agent. This information gathering about a specific user serves, first and foremost, as the starting point for any user modeling technique. We categorize the data collection approaches for user profiling into: *explicit*, *pseudo-explicit*, *implicit*, and *hybrid*.

Explicit user profiling *Explicit profiling* approaches, also known as *static* or *factual profiling*, rely on manual techniques that require user intervention through the completion of online forms, the fulfillment of questionnaires, or the explicit provision of ratings and preferences. These techniques were originally adopted by the earlier contributions (examples are described in Raghu et al. [2001], Poo et al. [2003], Brusilovski et al. [2007] and Schiaffino and Amandi [2009]). To offer specific instances, Kern et al. [2008] investigated user attitudes towards explicit profile generation for targeted advertising on public electronic displays. The study reveals a preference among users for explicit systems that grant them the ability to view and edit their profiles, despite the additional effort required. It also indicates that users are inclined to accept a less convenient system if it offers them greater control over their personal data. Pannu et al. [2011] addressed the problem of low-quality web search results by proposing a system that enhances search outcomes through explicit profiling. The system employs the Vector Space Model (VSM) to construct user profiles that reflect individual preferences and interests. These profiles are then used to filter web documents by assessing the similarity between the user profile and the document content.

Another side of this area considers research relying only on analyzing user's predictable and static characteristics. As illustrated in Section 4.1.1, static content includes users' demographic information, background, knowledge, skills, goals, needs, and personality traits. Generally, a static profiling contribution analyzes and studies different static features at the same time (e.g., [Gao et al., 2013; Kim et al., 2013; Gou et al., 2014]). Zhou and Conati [2003] developed a model for recognizing student emotions in real-time, which employs the OCC cognitive theory of emotions (named after its developers, Ortony, Clore, and Collins [Ortony et al., 1988]) and is structured using Dynamic Decision Networks. The study conducted to refine the model looked at student interaction patterns and goals, finding correlations between personality traits and goals. More recently, Dong et al. [2017] proposed a method called CoupledMFG (Multiple Label Factor Graph Model) for demographic prediction in coupled networks, which are characterized by users who have limited historical data within the network (i.e., a cold start problem). This model captures the correlations between users' communication behaviors and demographic profiles, as well as the interrelations among different demographic attributes. It utilizes both nonstructural attribute features and structural features to infer demographic information. Fernandez-Lanvin et al. [2018] provided a comprehensive examination of user attitudes and behaviors in the realm of e-commerce, delving into various facets such as user adaptation, success factors for online entrepreneurship, personality modeling, and demographic-specific interaction strategies. A key focus of the study is the impact of age and gender on web interaction performance. The findings revealed that both age and gender play a significant role in influencing user performance on e-commerce sites. Notably, the study observed consistent performance across different interaction tasks among individuals, suggesting the feasibility of developing a system that could automatically classify users based on their interaction behaviors. Guo et al. [2018a] presented an in-depth discussion on the evolution of user models and introduced the Cyber-I model, an innovative approach aimed at creating a comprehensive digital representation of an individual. The Cyber-I model is designed to encapsulate the personality traits, characteristics, and behaviors of users in the digital realm, striving to closely mirror the real individual. Rozen et al. [2021] introduced ProfBERT, a model that leverages a BERT-based framework combined with attention networks to generate user representations from comments on news articles. This model utilizes both user-generated comments and the summaries of the articles they comment on to create detailed user profiles. The attributes predicted include gender, location type, and mobile device usage.

Pseudo-explicit user profiling The practice of utilizing static data for user profiling has evolved in recent years. This information is extracted from public data that users have willingly shared for various reasons, such as setting up social networking accounts or using travel platforms. We propose the term *pseudo-explicit user profiling* for this newly emerged category. To elaborate, pseudo-explicit user profiling refers to a method where explicit user information is gathered not directly from the user for the purpose of profiling, but indirectly from data that the user has shared publicly for other purposes. This could include data shared on social media platforms, travel booking sites, online forums, and more. This method offers a new approach to user profiling, leveraging the wealth of data users generate as they interact with various platforms on the internet. It is called "pseudo-explicit" because while the information is explicit and voluntarily provided by the users, it was not shared with the intention of being used for profiling. The papers by Shu et al. [2018, 2019] focused on the role of user profiles in the context of fake news detection on social media, by exploiting explicit information extracted directly from metadata returned by querying social network APIs. Zhang et al. [2020] demonstrated that the daily EV charging load profiles vary with different demographic and social attributes by presenting a refined EV charging load simulation method considering people's demographics and social characteristics (e.g., gender, age, education level) retrieved from the US National Household Travel Survey.

Implicit user profiling Exclusively depending on explicit profiling became a challenge as users hesitated to share their information due to privacy concerns or found the process of filling out forms to be unmanageable, leading to avoidance. Modern systems have changed their perspective by giving more importance to *implicit user profiling*, also known as *behavioral*, *dynamic*, or *adaptive profiling*. This involves the passive collection and analysis of dynamic user data, including observing user behavior, interactions, and preferences, without necessitating direct input from the user (e.g., [Kasper et al., 2017; Pujahari and Sisodia, 2022; Qi et al., 2022a; Li et al., 2023b]). Implicit profiling approaches involve several aspects, including *behavior*, *preference*, *interest*, and *intention modeling*.

Behavior modeling is about observing and analyzing users' actions, interactions, and patterns while they engage with a system or application. This could include tracking the pages they visit, the time spent on different tasks, and the sequences of actions performed (e.g., [Zhong et al., 2012; Covington et al., 2016; Zhou et al., 2018; Wu et al., 2020b; Morshed Fahid et al., 2021; Zhao et al., 2021; Agarwal et al., 2022; Fan et al., 2022; Qian et al., 2022; He et al., 2023]). Wang et al. [2020a] presented a deep learning architecture to predict user attributes by learning from spatiotemporal behavior. Gu et al. [2021c] introduced a framework designed to enhance ranking models in e-commerce by leveraging user behaviors and utilizing a two-stage approach: pre-training on users' spontaneous behaviors and fine-tuning on implicit feedback across multiple e-commerce scenarios. Zhu et al. [2021] designed a system to enhance document ranking by optimizing the representation of user behavior sequences through contrastive learning. The system focuses on capturing the nuances of user behavior sequences to improve document ranking. Several methods introduced approaches for constructing user profiles which rely on the implicit collection of user browsing data to generate precise profiles, whose accuracy can be improved by integrating various sources of browsing data and by differentiating between significant and insignificant concepts (e.g., [Kulkarni et al., 2019; El-Ansari et al., 2020; Gu et al., 2021c; Bedi et al., 2022; Han et al., 2022; Yan et al., 2022]). Different contributions exploited the user's dialogue history from conversational platforms to build the profiles (e.g., [Ma et al., 2021; Qian et al., 2021; Li et al., 2022c]).

The analysis of behavior profiling has advanced considerably in the last few years, incorporating a range of refined modeling techniques that offer a more profound insight into user behavior across diverse contexts:

- ***Micro*** and ***macro behavior modeling*** refers to the study of different levels of user interactions and activities within an online platform, particularly in the context of e-commerce and recommender systems, reflecting, respectively, short-term and long-term user preferences or interests. Gu et al. [2020] developed a deep learning framework to capture user actions and dynamically model their interests at different temporal levels. Wen et al. [2021] introduced a deep neural recommendation model designed to address two critical challenges in the field: sample selection bias and data sparsity. They achieved this by incorporating both micro and macro user behaviors into a unified framework, which allows for a more comprehensive understanding of user interactions.
- ***Multi-behavior modeling*** integrates diverse user interactions with items, moving beyond dependence on a single type of interaction (e.g., [Jin et al., 2020; Xia et al., 2021a,b; Zhang et al., 2022; Cheng et al., 2023]). To cite specific recent cases, Cho et al. [2023] introduced two user modeling approaches, DyMuS and DyMuS+,

designed to address the inherent challenges in multi-behavior data, such as data imbalance, heterogeneity, and the need for personalized recommendations. Xuan et al. [2023] proposed the Knowledge Enhancement Multi-Behavior Contrastive Learning Recommendation (KMCLR) framework, aiming to augment user modeling in recommender systems through the utilization of multi-behavior information. This strategy recognizes that various behaviors can indicate different degrees of user preference and intent, thereby offering a more comprehensive and nuanced comprehension of user interests.

- ***Sequential behavior modeling*** considers the order and timing of user actions, acknowledging that the sequence of behaviors can impact a user's interests. This temporal aspect holds significance in many application domains, as the sequence of user interactions can unveil evolving preferences and contribute to predicting future actions (e.g., [Ren et al., 2019; Yuan et al., 2020a; Cao et al., 2022]). To provide explicit samples, Bian et al. [2021] presented a Contrastive Curriculum Learning (CCL) framework designed to enhance the modeling of sequential user behaviors and produce more effective user behavior representations. Chen et al. [2022a] introduced the Auto-Session-Encoder (ASE), a novel model designed to improve the modeling of user behavior sequences in session search. The conducted experimental studies revealed that the proposed model benefits more from predicting future sequences and clicked documents rather than recovering historical ones.
- ***Hierarchical user profiling*** is relevant to personalized e-commerce recommendations and models real-time interests at varying levels. Strictly related to the concepts of *micro* and *macro behavior modeling*, this yields nuanced insights for accurate predictions, enhancing precision and tailoring user experiences in the dynamic e-commerce landscape. Gu et al. [2020] engineered a Hierarchical User Profiling (HUP) framework to capture and model users' real-time interests at varying levels of granularity, acknowledging the hierarchical structure inherent in product categories and user interactions. Wen et al. [2021] introduced a deep neural recommendation model, designed to enhance conversion rate prediction by hierarchically modeling both micro and macro behaviors. By considering both levels of behavior, the model can better understand and anticipate user actions, leading to more effective recommendations and higher conversion rates. In the same research territory, Li et al. [2022a] designed a framework for enhancing cross-domain click-through rate prediction by incorporating a hierarchical user behavior modeling approach that leverages an element-wise behavior transfer layer and a user representation layer. Wei et al. [2022] and Xue et al. [2022] employed Graph Neural Networks to hierarchically analyze multi-level user intents and item representations to improve the accuracy of recommendations.
- ***Mobile user profiling*** identifies user interests and behavior patterns from their mobile device activities. With smartphones being widespread and generating substantial data, this profiling is vital for delivering personalized content and services that suit users' dynamic lifestyles. Bhogi et al. [2019] presented an approach to user profiling for mobile phone users, particularly focusing on the challenge of creating accurate profiles without access to ground truth data. The core of the proposed approach is the identification of seed features that are indicative of certain user attributes. These features are derived from user behavior and are used to train a positive unlabeled learning model. Wang et al. [2019b, 2020b, 2021b] are particularly active in this area. They proposed several innovative deep learning approaches for studying the unique characteristics and preferences of mobile users. Zhao et al. [2022] introduced a graph-based model for improving mobile user profiling by leveraging app text data. Traditional methods struggle with the sparse semantics and limited context of this kind of data, but the proposed model addresses these issues by constructing two heterogeneous graphs and applying a selective-scale attention mechanism to better capture semantic information.

Preference modeling involves deducing user preferences based on their past interactions and choices. By analyzing the historical data of user preferences, systems can make predictions about what a user might prefer in the future. This is one of the historical areas exploited in user modeling research (e.g., [Amatriain et al., 2009; Lakiotaki et al., 2011; Fu et al., 2013]), and studies are currently applied in various contexts, such as recommendations, personalized user interfaces, or targeted advertising. To illustrate with particular examples, Zhao et al. [2019a] focused on modeling user-system interactions within recommender systems by implementing a two-stage framework and a specific neural model. The model is specifically designed to better capture user behavior and preferences by considering the temporal dynamics of user interactions. Wu et al. [2020a] developed a model to capture a more holistic view of user preferences by not only considering which articles are clicked but also how users interact with them in terms of reading time. The experimental results demonstrated that incorporating reading satisfaction into user modeling significantly enhances the quality of news recommendations. Kostric et al. [2021] presented a method for improving preference elicitation in conversational recommender systems. The core idea is to generate implicit questions that can be used to understand user preferences more effectively. Gomez Bruballa et al. [2022] introduced a recommender system specifically designed for an image marketplace, with the primary goal of learning and catering to users' preferred visual styles. Yang et al. [2022] proposed a user preference modeling approach in the context of online recruitment, specifically addressing the challenge of person-job fit.

Interest modeling focuses instead on identifying and understanding the topics, subjects, or content that capture a user's attention. This is often inferred from the content they engage with, the keywords they search for, or the types of products they explore. By building a model of user interests, systems can provide more relevant and tailored recommendations, content suggestions, or targeted information. Cami et al. [2019] introduced a Bayesian non-parametric approach to capture and adapt to the evolving preferences and interests of users. Yilma et al. [2021] developed a recommendation and guidance method that is sensitive to the interests and needs of multiple stakeholders, including visitors, curators, and those responsible for crowd management. The novelty of the proposed method lies in its ability to balance user interests with other factors, such as the popularity of Points of Interest (POIs) and the objectives set by the curators.

Other relevant contributions for preference and interest modeling can be found in Jiamthapthaksin and Aung [2017], Logesh et al. [2019], Majumder et al. [2019], Olaleke et al. [2021], Zhang and Challis [2021], Curmei et al. [2022], Fan et al. [2022], and Zheng et al. [2022a].

Noteworthy to mention is the simultaneous focused research on both ***short-*** and ***long-term preference*** (or *interest*) ***modeling*** (e.g., [An et al., 2019; Hu et al., 2020; Sun et al., 2020; Zhou et al., 2020a; Fazelnia et al., 2022; Liu et al., 2023b]). Guo et al. [2019] introduced a neural network model named ALSTP (Attentive Long- and Short-Term Preference) designed for personalized product search. The model aims to enhance search accuracy by incorporating both the long-term and short-term preferences of users, along with the current search query. Wu et al. [2019b] developed a model to recommend the next point of interest (POI) to users. The model is designed to incorporate both the long-term preferences and the short-term behaviors of users, as well as contextual factors like POI categories and check-in times. Yu et al. [2019] implemented a recommender that adeptly captures both short-term and long-term user preferences. The approach is tailored to address the dynamic nature of user behavior, which is characterized by changing time intervals and latent intents. Xu et al. [2022] presented a recommendation engine designed by Pinterest to address the dual temporal aspects of user behavior: long-term interests and short-term intentions. The engine incorporates user embeddings that are specifically optimized to predict long-term future actions, as well as sequences of real-time actions to capture immediate user intent.

Intention modeling covers an important part of the behavior modeling research. It involves predicting or understanding the user's goals, objectives, or intentions based on their behavior and interactions. By analyzing the sequence of actions and choices made by a user, systems can infer what the user is likely to pursue or achieve. This aspect is valuable in providing anticipatory and proactive support, aligning system responses with the user's intended outcomes. Intention modeling contributes to a more dynamic and responsive user experience, as the system can adapt to user goals in real-time, offering relevant assistance or suggestions. Lugo et al. [2021] presented an approach to user search task modeling, whose key aspect is its focus on user intent modeling, which is achieved by analyzing clicked URLs from a large-scale query-clicked document collection. Deng et al. [2022a] introduced a personalized search model that leverages a dual-feedback network to enhance the understanding of user search intentions. The model is designed to improve personalized search by incorporating multi-granular user feedback, both positive and negative, to accurately model the user's current search intention. Li et al. [2023a] proposed an approach that defines user intent as a probability distribution of item categories and behaviors. This allows the system to understand the user's multiple objectives and preferences more accurately. The model utilizes user intents as guidance for fusing user preferences across different behavior objectives, rather than learning user preference for each intent separately.

Hybrid user profiling This user profiling approach, which combines both implicit and explicit user profiling methods, integrates the benefits of both strategies. It considers static characteristics and retrieves behavioral information about a user, enhancing profiling efficiency. Examples can be found in Poo et al. [2003], Stanescu et al. [2013], Luo et al. [2014], and Liu [2015]. To supply detailed instances, Du et al. [2016] addressed the challenge of personalized resource search within collaborative tagging systems by introducing a novel hybrid user profiling model. The model is designed to enhance the personalization of search results by incorporating both tags and ratings, thereby capturing a user's preferences and aversions more accurately. In Natarajan and Moh [2016], the hybrid user profiles are constructed using a combination of click-through analysis, user tweet analysis, and user follower analysis. This multifaceted approach to profile building allows the system to capture a more comprehensive view of user preferences. Lately, Logesh et al. [2019] and Nkambou et al. [2023] provided hybrid approaches leveraging data encompassing contextual, behavioral, geographical, and categorical information, which is instrumental in understanding the user's preferences and activities, particularly in online social networks and recommender systems.

4.2.3 Data preprocessing

A significant portion of profile data obtained, especially dynamic content from social media and recommendation engines, is often incorrect. Consequently, there is a necessity to cleanse the acquired datasets to ensure that the extracted features for profile modeling yield improved performance results. Many researchers adopt diverse *data preprocessing* techniques in their studies on user profiling to ready their data for the subsequent analysis phase. For instance, Tang et al.

[2010] employed a Hidden Markov Model approach to efficiently purify data, improving the user profile system. This method successfully addressed the issue of disambiguation in collecting user profile information. Basic pre-processing techniques, including tokenization, stop word removal, and tagging, were applied. Tokenization involves segmenting textual data into tokens using a tokenizer, with each token being assigned a tag. Recently, Ali et al. [2020] provided a thorough examination of the data preprocessing steps necessary for effective web usage mining, which is the process of extracting useful information from web usage data to model user behavior. The paper outlines the various sources of web data, such as click-stream analysis and web server log files, and emphasizes the importance of preprocessing in the overall behavior user modeling process.

4.2.4 Feature extraction

Feature extraction is another important step in user modeling, involving the retrieval of user profile features from diverse domains. Various procedures have been employed by researchers in this field to extract these features, aiming to enhance modeling performance. Commonly used elements include content features, pattern features, profile features, term features, and user behavioral features. For instance, Hijikata [2004] proposed a method for text data extraction based on user mouse behavior features on web platforms. Tang et al. [2010] focused on authorship profiling, evaluating a set of profile features consisting of six sets of attributes in article publication data, such as publication title, abstract, venue, abstract authors, publication year, and references. These features were extracted from digital libraries (ACM, Springer, and IEEE) using heuristics and represented as a feature vector with the number of occurrences as values. Meftah et al. [2012] introduced a method that focuses on the extraction of relevant features from physiological data, such as electromyography (EMG) and respiration signals, which are critical for accurately identifying not only basic but also complex emotions. The feature extraction process is a part of the training module designed to discern patterns within the physiological signals that correspond to different emotional states. Li et al. [2014] utilized a supervised learning classifier to extract data from Twitter and train the model. However, this approach solely took into account network information, which proves insufficient for inferring user attributes. Ben Hassen et al. [2022] proposed a method to extract latent features from images of items, such as movie posters and clothing, by leveraging pre-trained deep learning models. The extracted features are then subjected to dimensionality reduction to make them more manageable and suitable for the subsequent stages of the recommendation process.

4.2.5 User profile representation

User profile representation refers to the way in which information stored in user profiles is structured and presented through a system or an application. The goal is to create an accurate portrayal of the user, enabling the system to make informed decisions and predictions about the user's interactions and preferences. We discuss several representation variants: *term-based*, *semantic-network*, *concept-based*, *graph-based*, *universal*, and *holistic*.

Term-based (Vector-space model) The prevalent representation of users' interests is through a keyword-based or vector-based user model, comprising a set of terms weighted by vectors of keywords. These vectors, utilized to expand user queries, can be developed using different methods like Boolean, Term Frequency (TF), or Term Frequency-Inverse Document Frequency (TF-IDF) [Shen et al., 2005]. User interest keywords, extracted from visited documents during browsing, can be represented by a single vector encompassing all interests or multiple vectors reflecting interests in various domains. The effectiveness of this model relies on the degree of generalization in the vectors [Gauch et al., 2007]. However, drawbacks include polysemy and potential misinterpretation of user interests. An interesting article was presented by Hu et al. [2017], who introduced an extraction algorithm that combines Word2Vec and TF-IDF to address shortcomings in the vector representation method.

Semantic-based (Ontology-based) To tackle the challenges of polysemy and synonymy in keyword-based profiles, a solution involves representing profiles using weighted concepts in a *semantic network*. However, this introduces complexities in system construction, requiring an existing mapping between words of interest and concepts, such as WordNet ontology, a learning system method, or manual intervention. Sieg et al. [2007] explored the concept of personalizing web search results through the use of ontological user profiles. These profiles are built by assigning interest scores to concepts within a domain ontology. Skillen et al. [2012] introduced an ontological user profile model designed to enhance adaptive, context-aware applications in mobile environments. The model emphasizes the importance of dynamic user attributes and contains classes that represent user preferences, education, health profiles, capabilities, interests, and contextual information. The goal of the model is to facilitate personalized services that can adapt to users as they transition through different environments. In the context of recommender systems, Rimitha et al. [2018] proposed an ontology that encapsulates various aspects of the job recommendation domain, such as location, education, salary ranges, job description, and job experience. The ontology is designed to provide a structured and standardized representation of user preferences and job characteristics, which includes defining classes and the relationships between them. For instance, it includes relations like "Has preferred salary" and "Has preferred location", which are crucial for matching users with suitable job opportunities. In the same domain, Olufisayo Dahunsi [2021] presented a proposal for an advanced user profiling methodology within the context of apparel recommender systems. The proposed methodology is centered around the development of an ontology-based knowledge base designed to enhance the personalization of apparel recommendations by mapping user features to garment and ensemble features, utilizing domain expert knowledge and predefined style rules.

Concept-based (Hierarchy-based) Concept-based profiles and semantic network-based profiling share the common approach of representing information through nodes of concepts and the relationships between them. Different methods are employed to assign weights indicating the user's level of interest in each topic. Nanas et al. [2003] utilized various techniques to categorize user interests within a hierarchical structure, employing a knowledge base for this purpose. The researchers applied a library classification system (LCS) to identify user interest hierarchies, while the edge weights were calculated using the TF-IDF mechanism. Malinowski and Zimányi [2006] introduced a conceptual framework designed to enhance data warehouses and Online Analytical Processing (OLAP) systems. The model builds upon the Entity-Relationship (ER) model, incorporating specific constructs to represent dimensions, hierarchies, and fact relationships, and provides a graphical notation for these elements. Recently, Wu et al. [2019a] developed a hierarchical user and item representation model that leverages a three-tier attention mechanism to enhance recommender systems. This model is designed to extract and learn representations from user and item reviews at multiple levels of granularity, including words, sentences, and reviews themselves.

Graph- and Knowledge graph-based Graph-based representation in user modeling involves utilizing graphs or networks to represent and analyze information about users. This approach is particularly effective in capturing complex relationships, dependencies, and interactions among various elements in a user's profile. The representation is typically structured with nodes representing entities or concepts and edges denoting relationships or connections between them. In the last few years, works leveraging graph-structures increased. Wang et al. [2019b] introduced an adversarial substructured learning framework tailored for mobile user profiling. The approach hinges on the construction of user activity graphs that encapsulate the unique characteristics and preferences of mobile users. The central challenge addressed is the learning of deep representations from these graphs to accurately profile users Chen et al. [2022b] presented a novel approach named Global and Personalized Graphs for Heterogeneous Sequential Recommendation (GPG4HSR) that enhances user profiling and modeling in the context of heterogeneous sequential recommender systems. The proposed model incorporates two distinct graph layers to improve user profiling. The first is a global graph layer that captures the transitions between different behaviors across all users, providing a macro-level view of user interactions. The second is a personalized graph layer that models the interaction sequences of individual users, taking into account the unique intentions and preferences of each user by focusing on the contextually relevant nodes adjacent to their interactions. Guan et al. [2022] implemented a novel approach designed to enhance the personalization of fashion compatibility recommendations by leveraging user preference modeling. The proposed model employs a heterogeneous graph that integrates users, items, and attribute entities, along with their interrelations, to create a comprehensive representation of the fashion domain. Other relevant contributions in the area can be seen in Guo et al. [2018a], Wanda and Jie [2020], Wang et al. [2020b], Yang et al. [2022], and Yang et al. [2023].

Knowledge graphs are essential in user modeling, providing a robust framework to organize and represent complex relationships. In user modeling, they efficiently capture users' preferences and behaviors, enabling personalized experiences and enhancing recommender systems. By mapping connections between users and their interests, knowledge graphs facilitate a nuanced understanding of individual profiles, allowing systems to adapt dynamically to users' unique needs and preferences. Wang et al. [2020b] presented an innovative approach to mobile user profiling by proposing an integrated reinforcement learning framework that incorporates spatial knowledge graphs. Anelli et al. [2021] introduced a knowledge-aware recommender system that emphasizes user modeling through a sparse factorization approach. By analyzing historical data and item attributes, the model constructs a detailed model of user-item interactions, which is essential for understanding user preferences and tailoring recommendations. Instances of similar works are seen in Huang et al. [2019], Wang et al. [2019b], Wang et al. [2021a], and Xuan et al. [2023].

Universal user representation It aims to create a generalized user representation that encapsulates the essential characteristics and behaviors of a user. This representation is constructed to be versatile and applicable across a variety of real-world applications, without the need for specific adjustments for each task. Universal user representation emphasizes adaptability and versatility to accommodate a wide range of users and their diverse needs, seeking to create a model that can be applied across different contexts and user groups. For instance, Ni et al. [2018] developed a deep learning framework designed to create universal user representations for a variety of e-commerce personalization tasks. The proposed architecture is capable of simultaneously performing multiple personalization tasks, such as click-through rate (CTR) prediction, learning to rank (L2R), price preference prediction, fashion icon following prediction, and shop preference prediction. The model is trained on a substantial offline dataset from Taobao, one of the largest e-commerce platforms. Yuan et al. [2020a] introduced a transfer learning architecture designed to create universal user representations for recommender systems, which consists of two stages: the first involves pre-training on large-scale datasets to capture universal user behaviors, and the second involves fine-tuning with supervised labels to adapt the pre-trained representations to several different tasks. Gu et al. [2021b] presented an approach for learning universal user representations from unlabeled behavior data. The primary objective is to generate user representations that encapsulate a wealth of information, enabling their application across a variety of downstream tasks, such as predicting user preferences and inferring user profiles. Yuan et al. [2021] developed a method of user modeling that embodies the "One Person, One Model, One World" paradigm. This paradigm is designed to create a universal user representation that can continually learn across different tasks without succumbing to catastrophic forgetting, which is the loss of previously acquired knowledge when new information is learned. An innovative technique in this area has been proposed by Kim et al. [2023], where they introduced a continual user representation learning method. Their main idea is to use task embeddings to generate task-specific soft masks, allowing model parameters to be updated throughout the training sequence and capturing the relationship between tasks. Additionally, a knowledge retention module with a pseudo-labeling strategy is introduced to alleviate catastrophic forgetting.

Holistic user modeling Although it can be related to *universal user representation* as both concepts aim to create generalized user models, *holistic user modeling* is about building a detailed and comprehensive model that takes into account all relevant aspects of a user's interaction with a system. This includes not only the user's actions but also their expectations, preferences, and limitations. It is more focused on the integration of various data sources to create a complete picture of the user. Specific examples can be found in Gong and Wang [2018] and Gong et al. [2020]. In the former work, they designed a probabilistic generative model for holistic user behavior modeling in social media. It integrates opinionated content modeling with social network structure modeling to capture the consistency and heterogeneity of user behavior across various user-generated data modalities. In the latter, the authors proposed a solution that learns user representations in social networks from both network structure and text content by capturing the dependency between these two modalities in the latent topic space. This approach uses statistical topic models to handle the unstructured nature of the text and embeds both users and topics in a low-dimensional space to capture their mutual dependency. The user's affinity to a topic is characterized by their proximity to the topic's embedding, which is used to generate text documents, while the affinity between users is modeled by the proximity between their embeddings, which is used to generate social network connections. Another robust line of research in this area has been conducted by Musto et al., from 2018 and 2021. In Musto et al. [2018], the authors discussed the development of a holistic user profile framework that integrates a user's digital footprints from both social networks and personal devices to create a comprehensive digital identity. This framework collects data from platforms such as Twitter and Facebook, as well as from devices like Android smartphones and FitBit wristbands. The collected data undergoes processing and enrichment to form a unique user model that reflects the individual's behavior and interests. Musto et al. [2020c] presented a knowledge-aware food recommender system designed to provide personalized recipe suggestions based on user characteristics and health-related constraints. The system incorporates a holistic user model to re-rank recipes and was assessed through a web-based experiment. The findings indicate that holistic user profiles significantly influence user preferences. Musto et al. [2020a,b, 2021] discussed the implementation of Myrror and MyrrorBot. Myrror is a platform designed to create a holistic user model by integrating data from social networks, smartphones, and wearable devices. The platform's goal is to alleviate the problem of information overload and offer personalized services based on the user's profile. MyrrorBot is a conversational agent developed to enable users to interact with and query their user models using natural language and is built on the Myrror platform. The core components of MyrrorBot include the Intent Recognizer module, which interprets user requests, and the Generator module, which formulates responses in natural language. The system's conversational interface aims to enhance traditional web interfaces, allowing for a more intuitive and efficient way for users to access and inspect the information contained in their profiles.

4.2.6 Modeling techniques

Once the information is organized, the next step is to select suitable techniques with varying characteristics to build a user profile. This phase is essentially about the creation of a computational model, which is constructed using the extracted features and is capable of predicting the needs or preferences of the user. In the proposed categorization, whose specific taxonomy is displayed in Figure 3, we present in detail recent relevant works for each topic. It is also important to note that some techniques may span multiple categories depending on their specific implementation and use case. We examine each method within the category in which it is most discussed in the literature in the context of user modeling.

Rule-based *Rule-based user modeling* involves creating a set of predefined rules or conditions that determine user behavior or preferences. These rules are typically designed based on expert knowledge or domain-specific guidelines

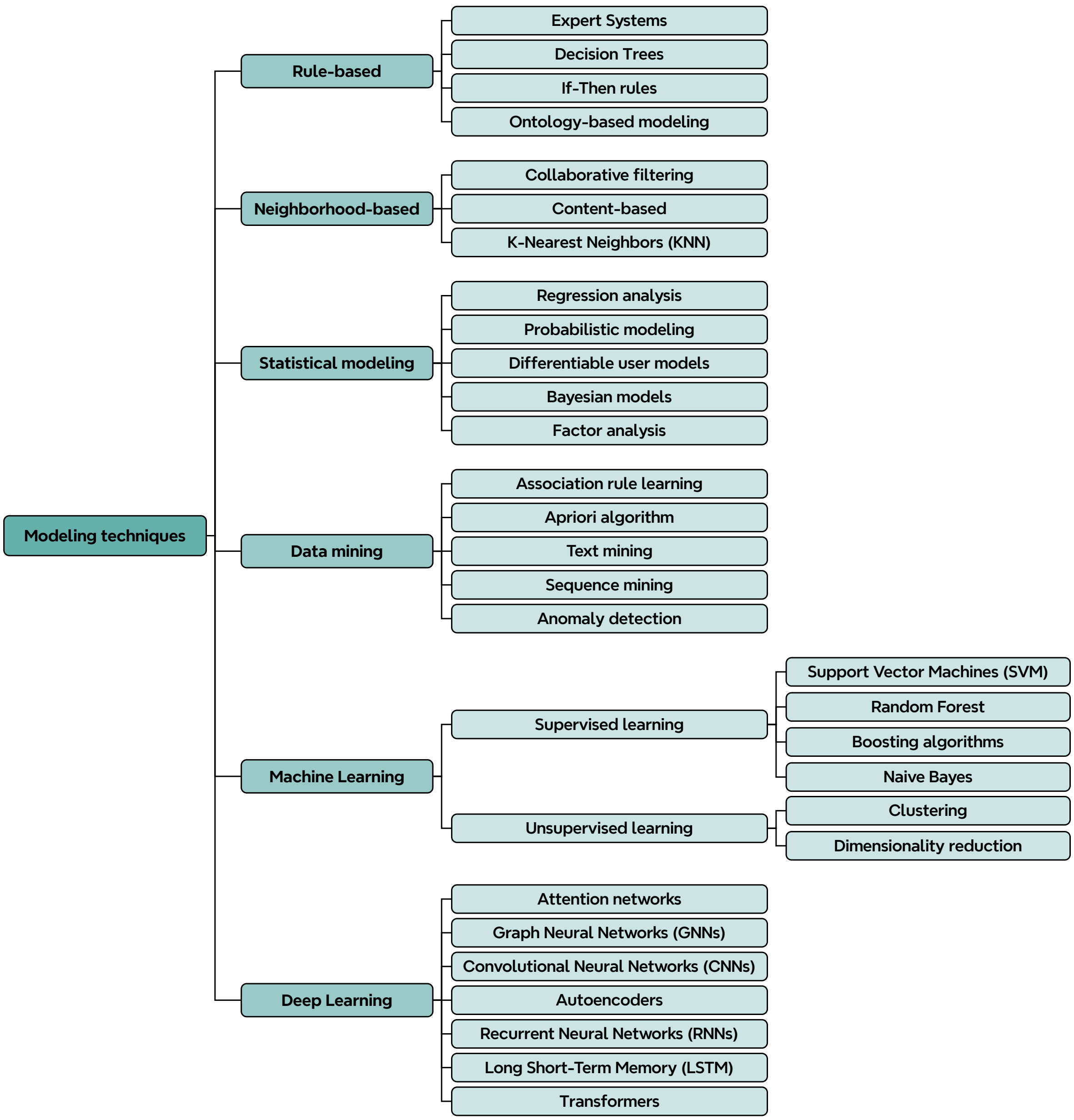

Figure 3: Specific taxonomy of the *Modeling techniques*.

(e.g., [Cheung Chiu and Webb, 1998; Adomavicius and Tuzhilin, 2001; Razmerita et al., 2003; Brut et al., 2009; Aleven, 2010]). Rule-based approaches are classified into:

- ***Expert systems*** refer to computer programs that emulate the decision-making ability of a human expert in a specific domain. They use a knowledge base of rules to draw inferences and make decisions. For example, Rizzo et al. [2016] explored the development of a rule-based expert system designed to model and infer mental workload in users, with the aim of enhancing user modeling techniques. The expert system is constructed by eliciting knowledge from domain experts and translating this knowledge into computational rules. These rules are then applied to model user's mental workloads, using heuristics to combine them into a numerical index. The system accounts for various attributes that contribute to the mental workloads, such as mental demand, temporal demand, effort, performance, and frustration.

- ***If-Then rules*** are a form of declarative knowledge representation where specific conditions (*if*) are defined to trigger certain actions or conclusions (*then*). In the context of user modeling, these rules are used to make decisions or predictions based on observed user behavior or input features. Sola et al. [2021] introduced a rule-based recommender system specifically designed to assist users in the task of business process modeling. In the context of user modeling, this approach is significant as it adapts to the user's input and the structure of the process model at hand. By analyzing a repository of BPMN 2.0 models, the system learns the common sequences and dependencies of activities, which reflects the collective expertise and practices encoded in these models.

- ***Decision trees*** involve creating a tree-like model where each node represents a decision based on input features. They are used for classification and regression tasks, making decisions by traversing the branches of the tree. To cite a specific work, Sarker et al. [2020] proposed the Behavioral Decision Tree (BehavDT) model, which is designed to predict smartphone user behavior by considering multi-dimensional contexts. Unlike traditional decision tree models, BehavDT emphasizes behavior-oriented generalization and individualized preference-oriented decision-making, which enhances its predictive accuracy. In a recent article, Streeb et al. [2022] provided a comprehensive survey of visualization techniques for decision trees and rule-based classifiers, with a focus on user modeling and the tasks associated with the development and application of these models.

- ***Ontology-based modeling*** concerns using ontologies, which define concepts and relationships in a domain, to represent and reason about user preferences, characteristics, and behavior. It utilizes ontological rules for making inferences about users. Rimitha et al. [2018] presented a method for enhancing personalized job RSs through the development of ontology-based user profiles. It underscores the significance of user profiles in delivering tailored job suggestions to individuals by accurately reflecting user preferences and experiences. Chari et al. [2020] introduced the Explanation Ontology, a comprehensive model specifically crafted to encapsulate the various facets of explanations within user-centered AI systems. The model is presented as a valuable tool for system designers, offering a structured approach to user modeling with ontology in the context of AI explanations. It emphasizes the importance of user-centric design in AI and the ongoing efforts to update and refine the ontology to support the dynamic landscape of user needs and system capabilities.

Neighborhood-based *Neighborhood-based user modeling* deals with the idea that users who are similar to each other in certain aspects are likely to have similar preferences. It involves analyzing the behavior or characteristics of a user in relation to their "neighborhood" or a group of similar users (e.g., [Konstan et al., 1997; Kim et al., 2011; Meftah et al., 2012; Subramaniyaswamy and Logesh, 2017; Cami et al., 2019; Sánchez and Bellogín, 2019; Javed et al., 2021]). We identify the following groups:

- ***Collaborative filtering*** relies on user-item interactions and recommendations from a group of users with similar tastes. It can be *user-based*, *item-based*, or a combination of both. Ma et al. [2022a] investigated the effects of rapid, population-scale concept drifts, such as those induced by pandemic-like events, on collaborative filtering models within RSs. The core of the study is the introduction of the NEST framework, which simulates the evolution of user needs and behaviors in response to non-stationary external events. Wang et al. [2022a] introduced a recommender system framework known as Time-aware Attention-based Deep Collaborative Filtering (TADCF), whose core is its ability to model dynamic user preferences over time.

- ***Content-based filtering***[2] recommends items based on the user's past preferences and the characteristics of the items. It considers the content features of items and user profiles. To offer a concrete example, Pujahari and Sisodia [2022] presented a wide approach to enhancing content-based user modeling in recommender systems. For user profile generation, the paper introduces an ensemble classifier that operates within an iterative learning framework. This classifier is designed to incrementally learn and update user preferences, allowing the system to adapt to user interactions and feedback over time. The iterative update rules ensure that the user profiles evolve, capturing the dynamic nature of user interests.
- ***K-Nearest Neighbors*** (KNN) is a technique that classifies or recommends based on the majority class or average of the k-nearest data points in feature space. For instance, Nagaraj et al. [2022] developed a recommender system aimed at aiding undergraduate and graduate students in selecting the most suitable colleges based on their individual profiles. The system employs user modeling through the KNN algorithm to calculate weighted scores for college recommendations. By analyzing factors such as SAT scores, tuition fees, and academic records, the KNN algorithm helps to match students with institutions where they have the highest likelihood of acceptance and success.

Statistical modeling *Statistical modeling* for user behavior refers to the use of statistical methods to analyze and model patterns in user data, along with understanding relationships and making predictions (e.g., [Horvitz et al., 1998; Zukerman and Albrecht, 2001; Zigoris and Zhang, 2006; Zhang and Koren, 2007; Harvey et al., 2011; Seroussi et al., 2011; Benmakrelouf et al., 2015; Tomeo et al., 2015; Vu et al., 2015; Yadav and Selvakumar, 2015; Chen et al., 2019a]). This category includes:

- ***Regression analysis*** involves modeling the relationship between a dependent variable and one or more independent variables. It is used to understand and predict the impact of changes in the independent variables on the dependent variable. To cite a relevant paper, Gao et al. [2017] introduced an item recommendation model named CDUE, which stands for Collaborative Dynamic User profile Evolution. This model is designed to predict a user's future interests by incorporating a regression approach that accounts for the temporal dynamics of both user interests and item topics. Specifically, the model employs a dynamic sparse topic regression to track how item topics evolve over time, ensuring that the recommendations remain relevant as the content changes.
- ***Probabilistic modeling*** concerns the use of probability distributions to represent uncertainty and variability in user behavior or preferences. This approach allows for the incorporation of statistical methods, likelihoods, and estimation techniques to capture the inherent uncertainty in modeling user characteristics based on observed data. Probabilistic modeling encompasses a variety of statistical techniques that utilize probability theory to model and understand complex relationships within user data. To illustrate with particular examples, Hadoux and Hunter [2018] introduced a framework for probabilistic user modeling in the context of persuasive argumentation. The core of the framework is the use of beta distributions to represent the uncertainty in user beliefs, which is a departure from traditional models that use sharp, deterministic values. An intriguing approach has been proposed in Vardasbi et al. [2020] and Oosterhuis and de Rijke [2021]. A key aspect of the papers is the use of probabilistic user models for simulating user interactions in the experimental setup. These models are crucial for generating data that reflects the biases present in real-world scenarios. By employing probabilistic user models, the authors are able to create a more realistic testing environment for their proposed affine estimator.
- ***Differentiable user models*** are computational constructs that enable efficient probabilistic user modeling by providing a differentiable approximation of cognitive behavior simulators, which are often non-differentiable and computationally prohibitive for practical applications. These models are designed to be compatible with modern machine learning frameworks, often implemented using neural networks, and allow for real-time applications even with advanced cognitive models that lack a closed-form likelihood. The most important work on this topic has been written by Hämäläinen et al. [2023], where the authors introduced this innovative approach to cognitive user modeling by employing differentiable surrogates, which significantly enhance computational efficiency and enable real-time applications. The differentiable surrogates are trained offline and are designed to be utilized online, effectively addressing the computational challenges that have traditionally limited the use of probabilistic user modeling based on cognitive models. The differentiable user models are

[2] *Content-based filtering* is placed under the "*Neighborhood-based*" category to highlight its similarity to *collaborative filtering* in terms of creating a neighborhood of similar items. In content-based filtering, this neighborhood is formed based on the content features of items and the user's historical interactions. The placement acknowledges that, in a sense, content-based filtering creates a "content-based neighborhood" for recommendations. However, it is important to note that content-based filtering is often considered a separate and distinct approach due to its emphasis on item characteristics and individual user profiles.

shown to overcome the limitations of existing likelihood-free inference methods, providing a solution that is both computationally viable for online applications and maintains user modeling accuracy.

- ***Bayesian models*** specifically adhere to the principles of Bayesian probability theory to update beliefs about user preferences or behavior based on new evidence. They provide a framework for incorporating prior knowledge and updating it with observed data. Shen et al. [2021a] developed a user profiling system for inferring gender and personality traits from non-linguistic audio data during conversations. The core component of the system is a voice activity detection (VAD) mechanism and a feature extraction process that focuses on conversational dynamics. The VAD component utilizes a Bayesian algorithm to distinguish between speech and non-speech segments within the audio data, which is crucial for accurately capturing the conversational features relevant to user profiling.
- ***Factor analysis*** is a statistical method used to identify *latent* (i.e., unobservable) *factors* that explain patterns of correlations within observed variables. It is often applied to uncover underlying dimensions in user behavior or preferences. An interesting work has been presented by Yuan et al. [2020b]. The paper introduces a Generalized and Fast-converging Non-negative Latent Factor (GFNLF) model designed to predict user preferences in recommender systems. The GFNLF model aims to overcome the limitations of slow convergence and restricted representational capabilities observed in traditional latent factor models.

Data mining *Data mining* refers to the process of discovering patterns, associations, and trends within large datasets. Techniques like association rule mining and clustering are used to extract valuable information and insights from user-related data (e.g., [Eirinaki and Vazirgiannis, 2003; Pierrakos et al., 2003; Mobasher, 2007; Xie and Yu, 2009; Angeline, 2013; Erlandsson et al., 2016; Burgos et al., 2018; Sarker and Salim, 2018; Abu Sulayman and Ouda, 2019; Shazad et al., 2019]). The topics pertaining to data mining are:

- ***Association rule learning*** is a technique designed to unveil meaningful relationships, patterns, or associations among variables (in our context, user behaviors or preferences) within extensive datasets. This method seeks to identify rules expressing correlations or co-occurrences between different user actions or characteristics. To provide some samples, Si et al. [2019] presented an innovative use of association rules to uncover and analyze the interests of users on social networks, with a particular focus on Twitter and LinkedIn. For Twitter, the authors propose a method that reorders a user's interests based on association rules derived from user behavior. On LinkedIn, the researchers collected profile data to identify the distribution of user interests. They applied association rules to this dataset and discovered a substantial number of correlations between various human interests. Agouti [2022] proposed an innovative algorithm named Diffusion-Graph-Based Influence Maximization (DGIM), which leverages association rule mining to model the spread of influence and to detect relationships between users concerning specific topics.
- ***Apriori algorithm*** is specifically tailored association rule learning in user modeling and is employed to identify frequent item sets and generate association rules. Following the "*apriori*" principle, it iteratively refines rules based on user behavior, helping to reveal patterns and associations in interactions or preferences. Singh et al. [2021] developed an optimized collaborative filtering algorithm for recommenders that utilizes the apriori algorithm to enhance user profile creation. The paper details how the apriori algorithm is employed to generate detailed user profiles by analyzing users' interactions with items. These profiles are then used to modify the similarity measure for finding similar neighbors, which is a critical step in collaborative filtering algorithms.
- ***Text mining*** involves extracting meaningful information and patterns from unstructured text data. It includes techniques such as natural language processing, sentiment analysis, and text clustering to understand and model user preferences expressed in textual form. Greco and Polli [2020] explored the use of Emotional Text Mining (ETM) as a tool for user profiling in the context of brand management, with a specific focus on analyzing Twitter messages about a sportswear brand. The paper demonstrates how ETM can be leveraged for user profiling in brand management, providing theoretical and managerial insights. It showcases the method's ability to simplify the analysis of large textual datasets and its contribution to the field through the extraction of actionable information for enhancing customer understanding and brand strategy. Heidari et al. [2020] presented, in the same domain of social networks, an approach to detecting social bots on Twitter by focusing on user profiling extracted from tweet text.
- ***Sequence mining*** focuses on discovering patterns or relationships within sequential data. It is commonly used to identify sequences of events or actions in a user's interactions over time, providing insights into behavior patterns. An interesting approach has been proposed by Gurbanov and Ricci [2017]. They developed a hybrid recommender system that integrates sequence mining with collaborative filtering to enhance the prediction of user actions on an online career-oriented social networking platform. The focus of the system is to utilize the sequential patterns of user interactions, particularly with job postings, to forecast specific actions such as

replying to a job posting. The sequence mining component is crucial in the hybrid model as it is responsible for predicting the probability of the next user action based on the observed sequence of interactions.

- ***Anomaly detection***, in user modeling, aims to identify instances that deviate significantly from the expected or normal behavior. It involves detecting unusual patterns, outliers, or anomalies in user data that may indicate fraudulent activity, errors, or novel user behavior. To supply detailed instances, Böhmer and Rinderle-Ma [2020] presented an extended study on anomaly detection for temporal data in business processes, with a focus on user modeling. The authors propose a novel approach that leverages association rule mining to detect anomalies in process runtime behavior, aiming to differentiate between benign and malign anomalies, minimize false positives, and elucidate the root causes of anomalies to users. Sharma et al. [2020] introduced a procedure for anomaly detection in user behavior analytics by employing an unsupervised method. The primary objective is to identify insider threats by analyzing patterns in user session activities.

Machine learning *Machine learning* (ML) refers to a set of computational techniques that empower systems to automatically learn patterns, relationships, and predictions from user data and behaviors. Generally, ML methods are divided into two groups:

- ***Supervised learning*** involves training algorithms on labeled datasets to predict or classify user behavior based on provided examples, enabling the system to make accurate predictions for new user interactions (e.g., [Cufoglu et al., 2008; Tang et al., 2010; Santra and Jayasudha, 2012; Raghuram et al., 2016]). Specific applications in user modeling make use of the following supervised learning algorithms:
  - ***Support Vector Machines*** (SVM) are models that can be used for classification and regression tasks. They find a hyperplane that best separates classes or predicts a target variable. Ahmad et al. [2021] introduced a method for identifying spam tweets on Twitter by leveraging an SVM classifier, with a particular focus on analyzing user interactions. In this study, it is applied to differentiate between spam and non-spam tweets using a variety of features, including those derived from user interactions.
  - ***Random Forest*** is an ensemble learning method that constructs a multitude of decision trees during training and outputs the class that is the mode of the classes from individual trees. Chen et al. [2021a] presented a study that evaluates the effectiveness of the random forest algorithm in identifying high-risk users within public opinion discussions on digital platforms. In particular, is used to classify users based on their risk of contributing to negative public opinion.
  - ***Boosting algorithms*** are a set of ensemble learning techniques that combine the predictions of multiple weak models to create a robust and accurate predictive model. These algorithms sequentially train weak learners, with each subsequent model focusing on the mistakes of its predecessors. Popular boosting algorithms include *AdaBoost* and *Gradient Boosting*, which are applied to capture complex relationships in user data. An extensive study on the application of boosting algorithms for user profiling, specifically for predicting student performance in higher education, has been presented by Hamim et al. [2022]. To achieve this, the analysis compares different research studies that utilize boosting algorithms for student profile modeling. The paper also explores the impact of student behaviors and characteristics on their academic performance. It proposes a student profile model that leverages educational data mining techniques to predict, classify, and adaptively support students' learning processes. This model can also be used for e-RSs that tailor educational content to individual student needs.
  - ***Naïve Bayes*** is a probabilistic algorithm based on Bayes' theorem. It assumes that features are conditionally independent, making it efficient and effective for classification tasks. A valuable research paper in the student profiling domain has also been provided for this specific algorithm. Specifically, Tripathi et al. [2019] presented a study on student profile modeling, with a particular focus on predicting student performance. The core of the study is the application of the Naïve Bayes classifier, which is compared against the existing Support Vector Machine (SVM) classifier. The results indicate that the Naïve Bayes classifier outperforms the SVM in terms of both accuracy and execution time, making it a more efficient and effective tool for predicting student performance.
- ***Unsupervised learning*** harnesses input data devoid of explicit labels to uncover inherent patterns or structures within user behavior, providing valuable insights into the underlying data structures without the need for predefined categories or outcomes (e.g., [Castellano et al., 2007; Boratto and Carta, 2014; Benmakrelouf et al., 2015; van Dam and van de Velden, 2015; Cañigueral and Meléndez, 2021; Yang et al., 2021]. Algorithms belonging to this group are:
  - ***Cluster analysis*** (or simply *clustering*) groups data points based on similarities, creating clusters or groups of similar instances. Common algorithms include *k-means clustering* and *hierarchical clustering*. Clustering helps identify user segments with similar behavior or preferences. To provide concrete

examples, Ouaftouh et al. [2019] proposed a clustering-based approach to enhance social recommender systems. The core of the research is the application of partitional clustering algorithms, with a focus on the K-means algorithm, to group user profiles into clusters. These clusters are intended to represent users with similar interests and preferences, which can then be used to provide more accurate recommendations within an e-commerce environment.

  – ***Dimensionality reduction*** techniques reduce the number of features in the dataset while retaining its essential information. Reducing dimensionality aids in visualizing user data patterns and improving computational efficiency. *Principal Component Analysis* (PCA) is the most popular method of this type. Bi et al. [2016] introduced an anomaly detection model to scrutinize user behavior within database systems and web browsing environments. PCA analyzes user behavior by calculating covariance matrices and extracting significant behavior features. This statistical approach simplifies the complexity of user behavior data, allowing the model to distinguish between normal and abnormal patterns effectively.

Deep learning *Deep learning* (DL) involves using *deep neural networks* (i.e., neural networks with multiple layers) to capture complex patterns and representations in user data. It excels at handling large and unstructured user data, making them suitable for tasks such as user behavior prediction and personalized recommendations. As observed in various fields, plenty of articles have been published in user modeling employing several DL techniques and architectures (e.g., [Elkahky et al., 2015; An et al., 2019; Ren et al., 2019; Heidari et al., 2020; Zhou et al., 2020b; Wang et al., 2021b; Wen et al., 2021; Zhao et al., 2021; Zhou et al., 2023]). A description of these methods and examples of contributions for each of them are provided below. It is important to highlight that a single approach can include more than one category. We consider these cases only under one topic.

- ***Attention networks*** (or *mechanisms*) allocate varying degrees of importance to different parts of the input sequence. This enables the model to focus on specific aspects of user behavior, enhancing its ability to capture and understand intricate patterns in the data (e.g., [Fazil et al., 2021; Chu et al., 2022; Qi et al., 2022b]). To detail specific works, Qi et al. [2021] introduced TRISAN (Trilateral Spatiotemporal Attention Network), an attention-based neural model designed for user behavior modeling in the context of location-based search. TRISAN is unique in its ability to incorporate temporal relatedness into the analysis of user behavior, particularly in how it relates to the geographic proximity of items and user requests. This is achieved through a specialized fusion mechanism that considers not only physical distance but also semantic similarity to model geographic closeness. Wang et al. [2020c] and Wang et al. [2022b] combines *graph neural networks* and *attention mechanisms*. In the former article, the authors presented UIL-HGAN, a model for user identity linkage across social networks, emphasizing the enhancement of user modeling. UIL-HGAN stands for User Identity Linkage using a Heterogeneous Graph Attention Network, a method that integrates user profiles, user-generated content, and structural information within a heterogeneous social network graph. In the latter, an approach to enhance user profiling in the context of personalized point-of-interest (POI) recommendations is proposed. The paper introduces the Spatial-Temporal Graph Convolutional Attention Network (STGCAN), a model that leverages a knowledge graph with temporal information to capture the dynamic and evolving preferences of users with respect to various locations.
- ***Graph Neural Networks*** (GNNs) are designed to handle graph-structured data, representing relationships between entities. They are proficient in capturing the complex interdependencies within user networks or interaction graphs, providing a comprehensive view of user relationships and preferences (e.g., [Chen et al., 2019b; Hu et al., 2020; Wang et al., 2020a,c; Chen et al., 2021b; Dai and Wang, 2021; Wu et al., 2020a; Xia et al., 2021a,b; Yan et al., 2021; Luo et al., 2022; Wang et al., 2022b; Zhao et al., 2022]). To provide specific instances, Agarwal et al. [2022] introduced SEINE (Spam Detection using Interaction Networks), a graph neural network model tailored for identifying spam users on web-scale social media platforms. SEINE's primary innovation lies in its sophisticated user behavior and interaction modeling, which is achieved through the construction of a user-entity graph. This graph is not merely a collection of nodes and edges but a rich, heterogeneous network that captures the multifaceted interactions between users and various entities such as posts, comments, and likes. Han et al. [2022] developed the Multi-Aggregator Time-Warping Heterogeneous Graph Neural Network (MTHGNN), a model for personalized micro-video recommendation, with a strong emphasis on user modeling. The MTHGNN is designed to capture the dynamic and multi-faceted nature of user preferences in the context of micro-video content, such as that found on platforms like TikTok. Yan et al. [2022] presented a framework named Interaction-aware Hypergraph Neural Networks (IHNN) specifically designed for enhancing user profiling on e-commerce and social media platforms. IHNN employs hypergraph and meta-path based graphs to effectively model user interactions and attributes. The framework is constructed with a multi-view hypergraph approach and utilizes convolutional operations to aggregate high-order user information comprehensively. It also incorporates a semi-supervised learning approach for predicting user profiles. This method is particularly useful for tasks such as predicting user characteristics like age and

gender. Cheng et al. [2023] introduced a model named Multi-Behavior Recommendation with Cascading Graph Convolution Networks (MB-CGCN), designed to enhance recommendations by leveraging multiple user behaviors. The architecture is structured around a sequence of Graph Convolutional Network (GCN) blocks, each representing a different user behavior in a behavior chain. The key innovation of MB-CGCN lies in its ability to capture the dependencies between various behaviors to improve the accuracy of recommendations.

- ***Convolutional Neural Networks*** (CNNs) leverage convolutional layers to learn hierarchical features and spatial relationships within sequential or tabular data. While traditionally used in image processing, CNNs can be adapted to understand complex patterns in user interactions, identifying important temporal and contextual features for effective representation learning in user behavior (e.g., [Karatzoglou et al., 2018; Wang et al., 2019b; Wanda and Jie, 2020; Cura et al., 2021; Mekruksavanich and Jitpattanakul, 2021]). Other contributions are, for example, Yuan et al. [2021], who introduced Conure, a continual learning framework that utilizes a Temporal Convolutional Network (TCN) architecture to represent users. It is specifically engineered to handle sequential tasks and is adept at transferring knowledge from one task to another while retaining important information from past tasks. Qi et al. [2022b] presented an approach to personalized news recommendation through a Candidate-aware User Modeling (CAUM) framework. By using a candidate-aware self-attention network, a candidate-aware convolutional neural network, and a candidate-aware attention network, the CAUM framework is designed to capture both global and short-term user interests that are specifically relevant to the candidate news items. This convolutional neural network is adapted to process user behavior data with a focus on candidate news, helping to capture local and sequential patterns that are indicative of user interests.
- ***Autoencoders*** are neural network architectures designed for unsupervised learning. They aim to reconstruct input data, and in the context of user modeling, autoencoders can be employed for tasks such as feature learning and data compression to uncover latent representations in user behavior (e.g., [Rajashekar et al., 2016; Abu Sulayman and Ouda, 2019; Wang et al., 2019b; Pan et al., 2020; Sharma et al., 2020]). Noteworthy specific publications include the work by Deng et al. [2022b], who introduced a user behavior analysis model that leverages stacked autoencoders for dimensionality reduction and feature selection in the context of a complex power grid environment. The model is designed to optimize resource coordination and planning by analyzing user behavior characteristics. Fazelnia et al. [2022] developed a user modeling approach named FS-VAE, which employs a variational autoencoder (VAE) framework that leverages user-item interaction data to learn effective user representations in the music recommender systems domain. Liu et al. [2023c] proposed Hierarchical Personalized Federated Learning (HPFL), a model designed to tackle a number of heterogeneity challenges. In its "augmented" version (i.e., AHPFL), the authors incorporate augmented mechanisms to filter out low-quality information and integrate high-quality information, such as singular value decomposition (SVD) and autoencoders, to improve the effectiveness of user models.
- ***Recurrent Neural Networks*** (RNNs) are tailored for sequential data, capturing dependencies over time. Their cyclic connections make them adept at understanding the temporal aspects of user behavior, making them suitable for tasks involving sequential interactions (e.g., [Carvalho et al., 2017; Ishitaki et al., 2017; Ni et al., 2018; Tripathi et al., 2018; Yu et al., 2019; Gu et al., 2020]). Interesting works can be found, for instance, in Donkers et al. [2017], where the authors proposed an approach to sequential recommender systems by incorporating user-specific information into RNNs. The paper introduces a user-based RNN model that personalizes recommendations by considering the unique preferences and behavioral patterns of individual users. To achieve this, they extend traditional RNNs with a gated architecture using Gated Recurrent Units (GRUs), which facilitates the integration of user data into the sequential learning process. Ge et al. [2018] designed a framework to personalize search engine results by leveraging a hierarchical recurrent neural network (HRNN) with a query-aware attention mechanism. The framework's objective is to utilize sequential data from users' past interactions to construct dynamic user profiles, thereby enhancing the personalization of search results. Chu et al. [2022] presented a methodology for predicting student performance in online learning environments, with a focus on enhancing user modeling across diverse demographic groups such as race and gender. Utilizing RNNs, specifically an attention-based Gated Recurrent Unit (GRU) with a self-attention mechanism, the model predicts course passing likelihood based on students' activity sequences. Li et al. [2022b] implemented a user profiling procedure that combines semantic behavior modeling with RNNs by proposing a methodology that enriches user behavior data with semantic information to enhance the accuracy of user profiling.
- ***Long Short Term Memory*** (LSTM) represents a specialized form of recurrent neural network. LSTMs address the vanishing gradient problem, enabling effective modeling of long-term dependencies in sequential user data, leading to an improved understanding of user preferences over time (e.g., [Zhu et al., 2017; Żołna and Romański, 2017; Singh et al., 2019; Sharma et al., 2020; Cura et al., 2021; Fazil et al., 2021]). To cite specific relevant contributions, Gu et al. [2020] developed a hierarchical user profiling framework, whose core is the integration of Pyramid RNNs with a specialized component known as Behavior-LSTM. The Behavior-LSTM

layer is particularly crucial as it models the temporal sequence of user behaviors, providing a dynamic and evolving representation of user interests. Another valuable LSTM-based framework, named Time Information Enhanced Personalized Search (PSTIE), has been proposed by Ma et al. [2020]. The PSTIE framework utilizes time-aware LSTM architectures to model the evolution of user interests over time. This allows the model to calculate both short-term and long-term query intent and document interest. The framework also includes techniques for re-ranking by combining these interest representations. Sahoo and Gupta [2021] presented a system for detecting fake news on Facebook by leveraging user profile features alongside news content features. The approach involves using LSTM to effectively process and learn from the user profile features, which are indicative of the credibility of the news shared. Nkambou et al. [2023]

- ***Transformers*** utilize attention mechanisms to capture contextual information bidirectionally. They succeed in natural language understanding, providing rich representations of user-generated text data for various applications in user modeling (e.g., [Huertas-García et al., 2021; Zhu et al., 2021]). A specific case is provided by Avny Brosh et al. [2022], who introduced a neural network-based model, BRUCE, which focuses on personalized bundle recommendations. The main ability of BRUCE is modeling user preferences and the latent relationships between items within a bundle using a Transformer-based architecture. This architecture employs self-attention mechanisms to create contextualized item embeddings that reflect both the individual items' characteristics and their interactions within the bundle. The most important transformer-based model is BERT, which stands for Bidirectional Encoder Representations from Transformers (examples of BERT-based models in user modeling can be seen in Gu et al. [2021a] and Kota et al. [2021]). To provide some detailed instances, Wu et al. [2022] presented UserBERT, an approach for pre-training user models on unlabeled user behavior data. This method employs contrastive self-supervision to capture universal user information, which is crucial for enhancing personalization in various applications. UserBERT introduces two key self-supervision tasks: Masked Behavior Prediction, involving predicting user behaviors that have been intentionally masked in the input data, and Behavior Sequence Matching, required to determine whether two sequences of user behavior are from the same user, promoting the model's ability to discern patterns and similarities in user activities. To further refine the pre-training process, UserBERT incorporates a medium-hard negative sampling method. This technique selects negative samples that are neither too easy nor too difficult for the model to discriminate, providing an optimal challenge for learning. Zheng et al. [2022a] developed the Personalized Emoji Recommendation with Dynamic user preference (PERD) model. The core of PERD is a text encoder that utilizes a BERT model to capture the semantic representations of tweets. This allows the system to understand the context and content of user tweets effectively. Alongside the text encoder, the model incorporates a personalized attention mechanism. This mechanism is crucial as it sifts through a user's historical tweets to identify and emphasize those that are most informative for determining the user's preferences.

4.2.7 Performance evaluation

The evaluation phase is a critical step in any modeling problem as it allows for the assessment of a model's performance and its suitability for the given task. This phase is particularly important in user profiling, where standard evaluation measures are used to assess the performance of developed approaches. Common techniques for model evaluation include performance metrics like *accuracy*, *precision*, *recall*, *F-measure* (also known as *F1 score*), *mean reciprocal rank* (MRR), *cosine similarity*, and *Jaccard similarity* [Kaur et al., 2018; Costanzo et al., 2019; Eke et al., 2019].

Presently, there exist two principal approaches for assessing the efficacy of independent user profiling methods: (1) relating them to *classification tasks* and (2) adopting ad-hoc generated *simulated data*.

Evaluation as a classification task This strategy adheres to conventional evaluation protocols and entails appraising the proposed model or method through its proficiency in a classification task. Typically, this method employs machine learning techniques to classify user profiles, discerning between authentic and non-authentic ones. By subjecting the model to this classification task, it becomes possible to gauge its effectiveness in accurately identifying and categorizing users based on their personal attributes. This process is essential in understanding the model's performance and reliability in the context of user profiling. Clear recent demonstrations of user modeling methods assessed as a classification task can be found, for instance, in Chen et al. [2021b], Dai and Wang [2021], Yan et al. [2021], and Purificato et al. [2022].

Evaluation with simulated data The generation of simulated data is a means to curtail the volume of actual user data collected. This approach is designed not only to streamline the efficiency of profiling but also to uphold the privacy and confidentiality of users' personal information. By creating synthetic datasets that emulate the characteristics and patterns found in genuine user data, practitioners can significantly diminish the reliance on actual user information. This reduction in the dependence on real data serves a dual purpose: it mitigates potential privacy concerns by limiting the exposure of sensitive information, while concurrently ensuring that the profiling process remains effective and accurate. A comprehensive methodology for simulating and evaluating user interactions within search sessions has been presented by Zerhoudi et al. [2022]. The authors introduce the use of first-order Markov models and contextual Markov models as tools to replicate user search behavior. The realism of these simulated interactions is assessed using two main methods: Kolmogorov-Smirnov test and classification-based evaluation. The findings indicate that the simulated sessions closely resemble the real user log sessions, suggesting that the simulated interactions are representative of actual user behavior. In Keurulainen et al. [2023], the authors proposed an "amortised experimental design" for user models. The paper explores the use of Bayesian optimal experimental design and reinforcement learning to create a user model described as a simulation-based reinforcement learning model.

Take-home messages from building and modeling user profiles.

- ***Variety of user modeling methodologies****: A range of methods for creating user profiles is explored, including rule-based modeling that uses predefined rules, ontology-based modeling for structured knowledge representation, and collaborative filtering for leveraging user community data to predict individual preferences.*
- ***Advanced analytical techniques in user modeling****: Highlights the use of statistical modeling, machine learning, and deep learning techniques. These methods are crucial for analyzing complex user data, identifying patterns, and making accurate predictions about user behavior, along with preferences, interests, and intentions.*
- ***Importance of the evaluation phase****: Emphasizes the essential role of the evaluation phase in user modeling. This phase assesses the performance and appropriateness of models, using standard measures to ensure their reliability and effectiveness in representing and predicting user behavior.*

4.3 Beyond-accuracy approaches

The integration of advanced techniques surpassing mere accuracy represents a substantial paradigm shift across diverse domains, notably influencing user modeling and profiling. These methodologies go beyond the traditional emphasis on predictive precision, placing greater importance on core principles that also consider the ethical dimensions of user modeling, focusing on issues like privacy, transparency, and the responsible use of data. This broader view encourages the development of models that not only predict user actions accurately but also contribute positively to the user's overall interaction with a system, fostering a more holistic and user-centric approach to modeling. Within this context, we identify relevant contributions belonging to three topics: *explainable user modeling*, *fair user modeling*, and *privacy-preserving user modeling* (specifically referring to methods leveraging *federated learning* method).

4.3.1 Explainable user modeling

Balog et al. [2019] introduced a set-based recommendation technique that emphasizes the importance of user models that are transparent, scrutable, and explainable. Transparency is achieved by providing users with insights into how their preferences are understood by the system and how the recommendation process works. Scrutability is incorporated by allowing users to directly and meaningfully revise their model. Explainability is provided to the level of user preferences, rather than just explaining why a given item was recommended, as commonly done in related works. De Pauw et al. [2022] proposed a recommender system, named TEASER, which is particularly geared towards enhancing the user experience by providing recommendations that are not only relevant but also accompanied by detailed explanations. The transparency and interpretability of TEASER stem from its ability to articulate the reasoning behind its suggestions. Guesmi et al. [2022] focused on how transparency, user control, and personal characteristics influence the adoption of recommendation agents. The research introduces the Recommendation and Interest Modeling Application (RIMA), a tool designed to enhance transparency by providing explanations of user interest models at varying levels of detail. The study assesses the effectiveness of different explanation levels within the system and how they are perceived by users with diverse personal characteristics. Other examples of works addressing explainability in user modeling can be seen in Huang et al. [2019], Wang et al. [2019a], Chari et al. [2020], Hase and Bansal [2020], Xian et al. [2021], Minn et al. [2022], and Ding et al. [2023].

4.3.2 Fair user modeling

Dai and Wang [2021] designed FairGNN, a framework to ensure fairness in GNN-based user profiling (evaluated as a node classification task). The framework employs adversarial debiasing, where the adversary's goal is to ensure that the sensitive attributes cannot be accurately predicted from the node representations, thereby encouraging the GNN to learn fair representations. The theoretical analysis provided in the paper supports the effectiveness of this approach, showing that FairGNN can guarantee fair representations under specific conditions. To further promote fairness, a regularizer is added to the GNN classifier, and a covariance constraint is introduced to control the correlation between the sensitive attributes and the learned representations. These measures help to ensure that the predictions made by the GNN are not unfairly influenced by sensitive attributes. Within the same context of GNN-based user profiling models, Purificato et al. [2022] conducted a thorough investigation into the fairness of these models. The study specifically focuses on behavioral user profiling, which is a critical aspect of personalized services in various online platforms. The core of the research revolves around evaluating the fairness of these models in terms of how they might discriminate against certain user groups. To quantify fairness, the paper employs several disparate impact and disparate mistreatment metrics, utilizing two real-world datasets from e-commerce platforms in their experiments. This work is followed up by the implementation of a unified framework, i.e., FairUP [Abdelrazek et al., 2023], that allows researchers and practitioners to interact with state-of-the-art GNN-based models for user profiling and evaluate fairness on several graph data sources. Purificato and De Luca [2023] addressed the topic of algorithmic fairness within the realm of user profiling. It identifies a gap in current fairness analysis, which is predominantly applied to binary classification problems and relies on the absolute difference in fairness metrics. This approach, the authors argue, can result in evaluations that do not accurately reflect the fairness of a system. To illustrate their point, the authors present a case study on the use of GNN-based models for user profiling. They discuss the limitations of current practices and the potential ethical consequences that arise from these limitations. The paper aims to spark conversation within the academic community about these issues and to encourage more comprehensive and nuanced analyses of fairness in algorithmic systems. Another interesting framework for enhancing fairness in user modeling is proposed by Zhang et al. [2023b]. The framework employs an adversarial learning approach that includes a filter module and a discriminator module to minimize the mutual information between user representations and sensitive attributes. FairLISA operates by combining data with both known and unknown sensitive attributes. It consists of two main components: a filter that aims to remove sensitive information from user representations and a discriminator that attempts to detect any remaining sensitive information. Further contributions in this domain are Shen et al. [2021b], Chu et al. [2022], and Zheng et al. [2022b].

4.3.3 Privacy-preserving user modeling

The most relevant recent works about privacy-preserving in user modeling employ *federated learning* approaches. Chu et al. [2022] introduced a methodology for predicting student performance in online learning environments. The core of the procedure is a personalized federated learning framework that allows for the creation of individualized models for student subgroups, derived from a global model that aggregates data across all students. Liu et al. [2023c] proposed a federated learning technique for user modeling in environments characterized by inconsistent clients. The proposed approach, Hierarchical Personalized Federated Learning (HPFL), is designed to tackle the challenges of statistical heterogeneity, privacy heterogeneity, model heterogeneity, and quality heterogeneity that are prevalent in such settings. Zhang et al. [2023a] presented the Personalized Federated Recommendation (PFedRec) framework, a system that leverages federated learning to create user profile-specific recommendation models. PFedRec is designed to be deployed on smart devices, enabling a decentralized and privacy-preserving method for capturing user preferences. The proposed federated learning approach is centered around a dual personalization mechanism that allows for fine-grained personalization at both the user and item levels. This is a significant departure from traditional federated learning methods, which often focus on a single model that is shared across all users. Instead, PFedRec formulates a unified federated optimization framework that learns individual lightweight models tailored to each user's unique preferences. Privacy-preserving user modeling techniques have also been presented by Wu et al. [2021b] and Luo et al. [2022].

Take-home messages from beyond-accuracy approaches.

- ***Ethical advancements in user modeling****: A shift towards advanced user modeling techniques emphasizes ethical principles, focusing on privacy, transparency, and responsible data use. This approach aims to enhance both the accuracy and the overall user-system interaction.*
- ***Three key beyond-accuracy approaches****:*
  - ***Explainable user modeling*** *emphasizes the importance transparency and user understanding in modeling processes;*
  - ***Fair user modeling*** *focuses on creating unbiased models that prevent discrimination against specific user groups;*
  - ***Privacy-preserving user modeling*** *focuses on safeguarding privacy through techniques such as federated learning.*

4.4 Applications

User modeling and profiling techniques play a crucial role in various domains and applications, with different data being extracted and utilized based on the purpose and collection methods. User models, historically integral only to recommender systems and any kind of personalized platforms, are now widely employed across various applications.

4.4.1 Recommender systems

A recommender system, belonging to the category of information filtering systems, aims to predict item ratings or user preferences. The key components of a personalized recommender system include the efficient understanding of the user and recommending items aligned with their interests. Recommender systems always benefited from user profiling methods [Zimmerman and Kurapati, 2002; Middleton et al., 2004; Liu et al., 2007; Zhang and Koren, 2007; Berkovsky et al., 2008; Adomavicius and Tuzhilin, 2011; Lakiotaki et al., 2011; Konstan and Riedl, 2012; Liu, 2015]. Significant modern systems in this field naturally leverage the power of DL architectures (e.g., [An et al., 2019; Yu et al., 2019; Jin et al., 2020; Pan et al., 2020; Xia et al., 2021a; Han et al., 2022; Qi et al., 2022b; Wang et al., 2022a; Xue et al., 2022; Cheng et al., 2023] To provide specific examples, Wu et al. [2019a] developed a user representation model that employs a neural architecture to enhance recommendations from reviews. The model operates by first using a sentence-level CNN to capture contextual information within sentences. It then applies a sentence-level attention network to weigh the importance of different sentences. Hu et al. [2020] implemented a news recommender system that adopts a graph convolutional network for modeling long-term user interests. In contrast, short-term user interests are captured using an attention-based LSTM model. Another GNN-based recommender system, named Hierarchical User Intent Graph Network, has been provided by Wei et al. [2022]. The core idea is to leverage multi-level user intents and item representations to improve the accuracy of recommendations. The framework is composed of three main components: intra-level aggregation, inter-level aggregation, and interaction prediction. The Core Attribute Evolution Network (CAEN), developed by Ma et al. [2022b], incorporates a user behavior modeling method known as UB-GRUA (User Behavior with Gated Recurrent Unit Attention), which is part of the Personalized Attention Layer (PAL). This method is designed to capture and interpret user interactions with items, particularly under the influence of specific attributes. By employing a two-stage hierarchical attention network, CAEN can discern the significance of different attributes to individual users, leading to more accurate and personalized item recommendations.

Application domains covered include, among others, *e-commerce* (e.g., [Lin et al., 2019; Gu et al., 2020; Ma et al., 2022b]), *job recommendation* (e.g., [Rimitha et al., 2018; Kota et al., 2021]), and *news recommendation* (e.g., [Natarajan and Moh, 2016; An et al., 2019; Wu et al., 2021a; Yang et al., 2023]

4.4.2 Information retrieval

In the information retrieval context, user modeling research focuses particularly on personalized search, which is a process that prioritizes a user's interests when searching through a set of documents or web pages. This is achieved by creating a user profile based on the sites the user has searched for, thereby identifying their interests. The accuracy of the system is enhanced by predicting the user's interests more accurately than a typical search. In these personalized search systems, the search results are ranked not only based on the query information but also according to the user's interests. This approach ensures a more tailored and relevant search experience for the user. To cite specific cases, Zhou et al. [2020b] proposed a personalized search model that aims to improve the re-finding behavior of users when they search for previously encountered information. The model leverages memory networks to capture two distinct types of re-finding behavior: query-based and document-based. It utilizes Recurrent Neural Networks (RNNs) to process sequential data and generate refined vectors that represent user intent over multiple sessions. Zhou et al. [2021a] introduced a group-based model that employs both search behavior and friend networks to enhance search results for users, particularly those with sparse historical data. By grouping users into friend circles and utilizing neural networks, the model creates a more accurate semantic representation of user interests, leading to significant improvements in search personalization. Deng et al. [2022a] leveraged a dual-feedback network to enhance the understanding of user search intentions. The model is designed to improve personalized search by incorporating multi-granular user feedback, both positive and negative, to accurately model the user's current search intention. Other works can be seen in Du et al. [2016], Ma et al. [2020], and Zhou et al. [2021b].

4.4.3 Adaptive e-learning systems

An adaptive e-learning system in the context of user modeling refers to an educational technology platform that leverages user modeling techniques to dynamically tailor the learning experience to the individual needs, preferences, and abilities of each learner. In such a system, the emphasis is on creating and updating a personalized user model that captures relevant information about the learner, allowing the platform to adapt various aspects of the e-learning process.

Works in this area have always been proposed (e.g., [Brusilovsky, 2004; Brut et al., 2009; Li et al., 2009; Kim et al., 2013]). Recently, Kulkarni et al. [2019] addressed the issue of delivering relevant and high-quality content to users within e-learning systems, aiming to minimize the time users spend searching for information. User profiles are created by combining explicit information provided by the user with implicit data gathered from their interactions with the system, resulting in a dynamic and adaptive profile.

Along with ethical principles, there has also been an increasing recognition of the imperative for accessibility in digital platforms, driven by a growing awareness of the diverse needs of users and a commitment to ensuring inclusive and equitable access to information and services. In this scenario, techniques were also developed to generate user profiles that are tailored to the specific accessibility needs of users with disabilities (e.g., [Sanchez-Gordon et al., 2021]).

The last few years have witnessed a significant surge in the popularity of *Massive Open Online Courses* (MOOCs) within the realm of e-learning platforms, with the COVID-19 pandemic further accelerating their adoption as individuals sought flexible and accessible online learning options. Sunar et al. [2020] investigated the role of social engagement in MOOCs and its correlation with course completion rates. The research specifically examines user behavior aiming to model and understand the patterns of social interactions among participants. The authors introduce the concept of "behavior chains" to model the social engagement of learners. The study reveals that learners who engage more deeply in peer interactions and contribute consistently over the duration of the course are more likely to complete it. Jin [2023] focused, instead, on the development of a predictive model to identify students at risk of dropping out of MOOCs by analyzing their learning behavior data. The model employs Support Vector Regression (SVR) as the core predictive algorithm due to its suitability for the task. To enhance the performance of the SVR, the paper introduces an Improved Quantum-behaved Particle Swarm Optimization (IQPSO) algorithm for optimizing its parameters.

4.4.4 Fake news detection

The innovative application of user modeling has seen a notable rise in the development of advanced approaches for detecting fake news, underscoring the growing importance of leveraging personalized user profiles to enhance the accuracy and effectiveness of misinformation detection in digital environments. In the user modeling context, the majority of work analyzes social media platforms and social networks (e.g., [Shu et al., 2018; Monti et al., 2019; Shu et al., 2019]). A specific example is the paper by Sahoo and Gupta [2021], where the authors presented a framework for detecting fake news on Facebook by leveraging user profile features alongside news content features. The system employs a combination of machine learning and deep learning techniques to analyze the behavior of Facebook accounts. By collecting data through a crawler and constructing datasets for classification, the study utilizes user profile information as a critical component in identifying fake news. Concerning ethical implications in AI systems, particularly the risks of mislabeling news and unjust profiling, Allein et al. [2023] proposed an ethical fake news detection approach that incorporates user insights without relying on direct profiling, addressing the challenge of profiling-dependent fake news detection. The proposed algorithm is designed to leverage the social context of Twitter users during the training phase but excludes user information during the evaluation of news article veracity, thus avoiding decision-making based on profiling. The study employs a multimodal learning algorithm that uses a cross-modal loss function inspired by social sciences to analyze the relationship between news articles, their creators, and the audience.

4.4.5 Cybersecurity

The innovative application of user modeling has witnessed a surge in the integration of cybersecurity approaches, reflecting a heightened awareness of the crucial role personalized user profiles play in enhancing digital security and safeguarding against evolving cyber threats. Lashkari et al. [2019] presented a broad examination of user profiling as a critical component in cybersecurity, specifically for anomaly detection. The authors review existing user profiling models, highlighting their strengths and weaknesses, and propose a novel user profiling model designed to enhance the detection of suspicious activities in cyberspace. Addae et al. [2019] investigated the factors that influence users' cybersecurity behaviors and the adoption of personalized adaptive cybersecurity measures. The study integrates insights from behavioral science, machine learning, and theoretical models such as the Technology Acceptance Model (TAM) and Protection Motivation Theory (PMT) to understand and predict user behavior in non-corporate environments.

Take-home messages from applications.

- ***Wide-ranging applications**: User modeling and profiling techniques are crucial in a variety of domains. While initially integral to recommender systems and personalized platforms, these techniques are now employed in a broader range of applications, including adaptive e-learning systems, fake news detection, and cybersecurity.*
- ***Adaptation to diverse data and purposes**: These techniques involve extracting and utilizing different types of data based on the specific purpose and method of collection in each application.*

5 Discussion and Future Research Directions

In this survey, we embarked on a comprehensive exploration of the evolving landscape of *user modeling* and *user profiling*. Our journey commenced with a thorough historical overview, tracing the roots of user modeling to provide a contextual foundation for understanding its evolution. Subsequently, we conducted an in-depth examination of existing surveys, critically analyzing their contributions and consolidating diverse perspectives to glean insights into the overarching developments. The analysis of terminology emerged as a pivotal undertaking, revealing the semantic intricacies that permeate user modeling and user profiling literature. By dissecting and categorizing the terminological landscape, we aimed to foster a clearer understanding of the field's conceptual foundations, facilitating a more coherent discourse among researchers and practitioners alike. As a culmination of this effort, we have ventured to contribute to the field by providing two novel definitions that encapsulate the essence of "user model" (or "user profile") and "user modeling" (or "user profiling"). A pivotal focus on paradigm shifts and new trends unveiled the transformative forces shaping user modeling methodologies. This section not only scrutinized historical transitions but also projected forward, anticipating emerging trends that could redefine the landscape. Concluding our exploration, we present the current taxonomy of user modeling, synthesizing the diverse strands of research into a cohesive framework. This taxonomy serves as a guidepost for researchers, offering a structured lens through which to comprehend the evolving facets of user-centric modeling.

Despite the paradigm shifts that have characterized the evolution of user modeling and profiling, certain core topics have exhibited remarkable resilience, persisting as focal points throughout the discipline's history. The continual examination of users' preferences, interests, and needs serves as a foundational element, exemplifying an enduring pursuit to comprehend the complexities of human behavior across diverse interactive contexts. Statistical approaches, a traditional cornerstone of user modeling research, have weathered the transformative waves of technological advancements, highlighting their robustness in deciphering patterns within user data. Moreover, the faithful applications of user modeling in recommender systems and personalized, adaptive interfaces underscore the enduring relevance of tailoring technological interactions to individual user characteristics. As we navigate the currents of change, these enduring themes serve as anchors, guiding and grounding user modeling research, ensuring continuity of inquiry even in the face of evolving methodologies and technological landscapes.

With a future-oriented outlook, the principles of *Human-Centered AI* (HCAI) [Shneiderman, 2022] and *Responsible AI* [Dignum, 2019], as well as the specific regulations for the development of trustworthy AI systems, such as the *EU AI Act*[3], are gaining widespread attention for their potential to shape the future of technology in ways that serve human needs more effectively. These principles emphasize designing AI systems that support human autonomy, enhance human performance, and ensure that technology serves to empower people rather than replace them. Building on these foundational concepts, research in user modeling will probably undergo a significant transformation, highlighting the importance of developing systems that are not only technologically advanced but also deeply aligned with human values and needs. We can thus identify the following emerging directions:

Human-AI Collaboration The significance of human-AI collaboration is increasingly recognized as a fundamental aspect of the future of research in user modeling, highlighting the transformative potential of melding human intuition with AI's analytical prowess. Developing computational tools that act as interactive assistants exemplifies this collaborative approach, where AI systems serve as partners in the modeling process, aiding human modelers even in the absence of fully specified outcomes. This symbiotic relationship enables a more adaptable and responsive modeling process, attuned to the dynamic needs of users [Çelikok et al., 2023]. Among recent contributions, the work of Gao et al. [2020] proposes an explainable AI framework aimed at achieving human-like communication in human-robot collaborations. By constructing a hierarchical mind model of the human user, their approach allows for the generation of explanations based on online Bayesian inference of the user's mental state, significantly enhancing collaboration performance and user perception of the robot. Similarly, Banerjee et al. [2023] address the challenge of AI bots lacking

[3] `https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/698792/EPRS_BRI(2021)698792_EN.pdf`

personalization and understanding of user intent by developing a system where a human support agent collaborates with an AI agent to answer customer queries, showcasing the potential of human-AI collaboration to enhance user experience. These examples underscore the critical role of human-AI collaboration in enhancing the adaptability, effectiveness, and ethical grounding of user modeling systems. By fostering a collaborative dynamic between humans and AI, the field of user modeling is set to advance towards developing technologies that are not only sophisticated and efficient but also deeply aligned with human values and needs.

Advanced User Models Focusing on the development of user models that regard the user as an active decision-maker engaged in a two-agent interaction with an AI collaborator highlights the need for understanding not only the user's goals but also their cognitive computational capacity [Çelikok et al., 2023]. This perspective is critical, as emphasized by Nasrudin et al. [2023], who underscore the importance of models that accurately reflect the complex nature of human behavior by considering user goals, cognitive capacities, and perceptions, thereby impacting the sustainability of applications. Additional contributions to this field include the work of Jégou and Chevaillier [2018], who propose a computational model to facilitate turn-taking behaviors in user-agent interactions, illustrating the significance of continuous decision-making based on both the agent's goals and the user's intentions. Similarly, Humann et al. [2023] present a graphical user interface tool that optimizes multi-robot, multi-operator systems according to user preferences, serving as a testament to the importance of tailoring computational models to accommodate diverse user needs. These references collectively underscore the evolving complexity and necessity of advanced user models that not only acknowledge the user as a key decision-maker but also adapt to their unique cognitive landscapes, thereby paving the way for more personalized and effective human-AI collaborations.

Ethical and Equitable User Modeling In line with Human-Centered AI (HCAI) principles, the ethical dimensions of user modeling, including data sovereignty and privacy, hold significant importance. Nigel Shadbolt [2020] discusses methodologies for ensuring data privacy and fostering individual autonomy within digital ecosystems, emphasizing a critical aspect of responsible AI development. This focus on ethical considerations is essential in the development and deployment of user modeling systems, ensuring that they align with broader societal values and individual rights. Further exploration into the ethical dimensions of user modeling reveals a growing body of research dedicated to addressing these concerns. For instance, work by Shahar [2021] on advanced user models in shared medical decision-making showcases the potential to address human cognitive limitations while ensuring ethical decision-making, highlighting the balance between AI assistance and human autonomy. By focusing on privacy, autonomy, and transparency, the field can advance toward developing technologies that are advanced and efficient, as well as ethically grounded and aligned with human values and societal norms.

Integration of Cognitive Sciences Combining insights from cognitive sciences, psychology, and human-computer interaction, an interdisciplinary approach to user modeling is essential for developing more advanced and accurate user models [Çelikok et al., 2023]. This integration offers significant potential to enhance our understanding of user behavior, informing the development of systems that can adapt to human actions in a nuanced and personalized manner. Streicher and Bauer [2024]'s application of a Bayesian cognitive state modeling approach to adaptive educational serious games showcases how cognitive modeling can dynamically adapt in serious gaming environments, illustrating the impact of cognitive insights on user model effectiveness. Madsen et al. [2019] discuss the use of agent-based models in cognitive sciences for predicting behaviors in dynamic, adaptive, and heterogeneous agents, highlighting the utility of agent-based models in scaling cognitive models within social networks and validating model predictions. This work serves as a crucial link between individual and socially oriented models. Incorporating cognitive principles and methodologies allows researchers and developers to create user models that are not only more aligned with human thought processes and behaviors but also capable of fostering more engaging and effective human-machine interactions. This interdisciplinary approach is foundational for creating systems that truly understand and adapt to user needs in a personalized manner.

AI Systems Understanding User Goals Creating AI systems capable of understanding and adapting to user goals is pivotal for the advancement of responsive and supportive technologies [Çelikok et al., 2023]. This notion is reinforced by Zeng [2021]'s exploration into human-centered intelligent gaming systems, which utilize machine learning algorithms to enhance player experiences by personalizing gameplay and understanding player motivations, underscores the significance of adapting AI systems to user goals. This approach not only enhances user engagement but also fosters the development of human-like characters and adaptive recommender systems, marking a step forward in creating more immersive and personalized interactive environments. Moreover, the study by Virós-i Martin and Selva [2022] on AI assistants that adapt to designers' learning goals during design space exploration illustrates the potential benefits of AI systems that adjust to user preferences and objectives. Their research highlights the importance of AI systems in improving users' understanding of complex tasks, even though it may affect task performance due to changes in user interaction patterns. Collectively, these insights underline the critical role of AI systems designed to understand and adapt to user goals. Such systems not only promise to revolutionize how we interact with technology but also pave the way for more personalized, intuitive, and effective human-machine collaborations.

Cross-Modal User Interaction Cross-modal user interaction has seen notable advancements, particularly in enhancing user experiences by bridging diverse modalities. The development of a method for user-generalized cross-modal retrieval is a prime example of this progress, providing significant improvements in user experience across different interaction modes [Ma et al., 2022c]. This advancement emphasizes the evolving landscape of user modeling research, where understanding and catering to the multifaceted needs and preferences of users through diverse sensory modalities are becoming increasingly important. In the educational domain, implementing a cross-modal UX course for industrial design students, incorporating auditory and haptic techniques, aims to create inclusive and accessible user experiences. This initiative highlights the potential of cross-modal approaches in fostering a more comprehensive understanding of user interaction within user modeling research [Temor et al., 2022]. Moreover, the exploration of "cued-gaze" with voice agents by Jaber and McMillan [2022] reveals that integrating visual cues with auditory instructions through cross-modality repair is more effective than speech reformulation alone. This finding emphasizes the importance of multimodal interactions in advancing user modeling, suggesting that user experiences can be significantly enriched by understanding and leveraging the interplay between different sensory modalities. These advancements in Cross-Modal User Interaction directly contribute to the field of user modeling by offering new insights into how users interact with and perceive multimodal systems. By integrating diverse modalities, researchers can develop more nuanced and comprehensive models of user behavior, preferences, and needs. This opens new avenues for designing more accessible, intuitive, and engaging human-computer interfaces, accentuating the symbiotic relationship between cross-modal interaction and user modeling research.

> **Consideration**. *These novel research directions in user modeling, underpinned by the principles of Human-Centered AI and Responsible AI, represent a significant shift towards developing technologies that are not only advanced but also deeply aligned with human values, needs, and ethical considerations. By focusing on these areas, the field of user modeling is poised to contribute to the creation of more personalized, efficient, and intuitive interactions between humans and technology, ultimately fostering a more humane and sustainable future.*

References

Mohamed Abdelrazek, Erasmo Purificato, Ludovico Boratto, and Ernesto William De Luca. FairUP: A Framework for Fairness Analysis of Graph Neural Network-Based User Profiling Models. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '23, pages 3165–3169, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 978-1-4503-9408-6. doi:10.1145/3539618.3591814. URL https://dl.acm.org/doi/10.1145/3539618.3591814.

Fabian Abel, Qi Gao, Geert-Jan Houben, and Ke Tao. Analyzing User Modeling on Twitter for Personalized News Recommendations. In Joseph A. Konstan, Ricardo Conejo, José L. Marzo, and Nuria Oliver, editors, *User Modeling, Adaption and Personalization*, Lecture Notes in Computer Science, pages 1–12, Berlin, Heidelberg, 2011. Springer. ISBN 978-3-642-22362-4. doi:10.1007/978-3-642-22362-4_1.

Sara Abri, Rayan Abri, and Salih Cetin. A Classification on Different Aspects of User Modelling in Personalized Web Search. In *Proceedings of the 4th International Conference on Natural Language Processing and Information Retrieval*, NLPIR '20, pages 194–199, New York, NY, USA, February 2021. Association for Computing Machinery. ISBN 978-1-4503-7760-7. doi:10.1145/3443279.3443291. URL https://dl.acm.org/doi/10.1145/3443279.3443291.

Iman I. M. Abu Sulayman and Abdelkader Ouda. User Modeling via Anomaly Detection Techniques for User Authentication. In *2019 IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, pages 0169–0176, Vancouver, BC, Canada, October 2019. IEEE. ISBN 978-1-72812-530-5. doi:10.1109/IEMCON.2019.8936183. URL https://ieeexplore.ieee.org/document/8936183/.

Joyce H. Addae, Xu Sun, Dave Towey, and Milena Radenkovic. Exploring user behavioral data for adaptive cybersecurity. *User Modeling and User-Adapted Interaction*, 29(3):701–750, July 2019. ISSN 1573-1391. doi:10.1007/s11257-019-09236-5. URL https://doi.org/10.1007/s11257-019-09236-5.

Gediminas Adomavicius and Alexander Tuzhilin. Expert-Driven Validation of Rule-Based User Models in Personalization Applications. *Data Mining and Knowledge Discovery*, 5(1):33–58, January 2001. ISSN 1573-756X. doi:10.1023/A:1009839827683. URL https://doi.org/10.1023/A:1009839827683.

Gediminas Adomavicius and Alexander Tuzhilin. Context-Aware Recommender Systems. In Francesco Ricci, Lior Rokach, Bracha Shapira, and Paul B. Kantor, editors, *Recommender Systems Handbook*, pages 217–253.

Springer US, Boston, MA, 2011. ISBN 978-0-387-85820-3. doi:10.1007/978-0-387-85820-3_7. URL https://doi.org/10.1007/978-0-387-85820-3_7.

Prabhat Agarwal, Manisha Srivastava, Vishwakarma Singh, and Charles Rosenberg. Modeling User Behavior With Interaction Networks for Spam Detection. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2437–2442, Madrid Spain, July 2022. ACM. ISBN 978-1-4503-8732-3. doi:10.1145/3477495.3531875. URL https://dl.acm.org/doi/10.1145/3477495.3531875.

Erfan Aghasian, Saurabh Garg, Longxiang Gao, Shui Yu, and James Montgomery. Scoring Users' Privacy Disclosure Across Multiple Online Social Networks. *IEEE Access*, 5:13118–13130, 2017. ISSN 2169-3536. doi:10.1109/ACCESS.2017.2720187. URL https://ieeexplore.ieee.org/abstract/document/7959160.

Tarik Agouti. Graph-based modeling using association rule mining to detect influential users in social networks. *Expert Systems with Applications*, 202:117436, September 2022. ISSN 0957-4174. doi:10.1016/j.eswa.2022.117436. URL https://www.sciencedirect.com/science/article/pii/S0957417422007722.

Saleh Beyt Sheikh Ahmad, Mahnaz Rafie, and Seyed Mojtaba Ghorabie. Spam detection on Twitter using a support vector machine and users' features by identifying their interactions. *Multimedia Tools and Applications*, 80(8): 11583–11605, March 2021. ISSN 1573-7721. doi:10.1007/s11042-020-10405-7. URL https://doi.org/10.1007/s11042-020-10405-7.

Mohammad Yahya H. Al-Shamri. User profiling approaches for demographic recommender systems. *Knowledge-Based Systems*, 100:175–187, May 2016. ISSN 0950-7051. doi:10.1016/j.knosys.2016.03.006. URL https://www.sciencedirect.com/science/article/pii/S0950705116001192.

Sara Alaoui, Younès El Bouzekri El Idrissi, and Rachida Ajhoun. Building Rich User Profile Based on Intentional Perspective. *Procedia Computer Science*, 73:342–349, 2015. ISSN 18770509. doi:10.1016/j.procs.2015.12.002. URL https://linkinghub.elsevier.com/retrieve/pii/S1877050915034638.

Vincent Aleven. Rule-Based Cognitive Modeling for Intelligent Tutoring Systems. In Roger Nkambou, Jacqueline Bourdeau, and Riichiro Mizoguchi, editors, *Advances in Intelligent Tutoring Systems*, Studies in Computational Intelligence, pages 33–62. Springer, Berlin, Heidelberg, 2010. ISBN 978-3-642-14363-2. doi:10.1007/978-3-642-14363-2_3. URL https://doi.org/10.1007/978-3-642-14363-2_3.

Noaman M. Ali, Ahmed M. Gadallah, Hesham A. Hefny, and Boris Novikov. An Integrated Framework for Web Data Preprocessing Towards Modeling User Behavior. In *2020 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon)*, pages 1–8, October 2020. doi:10.1109/FarEastCon50210.2020.9271467. URL https://ieeexplore.ieee.org/abstract/document/9271467.

Liesbeth Allein, Marie-Francine Moens, and Domenico Perrotta. Preventing profiling for ethical fake news detection. *Information Processing & Management*, 60(2):103206, March 2023. ISSN 0306-4573. doi:10.1016/j.ipm.2022.103206. URL https://www.sciencedirect.com/science/article/pii/S0306457322003077.

Cliff Allen, Beth Yaeckel, and Deborah Kania. *Internet world guide to one-to-one web marketing*. John Wiley & Sons, Inc., 1998.

Jürgen Allgayer, Karin Harbusch, Alfred Kobsa, Carola Reddig, Norbert Reithinger, and Dagmar Schmauks. XTRA: a natural-language access system to expert systems. *International Journal of Man-Machine Studies*, 31(2):161–195, August 1989. ISSN 0020-7373. doi:10.1016/0020-7373(89)90026-6. URL https://www.sciencedirect.com/science/article/pii/0020737389900266.

Giuseppe Amato and Umberto Straccia. User Profile Modeling and Applications to Digital Libraries. In *Research and Advanced Technology for Digital Libraries*, volume 1696, pages 184–197. Springer Berlin Heidelberg, Berlin, Heidelberg, 1999. ISBN 978-3-540-66558-8 978-3-540-48155-3. doi:10.1007/3-540-48155-9_13. URL http://link.springer.com/10.1007/3-540-48155-9_13.

Xavier Amatriain, Josep M. Pujol, Nava Tintarev, and Nuria Oliver. Rate it again: increasing recommendation accuracy by user re-rating. In *Proceedings of the third ACM conference on Recommender systems*, RecSys '09, pages 173–180, New York, NY, USA, 2009. Association for Computing Machinery. ISBN 978-1-60558-435-5. doi:10.1145/1639714.1639744. URL https://dl.acm.org/doi/10.1145/1639714.1639744.

Mingxiao An, Fangzhao Wu, Chuhan Wu, Kun Zhang, Zheng Liu, and Xing Xie. Neural News Recommendation with Long- and Short-term User Representations. In Anna Korhonen, David Traum, and Lluís Màrquez, editors, *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 336–345, Florence, Italy, July 2019. Association for Computational Linguistics. doi:10.18653/v1/P19-1033. URL https://aclanthology.org/P19-1033.

Vito Walter Anelli, Tommaso Di Noia, Eugenio Di Sciascio, Antonio Ferrara, and Alberto Carlo Maria Mancino. Sparse Feature Factorization for Recommender Systems with Knowledge Graphs. In *Fifteenth ACM Conference on*

Recommender Systems, pages 154–165, Amsterdam Netherlands, September 2021. ACM. ISBN 978-1-4503-8458-2. doi:10.1145/3460231.3474243. URL https://dl.acm.org/doi/10.1145/3460231.3474243.

D. Magdalene Delighta Angeline. Association Rule Generation for Student Performance Analysis using Apriori Algorithm. *The SIJ Transactions on Computer Science Engineering & its Applications (CSEA)*, 01(01):16–20, April 2013. ISSN 23212373, 23212381. doi:10.9756/SIJCSEA/V1I1/01010252. URL http://www.thesij.com/TableOfContentArticleDetails.aspx?JournalID=1&IssueID=29.

Liliana Ardissono and Dario Sestero. Using dynamic user models in the recognition of the plans of the user. *User Modeling and User-Adapted Interaction*, 5(2):157–190, June 1995. ISSN 1573-1391. doi:10.1007/BF01099760. URL https://doi.org/10.1007/BF01099760.

Mozhdeh Ariannezhad, Ming Li, Sebastian Schelter, and Maarten De Rijke. A Personalized Neighborhood-based Model for Within-basket Recommendation in Grocery Shopping. In *Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining*, pages 87–95, Singapore Singapore, February 2023. ACM. ISBN 978-1-4503-9407-9. doi:10.1145/3539597.3570417. URL https://dl.acm.org/doi/10.1145/3539597.3570417.

Lora Aroyo and Geert-Jan Houben. User modeling and adaptive Semantic Web. *Semantic Web*, 1(1-2):105–110, January 2010. ISSN 1570-0844. doi:10.3233/SW-2010-0006. URL https://content.iospress.com/articles/semantic-web/sw006.

Tzoof Avny Brosh, Amit Livne, Oren Sar Shalom, Bracha Shapira, and Mark Last. BRUCE: Bundle Recommendation Using Contextualized item Embeddings. In *Proceedings of the 16th ACM Conference on Recommender Systems*, pages 237–245, Seattle WA USA, September 2022. ACM. ISBN 978-1-4503-9278-5. doi:10.1145/3523227.3546754. URL https://dl.acm.org/doi/10.1145/3523227.3546754.

Fedor Bakalov, Birgitta König-Ries, Andreas Nauerz, and Martin Welsch. IntrospectiveViews: An Interface for Scrutinizing Semantic User Models. In Paul De Bra, Alfred Kobsa, and David Chin, editors, *User Modeling, Adaptation, and Personalization*, Lecture Notes in Computer Science, pages 219–230, Berlin, Heidelberg, 2010. Springer. ISBN 978-3-642-13470-8. doi:10.1007/978-3-642-13470-8_21.

Krisztian Balog and ChengXiang Zhai. User Simulation for Evaluating Information Access Systems. In *Proceedings of the Annual International ACM SIGIR Conference on Research and Development in Information Retrieval in the Asia Pacific Region*, SIGIR-AP '23, pages 302–305, New York, NY, USA, November 2023. Association for Computing Machinery. ISBN 9798400704086. doi:10.1145/3624918.3629549. URL https://dl.acm.org/doi/10.1145/3624918.3629549.

Krisztian Balog, Toine Bogers, Leif Azzopardi, Maarten de Rijke, and Antal van den Bosch. Broad expertise retrieval in sparse data environments. In *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval*, SIGIR '07, pages 551–558, New York, NY, USA, 2007. Association for Computing Machinery. ISBN 978-1-59593-597-7. doi:10.1145/1277741.1277836. URL https://dl.acm.org/doi/10.1145/1277741.1277836.

Krisztian Balog, Yi Fang, Maarten De Rijke, Pavel Serdyukov, Luo Si, et al. Expertise retrieval. *Foundations and Trends® in Information Retrieval*, 6(2–3):127–256, 2012.

Krisztian Balog, Filip Radlinski, and Shushan Arakelyan. Transparent, Scrutable and Explainable User Models for Personalized Recommendation. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 265–274, Paris France, July 2019. ACM. ISBN 978-1-4503-6172-9. doi:10.1145/3331184.3331211. URL https://dl.acm.org/doi/10.1145/3331184.3331211.

Debayan Banerjee, Mathis Poser, Christina Wiethof, Varun Shankar Subramanian, Richard Paucar, Eva A. C. Bittner, and Chris Biemann. A System for Human-AI collaboration for Online Customer Support, February 2023. URL http://arxiv.org/abs/2301.12158. arXiv:2301.12158 [cs].

Ahmad Barforoush, Hossein Shirazi, and Hojjat Emami. A New Classification Framework to Evaluate the Entity Profiling on the Web: Past, Present and Future. *ACM Computing Surveys*, 50(3):39:1–39:39, June 2017. ISSN 0360-0300. doi:10.1145/3066904. URL https://dl.acm.org/doi/10.1145/3066904.

Tim Barnett, Allison W Pearson, Rodney Pearson, and Franz W Kellermanns. Five-factor model personality traits as predictors of perceived and actual usage of technology. *European Journal of Information Systems*, 24(4):374–390, July 2015. ISSN 1476-9344. doi:10.1057/ejis.2014.10. URL https://doi.org/10.1057/ejis.2014.10.

Debjanee Barua, Judy Kay, Bob Kummerfeld, and Cécile Paris. Modelling Long Term Goals. In Vania Dimitrova, Tsvi Kuflik, David Chin, Francesco Ricci, Peter Dolog, and Geert-Jan Houben, editors, *User Modeling, Adaptation, and Personalization*, Lecture Notes in Computer Science, pages 1–12, Cham, 2014. Springer International Publishing. ISBN 978-3-319-08786-3. doi:10.1007/978-3-319-08786-3_1.

Pradeep Bedi, S. B. Goyal, Anand Singh Rajawat, Rabindra Nath Shaw, and Ankush Ghosh. A Framework for Personalizing Atypical Web Search Sessions with Concept-Based User Profiles Using Selective Machine Learning Techniques. In Monica Bianchini, Vincenzo Piuri, Sanjoy Das, and Rabindra Nath Shaw, editors, *Advanced Computing and Intelligent Technologies*, Lecture Notes in Networks and Systems, pages 279–291, Singapore, 2022. Springer. ISBN 9789811621642. doi:10.1007/978-981-16-2164-2_23.

Aymen Ben Hassen, Sonia Ben Ticha, and Anja Habacha Chaibi. Deep Learning for Visual-Features Extraction Based Personalized User Modeling. *SN Computer Science*, 3(4):261, April 2022. ISSN 2661-8907. doi:10.1007/s42979-022-01131-y. URL `https://doi.org/10.1007/s42979-022-01131-y`.

Fabrício Benevenuto, Tiago Rodrigues, Meeyoung Cha, and Virgílio Almeida. Characterizing user behavior in online social networks. In *Proceedings of the 9th ACM SIGCOMM conference on Internet measurement*, IMC '09, pages 49–62, New York, NY, USA, November 2009. Association for Computing Machinery. ISBN 978-1-60558-771-4. doi:10.1145/1644893.1644900. URL `https://dl.acm.org/doi/10.1145/1644893.1644900`.

Souhila Benmakrelouf, Neila Mezghani, and Nadjia Kara. Towards the Identification of Players' Profiles Using Game's Data Analysis Based on Regression Model and Clustering. In *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015*, ASONAM '15, pages 1403–1410, New York, NY, USA, 2015. Association for Computing Machinery. ISBN 978-1-4503-3854-7. doi:10.1145/2808797.2809429. URL `https://dl.acm.org/doi/10.1145/2808797.2809429`.

Shlomo Berkovsky, Tsvi Kuflik, and Francesco Ricci. Mediation of user models for enhanced personalization in recommender systems. *User Modeling and User-Adapted Interaction*, 18(3):245–286, August 2008. ISSN 1573-1391. doi:10.1007/s11257-007-9042-9. URL `https://doi.org/10.1007/s11257-007-9042-9`.

Shlomo Berkovsky, Ronnie Taib, Irena Koprinska, Eileen Wang, Yucheng Zeng, Jingjie Li, and Sabina Kleitman. Detecting Personality Traits Using Eye-Tracking Data. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI '19, pages 1–12, New York, NY, USA, May 2019. Association for Computing Machinery. ISBN 978-1-4503-5970-2. doi:10.1145/3290605.3300451. URL `https://dl.acm.org/doi/10.1145/3290605.3300451`.

Suleep Kumar Bhogi, Kushal Singla, and Joy Bose. User Profile in Absence of Ground Truth for Mobile Users. In *2019 IEEE 13th International Conference on Semantic Computing (ICSC)*, pages 170–173, January 2019. doi:10.1109/ICOSC.2019.8665580. URL `https://ieeexplore.ieee.org/document/8665580`.

Meng Bi, Jian Xu, Mo Wang, and Fucai Zhou. Anomaly detection model of user behavior based on principal component analysis. *Journal of Ambient Intelligence and Humanized Computing*, 7(4):547–554, August 2016. ISSN 1868-5145. doi:10.1007/s12652-015-0341-4. URL `https://doi.org/10.1007/s12652-015-0341-4`.

Shuqing Bian, Wayne Xin Zhao, Kun Zhou, Jing Cai, Yancheng He, Cunxiang Yin, and Ji-Rong Wen. Contrastive Curriculum Learning for Sequential User Behavior Modeling via Data Augmentation. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 3737–3746, Virtual Event Queensland Australia, October 2021. ACM. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3481905. URL `https://dl.acm.org/doi/10.1145/3459637.3481905`.

Pradipta Biswas and Peter Robinson. A brief survey on user modelling in HCI. In *Proceedings of the International Conference on Intelligent Human Computer Interaction (IHCI)*, 2010.

Ludovico Boratto and Salvatore Carta. Modeling the Preferences of a Group of Users Detected by Clustering: a Group Recommendation Case-Study. In *Proceedings of the 4th International Conference on Web Intelligence, Mining and Semantics (WIMS14)*, WIMS '14, pages 1–7, New York, NY, USA, 2014. Association for Computing Machinery. ISBN 978-1-4503-2538-7. doi:10.1145/2611040.2611073. URL `https://dl.acm.org/doi/10.1145/2611040.2611073`.

Ludovico Boratto and Salvatore Carta. ART: group recommendation approaches for automatically detected groups. *International Journal of Machine Learning and Cybernetics*, 6(6):953–980, December 2015. ISSN 1868-808X. doi:10.1007/s13042-015-0371-4. URL `https://doi.org/10.1007/s13042-015-0371-4`.

Giorgio Brajnik and Carlo Tasso. A shell for developing non-monotonic user modeling systems. *International Journal of Human-Computer Studies*, 40(1):31–62, January 1994. ISSN 1071-5819. doi:10.1006/ijhc.1994.1003. URL `https://www.sciencedirect.com/science/article/pii/S1071581984710032`.

Sviatoslav Braynov. Personalization and Customization Technologies. In Hossein Bidgoli, editor, *The Internet Encyclopedia*. Wiley, 1 edition, January 2004. ISBN 978-0-471-22201-9 978-0-471-48296-3. doi:10.1002/047148296X.tie141. URL `https://onlinelibrary.wiley.com/doi/10.1002/047148296X.tie141`.

Peter Brusilovski, Alfred Kobsa, and Wolfgang Nejdl. *The Adaptive Web: Methods and Strategies of Web Personalization*. Springer Science & Business Media, April 2007. ISBN 978-3-540-72078-2.

Peter Brusilovsky. Adaptive Hypermedia. *User Modeling and User-Adapted Interaction*, 11(1):87–110, March 2001. ISSN 1573-1391. doi:10.1023/A:1011143116306. URL https://doi.org/10.1023/A:1011143116306.

Peter Brusilovsky. KnowledgeTree: a distributed architecture for adaptive e-learning. In *Proceedings of the 13th international World Wide Web conference on Alternate track papers & posters - WWW Alt. '04*, page 104, New York, NY, USA, 2004. ACM Press. ISBN 978-1-58113-912-9. doi:10.1145/1013367.1013386. URL http://portal.acm.org/citation.cfm?doid=1013367.1013386.

Peter Brusilovsky and Mark T Maybury. From adaptive hypermedia to the adaptive web. *Communications of the ACM*, 45(5):30–33, 2002.

Peter Brusilovsky and Eva Millán. User Models for Adaptive Hypermedia and Adaptive Educational Systems. In Peter Brusilovsky, Alfred Kobsa, and Wolfgang Nejdl, editors, *The Adaptive Web: Methods and Strategies of Web Personalization*, Lecture Notes in Computer Science, pages 3–53. Springer, Berlin, Heidelberg, 2007. ISBN 978-3-540-72079-9. URL https://doi.org/10.1007/978-3-540-72079-9_1.

Peter Brusilovsky, Alfred Kobsa, and Julita Vassileva, editors. *Adaptive Hypertext and Hypermedia*. Springer Netherlands, Dordrecht, 1998. ISBN 978-90-481-4944-5 978-94-017-0617-9. URL https://link.springer.com/10.1007/978-94-017-0617-9.

Mihaela Brut, Laura Asandului, and Gheorghe Grigoras. A Rule-Based Approach for Developing a Competency-Oriented User Model for E-Learning Systems. In *2009 Fourth International Conference on Internet and Web Applications and Services*, pages 555–560, May 2009. doi:10.1109/ICIW.2009.90.

Concepción Burgos, María L. Campanario, David de la Peña, Juan A. Lara, David Lizcano, and María A. Martínez. Data mining for modeling students' performance: A tutoring action plan to prevent academic dropout. *Computers & Electrical Engineering*, 66:541–556, February 2018. ISSN 0045-7906. doi:10.1016/j.compeleceng.2017.03.005. URL https://www.sciencedirect.com/science/article/pii/S0045790617305220.

Kristof Böhmer and Stefanie Rinderle-Ma. Mining association rules for anomaly detection in dynamic process runtime behavior and explaining the root cause to users. *Information Systems*, 90, May 2020. ISSN 0306-4379. doi:10.1016/j.is.2019.101438. URL https://www.sciencedirect.com/science/article/pii/S0306437919304909.

Alper Caglayan, Magnus Snorrason, Jennifer Jacoby, James Mazzu, Robin Jones, and Krishna Kumar. Learn sesame a learning agent engine. *Applied Artificial Intelligence*, 11(5):393–412, July 1997. ISSN 0883-9514. doi:10.1080/088395197118109. URL https://doi.org/10.1080/088395197118109.

Silvia Calegari and Gabriella Pasi. Ontology-Based Information Behaviour to Improve Web Search. *Future Internet*, 2(4): 533–558, December 2010. ISSN 1999-5903. doi:10.3390/fi2040533. URL https://www.mdpi.com/1999-5903/2/4/533.

Bagher Rahimpour Cami, Hamid Hassanpour, and Hoda Mashayekhi. User preferences modeling using dirichlet process mixture model for a content-based recommender system. *Knowledge-Based Systems*, 163:644–655, January 2019. ISSN 09507051. doi:10.1016/j.knosys.2018.09.028. URL https://linkinghub.elsevier.com/retrieve/pii/S0950705118304799.

Yue Cao, Xiaojiang Zhou, Jiaqi Feng, Peihao Huang, Yao Xiao, Dayao Chen, and Sheng Chen. Sampling Is All You Need on Modeling Long-Term User Behaviors for CTR Prediction. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, pages 2974–2983, Atlanta GA USA, October 2022. ACM. ISBN 978-1-4503-9236-5. doi:10.1145/3511808.3557082. URL https://dl.acm.org/doi/10.1145/3511808.3557082.

Francesca Carmagnola, Federica Cena, and Cristina Gena. User model interoperability: a survey. *User Modeling and User-Adapted Interaction*, 21(3):285–331, August 2011. ISSN 1573-1391. doi:10.1007/s11257-011-9097-5. URL https://doi.org/10.1007/s11257-011-9097-5.

Eduardo Carvalho, Bruno V. Ferreira, Jair Ferreira, Cleidson de Souza, Hanna V. Carvalho, Yoshihiko Suhara, Alex Sandy Pentland, and Gustavo Pessin. Exploiting the use of recurrent neural networks for driver behavior profiling. In *2017 International Joint Conference on Neural Networks (IJCNN)*, pages 3016–3021, May 2017. doi:10.1109/IJCNN.2017.7966230. URL https://ieeexplore.ieee.org/abstract/document/7966230?casa_token=qdBQ6ZJHlKsAAAAA:G2UJiXLEDC-EizefHgvpQZB0Dn6YZnHsYu0V1PrBUQX2Le9n1kjsh0rgclteaWIHyZpw7MEgm41P. ISSN: 2161-4407.

Giovanna Castellano, A. Maria Fanelli, Corrado Mencar, and M. Alessandra Torsello. Similarity-Based Fuzzy Clustering for User Profiling. In *2007 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology - Workshops*, pages 75–78, November 2007. doi:10.1109/WI-IATW.2007.32.

Marc Cañigueral and Joaquim Meléndez. Flexibility management of electric vehicles based on user profiles: The Arnhem case study. *International Journal of Electrical Power & Energy Systems*, 133:107195, December 2021. ISSN 01420615. doi:10.1016/j.ijepes.2021.107195. URL `https://linkinghub.elsevier.com/retrieve/pii/S0142061521004348`.

Federica Cena, Antonina Dattolo, Ernesto William De Luca, Pasquale Lops, Till Plumbaum, and Julita Vassileva. Semantic Adaptive Social Web. In Liliana Ardissono and Tsvi Kuflik, editors, *Advances in User Modeling*, Lecture Notes in Computer Science, pages 176–180, Berlin, Heidelberg, 2012. Springer. ISBN 978-3-642-28509-7. doi:10.1007/978-3-642-28509-7_17.

Federica Cena, Silvia Likavec, and Amon Rapp. Real World User Model: Evolution of User Modeling Triggered by Advances in Wearable and Ubiquitous Computing. *Information Systems Frontiers*, 21(5):1085–1110, October 2019. ISSN 1572-9419. doi:10.1007/s10796-017-9818-3. URL `https://doi.org/10.1007/s10796-017-9818-3`.

Federica Cena, Cristina Gena, Claudio Mattutino, Michele Mioli, Barbara Treccani, Fabiana Vernero, and Massimo Zancanaro. Incorporating Personality Traits in User Modeling for EUD. In *Proceedings of the 3rd International Workshop on Empowering People in Dealing with Internet of Things Ecosystems co-located with International Conference on Advanced Visual Interfaces (AVI) 2022*, Frascati, Italy, June 2022.

Shruthi Chari, Oshani Seneviratne, Daniel M. Gruen, Morgan A. Foreman, Amar K. Das, and Deborah L. McGuinness. Explanation Ontology: A Model of Explanations for User-Centered AI. In Jeff Z. Pan, Valentina Tamma, Claudia d'Amato, Krzysztof Janowicz, Bo Fu, Axel Polleres, Oshani Seneviratne, and Lalana Kagal, editors, *The Semantic Web – ISWC 2020*, Lecture Notes in Computer Science, pages 228–243, Cham, 2020. Springer International Publishing. ISBN 978-3-030-62466-8. doi:10.1007/978-3-030-62466-8_15.

Haonan Chen, Zhicheng Dou, Yutao Zhu, Zhao Cao, Xiaohua Cheng, and Ji-Rong Wen. Enhancing User Behavior Sequence Modeling by Generative Tasks for Session Search. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, pages 180–190, Atlanta GA USA, October 2022a. ACM. ISBN 978-1-4503-9236-5. doi:10.1145/3511808.3557310. URL `https://dl.acm.org/doi/10.1145/3511808.3557310`.

Jing Chen, Long Cheng, Xi Yang, Jun Liang, Bing Quan, and Shoushan Li. Joint Learning with both Classification and Regression Models for Age Prediction. *Journal of Physics: Conference Series*, 1168(3):032016, February 2019a. ISSN 1742-6596. doi:10.1088/1742-6596/1168/3/032016. URL `https://dx.doi.org/10.1088/1742-6596/1168/3/032016`.

Tinggui Chen, Xiaohua Yin, Lijuan Peng, Jingtao Rong, Jianjun Yang, and Guodong Cong. Monitoring and Recognizing Enterprise Public Opinion from High-Risk Users Based on User Portrait and Random Forest Algorithm. *Axioms*, 10 (2), June 2021a. ISSN 2075-1680. doi:10.3390/axioms10020106. URL `https://www.mdpi.com/2075-1680/10/2/106`. Number: 2 Publisher: Multidisciplinary Digital Publishing Institute.

Weijian Chen, Yulong Gu, Zhaochun Ren, Xiangnan He, Hongtao Xie, Tong Guo, Dawei Yin, and Yongdong Zhang. Semi-supervised User Profiling with Heterogeneous Graph Attention Networks. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence*, pages 2116–2122, Macao, China, August 2019b. International Joint Conferences on Artificial Intelligence Organization. ISBN 978-0-9992411-4-1. doi:10.24963/ijcai.2019/293. URL `https://www.ijcai.org/proceedings/2019/293`.

Weijian Chen, Fuli Feng, Qifan Wang, Xiangnan He, Chonggang Song, Guohui Ling, and Yongdong Zhang. CatGCN: Graph Convolutional Networks with Categorical Node Features. *IEEE Transactions on Knowledge and Data Engineering*, pages 1–1, 2021b. ISSN 1558-2191. doi:10.1109/TKDE.2021.3133013.

Weixin Chen, Mingkai He, Yongxin Ni, Weike Pan, Li Chen, and Zhong Ming. Global and Personalized Graphs for Heterogeneous Sequential Recommendation by Learning Behavior Transitions and User Intentions. In *Proceedings of the 16th ACM Conference on Recommender Systems*, pages 268–277, Seattle WA USA, September 2022b. ACM. ISBN 978-1-4503-9278-5. doi:10.1145/3523227.3546761. URL `https://dl.acm.org/doi/10.1145/3523227.3546761`.

Zhiyong Cheng, Sai Han, Fan Liu, Lei Zhu, Zan Gao, and Yuxin Peng. Multi-Behavior Recommendation with Cascading Graph Convolution Networks. In *Proceedings of the ACM Web Conference 2023*, WWW '23, pages 1181–1189, New York, NY, USA, April 2023. Association for Computing Machinery. ISBN 978-1-4503-9416-1. doi:10.1145/3543507.3583439. URL `https://dl.acm.org/doi/10.1145/3543507.3583439`.

Bark Cheung Chiu and Geoffrey I. Webb. Using Decision Trees for Agent Modeling: Improving Prediction Performance. *User Modeling and User-Adapted Interaction*, 8(1):131–152, March 1998. ISSN 1573-1391. doi:10.1023/A:1008296930163. URL `https://doi.org/10.1023/A:1008296930163`.

Junsu Cho, Dongmin Hyun, Dong won Lim, Hyeon jae Cheon, Hyoung-iel Park, and Hwanjo Yu. Dynamic Multi-Behavior Sequence Modeling for Next Item Recommendation. *Proceedings of the AAAI Conference on Artificial*

Intelligence, 37(4):4199–4207, June 2023. ISSN 2374-3468. doi:10.1609/aaai.v37i4.25537. URL https://ojs.aaai.org/index.php/AAAI/article/view/25537.

Yun-Wei Chu, Seyyedali Hosseinalipour, Elizabeth Tenorio, Laura Cruz, Kerrie Douglas, Andrew Lan, and Christopher Brinton. Mitigating Biases in Student Performance Prediction via Attention-Based Personalized Federated Learning. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, pages 3033–3042, Atlanta GA USA, October 2022. ACM. ISBN 978-1-4503-9236-5. doi:10.1145/3511808.3557108. URL https://dl.acm.org/doi/10.1145/3511808.3557108.

Victor Codina, Jose Mena, and Luis Oliva. Context-Aware User Modeling Strategies for Journey Plan Recommendation. In Francesco Ricci, Kalina Bontcheva, Owen Conlan, and Séamus Lawless, editors, *User Modeling, Adaptation and Personalization*, Lecture Notes in Computer Science, pages 68–79, Cham, 2015. Springer International Publishing. ISBN 978-3-319-20267-9. doi:10.1007/978-3-319-20267-9_6.

Philip R. Cohen and C. Raymond Perrault. Elements of a Plan-Based Theory of Speech Acts. *Cognitive Science*, 3 (3):177–212, 1979. ISSN 1551-6709. doi:10.1207/s15516709cog0303_1. URL https://onlinelibrary.wiley.com/doi/abs/10.1207/s15516709cog0303_1.

Luca Luciano Costanzo, Yashar Deldjoo, Maurizio Ferrari Dacrema, Markus Schedl, and Paolo Cremonesi. Towards Evaluating User Profiling Methods Based on Explicit Ratings on Item Features. In *Proceedings of the 6th Joint Workshop on Interfaces and Human Decision Making for Recommender Systems co-located with 13th ACM Conference on Recommender Systems(RecSys 2019)*, Copenhagen, Denmark, September 2019.

Paul Covington, Jay Adams, and Emre Sargin. Deep Neural Networks for YouTube Recommendations. In *Proceedings of the 10th ACM Conference on Recommender Systems*, RecSys '16, pages 191–198, New York, NY, USA, 2016. Association for Computing Machinery. ISBN 978-1-4503-4035-9. doi:10.1145/2959100.2959190. URL https://dl.acm.org/doi/10.1145/2959100.2959190.

Nick Craswell, Arjen de Vries, and Ian Soboroff. Overview of the TREC-2005 enterprise track. In *TREC*, volume 5, pages 1–7, January 2005.

Ayse Cufoglu. User Profiling - A Short Review. *International Journal of Computer Applications*, 108(3):1–9, December 2014. ISSN 09758887. doi:10.5120/18888-0179. URL http://research.ijcaonline.org/volume108/number3/pxc3900179.pdf.

Ayse Cufoglu, Mahi Lohi, and Kambiz Madani. A Comparative Study of Selected Classification Accuracy in User Profiling. In *2008 Seventh International Conference on Machine Learning and Applications*, pages 787–791, December 2008. doi:10.1109/ICMLA.2008.139. URL https://ieeexplore.ieee.org/abstract/document/4725067.

Aslıhan Cura, Haluk Küçük, Erdem Ergen, and İsmail Burak Öksüzoğlu. Driver Profiling Using Long Short Term Memory (LSTM) and Convolutional Neural Network (CNN) Methods. *IEEE Transactions on Intelligent Transportation Systems*, 22(10):6572–6582, October 2021. ISSN 1558-0016. doi:10.1109/TITS.2020.2995722. URL https://ieeexplore.ieee.org/abstract/document/9110758?casa_token=fkFYuzEvG9AAAAAA:b5kKbGrpRUK8J4vLP3XbWQMLBIvfoHvosQb6ykSetomcyvULuGAPfgtX9U7Zs7Kcisbdxt3-t4Em.

Mihaela Curmei, Andreas A. Haupt, Benjamin Recht, and Dylan Hadfield-Menell. Towards Psychologically-Grounded Dynamic Preference Models. In *Proceedings of the 16th ACM Conference on Recommender Systems*, pages 35–48, Seattle WA USA, September 2022. ACM. ISBN 978-1-4503-9278-5. doi:10.1145/3523227.3546778. URL https://dl.acm.org/doi/10.1145/3523227.3546778.

Enyan Dai and Suhang Wang. Say No to the Discrimination: Learning Fair Graph Neural Networks with Limited Sensitive Attribute Information. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*, WSDM '21, pages 680–688, New York, NY, USA, March 2021. Association for Computing Machinery. ISBN 978-1-4503-8297-7. doi:10.1145/3437963.3441752. URL https://dl.acm.org/doi/10.1145/3437963.3441752.

Paul De Bra, Peter Brusilovsky, and Geert-Jan Houben. Adaptive hypermedia: from systems to framework. *ACM Computing Surveys*, 31(4es):12, December 1999. ISSN 0360-0300, 1557-7341. doi:10.1145/345966.345996. URL https://dl.acm.org/doi/10.1145/345966.345996.

Luis M. De Campos, Juan M. Fernandez-Luna, Juan F. Huete, and Eduardo Vicente-Lopez. Using Personalization to Improve XML Retrieval. *IEEE Transactions on Knowledge and Data Engineering*, 26(5):1280–1292, May 2014. ISSN 1041-4347. doi:10.1109/TKDE.2013.75. URL http://ieeexplore.ieee.org/document/6514872/.

Ernesto William De Luca, Till Plumbaum, Jérôme Kunegis, and Sahin Albayrak. Multilingual ontology-based user profile enrichment. In *MSW*, pages 41–42, 2010.

Joey De Pauw, Koen Ruymbeek, and Bart Goethals. Who do you think I am? Interactive User Modelling with Item Metadata. In *Proceedings of the 16th ACM Conference on Recommender Systems*, pages 640–643, Seattle WA USA, September 2022. ACM. ISBN 978-1-4503-9278-5. doi:10.1145/3523227.3551470. URL https://dl.acm.org/doi/10.1145/3523227.3551470.

Chenlong Deng, Yujia Zhou, and Zhicheng Dou. Improving Personalized Search with Dual-Feedback Network. In *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining*, pages 210–218, Virtual Event AZ USA, February 2022a. ACM. ISBN 978-1-4503-9132-0. doi:10.1145/3488560.3498447. URL https://dl.acm.org/doi/10.1145/3488560.3498447.

Song Deng, Qingyuan Cai, Zi Zhang, and Xindong Wu. User Behavior Analysis Based on Stacked Autoencoder and Clustering in Complex Power Grid Environment. *IEEE Transactions on Intelligent Transportation Systems*, 23(12): 25521–25535, December 2022b. ISSN 1558-0016. doi:10.1109/TITS.2021.3076607. URL https://ieeexplore.ieee.org/abstract/document/9430771. Conference Name: IEEE Transactions on Intelligent Transportation Systems.

Zhengyu Deng, Jitao Sang, and Changsheng Xu. Personalized video recommendation based on cross-platform user modeling. In *2013 IEEE International Conference on Multimedia and Expo (ICME)*, pages 1–6, July 2013. doi:10.1109/ICME.2013.6607513. URL https://ieeexplore.ieee.org/abstract/document/6607513?casa_token=6o5upYPGcmEAAAAA:LBu07wRx214QnmK_7zMR4-Jh79MA77Pv0U8wH96AgcittffEn1tzHfkU8WNyudM6QwNVNdta6w.

Virginia Dignum. *Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way*. Artificial Intelligence: Foundations, Theory, and Algorithms. Springer International Publishing, Cham, 2019. ISBN 978-3-030-30370-9 978-3-030-30371-6. doi:10.1007/978-3-030-30371-6. URL http://link.springer.com/10.1007/978-3-030-30371-6.

Rui Ding, Ruobing Xie, Xiaobo Hao, Xiaochun Yang, Kaikai Ge, Xu Zhang, Jie Zhou, and Leyu Lin. Interpretable User Retention Modeling in Recommendation. In *Proceedings of the 17th ACM Conference on Recommender Systems*, pages 702–708, Singapore Singapore, September 2023. ACM. ISBN 9798400702419. doi:10.1145/3604915.3608818. URL https://dl.acm.org/doi/10.1145/3604915.3608818.

Simona D'Oca and Tianzhen Hong. A data-mining approach to discover patterns of window opening and closing behavior in offices. *Building and Environment*, 82:726–739, December 2014. ISSN 0360-1323. doi:10.1016/j.buildenv.2014.10.021. URL https://www.sciencedirect.com/science/article/pii/S0360132314003424.

Xin Dong, Tong Li, Rui Song, and Zhiming Ding. Profiling users via their reviews: an extended systematic mapping study. *Software and Systems Modeling*, 20(1):49–69, February 2021. ISSN 1619-1374. doi:10.1007/s10270-020-00790-w. URL https://doi.org/10.1007/s10270-020-00790-w.

Yuxiao Dong, Nitesh V. Chawla, Jie Tang, Yang Yang, and Yang Yang. User Modeling on Demographic Attributes in Big Mobile Social Networks. *ACM Transactions on Information Systems*, 35(4):35:1–35:33, 2017. ISSN 1046-8188. doi:10.1145/3057278. URL https://dl.acm.org/doi/10.1145/3057278.

Tim Donkers, Benedikt Loepp, and Jürgen Ziegler. Sequential User-based Recurrent Neural Network Recommendations. In *Proceedings of the Eleventh ACM Conference on Recommender Systems*, RecSys '17, pages 152–160, New York, NY, USA, 2017. Association for Computing Machinery. ISBN 978-1-4503-4652-8. doi:10.1145/3109859.3109877. URL https://dl.acm.org/doi/10.1145/3109859.3109877.

Qing Du, Haoran Xie, Yi Cai, Ho-fung Leung, Qing Li, Huaqing Min, and Fu Lee Wang. Folksonomy-based personalized search by hybrid user profiles in multiple levels. *Neurocomputing*, 204:142–152, September 2016. ISSN 0925-2312. doi:10.1016/j.neucom.2015.10.135. URL https://www.sciencedirect.com/science/article/pii/S0925231216301163.

Alberto Díaz and Pablo Gervás. Adaptive User Modeling for Personalization of Web Contents. In Paul M. E. De Bra and Wolfgang Nejdl, editors, *Adaptive Hypermedia and Adaptive Web-Based Systems*, Lecture Notes in Computer Science, pages 65–74, Berlin, Heidelberg, 2004. Springer. ISBN 978-3-540-27780-4. doi:10.1007/978-3-540-27780-4_10.

Magdalini Eirinaki and Michalis Vazirgiannis. Web mining for web personalization. *ACM Transactions on Internet Technology*, 3(1):1–27, February 2003. ISSN 1533-5399. doi:10.1145/643477.643478. URL https://dl.acm.org/doi/10.1145/643477.643478.

Christopher Ifeanyi Eke, Azah Anir Norman, Liyana Shuib, and Henry Friday Nweke. A Survey of User Profiling: State-of-the-Art, Challenges, and Solutions. *IEEE Access*, 7:144907–144924, 2019. ISSN 2169-3536. doi:10.1109/ACCESS.2019.2944243.

Anas El-Ansari, Abderrahim Beni-Hssane, and Mostafa Saadi. An improved modeling method for profile-based personalized search. In *Proceedings of the 3rd International Conference on Networking, Information Systems & Security*, NISS '20, pages 1–6, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 978-1-4503-7634-1. doi:10.1145/3386723.3387874. URL https://dl.acm.org/doi/10.1145/3386723.3387874.

Youssouf Elallioui and Omar El Beqqali. User profile Ontology for the Personalization approach. *International Journal of Computer Applications*, 41:31–40, March 2012. doi:10.5120/5531-7577.

Ali Mamdouh Elkahky, Yang Song, and Xiaodong He. A Multi-View Deep Learning Approach for Cross Domain User Modeling in Recommendation Systems. In *Proceedings of the 24th International Conference on World Wide Web*, WWW '15, pages 278–288, Republic and Canton of Geneva, CHE, 2015. International World Wide Web Conferences Steering Committee. ISBN 978-1-4503-3469-3. doi:10.1145/2736277.2741667. URL https://dl.acm.org/doi/10.1145/2736277.2741667.

Fredrik Erlandsson, Piotr Bródka, Anton Borg, and Henric Johnson. Finding Influential Users in Social Media Using Association Rule Learning. *Entropy*, 18(5):164, May 2016. ISSN 1099-4300. doi:10.3390/e18050164. URL https://www.mdpi.com/1099-4300/18/5/164. Number: 5 Publisher: Multidisciplinary Digital Publishing Institute.

Zhifang Fan, Dan Ou, Yulong Gu, Bairan Fu, Xiang Li, Wentian Bao, Xin-Yu Dai, Xiaoyi Zeng, Tao Zhuang, and Qingwen Liu. Modeling Users' Contextualized Page-wise Feedback for Click-Through Rate Prediction in E-commerce Search. In *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining*, pages 262–270, Virtual Event AZ USA, February 2022. ACM. ISBN 978-1-4503-9132-0. doi:10.1145/3488560.3498478. URL https://dl.acm.org/doi/10.1145/3488560.3498478.

Marina Farid, Rania Elgohary, Ibrahim Moawad, and Mohamed Roushdy. User Profiling Approaches, Modeling, and Personalization, October 2018. URL https://papers.ssrn.com/abstract=3389811.

Aleksandr Farseev, Liqiang Nie, Mohammad Akbari, and Tat-Seng Chua. Harvesting Multiple Sources for User Profile Learning: a Big Data Study. In *Proceedings of the 5th ACM on International Conference on Multimedia Retrieval*, ICMR '15, pages 235–242, New York, NY, USA, 2015. Association for Computing Machinery. ISBN 978-1-4503-3274-3. doi:10.1145/2671188.2749381. URL https://dl.acm.org/doi/10.1145/2671188.2749381.

Ghazal Fazelnia, Eric Simon, Ian Anderson, Benjamin Carterette, and Mounia Lalmas. Variational User Modeling with Slow and Fast Features. In *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining*, pages 271–279, Virtual Event AZ USA, February 2022. ACM. ISBN 978-1-4503-9132-0. doi:10.1145/3488560.3498477. URL https://dl.acm.org/doi/10.1145/3488560.3498477.

Mohd Fazil, Amit Kumar Sah, and Muhammad Abulaish. DeepSBD: A Deep Neural Network Model With Attention Mechanism for SocialBot Detection. *IEEE Transactions on Information Forensics and Security*, 16:4211–4223, 2021. ISSN 1556-6013, 1556-6021. doi:10.1109/TIFS.2021.3102498. URL https://ieeexplore.ieee.org/document/9505695/.

D. Fernandez-Lanvin, J. de Andres-Suarez, M. Gonzalez-Rodriguez, and B. Pariente-Martinez. The dimension of age and gender as user model demographic factors for automatic personalization in e-commerce sites. *Computer Standards & Interfaces*, 59:1–9, August 2018. ISSN 0920-5489. doi:10.1016/j.csi.2018.02.001. URL https://www.sciencedirect.com/science/article/pii/S0920548917303070.

Tim Finin and David Drager. GUMS: A General User Modeling System. *Proceedings of the workshop on Strategic computing natural language of the Human Language Technology Conference*, pages 224–230, May 1986. URL https://ebiquity.umbc.edu/paper/abstract/id/325/GUMS-A-General-User-Modeling-System.

Josef Fink and Alfred Kobsa. A Review and Analysis of Commercial User Modeling Servers for Personalization on the World Wide Web. *User Modeling and User-Adapted Interaction*, 10(2):209–249, June 2000. ISSN 1573-1391. doi:10.1023/A:1026597308943. URL https://doi.org/10.1023/A:1026597308943.

E. Frias-Martinez, G. Magoulas, S. Chen, and R. Macredie. Modeling human behavior in user-adaptive systems: Recent advances using soft computing techniques. *Expert Systems with Applications*, 29(2):320–329, August 2005. ISSN 0957-4174. doi:10.1016/j.eswa.2005.04.005. URL https://www.sciencedirect.com/science/article/pii/S0957417405000588.

E. Frias-Martinez, S.Y. Chen, and X. Liu. Survey of Data Mining Approaches to User Modeling for Adaptive Hypermedia. *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, 36(6):734–749, November 2006. ISSN 1094-6977. doi:10.1109/TSMCC.2006.879391. URL http://ieeexplore.ieee.org/document/1715503/.

Bin Fu, Jialiu Lin, Lei Li, Christos Faloutsos, Jason Hong, and Norman Sadeh. Why people hate your app: making sense of user feedback in a mobile app store. In *Proceedings of the 19th ACM SIGKDD international conference on*

Knowledge discovery and data mining, KDD '13, pages 1276–1284, New York, NY, USA, 2013. Association for Computing Machinery. ISBN 978-1-4503-2174-7. doi:10.1145/2487575.2488202. URL https://dl.acm.org/doi/10.1145/2487575.2488202.

Li Gao, Jia Wu, Chuan Zhou, and Yue Hu. Collaborative Dynamic Sparse Topic Regression with User Profile Evolution for Item Recommendation. *Proceedings of the AAAI Conference on Artificial Intelligence*, 31(1), February 2017. ISSN 2374-3468. doi:10.1609/aaai.v31i1.10726. URL https://ojs.aaai.org/index.php/AAAI/article/view/10726.

Min Gao, Kecheng Liu, and Zhongfu Wu. Personalisation in web computing and informatics: Theories, techniques, applications, and future research. *Information Systems Frontiers*, 12(5):607–629, November 2010. ISSN 1572-9419. doi:10.1007/s10796-009-9199-3. URL https://doi.org/10.1007/s10796-009-9199-3.

Rui Gao, Bibo Hao, Shuotian Bai, Lin Li, Ang Li, and Tingshao Zhu. Improving user profile with personality traits predicted from social media content. In *Proceedings of the 7th ACM conference on Recommender systems*, RecSys '13, pages 355–358, New York, NY, USA, 2013. Association for Computing Machinery. ISBN 978-1-4503-2409-0. doi:10.1145/2507157.2507219. URL https://dl.acm.org/doi/10.1145/2507157.2507219.

Xiaofeng Gao, Ran Gong, Yizhou Zhao, Shu Wang, Tianmin Shu, and Song-Chun Zhu. Joint Mind Modeling for Explanation Generation in Complex Human-Robot Collaborative Tasks. In *2020 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, pages 1119–1126, August 2020. doi:10.1109/RO-MAN47096.2020.9223595. URL https://ieeexplore.ieee.org/document/9223595. ISSN: 1944-9437.

Susan Gauch, Mirco Speretta, Aravind Chandramouli, and Alessandro Micarelli. User Profiles for Personalized Information Access. In Peter Brusilovsky, Alfred Kobsa, and Wolfgang Nejdl, editors, *The Adaptive Web: Methods and Strategies of Web Personalization*, Lecture Notes in Computer Science, pages 54–89. Springer, Berlin, Heidelberg, 2007. ISBN 978-3-540-72079-9. doi:10.1007/978-3-540-72079-9_2. URL https://doi.org/10.1007/978-3-540-72079-9_2.

Songwei Ge, Zhicheng Dou, Zhengbao Jiang, Jian-Yun Nie, and Ji-Rong Wen. Personalizing Search Results Using Hierarchical RNN with Query-aware Attention. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, pages 347–356, Torino Italy, October 2018. ACM. ISBN 978-1-4503-6014-2. doi:10.1145/3269206.3271728. URL https://dl.acm.org/doi/10.1145/3269206.3271728.

Justin Gilbert, Suraya Hamid, Ibrahim Abaker Targio Hashem, Norjihan Abdul Ghani, and Fatokun Faith Boluwatife. The rise of user profiling in social media: review, challenges and future direction. *Social Network Analysis and Mining*, 13(1):137, October 2023. ISSN 1869-5469. doi:10.1007/s13278-023-01146-0. URL https://doi.org/10.1007/s13278-023-01146-0.

Daniela Godoy and Analia Amandi. User profiling in personal information agents: a survey. *The Knowledge Engineering Review*, 20(4):329–361, December 2005. ISSN 1469-8005, 0269-8889. doi:10.1017/S0269888906000397. URL https://www.cambridge.org/core/journals/knowledge-engineering-review/article/user-profiling-in-personal-information-agents-a-survey/383527ACC2A6C40746AD7FE48E7E8B1D.

Raul Gomez Bruballa, Lauren Burnham-King, and Alessandra Sala. Learning Users' Preferred Visual Styles in an Image Marketplace. In *Proceedings of the 16th ACM Conference on Recommender Systems*, pages 466–468, Seattle WA USA, September 2022. ACM. ISBN 978-1-4503-9278-5. doi:10.1145/3523227.3547382. URL https://dl.acm.org/doi/10.1145/3523227.3547382.

Lin Gong and Hongning Wang. When Sentiment Analysis Meets Social Network: A Holistic User Behavior Modeling in Opinionated Data. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1455–1464, London United Kingdom, July 2018. ACM. ISBN 978-1-4503-5552-0. doi:10.1145/3219819.3220120. URL https://dl.acm.org/doi/10.1145/3219819.3220120.

Lin Gong, Lu Lin, Weihao Song, and Hongning Wang. JNET: Learning User Representations via Joint Network Embedding and Topic Embedding. In *Proceedings of the 13th International Conference on Web Search and Data Mining*, WSDM '20, pages 205–213, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 978-1-4503-6822-3. doi:10.1145/3336191.3371770. URL https://dl.acm.org/doi/10.1145/3336191.3371770.

Liang Gou, Michelle X. Zhou, and Huahai Yang. KnowMe and ShareMe: understanding automatically discovered personality traits from social media and user sharing preferences. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '14, pages 955–964, New York, NY, USA, April 2014. Association for Computing Machinery. ISBN 978-1-4503-2473-1. doi:10.1145/2556288.2557398. URL https://dl.acm.org/doi/10.1145/2556288.2557398.

Francesca Greco and Alessandro Polli. Emotional Text Mining: Customer profiling in brand management. *International Journal of Information Management*, 51:101934, April 2020. ISSN 0268-4012. doi:10.1016/j.ijinfomgt.2019.04.007. URL https://www.sciencedirect.com/science/article/pii/S0268401218313598.

Jia-Chen Gu, Hui Liu, Zhen-Hua Ling, Quan Liu, Zhigang Chen, and Xiaodan Zhu. Partner Matters! An Empirical Study on Fusing Personas for Personalized Response Selection in Retrieval-Based Chatbots. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 565–574, Virtual Event Canada, July 2021a. ACM. ISBN 978-1-4503-8037-9. doi:10.1145/3404835.3462858. URL https://dl.acm.org/doi/10.1145/3404835.3462858.

Jie Gu, Feng Wang, Qinghui Sun, Zhiquan Ye, Xiaoxiao Xu, Jingmin Chen, and Jun Zhang. Exploiting Behavioral Consistence for Universal User Representation. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(5): 4063–4071, May 2021b. ISSN 2374-3468, 2159-5399. doi:10.1609/aaai.v35i5.16527. URL https://ojs.aaai.org/index.php/AAAI/article/view/16527.

Yulong Gu, Zhuoye Ding, Shuaiqiang Wang, and Dawei Yin. Hierarchical User Profiling for E-commerce Recommender Systems. In *Proceedings of the 13th International Conference on Web Search and Data Mining*, WSDM '20, pages 223–231, New York, NY, USA, January 2020. Association for Computing Machinery. ISBN 978-1-4503-6822-3. doi:10.1145/3336191.3371827. URL https://dl.acm.org/doi/10.1145/3336191.3371827.

Yulong Gu, Wentian Bao, Dan Ou, Xiang Li, Baoliang Cui, Biyu Ma, Haikuan Huang, Qingwen Liu, and Xiaoyi Zeng. Self-Supervised Learning on Users' Spontaneous Behaviors for Multi-Scenario Ranking in E-commerce. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 3828–3837, Virtual Event Queensland Australia, October 2021c. ACM. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3481953. URL https://dl.acm.org/doi/10.1145/3459637.3481953.

Weili Guan, Fangkai Jiao, Xuemeng Song, Haokun Wen, Chung-Hsing Yeh, and Xiaojun Chang. Personalized Fashion Compatibility Modeling via Metapath-guided Heterogeneous Graph Learning. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 482–491, Madrid Spain, July 2022. ACM. ISBN 978-1-4503-8732-3. doi:10.1145/3477495.3532038. URL https://dl.acm.org/doi/10.1145/3477495.3532038.

Mouadh Guesmi, Mohamed Amine Chatti, Laura Vorgerd, Thao Ngo, Shoeb Joarder, Qurat Ul Ain, and Arham Muslim. Explaining User Models with Different Levels of Detail for Transparent Recommendation: A User Study. In *Adjunct Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization*, UMAP '22 Adjunct, pages 175–183, New York, NY, USA, 2022. Association for Computing Machinery. ISBN 978-1-4503-9232-7. doi:10.1145/3511047.3537685. URL https://dl.acm.org/doi/10.1145/3511047.3537685.

Ao Guo, Jianhua Ma, and Kevin I-Kai Wang. From User Models to the Cyber-I Model: Approaches, Progresses and Issues. In *2018 IEEE 16th Intl Conf on Dependable, Autonomic and Secure Computing, 16th Intl Conf on Pervasive Intelligence and Computing, 4th Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress(DASC/PiCom/DataCom/CyberSciTech)*, pages 33–40, Athens, August 2018a. IEEE. ISBN 978-1-5386-7518-2. doi:10.1109/DASC/PiCom/DataCom/CyberSciTec.2018.00021. URL https://ieeexplore.ieee.org/document/8511864/.

Yangyang Guo, Zhiyong Cheng, Liqiang Nie, Xin-Shun Xu, and Mohan Kankanhalli. Multi-modal Preference Modeling for Product Search. In *Proceedings of the 26th ACM international conference on Multimedia*, MM '18, pages 1865–1873, New York, NY, USA, 2018b. Association for Computing Machinery. ISBN 978-1-4503-5665-7. doi:10.1145/3240508.3240541. URL https://dl.acm.org/doi/10.1145/3240508.3240541.

Yangyang Guo, Zhiyong Cheng, Liqiang Nie, Yinglong Wang, Jun Ma, and Mohan Kankanhalli. Attentive Long Short-Term Preference Modeling for Personalized Product Search. *ACM Transactions on Information Systems*, 37(2): 19:1–19:27, 2019. ISSN 1046-8188. doi:10.1145/3295822. URL https://dl.acm.org/doi/10.1145/3295822.

Tural Gurbanov and Francesco Ricci. Action prediction models for recommender systems based on collaborative filtering and sequence mining hybridization. In *Proceedings of the Symposium on Applied Computing*, SAC '17, pages 1655–1661, New York, NY, USA, April 2017. Association for Computing Machinery. ISBN 978-1-4503-4486-9. doi:10.1145/3019612.3019759. URL https://dl.acm.org/doi/10.1145/3019612.3019759.

E. Hadoux and A. Hunter. Learning and Updating User Models for Subpopulations in Persuasive Argumentation Using Beta Distribution, July 2018. URL https://dl.acm.org/citation.cfm?id=3237865.

Touria Hamim, Faouzia Benabbou, and Nawal Sael. Student Profile Modeling Using Boosting Algorithms. *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT)*, 17 (5):1–13, September 2022. ISSN 1548-1093. doi:10.4018/IJWLTT.20220901.oa4. URL https://www.igi-global.com/article/student-profile-modeling-using-boosting-algorithms/www.igi-global.com/article/student-profile-modeling-using-boosting-algorithms/284084.

Jinkun Han, Wei Li, Zhipeng Cai, and Yingshu Li. Multi-Aggregator Time-Warping Heterogeneous Graph Neural Network for Personalized Micro-Video Recommendation. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, pages 676–685, Atlanta GA USA, October 2022. ACM. ISBN 978-1-4503-9236-5. doi:10.1145/3511808.3557403. URL https://dl.acm.org/doi/10.1145/3511808.3557403.

Morgan Harvey, Mark J. Carman, Ian Ruthven, and Fabio Crestani. Bayesian latent variable models for collaborative item rating prediction. In *Proceedings of the 20th ACM international conference on Information and knowledge management*, CIKM '11, pages 699–708, New York, NY, USA, 2011. Association for Computing Machinery. ISBN 978-1-4503-0717-8. doi:10.1145/2063576.2063680. URL https://dl.acm.org/doi/10.1145/2063576.2063680.

Peter Hase and Mohit Bansal. Evaluating Explainable AI: Which Algorithmic Explanations Help Users Predict Model Behavior? In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5540–5552, Online, July 2020. Association for Computational Linguistics. doi:10.18653/v1/2020.acl-main.491. URL https://aclanthology.org/2020.acl-main.491.

Taha Hassan, Bob Edmison, Timothy Stelter, and D. Scott McCrickard. Learning to Trust: Understanding Editorial Authority and Trust in Recommender Systems for Education. In *Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization*, pages 24–32, Utrecht Netherlands, June 2021. ACM. ISBN 978-1-4503-8366-0. doi:10.1145/3450613.3456811. URL https://dl.acm.org/doi/10.1145/3450613.3456811.

Zhicheng He, Weiwen Liu, Wei Guo, Jiarui Qin, Yingxue Zhang, Yaochen Hu, and Ruiming Tang. A Survey on User Behavior Modeling in Recommender Systems, February 2023. URL http://arxiv.org/abs/2302.11087.

Maryam Heidari, James H Jones, and Ozlem Uzuner. Deep Contextualized Word Embedding for Text-based Online User Profiling to Detect Social Bots on Twitter. In *2020 International Conference on Data Mining Workshops (ICDMW)*, pages 480–487, November 2020. doi:10.1109/ICDMW51313.2020.00071.

Yoshinori Hijikata. Implicit user profiling for on demand relevance feedback. In *Proceedings of the 9th international conference on Intelligent user interfaces*, IUI '04, pages 198–205, New York, NY, USA, January 2004. Association for Computing Machinery. ISBN 978-1-58113-815-3. doi:10.1145/964442.964480. URL https://dl.acm.org/doi/10.1145/964442.964480.

Robert D Hof, Heather Green, and Linda Himelstein. Now it's your web. *Business Week*, pages 68–74, 1998.

Eric Horvitz, Jack Breese, David Heckerman, David Hovel, and Koos Rommelse. The lumière project: Bayesian user modeling for inferring the goals and needs of software users. In *Proceedings of the Fourteenth conference on Uncertainty in artificial intelligence*, UAI'98, pages 256–265, San Francisco, CA, USA, 1998. Morgan Kaufmann Publishers Inc. ISBN 978-1-55860-555-8.

Jianqiao Hu, Feng Jin, Guigang Zhang, Jian Wang, and Yi Yang. A User Profile Modeling Method Based on Word2Vec. In *2017 IEEE International Conference on Software Quality, Reliability and Security Companion (QRS-C)*, pages 410–414, July 2017. doi:10.1109/QRS-C.2017.74. URL https://ieeexplore.ieee.org/abstract/document/8004351?casa_token=LBqpMSiajuYAAAAA:eDejrNq_k8xXgSujFmX9zOZzFk3S3O2oNpGrWOqu0IC-Zr3eXts_D4dtTZwxbYrQETOuiip6wQ.

Linmei Hu, Chen Li, Chuan Shi, Cheng Yang, and Chao Shao. Graph neural news recommendation with long-term and short-term interest modeling. *Information Processing & Management*, 57(2):102142, March 2020. ISSN 0306-4573. doi:10.1016/j.ipm.2019.102142. URL https://www.sciencedirect.com/science/article/pii/S0306457319307800.

Xiaowen Huang, Quan Fang, Shengsheng Qian, Jitao Sang, Yan Li, and Changsheng Xu. Explainable Interaction-driven User Modeling over Knowledge Graph for Sequential Recommendation. In *Proceedings of the 27th ACM International Conference on Multimedia*, MM '19, pages 548–556, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 978-1-4503-6889-6. doi:10.1145/3343031.3350893. URL https://dl.acm.org/doi/10.1145/3343031.3350893.

Alvaro Huertas-García, Javier Huertas-Tato, Alejandro Martín, and David Camacho. Profiling Hate Speech Spreaders on Twitter: Transformers and mixed pooling. In *Proceedings of the Working Notes of CLEF 2021 - Conference and Labs of the Evaluation Forum*, volume 2936, pages 1772–1789, Bucharest, Romania, 2021. CEUR Workshop Proceedings.

James Humann, TaLena Fletcher, and John Gerdes. Modeling, simulation, and trade-off analysis for multirobot, multioperator surveillance. *Systems Engineering*, 26(5):627–640, 2023. ISSN 1520-6858. doi:10.1002/sys.21685. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/sys.21685.

Alex Hämäläinen, Mustafa Mert Çelikok, and Samuel Kaski. Differentiable user models. In *Proceedings of the Thirty-Ninth Conference on Uncertainty in Artificial Intelligence*, pages 798–808. PMLR, July 2023. URL https://proceedings.mlr.press/v216/hamalainen23a.html.

Jim Isaak and Mina J. Hanna. User Data Privacy: Facebook, Cambridge Analytica, and Privacy Protection. *Computer*, 51(8):56–59, August 2018. ISSN 1558-0814. doi:10.1109/MC.2018.3191268. URL https://ieeexplore.ieee.org/abstract/document/8436400.

Taro Ishitaki, Ryoichiro Obukata, Tetsuya Oda, and Leonard Barolli. Application of Deep Recurrent Neural Networks for Prediction of User Behavior in Tor Networks. In *2017 31st International Conference on Advanced Information Networking and Applications Workshops (WAINA)*, pages 238–243, March 2017. doi:10.1109/WAINA.2017.63. URL https://ieeexplore.ieee.org/abstract/document/7929684?casa_token=9Iq9cw7U8csAAAAA:Ie_jgGdZHnR-3WUz8eDK3QyRdEHOc9XmrAp3O7-CCt_ejaP8mTWHBfuOPcab3ebzftpuZVa-wRVE.

Alexei V Ivanov, Giuseppe Riccardi, Adam J Sporka, and Jakub Franc. Recognition of personality traits from human spoken conversations. In *Twelfth annual conference of the international speech communication association*, 2011.

Razan Jaber and Donald McMillan. Cross-Modal Repair: Gaze and Speech Interaction for List Advancement. In *Proceedings of the 4th Conference on Conversational User Interfaces*, CUI '22, pages 1–11, New York, NY, USA, 2022. Association for Computing Machinery. ISBN 978-1-4503-9739-1. doi:10.1145/3543829.3543833. URL https://dl.acm.org/doi/10.1145/3543829.3543833.

Umair Javed, Kamran Shaukat, Ibrahim A. Hameed, Farhat Iqbal, Talha Mahboob Alam, and Suhuai Luo. A Review of Content-Based and Context-Based Recommendation Systems. *International Journal of Emerging Technologies in Learning (iJET)*, 16(03):274–306, February 2021. ISSN 1863-0383. doi:10.3991/ijet.v16i03.18851. URL https://online-journals.org/index.php/i-jet/article/view/18851.

Rachsuda Jiamthapthaksin and Than Htike Aung. User preferences profiling based on user behaviors on Facebook page categories. In *2017 9th International Conference on Knowledge and Smart Technology (KST)*, pages 248–253, February 2017. doi:10.1109/KST.2017.7886077. URL https://ieeexplore.ieee.org/abstract/document/7886077?casa_token=RN8VjN1AFygAAAAA:F6a0e3SMgYc_k20YKeSoF1bskeADnQXWx3XBiT-3nbHbmqaEA93hoMyZwJX_XVpb3-KLLcAgBA&signout=success.

Bowen Jin, Chen Gao, Xiangnan He, Depeng Jin, and Yong Li. Multi-behavior Recommendation with Graph Convolutional Networks. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '20, pages 659–668, Virtual Event China, 2020. Association for Computing Machinery. ISBN 978-1-4503-8016-4. doi:10.1145/3397271.3401072. URL https://dl.acm.org/doi/10.1145/3397271.3401072.

Cong Jin. MOOC student dropout prediction model based on learning behavior features and parameter optimization. *Interactive Learning Environments*, 31(2):714–732, February 2023. ISSN 1049-4820. doi:10.1080/10494820.2020.1802300. URL https://doi.org/10.1080/10494820.2020.1802300.

Long Jin, Yang Chen, Tianyi Wang, Pan Hui, and Athanasios V. Vasilakos. Understanding user behavior in online social networks: a survey. *IEEE Communications Magazine*, 51(9):144–150, September 2013. ISSN 1558-1896. doi:10.1109/MCOM.2013.6588663. URL https://ieeexplore.ieee.org/abstract/document/6588663?casa_token=BLPT_wxLkJYAAAAA:EbmGps059bb8icyPPhAVSFS4c4AZROZ9G3JIoJzWNppvqeFhe_5rRzJpbmKk1AcuGOY8v-yl4g.

Mathieu Jégou and Pierre Chevaillier. A computational model for the emergence of turn-taking behaviors in user-agent interactions. *Journal on Multimodal User Interfaces*, 12(3):199–223, September 2018. ISSN 1783-8738. doi:10.1007/s12193-018-0265-3. URL https://doi.org/10.1007/s12193-018-0265-3.

Sumitkumar Kanoje, Sheetal Girase, and Debajyoti Mukhopadhyay. User Profiling Trends, Techniques and Applications, March 2015. URL http://arxiv.org/abs/1503.07474.

Antonios Karatzoglou, Nikolai Schnell, and Michael Beigl. A Convolutional Neural Network Approach for Modeling Semantic Trajectories and Predicting Future Locations. In Věra Kůrková, Yannis Manolopoulos, Barbara Hammer, Lazaros Iliadis, and Ilias Maglogiannis, editors, *Artificial Neural Networks and Machine Learning – ICANN 2018*, Lecture Notes in Computer Science, pages 61–72, Cham, 2018. Springer International Publishing. ISBN 978-3-030-01418-6. doi:10.1007/978-3-030-01418-6_7.

Gerrit Kasper, Diego de Siqueira Braga, Denis Mayr Lima Martins, and Bernd Hellingrath. User profile acquisition: A comprehensive framework to support personal information agents. In *2017 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*, pages 1–6, November 2017. doi:10.1109/LA-CCI.2017.8285719. URL https://ieeexplore.ieee.org/document/8285719.

Ravneet Kaur, Sarbjeet Singh, and Harish Kumar. AuthCom: Authorship verification and compromised account detection in online social networks using AHP-TOPSIS embedded profiling based technique. *Expert Systems with Applications*, 113:397–414, December 2018. ISSN 0957-4174. doi:10.1016/j.eswa.2018.07.011. URL https://www.sciencedirect.com/science/article/pii/S0957417418304275.

Rishabh Kaushal, Vasundhara Ghose, and Ponnurangam Kumaraguru. Methods for User Profiling across Social Networks. In *2019 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom)*, pages 1572–1579, Xiamen, China, December 2019. IEEE. ISBN 978-1-72814-328-6. doi:10.1109/ISPA-BDCloud-SustainCom-SocialCom48970.2019.00231. URL https://ieeexplore.ieee.org/document/9047322/.

Judy Kay. The um toolkit for reusable, long term user models. *User Modeling and User-Adapted Interaction*, 4(3): 149–196, 1995.

Judy Kay, Bob Kummerfeld, and Piers Lauder. Personis: A Server for User Models. In Gerhard Goos, Juris Hartmanis, Jan Van Leeuwen, Paul De Bra, Peter Brusilovsky, and Ricardo Conejo, editors, *Adaptive Hypermedia and Adaptive Web-Based Systems*, volume 2347, pages 203–212. Springer Berlin Heidelberg, Berlin, Heidelberg, 2002. ISBN 978-3-540-43737-6 978-3-540-47952-9. URL http://link.springer.com/10.1007/3-540-47952-X_22.

Gudrun Kellner and Marcel Berthold. I-know my users: user-centric profiling based on the perceptual preference questionnaire (PPQ). In *Proceedings of the 12th International Conference on Knowledge Management and Knowledge Technologies*, i-KNOW '12, pages 1–4, New York, NY, USA, September 2012. Association for Computing Machinery. ISBN 978-1-4503-1242-4. doi:10.1145/2362456.2362493. URL https://dl.acm.org/doi/10.1145/2362456.2362493.

Dagmar Kern, Michael Harding, Oliver Storz, Nigel Davis, and Albrecht Schmidt. Shaping how advertisers see me: user views on implicit and explicit profile capture. In *CHI '08 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '08, pages 3363–3368, New York, NY, USA, April 2008. Association for Computing Machinery. ISBN 978-1-60558-012-8. doi:10.1145/1358628.1358858. URL https://dl.acm.org/doi/10.1145/1358628.1358858.

Antti Keurulainen, Isak Rafael Westerlund, Oskar Keurulainen, and Andrew Howes. Amortised Experimental Design and Parameter Estimation for User Models of Pointing. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI '23, pages 1–17, New York, NY, USA, April 2023. Association for Computing Machinery. ISBN 978-1-4503-9421-5. doi:10.1145/3544548.3581483. URL https://dl.acm.org/doi/10.1145/3544548.3581483.

Heung-Nam Kim, Abdulmajeed Alkhaldi, Abdulmotaleb El Saddik, and Geun-Sik Jo. Collaborative user modeling with user-generated tags for social recommender systems. *Expert Systems with Applications*, 38(7):8488–8496, July 2011. ISSN 09574174. doi:10.1016/j.eswa.2011.01.048. URL https://linkinghub.elsevier.com/retrieve/pii/S0957417411000686.

Jieun Kim, Ahreum Lee, and Hokyoung Ryu. Personality and its effects on learning performance: Design guidelines for an adaptive e-learning system based on a user model. *International Journal of Industrial Ergonomics*, 43(5):450–461, September 2013. ISSN 0169-8141. doi:10.1016/j.ergon.2013.03.001. URL https://www.sciencedirect.com/science/article/pii/S0169814113000334.

Sein Kim, Namkyeong Lee, Donghyun Kim, Minchul Yang, and Chanyoung Park. Task Relation-aware Continual User Representation Learning. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, KDD '23, pages 1107–1119, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 9798400701030. doi:10.1145/3580305.3599516. URL https://dl.acm.org/doi/10.1145/3580305.3599516.

Alfred Kobsa. Modeling the user's conceptual knowledge in BGP-MS, a user modeling shell system1. *Computational Intelligence*, 6(4):193–208, 1990. ISSN 1467-8640. doi:10.1111/j.1467-8640.1990.tb00295.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-8640.1990.tb00295.x.

Alfred Kobsa. Generic User Modeling Systems. *User Modeling and User-Adapted Interaction*, 11(1):49–63, March 2001. ISSN 1573-1391. doi:10.1023/A:1011187500863. URL https://doi.org/10.1023/A:1011187500863.

Alfred Kobsa and Josef Fink. An LDAP-based User Modeling Server and its Evaluation. *User Modeling and User-Adapted Interaction*, 16(2):129–169, May 2006. ISSN 0924-1868, 1573-1391. doi:10.1007/s11257-006-9006-5. URL https://link.springer.com/10.1007/s11257-006-9006-5.

Alfred Kobsa and Wolfgang Pohl. The user modeling shell system BGP-MS. *User Modeling and User-Adapted Interaction*, 4(2):59–106, June 1994. ISSN 1573-1391. doi:10.1007/BF01099428. URL https://doi.org/10.1007/BF01099428.

Alfred Kobsa and Jörg Schreck. Privacy through pseudonymity in user-adaptive systems. *ACM Transactions on Internet Technology*, 3(2):149–183, 2003. ISSN 1533-5399. doi:10.1145/767193.767196. URL https://dl.acm.org/doi/10.1145/767193.767196.

Alfred Kobsa, Jürgen Koenemann, and Wolfgang Pohl. Personalised hypermedia presentation techniques for improving online customer relationships. *The Knowledge Engineering Review*, 16(2): 111–155, March 2001. ISSN 1469-8005, 0269-8889. doi:10.1017/S0269888901000108. URL https://www.cambridge.org/core/journals/knowledge-engineering-review/article/personalised-hypermedia-presentation-techniques-for-improving-online-customer-relationships/FBFF2DE0C1AA93E2796F7B9809FE01D2.

Joseph A. Konstan and John Riedl. Recommender systems: from algorithms to user experience. *User Modeling and User-Adapted Interaction*, 22(1):101–123, April 2012. ISSN 1573-1391. doi:10.1007/s11257-011-9112-x. URL https://doi.org/10.1007/s11257-011-9112-x.

Joseph A. Konstan, Bradley N. Miller, David Maltz, Jonathan L. Herlocker, Lee R. Gordon, and John Riedl. GroupLens: applying collaborative filtering to Usenet news. *Communications of the ACM*, 40(3):77–87, March 1997. ISSN 0001-0782, 1557-7317. doi:10.1145/245108.245126. URL https://dl.acm.org/doi/10.1145/245108.245126.

Ivica Kostric, Krisztian Balog, and Filip Radlinski. Soliciting User Preferences in Conversational Recommender Systems via Usage-related Questions. In *Fifteenth ACM Conference on Recommender Systems*, pages 724–729, Amsterdam Netherlands, September 2021. ACM. ISBN 978-1-4503-8458-2. doi:10.1145/3460231.3478861. URL https://dl.acm.org/doi/10.1145/3460231.3478861.

Nagaraj Kota, Venkatesh Duppada, Ashvini Jindal, and Mohit Wadhwa. Understanding Job Seeker Funnel for Search and Discovery Personalization. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 3888–3897, Virtual Event Queensland Australia, October 2021. ACM. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3481959. URL https://dl.acm.org/doi/10.1145/3459637.3481959.

Gokul S Krishnan and S Sowmya Kamath. Dynamic and temporal user profiling for personalized recommenders using heterogeneous data sources. In *2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, pages 1–7, July 2017. doi:10.1109/ICCCNT.2017.8203963. URL https://ieeexplore.ieee.org/document/8203963.

Bruce Krulwich. LIFESTYLE FINDER: Intelligent User Profiling Using Large-Scale Demographic Data. *AI Magazine*, 18(2):37–37, June 1997. ISSN 2371-9621. doi:10.1609/aimag.v18i2.1292. URL https://ojs.aaai.org/aimagazine/index.php/aimagazine/article/view/1292.

Tsvi Kuflik, Judy Kay, and Bob Kummerfeld. Challenges and Solutions of Ubiquitous User Modeling. In Antonio Krüger and Tsvi Kuflik, editors, *Ubiquitous Display Environments*, Cognitive Technologies, pages 7–30. Springer, Berlin, Heidelberg, 2012. ISBN 978-3-642-27663-7. doi:10.1007/978-3-642-27663-7_2. URL https://doi.org/10.1007/978-3-642-27663-7_2.

Tanay Kulkarni, Madhur Kabra, and Radha Shankarmani. User Profiling Based Recommendation System for E-Learning. In *2019 IEEE 16th India Council International Conference (INDICON)*, pages 1–4, December 2019. doi:10.1109/INDICON47234.2019.9028982. URL https://ieeexplore.ieee.org/document/9028982.

Hongkyun Kwon, Sangjin Lee, and Doowon Jeong. User profiling via application usage pattern on digital devices for digital forensics. *Expert Systems with Applications*, 168:114488, April 2021. ISSN 09574174. doi:10.1016/j.eswa.2020.114488. URL https://linkinghub.elsevier.com/retrieve/pii/S0957417420311349.

Kleanthi Lakiotaki, Nikolaos F. Matsatsinis, and Alexis Tsoukias. Multicriteria User Modeling in Recommender Systems. *IEEE Intelligent Systems*, 26(2):64–76, March 2011. ISSN 1541-1672. doi:10.1109/MIS.2011.33. URL http://ieeexplore.ieee.org/document/5751215/.

Pat Langley. User Modeling in Adaptive Interfaces. In *Proceedings of the Seventh International Conference on User Modeling*, 1999. doi:10.1007/978-3-7091-2490-1_48.

Arash Habibi Lashkari, Min Chen, and Ali A. Ghorbani. A Survey on User Profiling Model for Anomaly Detection in Cyberspace. *Journal of Cyber Security and Mobility*, pages 75–112, 2019. ISSN 2245-4578. doi:10.13052/2245-1439.814. URL https://journals.riverpublishers.com/index.php/JCSANDM.

Frederick W. B. Li, Rynson W. H. Lau, and Parthiban Dharmendran. A Three-Tier Profiling Framework for Adaptive e-Learning. In Marc Spaniol, Qing Li, Ralf Klamma, and Rynson W. H. Lau, editors, *Advances in Web Based Learning – ICWL 2009*, Lecture Notes in Computer Science, pages 235–244, Berlin, Heidelberg, 2009. Springer. ISBN 978-3-642-03426-8. doi:10.1007/978-3-642-03426-8_30.

Hai Li, Xin Dong, Lei Cheng, and Linjian Mo. A Hierarchical User Behavior Modeling Framework for Cross-Domain Click-Through Rate Prediction. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, pages 4163–4167, Atlanta GA USA, October 2022a. ACM. ISBN 978-1-4503-9236-5. doi:10.1145/3511808.3557531. URL https://dl.acm.org/doi/10.1145/3511808.3557531.

Jiayu Li, Peijie Sun, Zhefan Wang, Weizhi Ma, Yangkun Li, Min Zhang, Zhoutian Feng, and Daiyue Xue. Intent-aware Ranking Ensemble for Personalized Recommendation, April 2023a. URL http://arxiv.org/abs/2304.07450.

Jiwei Li, Alan Ritter, and Eduard Hovy. Weakly Supervised User Profile Extraction from Twitter. In Kristina Toutanova and Hua Wu, editors, *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 165–174, Baltimore, Maryland, June 2014. Association for Computational Linguistics. doi:10.3115/v1/P14-1016. URL https://aclanthology.org/P14-1016.

Lin Li, Zhenglu Yang, Botao Wang, and Masaru Kitsuregawa. Dynamic Adaptation Strategies for Long-Term and Short-Term User Profile to Personalize Search. In Guozhu Dong, Xuemin Lin, Wei Wang, Yun Yang, and Jeffrey Xu Yu, editors, *Advances in Data and Web Management*, Lecture Notes in Computer Science, pages 228–240, Berlin, Heidelberg, 2007. Springer. ISBN 978-3-540-72524-4. doi:10.1007/978-3-540-72524-4_26.

Ming Li, Xingwang Han, Hua Sheng, Lin Ma, Hanzhang Kong, Weite Liu, and Bo Mao. A Novel RNN Model with Enhanced Behavior Semantic for Network User Profile. In *2022 Tenth International Conference on Advanced Cloud and Big Data (CBD)*, pages 190–193, November 2022b. doi:10.1109/CBD58033.2022.00041. URL https://ieeexplore.ieee.org/document/10024536.

Sheng Li and Handong Zhao. A Survey on Representation Learning for User Modeling. In *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence*, pages 4997–5003, Yokohama, Japan, July 2020. International Joint Conferences on Artificial Intelligence Organization. ISBN 978-0-9992411-6-5. doi:10.24963/ijcai.2020/695. URL https://www.ijcai.org/proceedings/2020/695.

Shuokai Li, Ruobing Xie, Yongchun Zhu, Xiang Ao, Fuzhen Zhuang, and Qing He. User-Centric Conversational Recommendation with Multi-Aspect User Modeling. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 223–233, Madrid Spain, July 2022c. ACM. ISBN 978-1-4503-8732-3. doi:10.1145/3477495.3532074. URL https://dl.acm.org/doi/10.1145/3477495.3532074.

Wanda Li, Wenhao Zheng, Xuanji Xiao, and Suhang Wang. STAN: Stage-Adaptive Network for Multi-Task Recommendation by Learning User Lifecycle-Based Representation, June 2023b. URL http://arxiv.org/abs/2306.12232.

Shangsong Liang and Maarten De Rijke. Formal language models for finding groups of experts. *Information Processing & Management*, 52(4):529–549, July 2016. ISSN 03064573. doi:10.1016/j.ipm.2015.11.005. URL https://linkinghub.elsevier.com/retrieve/pii/S0306457315001405.

Tzu-Heng Lin, Chen Gao, and Yong Li. CROSS: Cross-platform Recommendation for Social E-Commerce. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR'19, pages 515–524, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 978-1-4503-6172-9. doi:10.1145/3331184.3331191. URL https://dl.acm.org/doi/10.1145/3331184.3331191.

Jiahao Liu, Dongsheng Li, Hansu Gu, Tun Lu, Peng Zhang, Li Shang, and Ning Gu. Triple Structural Information Modelling for Accurate, Explainable and Interactive Recommendation, April 2023a. URL http://arxiv.org/abs/2304.11528.

Jinbo Liu, Yunliang Chen, Xiaohui Huang, Jianxin Li, and Geyong Min. GNN-based long and short term preference modeling for next-location prediction. *Information Sciences*, 629:1–14, June 2023b. ISSN 00200255. doi:10.1016/j.ins.2023.01.131. URL https://linkinghub.elsevier.com/retrieve/pii/S0020025523001433.

Kangmiao Liu, Wei Chen, Jiajun Bu, Chun Chen, and Lijun Zhang. User Modeling for Recommendation in Blogspace. In *2007 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology - Workshops*, pages 79–82, November 2007. doi:10.1109/WI-IATW.2007.23. URL https://ieeexplore.ieee.org/abstract/document/4427544?casa_token=CSJ-JvzE2IcAAAAA:fnGYlRgTPH2l-2A6BUyuYwmYlaUrV1OCcJjtJrNrJzjMqq8aQ6xSRuSqfSJR9T-agEhn_mOPhw.

Qi Liu, Jinze Wu, Zhenya Huang, Hao Wang, Yuting Ning, Ming Chen, Enhong Chen, Jinfeng Yi, and Bowen Zhou. Federated User Modeling from Hierarchical Information. *ACM Transactions on Information Systems*, 41(2): 46:1–46:33, April 2023c. ISSN 1046-8188. doi:10.1145/3560485. URL https://dl.acm.org/doi/10.1145/3560485.

Xin Liu. Modeling users' dynamic preference for personalized recommendation. In *Proceedings of the 24th International Conference on Artificial Intelligence*, IJCAI'15, pages 1785–1791, Buenos Aires, Argentina, 2015. AAAI Press. ISBN 978-1-57735-738-4.

R. Logesh, V. Subramaniyaswamy, V. Vijayakumar, and Xiong Li. Efficient User Profiling Based Intelligent Travel Recommender System for Individual and Group of Users. *Mobile Networks and Applications*, 24(3): 1018–1033, June 2019. ISSN 1572-8153. doi:10.1007/s11036-018-1059-2. URL https://doi.org/10.1007/s11036-018-1059-2.

Hongyu Lu, Weizhi Ma, Min Zhang, Maarten De Rijke, Yiqun Liu, and Shaoping Ma. Standing in Your Shoes: External Assessments for Personalized Recommender Systems. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1523–1533, Virtual Event Canada, July 2021. ACM. ISBN 978-1-4503-8037-9. doi:10.1145/3404835.3462916. URL https://dl.acm.org/doi/10.1145/3404835.3462916.

Luis Lugo, Jose G. Moreno, and Gilles Hubert. Modeling User Search Tasks with a Language-Agnostic Unsupervised Approach. In Djoerd Hiemstra, Marie-Francine Moens, Josiane Mothe, Raffaele Perego, Martin Potthast, and Fabrizio Sebastiani, editors, *Advances in Information Retrieval*, Lecture Notes in Computer Science, pages 405–418, Cham, 2021. Springer International Publishing. ISBN 978-3-030-72113-8. doi:10.1007/978-3-030-72113-8_27.

Sichun Luo, Yuanzhang Xiao, and Linqi Song. Personalized Federated Recommendation via Joint Representation Learning, User Clustering, and Model Adaptation. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, pages 4289–4293, Atlanta GA USA, October 2022. ACM. ISBN 978-1-4503-9236-5. doi:10.1145/3511808.3557668. URL https://dl.acm.org/doi/10.1145/3511808.3557668.

Yang Luo, Boyi Xu, Hongming Cai, and Fenglin Bu. A Hybrid User Profile Model for Personalized Recommender System with Linked Open Data. In *2014 Enterprise Systems Conference*, pages 243–248, August 2014. doi:10.1109/ES.2014.16. URL https://ieeexplore.ieee.org/abstract/document/6997053?casa_token=_xtD5qA_nO4AAAAA:9HSZ6x8CnenACOzBxTXKmvWHPlPgnlSiWSC8pODWTZFEXfAcDpMYcJE3A6MB2plDw4FvITPtKA.

Chenglong Ma, Yongli Ren, Pablo Castells, and Mark Sanderson. NEST: Simulating Pandemic-like Events for Collaborative Filtering by Modeling User Needs Evolution. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, pages 1430–1440, Atlanta GA USA, October 2022a. ACM. ISBN 978-1-4503-9236-5. doi:10.1145/3511808.3557407. URL https://dl.acm.org/doi/10.1145/3511808.3557407.

Rui Ma, Ning Liu, Jingsong Yuan, Huafeng Yang, and Jiandong Zhang. CAEN: A Hierarchically Attentive Evolution Network for Item-Attribute-Change-Aware Recommendation in the Growing E-commerce Environment. In *Proceedings of the 16th ACM Conference on Recommender Systems*, pages 278–287, Seattle WA USA, September 2022b. ACM. ISBN 978-1-4503-9278-5. doi:10.1145/3523227.3546773. URL https://dl.acm.org/doi/10.1145/3523227.3546773.

Xinhong Ma, Xiaoshan Yang, Junyu Gao, and Changsheng Xu. The Model May Fit You: User-Generalized Cross-Modal Retrieval. *IEEE Transactions on Multimedia*, 24:2998–3012, 2022c. ISSN 1941-0077. doi:10.1109/TMM.2021.3091888. URL https://ieeexplore.ieee.org/document/9465686.

Zhengyi Ma, Zhicheng Dou, Guanyue Bian, and Ji-Rong Wen. PSTIE: Time Information Enhanced Personalized Search. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, pages 1075–1084, Virtual Event Ireland, October 2020. ACM. ISBN 978-1-4503-6859-9. doi:10.1145/3340531.3411877. URL https://dl.acm.org/doi/10.1145/3340531.3411877.

Zhengyi Ma, Zhicheng Dou, Yutao Zhu, Hanxun Zhong, and Ji-Rong Wen. One Chatbot Per Person: Creating Personalized Chatbots based on Implicit User Profiles. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 555–564, Virtual Event Canada, July 2021. ACM. ISBN 978-1-4503-8037-9. doi:10.1145/3404835.3462828. URL https://dl.acm.org/doi/10.1145/3404835.3462828.

Jens Koed Madsen, Richard Bailey, Ernesto Carrella, and Philipp Koralus. Analytic Versus Computational Cognitive Models: Agent-Based Modeling as a Tool in Cognitive Sciences. *Current Directions in Psychological Science*, 28 (3):299–305, June 2019. ISSN 0963-7214. doi:10.1177/0963721419834547. URL https://doi.org/10.1177/0963721419834547.

François Mairesse and Marilyn A. Walker. Towards personality-based user adaptation: psychologically informed stylistic language generation. *User Modeling and User-Adapted Interaction*, 20(3):227–278, August 2010. ISSN 0924-1868, 1573-1391. doi:10.1007/s11257-010-9076-2. URL http://link.springer.com/10.1007/s11257-010-9076-2.

Bodhisattwa Prasad Majumder, Shuyang Li, Jianmo Ni, and Julian McAuley. Generating Personalized Recipes from Historical User Preferences, August 2019. URL http://arxiv.org/abs/1909.00105.

E. Malinowski and E. Zimányi. Hierarchies in a multidimensional model: From conceptual modeling to logical representation. *Data & Knowledge Engineering*, 59(2):348–377, November 2006. ISSN 0169-023X. doi:10.1016/j.datak.2005.08.003. URL https://www.sciencedirect.com/science/article/pii/S0169023X0500145X.

Ana Belen Barragans Martinez, Jose J. Pazos Arias, Ana Fernandez Vilas, Jorge Garcia Duque, and Martin Lopez Nores. What's on TV tonight? An efficient and effective personalized recommender system of TV programs. *IEEE Transactions on Consumer Electronics*, 55(1):286–294, February 2009. ISSN 1558-4127. doi:10.1109/TCE.2009.4814447. URL https://ieeexplore.ieee.org/abstract/document/4814447?casa_token=_cS7kDsAFe0AAAAA:fpgwqYT9CfzLb2s-GpOxdIUKIrERDJh8sxUJYd8NdBwvyU2eEQNfcuPiD9cPyI_QkCtJUsV8aw.

Judith Masthoff. Group Modeling: Selecting a Sequence of Television Items to Suit a Group of Viewers. In *Personalized Digital Television: Targeting Programs to individual Viewers*, Human-Computer Interaction Series, pages 93–141. Springer Netherlands, Dordrecht, 2004. ISBN 978-1-4020-2164-0. URL https://doi.org/10.1007/1-4020-2164-X_5.

Judith Masthoff. Group Recommender Systems: Combining Individual Models. In Francesco Ricci, Lior Rokach, Bracha Shapira, and Paul B. Kantor, editors, *Recommender Systems Handbook*, pages 677–702. Springer US, Boston, MA, 2011. ISBN 978-0-387-85820-3. doi:10.1007/978-0-387-85820-3_21. URL https://doi.org/10.1007/978-0-387-85820-3_21.

Robert R. McCrae and Oliver P. John. An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality*, 60(2):175–215, 1992. ISSN 1467-6494. doi:10.1111/j.1467-6494.1992.tb00970.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-6494.1992.tb00970.x.

Nuria Medina-Medina and Lina García-Cabrera. A taxonomy for user models in adaptive systems: special considerations for learning environments. *The Knowledge Engineering Review*, 31(2):124–141, March 2016. ISSN 0269-8889, 1469-8005. doi:10.1017/S0269888916000035. URL https://www.cambridge.org/core/journals/knowledge-engineering-review/article/taxonomy-for-user-models-in-adaptive-systems-special-considerations-for-learning-environments/B46A2FF2E88ACEC48BFD5D0A1CF7E4BB.

Imen Tayari Meftah, Nhan Le Thanh, and Chokri Ben Amar. Emotion Recognition Using KNN Classification for User Modeling and Sharing of Affect States. In Tingwen Huang, Zhigang Zeng, Chuandong Li, and Chi Sing Leung, editors, *Neural Information Processing*, Lecture Notes in Computer Science, pages 234–242, Berlin, Heidelberg, 2012. Springer. ISBN 978-3-642-34475-6. doi:10.1007/978-3-642-34475-6_29.

Bhaskar Mehta, Claudia Niederee, Avare Stewart, Marco Degemmis, Pasquale Lops, and Giovanni Semeraro. Ontologically-Enriched Unified User Modeling for Cross-System Personalization. In Liliana Ardissono, Paul Brna, and Antonija Mitrovic, editors, *User Modeling 2005*, Lecture Notes in Computer Science, pages 119–123, Berlin, Heidelberg, 2005. Springer. ISBN 978-3-540-31878-1. doi:10.1007/11527886_16.

Sakorn Mekruksavanich and Anuchit Jitpattanakul. Convolutional Neural Network and Data Augmentation for Behavioral-Based Biometric User Identification. In Milan Tuba, Shyam Akashe, and Amit Joshi, editors, *ICT Systems and Sustainability*, Advances in Intelligent Systems and Computing, pages 753–761, Singapore, 2021. Springer. ISBN 9789811582899. doi:10.1007/978-981-15-8289-9_72.

Iván Tactuk Mercado, Nuthan Munaiah, and Andrew Meneely. The impact of cross-platform development approaches for mobile applications from the user's perspective. In *Proceedings of the International Workshop on App Market Analytics*, WAMA 2016, pages 43–49, New York, NY, USA, November 2016. Association for Computing Machinery. ISBN 978-1-4503-4398-5. doi:10.1145/2993259.2993268. URL https://dl.acm.org/doi/10.1145/2993259.2993268.

Manel Mezghani, Corinne Amel Zayani, Ikram Amous, and Faiez Gargouri. A user profile modelling using social annotations: a survey. In *Proceedings of the 21st International Conference on World Wide Web*, WWW '12 Companion, pages 969–976, New York, NY, USA, April 2012. Association for Computing Machinery. ISBN 978-1-4503-1230-1. doi:10.1145/2187980.2188230. URL https://dl.acm.org/doi/10.1145/2187980.2188230.

Stuart E. Middleton, Nigel R. Shadbolt, and David C. De Roure. Ontological user profiling in recommender systems. *ACM Transactions on Information Systems*, 22(1):54–88, 2004. ISSN 1046-8188. doi:10.1145/963770.963773. URL https://dl.acm.org/doi/10.1145/963770.963773.

Sein Minn, Jill-Jênn Vie, Koh Takeuchi, Hisashi Kashima, and Feida Zhu. Interpretable Knowledge Tracing: Simple and Efficient Student Modeling with Causal Relations. *Proceedings of the AAAI Conference on Artificial Intelligence*, 36(11):12810–12818, June 2022. ISSN 2374-3468. doi:10.1609/aaai.v36i11.21560. URL https://ojs.aaai.org/index.php/AAAI/article/view/21560.

Bamshad Mobasher. Data Mining for Web Personalization. In Peter Brusilovsky, Alfred Kobsa, and Wolfgang Nejdl, editors, *The Adaptive Web: Methods and Strategies of Web Personalization*, Lecture Notes in Computer Science, pages 90–135. Springer, Berlin, Heidelberg, 2007. ISBN 978-3-540-72079-9. doi:10.1007/978-3-540-72079-9_3. URL https://doi.org/10.1007/978-3-540-72079-9_3.

Federico Monti, Fabrizio Frasca, Davide Eynard, Damon Mannion, and Michael M. Bronstein. Fake News Detection on Social Media using Geometric Deep Learning, February 2019. URL https://arxiv.org/abs/1902.06673v1.

Fahmid Morshed Fahid, Xiaoyi Tian, Andrew Emerson, Joseph B. Wiggins, Dolly Bounajim, Andy Smith, Eric Wiebe, Bradford Mott, Kristy Elizabeth Boyer, and James Lester. Progression Trajectory-Based Student Modeling for Novice Block-Based Programming. In *Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization*, pages 189–200, Utrecht Netherlands, June 2021. ACM. ISBN 978-1-4503-8366-0. doi:10.1145/3450613.3456833. URL https://dl.acm.org/doi/10.1145/3450613.3456833.

Cataldo Musto, Giovanni Semeraro, Cosimo Lovascio, Marco de Gemmis, and Pasquale Lops. A Framework for Holistic User Modeling Merging Heterogeneous Digital Footprints. In *Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization*, UMAP '18, pages 97–101, New York, NY, USA, 2018. Association for Computing Machinery. ISBN 978-1-4503-5784-5. doi:10.1145/3213586.3226218. URL https://dl.acm.org/doi/10.1145/3213586.3226218.

Cataldo Musto, Fedelucio Narducci, Marco Polignano, Marco de Gemmis, Pasquale Lops, and Giovanni Semeraro. Towards Queryable User Profiles: Introducing Conversational Agents in a Platform for Holistic User Modeling. In *Adjunct Publication of the 28th ACM Conference on User Modeling, Adaptation and Personalization*, UMAP '20 Adjunct, pages 213–218, New York, NY, USA, 2020a. Association for Computing Machinery. ISBN 978-1-4503-7950-2. doi:10.1145/3386392.3399298. URL https://dl.acm.org/doi/10.1145/3386392.3399298.

Cataldo Musto, Marco Polignano, Giovanni Semeraro, Marco de Gemmis, and Pasquale Lops. Myrror: a platform for holistic user modeling. *User Modeling and User-Adapted Interaction*, 30(3):477–511, July 2020b. ISSN 1573-1391. doi:10.1007/s11257-020-09272-6. URL https://doi.org/10.1007/s11257-020-09272-6.

Cataldo Musto, Christoph Trattner, Alain Starke, and Giovanni Semeraro. Towards a Knowledge-aware Food Recommender System Exploiting Holistic User Models. In *Proceedings of the 28th ACM Conference on User Modeling, Adaptation and Personalization*, UMAP '20, pages 333–337, New York, NY, USA, 2020c. Association for Computing Machinery. ISBN 978-1-4503-6861-2. doi:10.1145/3340631.3394880. URL https://dl.acm.org/doi/10.1145/3340631.3394880.

Cataldo Musto, Fedelucio Narducci, Marco Polignano, Marco de Gemmis, Pasquale Lops, and Giovanni Semeraro. MyrrorBot: A Digital Assistant Based on Holistic User Models for Personalized Access to Online Services. *ACM Transactions on Information Systems*, 39(4):46:1–46:34, 2021. ISSN 1046-8188. doi:10.1145/3447679. URL https://dl.acm.org/doi/10.1145/3447679.

P Nagaraj, K Saiteja, K Kalyan Ram, K Mani Kanta, S Krishna Aditya, and Muneeswaran V. University Recommender System based on Student Profile using Feature Weighted Algorithm and KNN. In *2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*, pages 479–484, April 2022. doi:10.1109/ICSCDS53736.2022.9760852. URL https://ieeexplore.ieee.org/abstract/document/9760852?casa_token=8EDAS89mh7IAAAAA:2ewEa1q30-4U7jT_pGfCM9o3EBfWRT4tfJ6eq4BqMzPBztfFJkZxeaxLv74SlvJx1r8TOOr76-HZ.

Nikolaos Nanas, Victoria Uren, and Anne De Roeck. Building and applying a concept hierarchy representation of a user profile. In *Proceedings of the 26th annual international ACM SIGIR conference on Research and development in informaion retrieval*, SIGIR '03, pages 198–204, New York, NY, USA, 2003. Association for Computing Machinery. ISBN 978-1-58113-646-3. doi:10.1145/860435.860473. URL https://dl.acm.org/doi/10.1145/860435.860473.

Nur Hasni Nasrudin, Samsiah Ahmad, Khairulliza Ahmad Salleh, and Lily Adina Azahari. A Systematic Review of User Mental Models on Applications Sustainability. *International Journal of Sustainable Construction Engineering and Technology*, 14(3):376–389, September 2023. ISSN 2600-7959. URL https://publisher.uthm.edu.my/ojs/index.php/IJSCET/article/view/15283.

Suraj Natarajan and Melody Moh. Recommending News Based on Hybrid User Profile, Popularity, Trends, and Location. In *2016 International Conference on Collaboration Technologies and Systems (CTS)*, pages 204–211, October 2016. doi:10.1109/CTS.2016.0050. URL https://ieeexplore.ieee.org/abstract/document/7870988.

Yabo Ni, Dan Ou, Shichen Liu, Xiang Li, Wenwu Ou, Anxiang Zeng, and Luo Si. Perceive Your Users in Depth: Learning Universal User Representations from Multiple E-commerce Tasks. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD '18, pages 596–605, New York, NY, USA, 2018. Association for Computing Machinery. ISBN 978-1-4503-5552-0. doi:10.1145/3219819.3219828. URL https://dl.acm.org/doi/10.1145/3219819.3219828.

Sir Nigel Shadbolt. Architectures for Autonomy: Towards an Equitable Web of Data in the Age of AI. In *Proceedings of The Web Conference 2020*, WWW '20, pages 3141–3142, New York, NY, USA, April 2020. Association for Computing Machinery. ISBN 978-1-4503-7023-3. doi:10.1145/3366423.3382668. URL https://doi.org/10.1145/3366423.3382668.

Roger Nkambou, Janie Brisson, Ange Tato, and Serge Robert. Learning Logical Reasoning Using an Intelligent Tutoring System: A Hybrid Approach to Student Modeling. *Proceedings of the AAAI Conference on Artificial Intelligence*, 37(13):15930–15937, September 2023. ISSN 2374-3468. doi:10.1609/aaai.v37i13.26891. URL https://ojs.aaai.org/index.php/AAAI/article/view/26891.

Oluwafemi Olaleke, Ivan Oseledets, and Evgeny Frolov. Dynamic Modeling of User Preferences for Stable Recommendations. In *Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization*, pages 262–266, Utrecht Netherlands, June 2021. ACM. ISBN 978-1-4503-8366-0. doi:10.1145/3450613.3456830. URL https://dl.acm.org/doi/10.1145/3450613.3456830.

Bolanle Olufisayo Dahunsi. An Ontology-based Knowledgebase for User Profile and Garment Features in Apparel Recommender Systems. In *Fifteenth ACM Conference on Recommender Systems*, pages 851–854, Amsterdam Netherlands, September 2021. ACM. ISBN 978-1-4503-8458-2. doi:10.1145/3460231.3473901. URL https://dl.acm.org/doi/10.1145/3460231.3473901.

Harrie Oosterhuis and Maarten de de Rijke. Robust Generalization and Safe Query-Specializationin Counterfactual Learning to Rank. In *Proceedings of the Web Conference 2021*, WWW '21, pages 158–170, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 978-1-4503-8312-7. doi:10.1145/3442381.3450018. URL https://dl.acm.org/doi/10.1145/3442381.3450018.

Andrew Ortony, Gerald L Clore, and Allan Collins. *The cognitive structure of emotions*. Cambridge University Press, 1988.

Jon Orwant. Heterogeneous learning in the Doppelgänger user modeling system. *User Modeling and User-Adapted Interaction*, 4(2):107–130, June 1994. ISSN 1573-1391. doi:10.1007/BF01099429. URL https://doi.org/10.1007/BF01099429.

Sara Ouaftouh, Ahmed Zellou, and Ali Idri. User profile model: A user dimension based classification. In *2015 10th International Conference on Intelligent Systems: Theories and Applications (SITA)*, pages 1–5, Rabat, October 2015. IEEE. ISBN 978-1-5090-0220-7. doi:10.1109/SITA.2015.7358378. URL http://ieeexplore.ieee.org/document/7358378/.

Sara Ouaftouh, Ahmed Zellou, and Ali Idri. Social recommendation: A user profile clustering-based approach. *Concurrency and Computation: Practice and Experience*, 31(20):e5330, 2019. ISSN 1532-0634. doi:10.1002/cpe.5330. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/cpe.5330.

Mariam Ouanaim, Hamid Harroud, Aziz Berrado, and Mohammed Boulmalf. Dynamic user profiling approach for services discovery in mobile environments. In *Proceedings of the 6th International Wireless Communications and Mobile Computing Conference*, IWCMC '10, pages 550–554, New York, NY, USA, June 2010. Association for Computing Machinery. ISBN 978-1-4503-0062-9. doi:10.1145/1815396.1815523. URL https://dl.acm.org/doi/10.1145/1815396.1815523.

Wentao Ouyang, Xiuwu Zhang, Shukui Ren, Chao Qi, Zhaojie Liu, and Yanlong Du. Representation Learning-Assisted Click-Through Rate Prediction. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence*, pages 4561–4567, Macao, China, August 2019. International Joint Conferences on Artificial Intelligence Organization. ISBN 978-0-9992411-4-1. doi:10.24963/ijcai.2019/634. URL https://www.ijcai.org/proceedings/2019/634.

Ana Paiva and John Self. TAGUS — A user and learner modeling workbench. *User Modeling and User-Adapted Interaction*, 4(3):197–226, September 1994. ISSN 1573-1391. doi:10.1007/BF01100244. URL https://doi.org/10.1007/BF01100244.

Yiteng Pan, Fazhi He, and Haiping Yu. Learning social representations with deep autoencoder for recommender system. *World Wide Web*, 23(4):2259–2279, July 2020. ISSN 1573-1413. doi:10.1007/s11280-020-00793-z. URL https://doi.org/10.1007/s11280-020-00793-z.

Mandeep Pannu, Rachid Anane, Michael Odetayo, and Anne James. Explicit user profiles in web search personalisation. In *Proceedings of the 2011 15th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, pages 416–421, June 2011. doi:10.1109/CSCWD.2011.5960107. URL https://ieeexplore.ieee.org/abstract/document/5960107?casa_token=Bq9oEJKCwqwAAAAA:SfgXL9zUt1DP81HPlasEZi1CEmZm5wm4c8OwYkdTwRVtHNoj-luYxwaNEfpZLRjKFKgRbrEnAg.

Marco Pavan, Thebin Lee, and Ernesto William De Luca. Semantic enrichment for adaptive expert search. In *Proceedings of the 15th International Conference on Knowledge Technologies and Data-driven Business*, i-KNOW '15, pages 1–4, New York, NY, USA, 2015. Association for Computing Machinery. ISBN 978-1-4503-3721-2. doi:10.1145/2809563.2809621. URL https://dl.acm.org/doi/10.1145/2809563.2809621.

Jian Peng, Kim-Kwang Raymond Choo, and Helen Ashman. User profiling in intrusion detection: A review. *Journal of Network and Computer Applications*, 72:14–27, September 2016. ISSN 1084-8045. doi:10.1016/j.jnca.2016.06.012. URL https://www.sciencedirect.com/science/article/pii/S1084804516301412.

Don Peppers and Martha Rogers. *The one to one future: Building relationships one customer at a time*. Currency Doubleday, 1993.

Don Peppers and Martha Rogers. Enterprise one to one: Tools for competing in the interactive age. 1997.

C. Raymond Perrault, James F. Allen, and Philip R. Cohen. Speech Acts as a Basis for Understanding Dialogue Coherence. *American Journal of Computational Linguistics*, pages 32–39, December 1978. URL https://aclanthology.org/J78-3024.

Guangyuan Piao and John G. Breslin. Exploring Dynamics and Semantics of User Interests for User Modeling on Twitter for Link Recommendations. In *Proceedings of the 12th International Conference on Semantic Systems*, SEMANTiCS 2016, pages 81–88, New York, NY, USA, 2016. Association for Computing Machinery. ISBN 978-1-4503-4752-5. doi:10.1145/2993318.2993332. URL https://dl.acm.org/doi/10.1145/2993318.2993332.

Guangyuan Piao and John G. Breslin. Inferring user interests in microblogging social networks: a survey. *User Modeling and User-Adapted Interaction*, 28(3):277–329, August 2018. ISSN 0924-1868, 1573-1391. doi:10.1007/s11257-018-9207-8. URL http://link.springer.com/10.1007/s11257-018-9207-8.

Dimitrios Pierrakos, Georgios Paliouras, Christos Papatheodorou, and Constantine D. Spyropoulos. Web Usage Mining as a Tool for Personalization: A Survey. *User Modeling and User-Adapted Interaction*, 13(4):311–372, November 2003. ISSN 1573-1391. doi:10.1023/A:1026238916441. URL https://doi.org/10.1023/A:1026238916441.

Till Plumbaum, Songxuan Wu, Ernesto William De Luca, and Sahin Albayrak. User modeling for the social semantic web. In *Proceedings of the Second International Conference on Semantic Personalized Information Management: Retrieval and Recommendation - Volume 781*, SPIM'11, pages 78–89, Aachen, DEU, 2011. CEUR-WS.org.

Till Plumbaum, Andreas Lommatzsch, Ernesto William De Luca, and Sahin Albayrak. SERUM: Collecting Semantic User Behavior for Improved News Recommendations. In Liliana Ardissono and Tsvi Kuflik, editors, *Advances in User Modeling*, Lecture Notes in Computer Science, pages 402–405, Berlin, Heidelberg, 2012. Springer. ISBN 978-3-642-28509-7. doi:10.1007/978-3-642-28509-7_37.

D. Poo, B. Chng, and Jie-Mein Goh. A hybrid approach for user profiling. In *36th Annual Hawaii International Conference on System Sciences, 2003. Proceedings of the*, pages 9 pp.–, January 2003. doi:10.1109/HICSS.2003.1174242.

Abinash Pujahari and Dilip Singh Sisodia. Item feature refinement using matrix factorization and boosted learning based user profile generation for content-based recommender systems. *Expert Systems with Applications*, 206:117849, November 2022. ISSN 09574174. doi:10.1016/j.eswa.2022.117849. URL https://linkinghub.elsevier.com/retrieve/pii/S0957417422011046.

Erasmo Purificato and Ernesto William De Luca. What Are We Missing in Algorithmic Fairness? Discussing Open Challenges for Fairness Analysis in User Profiling with Graph Neural Networks. In Ludovico Boratto, Stefano Faralli, Mirko Marras, and Giovanni Stilo, editors, *Advances in Bias and Fairness in Information Retrieval*, Communications in Computer and Information Science, pages 169–175, Cham, 2023. Springer Nature Switzerland. ISBN 978-3-031-37249-0. doi:10.1007/978-3-031-37249-0_14.

Erasmo Purificato, Ludovico Boratto, and Ernesto William De Luca. Do Graph Neural Networks Build Fair User Models? Assessing Disparate Impact and Mistreatment in Behavioural User Profiling. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, CIKM '22, pages 4399–4403, New York, NY, USA, 2022. Association for Computing Machinery. ISBN 978-1-4503-9236-5. doi:10.1145/3511808.3557584. URL https://doi.org/10.1145/3511808.3557584.

Tao Qi, Fangzhao Wu, Chuhan Wu, and Yongfeng Huang. FUM: Fine-grained and Fast User Modeling for News Recommendation. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1974–1978, Madrid Spain, July 2022a. ACM. ISBN 978-1-4503-8732-3. doi:10.1145/3477495.3531790. URL https://dl.acm.org/doi/10.1145/3477495.3531790.

Tao Qi, Fangzhao Wu, Chuhan Wu, and Yongfeng Huang. News Recommendation with Candidate-aware User Modeling. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1917–1921, Madrid Spain, July 2022b. ACM. ISBN 978-1-4503-8732-3. doi:10.1145/3477495.3531778. URL https://dl.acm.org/doi/10.1145/3477495.3531778.

Xu Qi. Research on User Profiling Technology for Personalized Demands. In *2010 International Conference on Intelligent Computation Technology and Automation*, volume 3, pages 198–201, May 2010. doi:10.1109/ICICTA.2010.252. URL https://ieeexplore.ieee.org/document/5523259.

Yi Qi, Ke Hu, Bo Zhang, Jia Cheng, and Jun Lei. Trilateral Spatiotemporal Attention Network for User Behavior Modeling in Location-based Search. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 3373–3377, Virtual Event Queensland Australia, October 2021. ACM. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3482206. URL https://dl.acm.org/doi/10.1145/3459637.3482206.

Hao Qian, Qintong Wu, MingHao Li, Zhengwei Wu, Zhiqiang Zhang, Jun Zhou, Lihong Gu, and Jinjie Gu. FwSeqBlock: A Field-wise Approach for Modeling Behavior Representation in Sequential Recommendation. In *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, pages 4404–4408, Atlanta GA USA, October 2022. ACM. ISBN 978-1-4503-9236-5. doi:10.1145/3511808.3557601. URL https://dl.acm.org/doi/10.1145/3511808.3557601.

Hongjin Qian, Zhicheng Dou, Yutao Zhu, Yueyuan Ma, and Ji-Rong Wen. Learning Implicit User Profile for Personalized Retrieval-Based Chatbot. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 1467–1477, Virtual Event Queensland Australia, October 2021. ACM. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3482269. URL https://dl.acm.org/doi/10.1145/3459637.3482269.

Frederic Raber and Antonio Krüger. Transferring recommendations through privacy user models across domains. *User Modeling and User-Adapted Interaction*, 32(1):25–90, April 2022. ISSN 1573-1391. doi:10.1007/s11257-021-09307-6. URL https://doi.org/10.1007/s11257-021-09307-6.

T. S. Raghu, P. K. Kannan, H. R. Rao, and A. B. Whinston. Dynamic profiling of consumers for customized offerings over the Internet: a model and analysis. *Decision Support Systems*, 32(2):117–134, December 2001. ISSN 0167-9236. doi:10.1016/S0167-9236(01)00106-3. URL https://www.sciencedirect.com/science/article/pii/S0167923601001063.

M. A. Raghuram, K. Akshay, and K. Chandrasekaran. Efficient User Profiling in Twitter Social Network Using Traditional Classifiers. In Stefano Berretti, Sabu M. Thampi, and Soura Dasgupta, editors, *Intelligent Systems Technologies and Applications*, Advances in Intelligent Systems and Computing, pages 399–411, Cham, 2016. Springer International Publishing. ISBN 978-3-319-23258-4. doi:10.1007/978-3-319-23258-4_35.

Deepthi Rajashekar, A. Nur Zincir-Heywood, and Malcolm I. Heywood. Smart Phone User Behaviour Characterization Based on Autoencoders and Self Organizing Maps. In *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*, pages 319–326, December 2016. doi:10.1109/ICDMW.2016.0052. URL https://ieeexplore.ieee.org/abstract/document/7836683. ISSN: 2375-9259.

Liana Razmerita, Albert Angehrn, and Alexander Maedche. Ontology-Based User Modeling for Knowledge Management Systems. In Peter Brusilovsky, Albert Corbett, and Fiorella de Rosis, editors, *User Modeling 2003*, Lecture Notes in Computer Science, pages 213–217, Berlin, Heidelberg, 2003. Springer. ISBN 978-3-540-44963-8. doi:10.1007/3-540-44963-9_29.

Kan Ren, Jiarui Qin, Yuchen Fang, Weinan Zhang, Lei Zheng, Weijie Bian, Guorui Zhou, Jian Xu, Yong Yu, Xiaoqiang Zhu, and Kun Gai. Lifelong Sequential Modeling with Personalized Memorization for User Response Prediction. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 565–574, Paris France, July 2019. ACM. ISBN 978-1-4503-6172-9. doi:10.1145/3331184.3331230. URL https://dl.acm.org/doi/10.1145/3331184.3331230.

Elaine Rich. User Modeling via Stereotypes. *Cognitive Science*, 3(4):329–354, 1979. ISSN 1551-6709. doi:10.1207/s15516709cog0304_3. URL https://onlinelibrary.wiley.com/doi/abs/10.1207/s15516709cog0304_3.

S.R. Rimitha, Vedasamhitha Abburu, Annem Kiranmai, and K. Chandrasekaran. Ontologies to Model User Profiles in Personalized Job Recommendation. In *2018 IEEE Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER)*, pages 98–103, August 2018. doi:10.1109/DISCOVER.2018.8674084. URL https://ieeexplore.ieee.org/document/8674084.

Lucas Rizzo, Pierpaolo Dondio, Sarah Jane Delany, and Luca Longo. Modeling Mental Workload Via Rule-Based Expert System: A Comparison with NASA-TLX and Workload Profile. In Lazaros Iliadis and Ilias Maglogiannis, editors, *Artificial Intelligence Applications and Innovations*, IFIP Advances in Information and Communication Technology, pages 215–229, Cham, 2016. Springer International Publishing. ISBN 978-3-319-44944-9. doi:10.1007/978-3-319-44944-9_19.

Cristobal Romero and Sebastian Ventura. Data mining in education. *WIREs Data Mining and Knowledge Discovery*, 3 (1):12–27, 2013. ISSN 1942-4795. doi:10.1002/widm.1075. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/widm.1075.

Ohad Rozen, Joel Oren, and Ariel Raviv. Predicting User Demography and Device from News Comments. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '21, pages 1995–1999, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 978-1-4503-8037-9. doi:10.1145/3404835.3463024. URL https://dl.acm.org/doi/10.1145/3404835.3463024.

Hataichanok Saevanee, Nathan L. Clarke, and Steven M. Furnell. Multi-modal Behavioural Biometric Authentication for Mobile Devices. In Dimitris Gritzalis, Steven Furnell, and Marianthi Theoharidou, editors, *Information Security and Privacy Research*, IFIP Advances in Information and Communication Technology, pages 465–474, Berlin, Heidelberg, 2012. Springer. ISBN 978-3-642-30436-1. doi:10.1007/978-3-642-30436-1_38.

Hataichanok Saevanee, Nathan Clarke, Steven Furnell, and Valerio Biscione. Continuous user authentication using multi-modal biometrics. *Computers & Security*, 53:234–246, September 2015. ISSN 0167-4048. doi:10.1016/j.cose.2015.06.001. URL https://www.sciencedirect.com/science/article/pii/S0167404815000875.

Somya Ranjan Sahoo and B. B. Gupta. Multiple features based approach for automatic fake news detection on social networks using deep learning. *Applied Soft Computing*, 100:106983, March 2021. ISSN 1568-4946. doi:10.1016/j.asoc.2020.106983. URL https://www.sciencedirect.com/science/article/pii/S1568494620309224.

Alan Said, Shlomo Berkovsky, and Ernesto W. De Luca. Movie recommendation in context. *ACM Transactions on Intelligent Systems and Technology*, 4(13):1–9, February 2013. ISSN 2157-6904. doi:10.1145/2414425.2414438. URL https://dl.acm.org/doi/10.1145/2414425.2414438.

Mohammad Sajib Al Seraj. A Survey on User Modeling in HCI. *Computer Applications: An International Journal*, 5(1):21–28, February 2018. ISSN 23938455. doi:10.5121/caij.2018.5102. URL http://airccse.com/caij/papers/5118caij02.pdf.

Sandra Sanchez-Gordon, Carmen Aguilar-Mayanquer, and Tania Calle-Jimenez. Model for Profiling Users With Disabilities on e-Learning Platforms. *IEEE Access*, 9:74258–74274, 2021. ISSN 2169-3536. doi:10.1109/ACCESS.2021.3081061. URL https://ieeexplore.ieee.org/document/9432934.

AK Santra and S Jayasudha. Classification of web log data to identify interested users using naïve bayesian classification. *International Journal of Computer Science Issues (IJCSI)*, 9(1):381, 2012.

Iqbal H. Sarker and Flora D. Salim. Mining User Behavioral Rules from Smartphone Data Through Association Analysis. In Dinh Phung, Vincent S. Tseng, Geoffrey I. Webb, Bao Ho, Mohadeseh Ganji, and Lida Rashidi, editors, *Advances in Knowledge Discovery and Data Mining*, Lecture Notes in Computer Science, pages 450–461, Cham, 2018. Springer International Publishing. ISBN 978-3-319-93034-3. doi:10.1007/978-3-319-93034-3_36.

Iqbal H. Sarker, Alan Colman, Jun Han, Asif Irshad Khan, Yoosef B. Abushark, and Khaled Salah. BehavDT: A Behavioral Decision Tree Learning to Build User-Centric Context-Aware Predictive Model. *Mobile Networks and Applications*, 25(3):1151–1161, June 2020. ISSN 1572-8153. doi:10.1007/s11036-019-01443-z. URL https://doi.org/10.1007/s11036-019-01443-z.

Silvia Schiaffino and Analía Amandi. Intelligent User Profiling. In Max Bramer, editor, *Artificial Intelligence An International Perspective: An International Perspective*, Lecture Notes in Computer Science, pages 193–216. Springer, Berlin, Heidelberg, 2009. ISBN 978-3-642-03226-4. doi:10.1007/978-3-642-03226-4_11. URL https://doi.org/10.1007/978-3-642-03226-4_11.

J. Schreck. *Security and Privacy in User Modeling*. Springer Science & Business Media, January 2003. ISBN 978-1-4020-1130-6.

Giovanni Semeraro, Verner Andersen, Hans H. K. Andersen, Marco de Gemmis, and Pasquale Lops. User profiling and virtual agents: a case study on e-commerce services. *Universal Access in the Information Society*, 7(3):179–194, September 2008. ISSN 1615-5297. doi:10.1007/s10209-008-0116-1. URL https://doi.org/10.1007/s10209-008-0116-1.

Yanir Seroussi, Fabian Bohnert, and Ingrid Zukerman. Personalised rating prediction for new users using latent factor models. In *Proceedings of the 22nd ACM conference on Hypertext and hypermedia*, HT '11, pages 47–56, New York, NY, USA, 2011. Association for Computing Machinery. ISBN 978-1-4503-0256-2. doi:10.1145/1995966.1995976. URL https://dl.acm.org/doi/10.1145/1995966.1995976.

Bruno Sguerra, Viet-Anh Tran, and Romain Hennequin. Ex2Vec: Characterizing Users and Items from the Mere Exposure Effect. In *Proceedings of the 17th ACM Conference on Recommender Systems*, pages 971–977, Singapore Singapore, September 2023. ACM. ISBN 9798400702419. doi:10.1145/3604915.3608856. URL https://dl.acm.org/doi/10.1145/3604915.3608856.

Yuval Shahar. The Ethical Implications of Shared Medical Decision Making without Providing Adequate Computational Support to the Care Provider and to the Patient, February 2021. URL http://arxiv.org/abs/2102.01811.

Balaram Sharma, Prabhat Pokharel, and Basanta Joshi. User Behavior Analytics for Anomaly Detection Using LSTM Autoencoder - Insider Threat Detection. In *Proceedings of the 11th International Conference on Advances in Information Technology*, IAIT '20, pages 1–9, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 978-1-4503-7759-1. doi:10.1145/3406601.3406610. URL https://dl.acm.org/doi/10.1145/3406601.3406610.

Babar Shazad, Hikmat Ullah Khan, Zahoor-ur Rehman, Muhammad Farooq, Ahsan Mahmood, Irfan Mehmood, Seungmin Rho, and Yunyoung Nam. Finding Temporal Influential Users in Social Media Using Association Rule Learning. *Intelligent Automation and Soft Computing*, 2019. ISSN 1079-8587, 2326-005X. doi:10.31209/2019.100000130. URL http://autosoftjournal.net/paperShow.php?paper=100000130.

Jiaxing Shen, Oren Lederman, Jiannong Cao, Shaojie Tang, and Alex 'Sandy' Pentland. User Profiling based on Nonlinguistic Audio Data. In *2021 IEEE 37th International Conference on Data Engineering (ICDE)*, pages 2303–2308, April 2021a. doi:10.1109/ICDE51399.2021.00241. URL https://ieeexplore.ieee.org/document/9458756.

Qijie Shen, Wanjie Tao, Jing Zhang, Hong Wen, Zulong Chen, and Quan Lu. SAR-Net: A Scenario-Aware Ranking Network for Personalized Fair Recommendation in Hundreds of Travel Scenarios. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 4094–4103, Virtual Event Queensland Australia, October 2021b. ACM. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3481948. URL https://dl.acm.org/doi/10.1145/3459637.3481948.

Xuehua Shen, Bin Tan, and ChengXiang Zhai. Implicit user modeling for personalized search. In *Proceedings of the 14th ACM international conference on Information and knowledge management*, CIKM '05, pages 824–831, New York, NY, USA, 2005. Association for Computing Machinery. ISBN 978-1-59593-140-5. doi:10.1145/1099554.1099747. URL https://dl.acm.org/doi/10.1145/1099554.1099747.

Dong-Hee Shin. Cross-Platform Users' Experiences Toward Designing Interusable Systems. *International Journal of Human–Computer Interaction*, 32(7):503–514, July 2016. ISSN 1044-7318. doi:10.1080/10447318.2016.1177277. URL https://doi.org/10.1080/10447318.2016.1177277.

Ben Shneiderman. *Human-centered AI*. Oxford University Press, 2022.

Kai Shu, Suhang Wang, and Huan Liu. Understanding User Profiles on Social Media for Fake News Detection. In *2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR)*, pages 430–435, April 2018. doi:10.1109/MIPR.2018.00092. URL https://ieeexplore.ieee.org/abstract/document/8397048?casa_token=yFzmKSodQYwAAAAA:gXCf7euQLFE1d9A_TYH9Pv0T7VlTJB6rRu6CdiOz8XZ6Yxs0s4rR1Lg8QOtNfznG92juwPHIsg.

Kai Shu, Xinyi Zhou, Suhang Wang, Reza Zafarani, and Huan Liu. The role of user profiles for fake news detection. In *Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, pages 436–439, Vancouver British Columbia Canada, August 2019. ACM. ISBN 978-1-4503-6868-1. doi:10.1145/3341161.3342927. URL https://dl.acm.org/doi/10.1145/3341161.3342927.

Huayou Si, Jiayong Zhou, Zhihui Chen, Jian Wan, Neal N. Xiong, Wei Zhang, and Athanasios V. Vasilakos. Association Rules Mining Among Interests and Applications for Users on Social Networks. *IEEE Access*, 7:116014–116026, 2019. ISSN 2169-3536. doi:10.1109/ACCESS.2019.2925819. URL https://ieeexplore.ieee.org/abstract/document/8751963. Conference Name: IEEE Access.

Ahu Sieg, Bamshad Mobasher, and Robin Burke. Web search personalization with ontological user profiles. In *Proceedings of the sixteenth ACM conference on Conference on information and knowledge management*, pages 525–534, Lisbon Portugal, November 2007. ACM. ISBN 978-1-59593-803-9. doi:10.1145/1321440.1321515. URL https://dl.acm.org/doi/10.1145/1321440.1321515.

Malvika Singh, B.M. Mehtre, and S. Sangeetha. User Behavior Profiling using Ensemble Approach for Insider Threat Detection. In *2019 IEEE 5th International Conference on Identity, Security, and Behavior Analysis (ISBA)*, pages 1–8, January 2019. doi:10.1109/ISBA.2019.8778466. URL https://ieeexplore.ieee.org/abstract/document/8778466?casa_token=-dP5bf2m0PkAAAAA:qUdg7W27ArLk0Rg6ahD_Pz9NjOhlsCNYAeRl8Xz-l6HCq1XH3WtDVXCfGiiax6YKovKcvwvWxWoI.

Pradeep Kumar Singh, Esam Othman, Rafeeq Ahmed, Awais Mahmood, Habib Dhahri, and Prasenjit Choudhury. Optimized recommendations by user profiling using apriori algorithm. *Applied Soft Computing*, 106:107272, July 2021. ISSN 15684946. doi:10.1016/j.asoc.2021.107272. URL https://linkinghub.elsevier.com/retrieve/pii/S1568494621001952.

Kerry-Louise Skillen, Liming Chen, Chris D. Nugent, Mark P. Donnelly, William Burns, and Ivar Solheim. Ontological User Profile Modeling for Context-Aware Application Personalization. In José Bravo, Diego López-de Ipiña, and Francisco Moya, editors, *Ubiquitous Computing and Ambient Intelligence*, Lecture Notes in Computer Science, pages 261–268, Berlin, Heidelberg, 2012. Springer. ISBN 978-3-642-35377-2. doi:10.1007/978-3-642-35377-2_36.

D. Sleeman. UMFE: A user modelling front-end subsystem. *International Journal of Man-Machine Studies*, 23(1): 71–88, July 1985. ISSN 0020-7373. doi:10.1016/S0020-7373(85)80025-0. URL https://www.sciencedirect.com/science/article/pii/S0020737385800250.

Diana Sola, Christian Meilicke, Han van der Aa, and Heiner Stuckenschmidt. A Rule-Based Recommendation Approach for Business Process Modeling. In Marcello La Rosa, Shazia Sadiq, and Ernest Teniente, editors, *Advanced Information Systems Engineering*, Lecture Notes in Computer Science, pages 328–343, Cham, 2021. Springer International Publishing. ISBN 978-3-030-79382-1. doi:10.1007/978-3-030-79382-1_20.

Adir Solomon, Ariel Bar, Chen Yanai, Bracha Shapira, and Lior Rokach. Predict Demographic Information Using Word2vec on Spatial Trajectories. In *Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization*, UMAP '18, pages 331–339, New York, NY, USA, 2018. Association for Computing Machinery. ISBN 978-1-4503-5589-6. doi:10.1145/3209219.3209224. URL https://dl.acm.org/doi/10.1145/3209219.3209224.

Sergey Sosnovsky and Darina Dicheva. Ontological technologies for user modelling. *International Journal of Metadata, Semantics and Ontologies*, 5(1):32, 2010. ISSN 1744-2621, 1744-263X. doi:10.1504/IJMSO.2010.032649. URL http://www.inderscience.com/link.php?id=32649.

Ana Stanescu, Swapnil Nagar, and Doina Caragea. A Hybrid Recommender System: User Profiling from Keywords and Ratings. In *2013 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)*, volume 1, pages 73–80, November 2013. doi:10.1109/WI-IAT.2013.11. URL https://ieeexplore.ieee.org/abstract/document/6689996.

Dirk Streeb, Yannick Metz, Udo Schlegel, Bruno Schneider, Mennatallah El-Assady, Hansjorg Neth, Min Chen, and Daniel A. Keim. Task-Based Visual Interactive Modeling: Decision Trees and Rule-Based Classifiers. *IEEE Transactions on Visualization and Computer Graphics*, 28(9):3307–3323, September 2022. ISSN 1077-2626, 1941-0506, 2160-9306. doi:10.1109/TVCG.2020.3045560. URL https://ieeexplore.ieee.org/document/9321557/.

Alexander Streicher and Kolja Bauer. Cognitive User Modeling for Adaptivity in Serious Games. In *Intelligent Human Systems Integration (IHSI 2024): Integrating People and Intelligent Systems*, volume 119. AHFE Open Acces, 2024. ISBN 978-1-958651-95-7. doi:10.54941/ahfe1004472. URL https://openaccess.cms-conferences.org/publications/book/978-1-958651-95-7/article/978-1-958651-95-7_8.

V. Subramaniyaswamy and R. Logesh. Adaptive KNN based Recommender System through Mining of User Preferences. *Wireless Personal Communications*, 97(2):2229–2247, November 2017. ISSN 1572-834X. doi:10.1007/s11277-017-4605-5. URL https://doi.org/10.1007/s11277-017-4605-5.

K Sudhakar, Boussaadi Smail, Tatireddy Subba Reddy, S Shitharth, Diwakar Ramanuj Tripathi, and Mochammad Fahlevi. Web User Profile Generation and Discovery Analysis using LSTM Architecture. In *2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, pages 371–375, October 2022. doi:10.1109/ICTACS56270.2022.9988505. URL https://ieeexplore.ieee.org/document/9988505.

Ke Sun, Tieyun Qian, Tong Chen, Yile Liang, Quoc Viet Hung Nguyen, and Hongzhi Yin. Where to Go Next: Modeling Long- and Short-Term User Preferences for Point-of-Interest Recommendation. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(01):214–221, April 2020. ISSN 2374-3468. doi:10.1609/aaai.v34i01.5353. URL https://ojs.aaai.org/index.php/AAAI/article/view/5353.

Ayse Saliha Sunar, Rabeeh Ayaz Abbasi, Hugh C. Davis, Su White, and Naif R. Aljohani. Modelling MOOC learners' social behaviours. *Computers in Human Behavior*, 107:105835, June 2020. ISSN 0747-5632. doi:10.1016/j.chb.2018.12.013. URL https://www.sciencedirect.com/science/article/pii/S0747563218305995.

Pablo Sánchez and Alejandro Bellogín. Building user profiles based on sequences for content and collaborative filtering. *Information Processing & Management*, 56(1):192–211, January 2019. ISSN 0306-4573. doi:10.1016/j.ipm.2018.10.003. URL https://www.sciencedirect.com/science/article/pii/S0306457318302735.

Zhaoxuan Tan and Meng Jiang. User Modeling in the Era of Large Language Models: Current Research and Future Directions, December 2023. URL https://arxiv.org/abs/2312.11518v2.

Duyu Tang, Bing Qin, Ting Liu, and Yuekui Yang. User modeling with neural network for review rating prediction. In *Proceedings of the 24th International Conference on Artificial Intelligence*, IJCAI'15, pages 1340–1346, Buenos Aires, Argentina, 2015. AAAI Press. ISBN 978-1-57735-738-4.

Jie Tang, Limin Yao, Duo Zhang, and Jing Zhang. A Combination Approach to Web User Profiling. *ACM Transactions on Knowledge Discovery from Data*, 5(1):2:1–2:44, December 2010. ISSN 1556-4681. doi:10.1145/1870096.1870098. URL https://dl.acm.org/doi/10.1145/1870096.1870098.

Dieudonne Tchuente. User Modeling and Profiling in Information Systems: A Bibliometric Study and Future Research Directions. *Journal of Global Information Management (JGIM)*, 30(1):1–25, January 2022. ISSN 1062-7375. doi:10.4018/JGIM.307116. URL https://www.igi-global.com/article/user-modeling-and-profiling-in-information-systems/www.igi-global.com/article/user-modeling-and-profiling-in-information-systems/307116.

Lucas Temor, Zainab Husain, and Peter Coppin. A cross-modal UX design pedagogy for industrial design. In *Proceedings of the 17th International Audio Mostly Conference*, AM '22, pages 195–198, New York, NY, USA, 2022. Association for Computing Machinery. ISBN 978-1-4503-9701-8. doi:10.1145/3561212.3561241. URL https://doi.org/10.1145/3561212.3561241.

Maritzol Tenemaza. User models for recommendation systems. In *Human Factors and Systems Interaction*, volume 52. AHFE Open Acces, 2022. ISBN 978-1-958651-28-5. doi:10.54941/ahfe1002188. URL https://openaccess.cms-conferences.org/publications/book/978-1-958651-28-5/article/978-1-958651-28-5_56.

Paolo Tomeo, Tommaso Di Noia, Marco de Gemmis, Pasquale Lops, Giovanni Semeraro, and Eugenio Di Sciascio. Exploiting Regression Trees as User Models for Intent-Aware Multi-attribute Diversity. In *Proceedings of the 2nd Workshop on New Trends on Content-Based Recommender Systems co-located with 9th ACM Conference on Recommender Systems (RecSys 2015)*, pages 2–9, Vienna, Austria, 2015.

Abhishek Tripathi, Ashwin T.S., and Ram Mohana Reddy Guddeti. A Reinforcement Learning and Recurrent Neural Network Based Dynamic User Modeling System. In *2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT)*, pages 411–415, July 2018. doi:10.1109/ICALT.2018.00103. URL https://ieeexplore.ieee.org/abstract/document/8433551?casa_token=BpGaGAEPhu4AAAAA:x42YQHbh30JK5eSer5Mky4k8Y3pTxF-8YxZIZZ3qmN_7I2GYkMSuauIa9i2AJ1KP9Sj71CsT7KpL.

Akarshita Tripathi, Saumya Yadav, and Rajiv Rajan. Naive Bayes Classification Model for the Student Performance Prediction. In *2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT)*, volume 1, pages 1548–1553, July 2019. doi:10.1109/ICICICT46008.2019.8993237. URL https://ieeexplore.ieee.org/abstract/document/8993237.

Jan-Willem van Dam and Michel van de Velden. Online profiling and clustering of Facebook users. *Decision Support Systems*, 70:60–72, February 2015. ISSN 0167-9236. doi:10.1016/j.dss.2014.12.001. URL https://www.sciencedirect.com/science/article/pii/S0167923614002796.

Ali Vardasbi, Harrie Oosterhuis, and Maarten de Rijke. When Inverse Propensity Scoring does not Work: Affine Corrections for Unbiased Learning to Rank. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, CIKM '20, pages 1475–1484, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 978-1-4503-6859-9. doi:10.1145/3340531.3412031. URL https://dl.acm.org/doi/10.1145/3340531.3412031.

Julita Vassileva. Motivating participation in social computing applications: a user modeling perspective. *User Modeling and User-Adapted Interaction*, 22(1):177–201, April 2012. ISSN 1573-1391. doi:10.1007/s11257-011-9109-5. URL https://doi.org/10.1007/s11257-011-9109-5.

Katrien Verbert, Nikos Manouselis, Xavier Ochoa, Martin Wolpers, Hendrik Drachsler, Ivana Bosnic, and Erik Duval. Context-Aware Recommender Systems for Learning: A Survey and Future Challenges. *IEEE Transactions on Learning Technologies*, 5(4):318–335, October 2012. ISSN 1939-1382, 2372-0050. doi:10.1109/TLT.2012.11. URL https://ieeexplore.ieee.org/document/6189308/.

Antoni Virós-i Martin and Daniel Selva. Improving Designer Learning in Design Space Exploration by Adapting to the Designer's Learning Goals. In *International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*. American Society of Mechanical Engineers Digital Collection, November 2022. doi:10.1115/DETC2022-89207. URL https://dx.doi.org/10.1115/DETC2022-89207.

Marco Viviani, Nadia Bennani, and Elod Egyed-Zsigmond. A Survey on User Modeling in Multi-application Environments. In *2010 Third International Conference on Advances in Human-Oriented and Personalized Mechanisms, Technologies and Services*, pages 111–116, August 2010. doi:10.1109/CENTRIC.2010.30. URL https://ieeexplore.ieee.org/abstract/document/5600339.

Duc-Vinh Vo, Jessada Karnjana, and Van-Nam Huynh. An integrated framework of learning and evidential reasoning for user profiling using short texts. *Information Fusion*, 70:27–42, June 2021. ISSN 15662535. doi:10.1016/j.inffus.2020.12.004. URL https://linkinghub.elsevier.com/retrieve/pii/S1566253520304292.

Thanh Vu, Alistair Willis, Son N. Tran, and Dawei Song. Temporal Latent Topic User Profiles for Search Personalisation. In Allan Hanbury, Gabriella Kazai, Andreas Rauber, and Norbert Fuhr, editors, *Advances in Information Retrieval*, Lecture Notes in Computer Science, pages 605–616, Cham, 2015. Springer International Publishing. ISBN 978-3-319-16354-3. doi:10.1007/978-3-319-16354-3_67.

Wolfgang Wahlster and Alfred Kobsa. User Models in Dialog Systems. In Alfred Kobsa and Wolfgang Wahlster, editors, *User Models in Dialog Systems*, Symbolic Computation, pages 4–34, Berlin, Heidelberg, 1989. Springer. ISBN 978-3-642-83230-7. doi:10.1007/978-3-642-83230-7_1.

Putra Wanda and Huang Jin Jie. DeepProfile: Finding fake profile in online social network using dynamic CNN. *Journal of Information Security and Applications*, 52:102465, June 2020. ISSN 22142126. doi:10.1016/j.jisa.2020.102465. URL https://linkinghub.elsevier.com/retrieve/pii/S2214212619303801.

Chunyang Wang, Yanmin Zhu, Haobing Liu, Wenze Ma, Tianzi Zang, and Jiadi Yu. Enhancing User Interest Modeling with Knowledge-Enriched Itemsets for Sequential Recommendation. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 1889–1898, Virtual Event Queensland Australia, October 2021a. ACM. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3482256. URL https://dl.acm.org/doi/10.1145/3459637.3482256.

Daheng Wang, Meng Jiang, Munira Syed, Oliver Conway, Vishal Juneja, Sriram Subramanian, and Nitesh V. Chawla. Calendar Graph Neural Networks for Modeling Time Structures in Spatiotemporal User Behaviors. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD '20, pages 2581–2589, New York, NY, USA, 2020a. Association for Computing Machinery. ISBN 978-1-4503-7998-4. doi:10.1145/3394486.3403308. URL https://dl.acm.org/doi/10.1145/3394486.3403308.

Danding Wang, Qian Yang, Ashraf Abdul, and Brian Y. Lim. Designing Theory-Driven User-Centric Explainable AI. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI '19, pages 1–15, New York, NY, USA, 2019a. Association for Computing Machinery. ISBN 978-1-4503-5970-2. doi:10.1145/3290605.3300831. URL https://dl.acm.org/doi/10.1145/3290605.3300831.

Dongjie Wang, Pengyang Wang, Kunpeng Liu, Yuanchun Zhou, Charles E. Hughes, and Yanjie Fu. Reinforced Imitative Graph Representation Learning for Mobile User Profiling: An Adversarial Training Perspective. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(5):4410–4417, May 2021b. ISSN 2374-3468. doi:10.1609/aaai.v35i5.16567. URL https://ojs.aaai.org/index.php/AAAI/article/view/16567.

Jingkun Wang, Yongtao Jiang, Haochen Li, and Wen Zhao. Improving News Recommendation with Channel-Wise Dynamic Representations and Contrastive User Modeling. In *Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining*, pages 562–570, Singapore Singapore, February 2023. ACM. ISBN 978-1-4503-9407-9. doi:10.1145/3539597.3570447. URL https://dl.acm.org/doi/10.1145/3539597.3570447.

Pengyang Wang, Yanjie Fu, Hui Xiong, and Xiaolin Li. Adversarial Substructured Representation Learning for Mobile User Profiling. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD '19, pages 130–138, New York, NY, USA, 2019b. Association for Computing Machinery. ISBN 978-1-4503-6201-6. doi:10.1145/3292500.3330869. URL https://dl.acm.org/doi/10.1145/3292500.3330869.

Pengyang Wang, Kunpeng Liu, Lu Jiang, Xiaolin Li, and Yanjie Fu. Incremental Mobile User Profiling: Reinforcement Learning with Spatial Knowledge Graph for Modeling Event Streams. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD '20, pages 853–861, New York, NY, USA, August 2020b. Association for Computing Machinery. ISBN 978-1-4503-7998-4. doi:10.1145/3394486.3403128. URL https://dl.acm.org/doi/10.1145/3394486.3403128.

Ruiheng Wang, Hongliang Zhu, Lu Wang, Zhaoyun Chen, Mingcheng Gao, and Yang Xin. User Identity Linkage Across Social Networks by Heterogeneous Graph Attention Network Modeling. *Applied Sciences*, 10(16):5478, January 2020c. ISSN 2076-3417. doi:10.3390/app10165478. URL https://www.mdpi.com/2076-3417/10/16/5478.

Ruiqin Wang, Zongda Wu, Jungang Lou, and Yunliang Jiang. Attention-based dynamic user modeling and Deep Collaborative filtering recommendation. *Expert Systems with Applications*, 188:116036, February 2022a. ISSN 09574174. doi:10.1016/j.eswa.2021.116036. URL https://linkinghub.elsevier.com/retrieve/pii/S0957417421013816.

Xiaolin Wang, Guohao Sun, Xiu Fang, Jian Yang, and Shoujin Wang. Modeling Spatio-temporal Neighbourhood for Personalized Point-of-interest Recommendation. In *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence*, pages 3530–3536, Vienna, Austria, July 2022b. International Joint Conferences on Artificial

Intelligence Organization. ISBN 978-1-956792-00-3. doi:10.24963/ijcai.2022/490. URL https://www.ijcai.org/proceedings/2022/490.

Honghao Wei, Fuzheng Zhang, Nicholas Jing Yuan, Chuan Cao, Hao Fu, Xing Xie, Yong Rui, and Wei-Ying Ma. Beyond the Words: Predicting User Personality from Heterogeneous Information. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, WSDM '17, pages 305–314, New York, NY, USA, February 2017. Association for Computing Machinery. ISBN 978-1-4503-4675-7. doi:10.1145/3018661.3018717. URL https://dl.acm.org/doi/10.1145/3018661.3018717.

Yinwei Wei, Xiang Wang, Xiangnan He, Liqiang Nie, Yong Rui, and Tat-Seng Chua. Hierarchical User Intent Graph Network for Multimedia Recommendation. *IEEE Transactions on Multimedia*, 24:2701–2712, 2022. ISSN 1520-9210, 1941-0077. doi:10.1109/TMM.2021.3088307. URL https://ieeexplore.ieee.org/document/9453189/.

Hong Wen, Jing Zhang, Fuyu Lv, Wentian Bao, Tianyi Wang, and Zulong Chen. Hierarchically Modeling Micro and Macro Behaviors via Multi-Task Learning for Conversion Rate Prediction. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 2187–2191, Virtual Event Canada, July 2021. ACM. ISBN 978-1-4503-8037-9. doi:10.1145/3404835.3463053. URL https://dl.acm.org/doi/10.1145/3404835.3463053.

Chuhan Wu, Fangzhao Wu, Junxin Liu, and Yongfeng Huang. Hierarchical User and Item Representation with Three-Tier Attention for Recommendation. In Jill Burstein, Christy Doran, and Thamar Solorio, editors, *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 1818–1826, Minneapolis, Minnesota, June 2019a. Association for Computational Linguistics. doi:10.18653/v1/N19-1180. URL https://aclanthology.org/N19-1180.

Chuhan Wu, Fangzhao Wu, Tao Qi, and Yongfeng Huang. User Modeling with Click Preference and Reading Satisfaction for News Recommendation. In *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence*, pages 3023–3029, Yokohama, Japan, July 2020a. International Joint Conferences on Artificial Intelligence Organization. ISBN 978-0-9992411-6-5. doi:10.24963/ijcai.2020/418. URL https://www.ijcai.org/proceedings/2020/418.

Chuhan Wu, Fangzhao Wu, Tao Qi, Jianxun Lian, Yongfeng Huang, and Xing Xie. PTUM: Pre-training User Model from Unlabeled User Behaviors via Self-supervision. In Trevor Cohn, Yulan He, and Yang Liu, editors, *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1939–1944, Online, November 2020b. Association for Computational Linguistics. doi:10.18653/v1/2020.findings-emnlp.174. URL https://aclanthology.org/2020.findings-emnlp.174.

Chuhan Wu, Fangzhao Wu, Yongfeng Huang, and Xing Xie. User-as-Graph: User Modeling with Heterogeneous Graph Pooling for News Recommendation. In *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence*, pages 1624–1630, Montreal, Canada, August 2021a. International Joint Conferences on Artificial Intelligence Organization. ISBN 978-0-9992411-9-6. doi:10.24963/ijcai.2021/224. URL https://www.ijcai.org/proceedings/2021/224.

Chuhan Wu, Fangzhao Wu, Tao Qi, and Yongfeng Huang. UserBERT: Pre-training User Model with Contrastive Self-supervision. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '22, pages 2087–2092, New York, NY, USA, 2022. Association for Computing Machinery. ISBN 978-1-4503-8732-3. doi:10.1145/3477495.3531810. URL https://dl.acm.org/doi/10.1145/3477495.3531810.

Jinze Wu, Qi Liu, Zhenya Huang, Yuting Ning, Hao Wang, Enhong Chen, Jinfeng Yi, and Bowen Zhou. Hierarchical Personalized Federated Learning for User Modeling. In *Proceedings of the Web Conference 2021*, WWW '21, pages 957–968, New York, NY, USA, 2021b. Association for Computing Machinery. ISBN 978-1-4503-8312-7. doi:10.1145/3442381.3449926. URL https://dl.acm.org/doi/10.1145/3442381.3449926.

Yuxia Wu, Ke Li, Guoshuai Zhao, and Xueming Qian. Long- and Short-term Preference Learning for Next POI Recommendation. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, CIKM '19, pages 2301–2304, New York, NY, USA, November 2019b. Association for Computing Machinery. ISBN 978-1-4503-6976-3. doi:10.1145/3357384.3358171. URL https://dl.acm.org/doi/10.1145/3357384.3358171.

Lianghao Xia, Chao Huang, Yong Xu, Peng Dai, Xiyue Zhang, Hongsheng Yang, Jian Pei, and Liefeng Bo. Knowledge-Enhanced Hierarchical Graph Transformer Network for Multi-Behavior Recommendation. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(5):4486–4493, May 2021a. ISSN 2374-3468. doi:10.1609/aaai.v35i5.16576. URL https://ojs.aaai.org/index.php/AAAI/article/view/16576.

Lianghao Xia, Yong Xu, Chao Huang, Peng Dai, and Liefeng Bo. Graph Meta Network for Multi-Behavior Recommendation. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '21, pages 757–766, New York, NY, USA, 2021b. Association for Computing Machinery. ISBN 978-1-4503-8037-9. doi:10.1145/3404835.3462972. URL https://dl.acm.org/doi/10.1145/3404835.3462972.

Yikun Xian, Tong Zhao, Jin Li, Jim Chan, Andrey Kan, Jun Ma, Xin Luna Dong, Christos Faloutsos, George Karypis, S. Muthukrishnan, and Yongfeng Zhang. EX3: Explainable Attribute-aware Item-set Recommendations. In *Fifteenth ACM Conference on Recommender Systems*, pages 484–494, Amsterdam Netherlands, September 2021. ACM. ISBN 978-1-4503-8458-2. doi:10.1145/3460231.3474240. URL https://dl.acm.org/doi/10.1145/3460231.3474240.

Yi Xie and Shun-Zheng Yu. A Large-Scale Hidden Semi-Markov Model for Anomaly Detection on User Browsing Behaviors. *IEEE/ACM Transactions on Networking*, 17(1):54–65, February 2009. ISSN 1558-2566. doi:10.1109/TNET.2008.923716. URL https://ieeexplore.ieee.org/abstract/document/4515888?casa_token=ZOYglc4HMlIAAAAA:MBeNUBQELpOOPr41tN22uSBK3BB_zJUbsXvHR2bceHVLS-NN6NvK6W5awUZlSCBSH1Bu1I45z2Wr. Conference Name: IEEE/ACM Transactions on Networking.

Jiajing Xu, Andrew Zhai, and Charles Rosenberg. Rethinking Personalized Ranking at Pinterest: An End-to-End Approach. In *Proceedings of the 16th ACM Conference on Recommender Systems*, pages 502–505, Seattle WA USA, September 2022. ACM. ISBN 978-1-4503-9278-5. doi:10.1145/3523227.3547394. URL https://dl.acm.org/doi/10.1145/3523227.3547394.

Hongrui Xuan, Yi Liu, Bohan Li, and Hongzhi Yin. Knowledge Enhancement for Contrastive Multi-Behavior Recommendation. In *Proceedings of the Sixteenth ACM International Conference on Web Search and Data Mining*, pages 195–203, Singapore Singapore, February 2023. ACM. ISBN 978-1-4503-9407-9. doi:10.1145/3539597.3570386. URL https://dl.acm.org/doi/10.1145/3539597.3570386.

Lyuxin Xue, Deqing Yang, and Yanghua Xiao. Factorial User Modeling with Hierarchical Graph Neural Network for Enhanced Sequential Recommendation. In *2022 IEEE International Conference on Multimedia and Expo (ICME)*, pages 01–06, July 2022. doi:10.1109/ICME52920.2022.9859593. URL https://ieeexplore.ieee.org/abstract/document/9859593?casa_token=PAT2krzHwr4AAAAA:omo9Z2VMKd-NUqf84e9NK2JJCk8yYsivZV_VJljR-DOrRYlLzyXfYNaJS3CKG3h-yZo1oz-w6g.

Satyajit Yadav and S. Selvakumar. Detection of application layer DDoS attack by modeling user behavior using logistic regression. In *2015 4th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO) (Trends and Future Directions)*, pages 1–6, September 2015. doi:10.1109/ICRITO.2015.7359289. URL https://ieeexplore.ieee.org/abstract/document/7359289.

Qilong Yan, Yufeng Zhang, Qiang Liu, Shu Wu, and Liang Wang. Relation-aware Heterogeneous Graph for User Profiling. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, CIKM '21, pages 3573–3577, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3482170. URL https://doi.org/10.1145/3459637.3482170.

Shaojie Yan, Tao Zhao, and Jinsheng Deng. Interaction-aware Hypergraph Neural Networks for User Profiling. In *2022 IEEE 9th International Conference on Data Science and Advanced Analytics (DSAA)*, pages 1–10, Shenzhen, China, October 2022. IEEE. ISBN 978-1-66547-330-9. doi:10.1109/DSAA54385.2022.10032374. URL https://ieeexplore.ieee.org/document/10032374/.

Boming Yang, Dairui Liu, Toyotaro Suzumura, Ruihai Dong, and Irene Li. Going Beyond Local: Global Graph-Enhanced Personalized News Recommendations. In *Proceedings of the 17th ACM Conference on Recommender Systems*, pages 24–34, Singapore Singapore, September 2023. ACM. ISBN 9798400702419. doi:10.1145/3604915.3608801. URL https://dl.acm.org/doi/10.1145/3604915.3608801.

Chen Yang, Yupeng Hou, Yang Song, Tao Zhang, Ji-Rong Wen, and Wayne Xin Zhao. Modeling Two-Way Selection Preference for Person-Job Fit. In *Proceedings of the 16th ACM Conference on Recommender Systems*, pages 102–112, Seattle WA USA, September 2022. ACM. ISBN 978-1-4503-9278-5. doi:10.1145/3523227.3546752. URL https://dl.acm.org/doi/10.1145/3523227.3546752.

Longqi Yang, Tobias Schnabel, Paul N. Bennett, and Susan Dumais. Local Factor Models for Large-Scale Inductive Recommendation. In *Fifteenth ACM Conference on Recommender Systems*, pages 252–262, Amsterdam Netherlands, September 2021. ACM. ISBN 978-1-4503-8458-2. doi:10.1145/3460231.3474276. URL https://dl.acm.org/doi/10.1145/3460231.3474276.

Bereket Abera Yilma, Yannick Naudet, and Hervé Panetto. Personalisation in Cyber-Physical-Social Systems: A Multi-stakeholder aware Recommendation and Guidance. In *Proceedings of the 29th ACM Conference on User Modeling, Adaptation and Personalization*, pages 251–255, Utrecht Netherlands, June 2021. ACM. ISBN 978-1-4503-8366-0. doi:10.1145/3450613.3456847. URL https://dl.acm.org/doi/10.1145/3450613.3456847.

Zeping Yu, Jianxun Lian, Ahmad Mahmoody, Gongshen Liu, and Xing Xie. Adaptive User Modeling with Long and Short-Term Preferences for Personalized Recommendation. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence*, pages 4213–4219, Macao, China, August 2019. International Joint Conferences on Artificial Intelligence Organization. ISBN 978-0-9992411-4-1. doi:10.24963/ijcai.2019/585. URL `https://www.ijcai.org/proceedings/2019/585`.

Fajie Yuan, Xiangnan He, Alexandros Karatzoglou, and Liguang Zhang. Parameter-Efficient Transfer from Sequential Behaviors for User Modeling and Recommendation. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1469–1478, Virtual Event China, July 2020a. ACM. ISBN 978-1-4503-8016-4. doi:10.1145/3397271.3401156. URL `https://dl.acm.org/doi/10.1145/3397271.3401156`.

Fajie Yuan, Guoxiao Zhang, Alexandros Karatzoglou, Joemon Jose, Beibei Kong, and Yudong Li. One Person, One Model, One World: Learning Continual User Representation without Forgetting. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 696–705, Virtual Event Canada, July 2021. ACM. ISBN 978-1-4503-8037-9. doi:10.1145/3404835.3462884. URL `https://dl.acm.org/doi/10.1145/3404835.3462884`.

Ye Yuan, Xin Luo, Mingsheng Shang, and Di Wu. A Generalized and Fast-converging Non-negative Latent Factor Model for Predicting User Preferences in Recommender Systems. In *Proceedings of The Web Conference 2020*, WWW '20, pages 498–507, New York, NY, USA, April 2020b. Association for Computing Machinery. ISBN 978-1-4503-7023-3. doi:10.1145/3366423.3380133. URL `https://dl.acm.org/doi/10.1145/3366423.3380133`.

Reza Zafarani and Huan Liu. Connecting users across social media sites: a behavioral-modeling approach. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 41–49, Chicago Illinois USA, August 2013. ACM. ISBN 978-1-4503-2174-7. doi:10.1145/2487575.2487648. URL `https://dl.acm.org/doi/10.1145/2487575.2487648`.

Yilei Zeng. How Human Centered AI Will Contribute Towards Intelligent Gaming Systems. *Proceedings of the AAAI Conference on Artificial Intelligence*, 35(18):15742–15743, May 2021. ISSN 2374-3468. doi:10.1609/aaai.v35i18.17868. URL `https://ojs.aaai.org/index.php/AAAI/article/view/17868`.

Saber Zerhoudi, Michael Granitzer, Christin Seifert, and Joerg Schloetterer. Evaluating Simulated User Interaction and Search Behaviour. In Matthias Hagen, Suzan Verberne, Craig Macdonald, Christin Seifert, Krisztian Balog, Kjetil Nørvåg, and Vinay Setty, editors, *Advances in Information Retrieval*, Lecture Notes in Computer Science, pages 240–247, Cham, 2022. Springer International Publishing. ISBN 978-3-030-99739-7. doi:10.1007/978-3-030-99739-7_28.

Rim Zghal Rebaï, Leila Ghorbel, Corinne Amel Zayani, and Ikram Amous. An Adaptive Method for User Profile Learning. In Barbara Catania, Giovanna Guerrini, and Jaroslav Pokorný, editors, *Advances in Databases and Information Systems*, Lecture Notes in Computer Science, pages 126–134, Berlin, Heidelberg, 2013. Springer. ISBN 978-3-642-40683-6. doi:10.1007/978-3-642-40683-6_10.

Chunxu Zhang, Guodong Long, Tianyi Zhou, Peng Yan, Zijian Zhang, Chengqi Zhang, and Bo Yang. Dual Personalization on Federated Recommendation, May 2023a. URL `http://arxiv.org/abs/2301.08143`.

Jing Zhang, Jie Yan, Yongqian Liu, Haoran Zhang, and Guoliang Lv. Daily electric vehicle charging load profiles considering demographics of vehicle users. *Applied Energy*, 274:115063, September 2020. ISSN 03062619. doi:10.1016/j.apenergy.2020.115063. URL `https://linkinghub.elsevier.com/retrieve/pii/S0306261920305754`.

Qianqian Zhang, Xinru Liao, Quan Liu, Jian Xu, and Bo Zheng. Leaving No One Behind: A Multi-Scenario Multi-Task Meta Learning Approach for Advertiser Modeling. In *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining*, pages 1368–1376, Virtual Event AZ USA, February 2022. ACM. ISBN 978-1-4503-9132-0. doi:10.1145/3488560.3498479. URL `https://dl.acm.org/doi/10.1145/3488560.3498479`.

Wei Zhang and Chris Challis. Learning User Preferences Without Feedbacks. In *2021 IEEE 8th International Conference on Data Science and Advanced Analytics (DSAA)*, pages 1–2, Porto, Portugal, October 2021. IEEE. ISBN 978-1-66542-099-0. doi:10.1109/DSAA53316.2021.9564131. URL `https://ieeexplore.ieee.org/document/9564131/`.

Yi Zhang and Jonathan Koren. Efficient bayesian hierarchical user modeling for recommendation system. In *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval*, SIGIR '07, pages 47–54, New York, NY, USA, 2007. Association for Computing Machinery. ISBN 978-1-59593-597-7. doi:10.1145/1277741.1277752. URL `https://dl.acm.org/doi/10.1145/1277741.1277752`.

Zheng Zhang, Qi Liu, Hao Jiang, Fei Wang, Yan Zhuang, Le Wu, Weibo Gao, and Enhong Chen. FairLISA: Fair User Modeling with Limited Sensitive Attributes Information. In *Thirty-seventh Conference on Neural Information Processing Systems*, November 2023b. URL `https://openreview.net/forum?id=uFpjPJMkv6`.

Hongyu Zhao, Jiazhi Xie, and Hongbin Wang. Co-learning Graph Convolution Network for Mobile User Profiling. *Neural Processing Letters*, 54(6):5299–5316, December 2022. ISSN 1573-773X. doi:10.1007/s11063-022-10862-1. URL https://doi.org/10.1007/s11063-022-10862-1.

Pengyu Zhao, Kecheng Xiao, Yuanxing Zhang, Kaigui Bian, and Wei Yan. AMEIR: Automatic Behavior Modeling, Interaction Exploration and MLP Investigation in the Recommender System. In *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence*, pages 2104–2110, August 2021. doi:10.24963/ijcai.2021/290. URL http://arxiv.org/abs/2006.05933.

Qian Zhao, Martijn C. Willemsen, Gediminas Adomavicius, F. Maxwell Harper, and Joseph A. Konstan. From preference into decision making: modeling user interactions in recommender systems. In *Proceedings of the 13th ACM Conference on Recommender Systems*, RecSys '19, pages 29–33, New York, NY, USA, 2019a. Association for Computing Machinery. ISBN 978-1-4503-6243-6. doi:10.1145/3298689.3347065. URL https://dl.acm.org/doi/10.1145/3298689.3347065.

Sha Zhao, Shijian Li, Julian Ramos, Zhiling Luo, Ziwen Jiang, Anind K. Dey, and Gang Pan. User profiling from their use of smartphone applications: A survey. *Pervasive and Mobile Computing*, 59:101052, October 2019b. ISSN 15741192. doi:10.1016/j.pmcj.2019.101052. URL https://linkinghub.elsevier.com/retrieve/pii/S1574119219300124.

Xuanzhi Zheng, Guoshuai Zhao, Li Zhu, and Xueming Qian. PERD: Personalized Emoji Recommendation with Dynamic User Preference. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1922–1926, Madrid Spain, July 2022a. ACM. ISBN 978-1-4503-8732-3. doi:10.1145/3477495.3531779. URL https://dl.acm.org/doi/10.1145/3477495.3531779.

Zhi Zheng, Zhaopeng Qiu, Tong Xu, Xian Wu, Xiangyu Zhao, Enhong Chen, and Hui Xiong. CBR: Context Bias aware Recommendation for Debiasing User Modeling and Click Prediction. In *Proceedings of the ACM Web Conference 2022*, WWW '22, pages 2268–2276, New York, NY, USA, April 2022b. Association for Computing Machinery. ISBN 978-1-4503-9096-5. doi:10.1145/3485447.3512099. URL https://dl.acm.org/doi/10.1145/3485447.3512099.

Erheng Zhong, Wei Fan, Junwei Wang, Lei Xiao, and Yong Li. ComSoc: adaptive transfer of user behaviors over composite social network. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, KDD '12, pages 696–704, New York, NY, USA, 2012. Association for Computing Machinery. ISBN 978-1-4503-1462-6. doi:10.1145/2339530.2339641. URL https://dl.acm.org/doi/10.1145/2339530.2339641.

Guorui Zhou, Xiaoqiang Zhu, Chenru Song, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, and Kun Gai. Deep Interest Network for Click-Through Rate Prediction. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, KDD '18, pages 1059–1068, New York, NY, USA, 2018. Association for Computing Machinery. ISBN 978-1-4503-5552-0. doi:10.1145/3219819.3219823. URL https://dl.acm.org/doi/10.1145/3219819.3219823.

Peilin Zhou, Jingqi Gao, Yueqi Xie, Qichen Ye, Yining Hua, Jaeboum Kim, Shoujin Wang, and Sunghun Kim. Equivariant Contrastive Learning for Sequential Recommendation. In *Proceedings of the 17th ACM Conference on Recommender Systems*, pages 129–140, Singapore Singapore, September 2023. ACM. ISBN 9798400702419. doi:10.1145/3604915.3608786. URL https://dl.acm.org/doi/10.1145/3604915.3608786.

Xiaoming Zhou and Cristina Conati. Inferring user goals from personality and behavior in a causal model of user affect. In *Proceedings of the 8th international conference on Intelligent user interfaces*, IUI '03, pages 211–218, New York, NY, USA, 2003. Association for Computing Machinery. ISBN 978-1-58113-586-2. doi:10.1145/604045.604078. URL https://dl.acm.org/doi/10.1145/604045.604078.

Xujuan Zhou, Yue Xu, Yuefeng Li, Audun Josang, and Clive Cox. The state-of-the-art in personalized recommender systems for social networking. *Artificial Intelligence Review*, 37(2):119–132, February 2012. ISSN 0269-2821, 1573-7462. doi:10.1007/s10462-011-9222-1. URL http://link.springer.com/10.1007/s10462-011-9222-1.

Yujia Zhou, Zhicheng Dou, and Ji-Rong Wen. Encoding History with Context-aware Representation Learning for Personalized Search. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 1111–1120, Virtual Event China, July 2020a. ACM. ISBN 978-1-4503-8016-4. doi:10.1145/3397271.3401175. URL https://dl.acm.org/doi/10.1145/3397271.3401175.

Yujia Zhou, Zhicheng Dou, and Ji-Rong Wen. Enhancing Re-finding Behavior with External Memories for Personalized Search. In *Proceedings of the 13th International Conference on Web Search and Data Mining*, WSDM '20, pages 789–797, New York, NY, USA, 2020b. Association for Computing Machinery. ISBN 978-1-4503-6822-3. doi:10.1145/3336191.3371794. URL https://dl.acm.org/doi/10.1145/3336191.3371794.

Yujia Zhou, Zhicheng Dou, Bingzheng Wei, Ruobing Xie, and Ji-Rong Wen. Group based Personalized Search by Integrating Search Behaviour and Friend Network. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 92–101, Virtual Event Canada, July 2021a. ACM. ISBN 978-1-4503-8037-9. doi:10.1145/3404835.3462918. URL https://dl.acm.org/doi/10.1145/3404835.3462918.

Yujia Zhou, Zhicheng Dou, Yutao Zhu, and Ji-Rong Wen. PSSL: Self-supervised Learning for Personalized Search with Contrastive Sampling. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 2749–2758, Virtual Event Queensland Australia, October 2021b. ACM. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3482379. URL https://dl.acm.org/doi/10.1145/3459637.3482379.

Yu Zhu, Hao Li, Yikang Liao, Beidou Wang, Ziyu Guan, Haifeng Liu, and Deng Cai. What to do next: modeling user behaviors by time-LSTM. In *Proceedings of the 26th International Joint Conference on Artificial Intelligence*, IJCAI'17, pages 3602–3608, Melbourne, Australia, 2017. AAAI Press. ISBN 978-0-9992411-0-3.

Yutao Zhu, Jian-Yun Nie, Zhicheng Dou, Zhengyi Ma, Xinyu Zhang, Pan Du, Xiaochen Zuo, and Hao Jiang. Contrastive Learning of User Behavior Sequence for Context-Aware Document Ranking. In *Proceedings of the 30th ACM International Conference on Information & Knowledge Management*, pages 2780–2791, Virtual Event Queensland Australia, October 2021. ACM. ISBN 978-1-4503-8446-9. doi:10.1145/3459637.3482243. URL https://dl.acm.org/doi/10.1145/3459637.3482243.

Philip Zigoris and Yi Zhang. Bayesian adaptive user profiling with explicit & implicit feedback. In *Proceedings of the 15th ACM international conference on Information and knowledge management*, CIKM '06, pages 397–404, New York, NY, USA, November 2006. Association for Computing Machinery. ISBN 978-1-59593-433-8. doi:10.1145/1183614.1183672. URL https://dl.acm.org/doi/10.1145/1183614.1183672.

John Zimmerman and Kaushal Kurapati. Exposing profiles to build trust in a recommender. In *CHI '02 Extended Abstracts on Human Factors in Computing Systems*, CHI EA '02, pages 608–609, New York, NY, USA, April 2002. Association for Computing Machinery. ISBN 978-1-58113-454-4. doi:10.1145/506443.506507. URL https://dl.acm.org/doi/10.1145/506443.506507.

John Zimmerman, Kaushal Kauapati, Anna L. Buczak, Dave Schaffer, Srinivas Gutta, and Jacquelyn Martino. TV Personalization System. In *Personalized Digital Television: Targeting Programs to individual Viewers*, Human-Computer Interaction Series, pages 27–51. Springer Netherlands, Dordrecht, 2004. ISBN 978-1-4020-2164-0. doi:10.1007/1-4020-2164-X_2. URL https://doi.org/10.1007/1-4020-2164-X_2.

Ingrid Zukerman and David W. Albrecht. Predictive Statistical Models for User Modeling. *User Modeling and User-Adapted Interaction*, 11(1):5–18, March 2001. ISSN 1573-1391. doi:10.1023/A:1011175525451. URL https://doi.org/10.1023/A:1011175525451.

Mustafa Mert Çelikok, Pierre-Alexandre Murena, and Samuel Kaski. Modeling needs user modeling. *Frontiers in Artificial Intelligence*, 6, 2023. ISSN 2624-8212. doi:10.3389/frai.2023.1097891. URL https://www.frontiersin.org/articles/10.3389/frai.2023.1097891.

Konrad Żołna and Bartłomiej Romański. User Modeling Using LSTM Networks. *Proceedings of the AAAI Conference on Artificial Intelligence*, 31(1), February 2017. ISSN 2374-3468. doi:10.1609/aaai.v31i1.11068. URL https://ojs.aaai.org/index.php/AAAI/article/view/11068.