# Human Factors in User Modeling for Intelligent Systems

**Maria Soledad Pera, Federica Cena, Monica Landoni, Cataldo Musto, and Alain D. Starke**

**Abstract** In the current digital landscape, humans take center stage. This has caused a paradigm shift in the realm of intelligent technologies, prompting researchers and (industry) practitioners to reflect on the challenges and complexities involved in understanding the (potential) users of the technologies they develop. In this chapter, we provide an overview of human factors in user modeling, a core component of human-centered intelligent solutions. We discuss critical concepts, dimensions, and theories that inform the design of user models that are more attuned to human characteristics. Additionally, we emphasize the need for a comprehensive user model that simultaneously considers multiple factors to represent the intricacies of individuals' interests and behaviors. Such a holistic model can, in turn, shape the design of intelligent solutions that are better able to adapt and cater to a wide range of user groups.

Federica Cena, Monica Landoni, Cataldo Musto, Alain D. Starke—Contributed equally.

M. S. Pera (✉)
Web Information Systems - EWI - TU Delft, Delft, The Netherlands
e-mail: m.s.pera@tudelft.nl

F. Cena
Department of Computer Science, University of Torino, Torino, Italy
e-mail: federica.cena@unito.com

M. Landoni
Faculty of Informatics, Università della Svizzera Italiana, Lugano, Switzerland
e-mail: monica.landoni@usi.ch

C. Musto
Department of Computer Science, University of Bari, Bari, Italy
e-mail: cataldo.musto@uniba.it

A. D. Starke
Faculty of Social and Behavioural Sciences, University of Amsterdam, Amsterdam, The Netherlands

Department of Information Science and Media Studies, University of Bergen, Bergen, Norway
e-mail: a.d.starke@uva.nl



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## 1 Introduction

> While physics and mathematics may tell us how the universe began, they are not much use in predicting human behavior because there are far too many equations to solve - Stephen Hawkins [87].

Intelligent systems refer to advanced technologies that perceive and respond to the world around them [241]. Given the highly interconnected digital world we live in, the ubiquity of these systems is not unexpected; neither is their ability to enable the completion of numerous tasks in a very broad range of domains.

Among the many components that encompass intelligent systems, we find the **user model (UM)** essential for adaptability and personalization [31, 188]. In the Human-Computer Interaction field [85], the UM concept is used as a synonym of the Cognitive Model, which is a model created and used by human-focused researchers for describing different typologies of users, and then exploited by the interface designers to design effective user interfaces. Instead, our focus is on the concept of the UM within the *context of intelligent solutions* and therefore we refer to it as "*a representation of information about an individual user*" [31]. We see the UM as a *data structure* that contains all the features of a particular user known by the system at a certain time. In other words, at time $t$, the UM contains a snapshot of the characteristics of the user $U$, as collected, inferred, and stored by the system $S$[1] [185].

Although the amount and the nature of the data captured in a UM are largely dependent on the purpose of each specific intelligent solution [31], traditional UMs are known to include user-provided background information (e.g., demographic information) as well as users' implicit and explicit preferences and behavior (e.g., clicks, ratings, and other user-system interactions captured over time). In light of technological advances, and given the pursuit of a more profound understanding of users for adaptation and personalization, it is unsurprising that more research and development efforts are allocated to better serve a broad range of users. Notably, there is a shift toward allowing human factors to drive the design. This is evidenced, for example, by the consideration of other more intrinsic user characteristics as part of the user modeling process, including personality or affective states [31, 37, 185, 190].

In this chapter, we center our discussion on **human factors** and their connection to UMs in the context of human-centered intelligent solutions. To manage scope, we specifically delve into intelligent solutions that involve decision-making, in addition to seeking and utilizing presented information. This includes recommender systems, intelligent search systems, and learning systems, among others. Our primary objective is to bring awareness to human factors (and associated theories and methodologies) that are at the core of the design of UMs so that ultimately proposed solutions can aid a diverse range of users with distinct needs and expectations across various contexts, accomplishing a variety of tasks.

[1] By considering the system itself, we account for the fact that individual users—and hence their respective UMs—may change while they interact with the system.

In Sect. 2, we revisit foundational background work about UMs and the user modeling process. We also summarize the evolution of user modeling strategies over time. This is followed by an overview of human preferences and how they can impact user modeling and interaction with intelligent systems (Sect. 3). Savolainen [230] emphasizes the interplay between cognitive and affective factors in information seeking and use, whereas Deniz [66] highlights personality as another dimension of interest, particularly in decision-making. These perspectives play a crucial role in shaping how users are modeled and how they ultimately interact with intelligent systems within their ecosystems. With that in mind, in Sect. 4, we discuss different theories and methodologies that showcase which and how cognitive, affective, and personality traits can be modeled. In Sect. 5, we bring together the different concepts, theories, and dimensions presented in this chapter and introduce the notion of a holistic approach to user modeling—one that simultaneously accounts for multiple factors and perspectives. Lastly, in Sect. 6, we offer some concluding remarks.

In summary, the purpose of this chapter is twofold: (i) to provide a theoretical basis and (ii) to issue a call to action for researchers and practitioners responsible for creating the next generation of intelligent systems. Moreover, we underscore the crucial—albeit sometimes challenging—undertaking of integrating human factors into the design and development phases.

## 2 The User Modeling Process

In this section, we provide an overview of user modeling methods for intelligent systems and discuss how user modeling techniques have changed over the years. It is important to note that whenever we mention the term UM, we refer to an *individual* UM that stores information about a single user, and not to *group models* which represent groups of users (e.g., a class of learners) [112].

### *2.1 Processing User Models*

The *user modeling* process [28, 82] deals with establishing algorithms and methods for creating digital representations of users; inferring knowledge about the user based on past and present interactions; and utilizing UMs for adapting the interface or the content of (intelligent) systems (or technologies). Personalized systems maintain a model of the user and then employ it to adapt themselves to the user.

According to Kobsa et al. [138], the user modeling process involves six stages:

1. *Identification of the user features.*
2. *Acquisition of data about the user.*
3. *Representation of the UM.*
4. *Reasoning on user data.*

5. *Adaptation based on UM data.*
6. *Evaluation.*

Below, we provide a brief description of each stage. It is worth noting, however, that the process is iterative and, typically, the first four stages are performed in parallel [41].

### 2.1.1 Identification of User Features

The primary task in this stage involves determining which user features should be incorporated in the UM, given a specific scenario and domain. Traditionally, a UM can contain [136]: *user data* (demographic data, user knowledge and expertise, user preferences and interests, user goals and plans), *usage data* (data about observable usage, usage regularities), and *environment data* (information about software and hardware environment, location). The emergence of the Social Web and the Internet of Things introduces novel opportunities for gathering a wider range of data (Sect. 5).

UM features can be categorized as domain-independent (regarding the user as an individual, like demographics) or domain-dependent (user attitudes toward objects within a specific domain, like knowledge on some topics or preferences for certain items). The latter requires a domain representation as well. It is also necessary to decide the *lifetime* of the UM: whether it will be a *short-term UM* valid for a specific session/task or a *long-term UM* that stores knowledge, interests, demographics, etc., which are valid for longer periods. In the case of a long-term UM, it is necessary to explicitly manage the changing of interest over time (dynamic UM) [6, 68]. This requires a mechanism for updating the UM. One approach to meet this need is a critiquing approach, involving the update or refinement of a UM based on critiques or feedback provided by users [50]. Conversational agents could also be used to elicit feedback from users [116]. As an illustration, consider the work by Martina et al. [162] who propose a conversational agent that provides users with movie recommendations. Here, feedback from users is elicited through the dialogue, which is then used to update the profile based on whether the user liked the recommendation or not. In turn, genres or directors of a disliked movie are not proposed again.

### 2.1.2 Acquisition of Data About the User

In this stage, the goal is to find the best modality to gather user data.[2] Some data are easier to obtain or to infer than others. One option involves asking the user directly to explicitly provide their data by filling in a form [114, 205] or by rating and evaluating the items in the system [167, 277]. Alternatively, a system can simply gather (raw) user data by unobtrusively monitoring the user's interactions [130] and

[2] Information elicitation methods exploited by adaptive systems should be customized to account for individual preferences and differences, such as the level of expertise, to increase users' satisfaction [134, 135].

then infer some knowledge from raw data using some form of deductive reasoning or machine learning techniques. The primary source of raw data utilized in conventional user modeling stems from the World Wide Web, where users generate a substantial amount of traces in the form of their activities while browsing or engaging in social networking sites [20, 23, 234].

Regardless of how data is acquired, it is crucial to respect the privacy preferences and concerns of the users [133]. Users should be free to choose what personal information they wish to share about themselves. However, the repercussions of revealing personal information can be unclear, or even possibly unknown, which is why this choice is frequently difficult and burdensome. Special attention has to be paid when collecting data from vulnerable users, such as children, where legal requirements are particularly stringent, and rightly so. Ethical concerns are also relevant when it comes to user data collection, particularly in finding a balance between users' right to have their identity protected and the potential advantages they could derive from personalized solutions based on their profiles.

### 2.1.3 Representation of the User Model

Here, the goal is to choose *how* to represent the data in the UM. It is possible to explicitly represent user features in an explicit data structure (explicit UM) or the UM can be a function obtained by an inductive learning process (implicit UM).

*Explicit UMs* explicitly represent the relevant aspects of the users as closely as possible (heuristics-based approach). An explicit user profile can be depicted as a set of feature-value pairs or as vectors of terms. The simplest way to represent a UM is through a flat model comprised of variables and the respective associated values. Such variables can be represented in different forms, including attribute-value pairs [64], probability distributions [38], fuzzy intervals [40], plain vectors [158], bags of words [49], and Vector Space Models [177, 192]. If the UM contains aspects that are relatively broader and more general than others, then a hierarchical structure (like a tree or a directed acyclic graph like an ontology) can be used [109, 132, 154, 216]. Domain-dependent user attributes, such as interests or knowledge, can be represented by an *Overlay* over the domain (overlay UM) [30]. The user's current attitude concerning every item in the domain is recorded. The main advantages of explicit UMs are that they are intuitive, interpretable, and reproducible. However, they come with limitations in terms of scalability and extendability.

*Implicit UMs* refer to statistical models and machine-learned models. Model-based approaches can learn a regression or classification model starting from a collection of items rated, clicked, or reviewed by users. Implicit UMs are flexible and useful for dealing with huge quantities of data but they may be less intuitive for humans to interpret. This type of UM is often leveraged by modern knowledge-aware recommender systems [111] in which features that describe the items (typically available in exogenous knowledge sources, such as a knowledge graph) are used to infer general user preferences. For instance, Musto et al. [178] utilized features extracted from

DBpedia to populate user profiles, whereas in [179], the authors relied on textual descriptions processed through Word2Vec to infer user preferences.

Another popular lens to craft UMs are *personas* [212]—descriptions of fictitious users constructed from different forms of field data. Personas can originate from a combination of surveys, user interviews, observations, or other user research methods. They are grounded in real user data to avoid stereotypical representations, steering clear of common beliefs or the so-called "elastic" users that adapt to fit a system perspective. The persona creation process is typically based on the analysis of a substantial amount of user data [3]. Designers can also invite users to create personas, allowing them to represent their lives and explore perspectives beyond their own, a practice particularly common when users are children [173]. The use of personas increases end-user empathy and engagement, aiding designers in envisioning the end-user in future use situations and supporting different phases and iterations of the design process [189].

### 2.1.4 Reasoning on User Data

The user data in the UM can be used for deriving new knowledge. The process of interpreting the observations about the user can be done using conditions, rules, or other forms of deductive reasoning, and then the inferred knowledge is stored in the UM. When raw data (e.g., mouse clicks or visited pages) are abundant, they can be exploited as training sets for machine learning algorithms that yield models of users' preferences or behavior. Common modeling strategies include unsupervised approaches (e.g., k-means clustering [172], fuzzy clustering [119], association rules [54]), or supervised approaches (e.g., decision trees, Naïve Bayesian classifier [291], Support Vector Machine [225]). For example, Web traces, like pages visited, search history, tags, comments, and posts can be analyzed to learn further user features, such as user preferences [62, 119, 132, 172, 196, 286, 291], knowledge [4, 150, 224, 253], emotions and mood [70, 226, 273], goals [54, 225] as well as more complex user characteristics such as personality traits [13, 97, 273] or cognitive functions [56, 145, 237]. Similar strategies are also used in recent neuro-symbolic approaches that apply reasoning strategies to infer information about user preferences and needs [276, 285].

### 2.1.5 Adaptation Based on User Model Data

The ultimate objective of the user modeling procedure is to generate a digital picture of the user that can be employed to tailor a system. *Adaptive systems* are those that "reflect some features of the user in a user model and apply this model to adapt various visible aspects of the system to the user" [28]. For example, the system can show a selected number of documents or items deemed relevant to the user; display only selected relevant parts of a document; or simply provide a selected number of relevant links. Adaptive systems find applications in various domains, particularly in e-commerce, e-learning, online information systems, and web information retrieval.

According to Kobsa et al. [138], there are three categories of adaptation techniques: *adaptive content selection*, *adaptive presentation*, and *adaptive navigation support*. Adaptive content selection picks the most relevant items for a specific user. Recommender systems [115] are perhaps the most well-known type of adaptive systems [153, 218, 219, 251]. They filter items based on similarity with other items the user liked in the past (content-based) [146], or based on similarity among users (collaborative filtering) [167]. Adaptive presentation shows information to the user in a personalized way, according to their current level of knowledge, goals, etc. The content does not change, but the presentation and the modality of the content representation do [14, 15, 83, 99, 106, 186]. Adaptive navigation support selects the appropriate link to present, delete, or even generates new ones to support users in the exploration of the content. Different techniques can be used, such as link annotation [279], link ordering and hiding [27, 243], and link generation [9].

### 2.1.6 Evaluation

Measuring the quality of a UM is complex.[3] User-centered evaluation refers to the process of assessing and testing a system from the perspective of its end-users, ensuring that it aligns with their needs and expectations. To achieve this, it is crucial to involve users throughout every phase of the design process, rather than just at the end. In the case of user-adapted systems, it is needed to assess the (explicit) UM before implementing the whole adaptive system, often in the formative phase. Formative evaluations assess a model during its construction, involving end-users for determining, for example, whether the UM contains the relevant aspects for them and with the right value. This type of evaluation exploits both qualitative techniques (usability tests, observational methods, interviews, card sorting, etc.) and quantitative methods (questionnaires, experiments, etc.), mainly drawn from usability research [81].

Following the formative phase, there is a summative phase during which is essential to evaluate the accuracy of the final user-adaptive system (for example by measuring the prediction accuracy in the case of recommender systems). The effectiveness of the summative evaluation depends upon how appropriate the UM is. However, the fact that isolating the impact of the UM itself can be challenging cannot be overlooked. For this reason, and due to the complexity of adaptive systems, there is a need for a *layered-evaluation* [198], a combination of user-based evaluation with a dataset-based one. The latter assesses certain aspects of the UM, such as the accuracy of rating prediction, using standard metrics like Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The former relies on different techniques, such as

[3] Assessing the quality of a UM becomes more challenging with the introduction of human factors. As the number of human factors included in the UM increases, the evaluation approach becomes more user-centered than what is typically employed for assessing UMs.

User Surveys and Questionnaires, User Interviews, Heuristic Evaluation, Usability and Accessibility Testing, and A/B Testing, to gauge user engagement, satisfaction, or other relevant metrics.

## 2.2 User Modeling Over the Years

Methods, techniques, and approaches to user modeling have consistently evolved in response to technological advancements, adapting to new opportunities, challenges, and emerging techniques.

The origins of research on user modeling can be traced back to the initial work by Allen, Cohen, and Perrault [58, 203] as well as Rich [220]. They inspired the creation of many systems that can adapt to users in a variety of ways. The initial propositions lacked a precise differentiation between the constituent elements responsible for user modeling and those that fulfilled other functions. One of the earliest techniques to model a user was using *stereotypes* [220]. Systems that rely on stereotypes map users based on certain characteristics into a class and use the information about the class to suggest things to them.[4] Grundy [220] is one of the best-known stereotype-based systems, but other works in different areas also used stereotypes [5, 143, 292].

Early in 1990, the research started to focus on how to make the user modeling component reusable among systems. This led to the development of "*generic user modeling systems*," also known as "user modeling shell systems." A user modeling server [136] is a separate module that adaptive system developers can use by filling it with application-specific user knowledge. Examples of user modeling servers are TAGUS [194], um [126], MT [25], and BGP-MS [140]. Similarly, a user modeling server shares a UM in a centralized repository in a client-server architecture [84, 136, 139]. Examples are DOPPELÄNGER [193], Learn Sesame [34], GroupLens [141], LMS [160], Personis [128], MEDEA [265], Cumulate [29], and UMS [137]. Recently, Polignano et al. [211] proposed verticalizing these principles in the health domain. In particular, they presented a lifelong centralized health UM, based on a combination of explicit and implicit data.

Centralized user modeling systems had several shortcomings [139]: they were too rigid and restrictive; they also posed a potential central failure point for data protection. To address these issues, and with the advent of mobile computing devices with user data distributed across different platforms [127], the need for *decentralized* solutions for UMs started to arise [156]. Decentralized UMs collect UM fragments from the systems the user interacts with. Decentralized user modeling studies how to merge partial user data and make sense of them in a specific application domain [72, 108, 272]. Decentralized user modeling solutions are known to leverage semantic

[4] Although somewhat related, as they represent "classes of users," stereotypes are different from *personas*. The latter are tools distilled from large sets of user data and used by human designers to keep the user perspective during different stages of system development, whereas stereotypes are automatically created and used by technologies.

web technologies [21] to implement functions for mapping and integrating different models [26, 36, 39, 73, 108, 166, 288]. A decentralized architecture is represented by *UM Agents*, which depict the user and cooperate with different systems to satisfy the user's needs [156, 191]. Finally, we bring attention to *mixed solutions*, where each system maintains the private UM but refers to a centralized model for the most common concepts in the domain [19, 175, 269].

## 3 The Human Perspective

UMs are designed to capture different characteristics of the individuals who interact with intelligent technologies, namely human users. These models are built upon our comprehension of human traits and behavior. This understanding is typically derived from models developed in social science theories, such as those emerging from psychology and sociology. We argue that this human perspective is invaluable to user modeling in general, but more so when the focus is on (intelligent) technologies that strive to put the human at the center.

### *3.1 Decision-Making*

For constructing UMs, particularly those that aim to represent a "human" rather than merely a "user," it is fundamental first to understand how human preferences are formed and how individuals make decisions. The underlying rationale is that models should capture human behavior, cognition, judgment, and preferences as closely as it is feasible, given the constraints of the human-centered technology at play. However, such technologies are typically subjected to restrictions. This is reflected, for example, in how information filtering and retrieval models can be constructed, as well as how they relate to underlying user characteristics [107, 219].

An important concern about human-centered technologies is how to present the most relevant content to users. Research on such personalization can be characterized by the taxonomy of Hanani et al. [107], describing systems with different levels of information filtering—from how the type of filters that can be applied vary in terms of adaptivity to how closely they mimic human behavior. An early example of personalization with a human dimension was adaptive hypermedia [65, 102], which applied cognitive filtering through three distinct parts [65]: the relationship between different parts of the items, a UM describing how a user would acquire knowledge about the items, and an adaptation model driven by how users and items would relate.

Later approaches tended to focus on a general UM applicable across multiple platforms to enable personalization [171]. In doing so, human preferences were typically emulated and predicted through historical data. This made databases and datasets capturing such data fundamental to intelligent technologies [115]. A main assumption is the relative stability of these preferences, where past behavior serves as an indication of future interactions, such as choices and clicks [219]. This, however, is at odds with various theories on how human preferences are formed. For instance, the theory of constructive consumer processes posits that preferences are constructed upon decision-making [22], being strongly dependent on a user's underlying attitude as well as the decision-making interface at hand [260].

Another constraint to most user modeling approaches is their assumption of "rationality." Systems that predict how users will act or what they will like operate under the premise that individuals know exactly what they want. Moreover, there is an expectation that individuals will act and like similar things in similar ways over time. This assumption introduced the concept of "preference inertia," exemplified, for instance, when consumers have a degree of brand loyalty [289]. Arguably, this is not a realistic assumption for many systems, as people are known to explore new preferences, valuing diversity and serendipity [51, 255]. On the contrary, the rationale that the past can reliably predict the future stems from a more "homo economicus" perspective toward user preferences [204]. This perspective assumes that humans strive for efficiency and act as rational decision-makers [232]. According to this view, users interacting with systems would have a clear understanding of their own preferences, at any given time of the day and in any given behavior or decision scenario.

The rationality assumption, popular in economic theory and studies on game theory [18, 59], often does not hold when studying decision-making—a core process driving interactions with recommender systems or systems that enable information seeking. This has become apparent in various studies in (consumer) psychology and behavioral economics, demonstrating that humans have "bounded rationality" and that their judgment and decision-making are influenced by a number of biases and heuristics [71, 121, 122].

Behavioral economics is a scientific field that emerged from psychology to critique the rationality assumptions of economic models and theories [259, 260]. It has brought forth "Nudges" as a mainstream decision-making theory [259], which are defined as changes made to a choice architecture (e.g., an interface) that lead to a predictable change in behavior [261]. Research demonstrates that decisions are susceptible to biases that undermine typical "rational" user modeling and that these biases are systematic and, therefore, "predictable" [121, 122]. Consequently, we argue that algorithmic predictions are also bounded by the humans using them, as well as the utilized interface [118].

## *3.2 Human Cognition*

Models of human preferences and behavior are developed beyond the technological context. Studies performed in social science fields have introduced various theoretical frameworks that are used to model human behavior. To better account for human judgment and decision-making, we discuss models of human cognition that can aid the development of appropriate UMs; along the way, we mention relevant biases that underpin human decision-making.

Human cognition has been described by various psychological theories. The notion of bounded rationality is fundamental to most of them [121]. This refers to the limited processing capacity and decision-making capabilities that humans have, which prevents them from making a rational choice or the "best" decision possible [239]. The concept was coined by psychologist and Nobel laureate Herbert Simon and points toward humans often making "satisficing" decisions, rather than "maximizing" decisions [121]. This refers to a decision-making strategy where a human only invests time, costs, and effort to reach an outcome that is satisfactory or adequate [199]. Often, this is the result of a specific decision-making situation, such as when users are under time pressure (e.g., when ordering food at a restaurant), or when not all alternatives are known [22, 121].

### 3.2.1 Dual-Process Theory

Human cognition is commonly described through dual-process theory [46, 268]. This refers to how human thought is the result of two mostly parallel processes: one path is considered to be explicit and conscious, while the other is more implicit, uncontrolled, and unconscious [122]. The main distinctions are made based on the extent to which thought is processed consciously and explicitly.

Dual-process theory has been operationalized into multiple models of cognition and information processing. One model that is commonly used in studies on persuasion is the *Elaboration Likelihood Model* (ELM) [207]. This is an application of the dual-process theory that describes how attitudes can be changed through two routes of information processing: a central route and a peripheral route, which form a continuum between them [55, 271]. The central route relies on thoughtful processing of information, which may eventually lead to longer-lasting attitudinal change [271]. In contrast, the peripheral route concerns more automatic responses related to either positive or negative cues, such as mechanisms observed in classical conditioning or a person judging source credibility [55].

An individual's motivation is the main determinant in the ELM as to how information is processed [144]. Highly motivated individuals, or users of technologies for that matter, are more likely to engage in thoughtful deliberation of information presented or communicated to them [207]. Less motivated individuals can still be persuaded, be it often with more short-term effects. ELM is used in human-centered technologies that aim for behavioral change, as is often the goal in persuasive technologies [88, 270]. Such technologies aim to change attitudes with a specific behavior or a behavioral goal in mind. Nevertheless, such technologies do not apply to all domains, as there is, for instance, little behavior-specific persuasion involved in a movie recommender system (cf. [74, 100]). Instead, ELM is useful when convincing an individual to engage in a behavior for their "better self," such as health-related behaviors [55].

Another dual-process theory for learning is described by *two-system thinking*. Initially coined by Stanovich [244] and later popularized by Kahneman [121], two-system thinking differentiates between System 1 and System 2 for "implicit" and "explicit" forms of reasoning, respectively. System 1 encompasses more unconscious, automatic, and unintentional responses to information [80, 122]. Judgments are typically made without much control, deeming it the effortless and near-instantaneous form of reasoning. For example, people might respond to a threat before even recognizing what it is [122]. System 2 instead involves effortful and conscious deliberation, which is attributed to behavior and decisions that involve much effortful thought, such as complex purchase scenarios (e.g., buying a house).

Two-system thinking aligns closely with the general definition of dual-process theory. For this specific modeling, the distinction between both systems is valuable for predicting the types of decisions individuals are likely to make in specific scenarios. In the context of human-centered technology, different technologies may evoke varying responses based on how consciously involved humans are. For example, adapting the photos of recipes to make them visually more attractive can affect user preferences at a more unconscious level [248]. On the other hand, designing recommender systems that provide specific justifications for their content can assist users in deliberation, influencing preferences through informed decision-making or framing information [183, 247, 249], which are System 2 phenomena.

A confounding factor to human cognition regarding judgment and decision-making is *affect*. This refers to one's experienced feelings, emotions, and mood, either as a general state in time or with regard to a specific (attitudinal) object. These responses can be positively or negatively valenced [284] and experienced as (un)pleasant feelings. In the context of dual-process theory, affect is considered to play a role in System 1 reasoning [122]. Emotional attributions and responses typically influence snap, unconscious judgments. For example, if an individual has a bad feeling about a person they see on the street ("There is something off about this person"), this feeling often arises without much conscious thought. Reasons for a particular feeling are sometimes found afterward or may never be fully rationalized. Affect can moderate System 2 thoughts. In this sense, cognitive processes are typically the result of the sum of the two parts. However, judgments in both systems are prone to a number of mental shortcuts, as well as limitations.

### 3.2.2 Biases and Heuristics

Key in human-centered user modeling is recognizing the "irrationality" inherent in human cognition. Humans display systematic biases in their decision-making, where the bias is operationalized as the systematic deviation from an optimal decision or the norm [8]. The systematic nature of such biases also surfaces, for instance, in the definition of a nudge—"[...] choice architecture that alters people's behavior in a predictable way without forbidding any option or significantly changing their economic incentives" [262, p. 6]—which includes the word *predictable*.

A notable bias in human judgment and decision-making is prospect theory, also known as "loss-aversion" theory [91]. Coined by Kahneman and Tversky [123], it describes how human preferences for different options depend on how they are framed or presented. Loss aversion [123, 267], a key concept in prospect theory, describes the human tendency to be more sensitive to losses compared to equivalent gains. Put in simple terms, "losses loom larger than gains" [123], where losses are weighted more than twice as strongly as gains. This effect is demonstrated in discrete choice experiments [267], where participants are asked to choose between two wagers. People avoid risks when it comes to gains, but are risk-seeking regarding losses [122]. For example, when asked to choose between a 90% chance of gaining $100 or a certain gain of $90 (of note, both have an expected value of $90), most people will take $90. In contrast, when asked to choose between a 90% chance of losing $100 or a certain loss of $90, most individuals will take the 90% wager.

Loss aversion is observed beyond the wagers that corroborate prospect theory. Studies have found humans to value their current situation more highly than an alternative scenario [71, 228]. Another main theory describing this is the endowment effect, which explains how humans value items they own more than equivalent items they do not own [122]. Pioneering work done by Thaler [258] showed this effect in various experiments [90, 124]. For example, if one were to hand out mugs to only half of the students in a classroom and then ask both the mug-endowed and mug-less students how much they would pay for that mug, students who just received a mug would note down a much higher figure. The endowment effect is rather immediate and is also observed in situations without actual ownership. In other words, people are rather likely to accept default options, as shown by the effectiveness of opt-out systems in organ donation [117], but also tend to stick to whatever list or setting is shown to them *first* in a recommender interface [151, 245]. This can in part be explained by the *status-quo bias* in humans [228], underpinning the endowment effect [259].

Some biases are systematic, but also intentional. In certain decision-making scenarios, humans purposefully take a mental shortcut and use limited information to arrive at a judgment. This allows for faster decision-making. Such mental shortcuts are referred to as heuristics [95]. Similar to heuristics in computer science [202], they are in psychology associated with faster (mental) processing times [122]. They can be attributed to both System 1 and System 2 processes.

Heuristics typically ease the burden of judgment and decision-making by focusing on the most relevant aspects of a specific problem [96]. This tendency can be traced back to evolutionary foundations of humankind, where, for example, humans would judge the size of an animal to decide whether to engage or run away. Heuristics address the challenge of bounded rationality [95], acknowledging that, due to limitations in processing capacity, intentional or unintentional, humans tend to make decisions based on limited information. That is why, for example, framing effects in interfaces are rather effective at steering user preferences [247].

Heuristics are limited in what they can achieve in terms of decision accuracy. It is in this lack of accuracy that algorithmic predictions of human preferences might be at odds with what humans actually do. Take ratings for recipes in a food recommender system: these ratings might have been given after an elaborate experience process (cf. [75]), whereas subsequent decisions might be made under time pressure.

In the context of decision-making, various heuristics play a role in shaping judgments. These include heuristics related to the distortion of memory (e.g., availability heuristic), stereotyping (e.g., representativeness heuristic), and making inferences based on the behavior of others (e.g., social heuristics). Certain heuristics are simply the result of a decision-maker acting upon a bias [71, 122]. For example, when faced with uncertainty about what to choose, decision-makers may engage in various forms of social comparison, making them susceptible to biases like majority or authority bias. Specific heuristics have been applied in studies with digital systems, such as introducing social explanations in an energy recommender system [246], or examining which type of social explanation is the most effective on a social networking site [235]. In the context of web search, Rieger et al. [221, 222] mention that when individuals use shortcuts to simplify complex search tasks, like seeking information on debated topics, they may become more efficient. However, this efficiency comes with a susceptibility to cognitive biases that can introduce errors in judgments. Searchers can also be influenced by confirmation biases, causing them to click on retrieved resources that align with their beliefs.

## 4 Cognitive, Affective, and Personality Factors in User Modeling

Building computerized models that capture the multiple factors that can simultaneously influence human thinking in complex scenarios is challenging [47]. We argue that given the role these models play, in terms of impacting not only the design but also the overall user experience intelligent solutions can provide, understanding these models is of utmost importance. When thinking of cognitive computing, we often allude to technologies aiming to emulate human intelligence on a large scale [53, 103]. Cognitive computing has received attention from both academic and industry practitioners; still, technologies in this realm have so far focused on improving intelligence by inferring cognition from data and information [52]. This evinces the need to move beyond traditional modeling strategies driven solely by user interactions and explore models that capture contextual and dynamic aspects of human behavior [233]. Additionally, ethical considerations must be taken into account when (semi-)automatically predicting human aspects, such as personality or psychology [86, 176]. Consequently, it becomes imperative to further look into "human-centered intrinsic information such as emotions and mentality" [52]. In this emerging paradigm where the user is at the forefront, it becomes critical to consider the *broad spectrum of human factors* that can directly or indirectly impact user modeling, adaptation, personalization, and human interaction with intelligent solutions.

Informed by our discussion in Sect. 3, where we presented theories and models that could govern human-system interactions, in this section, we outline traits that depict users as "humans." When adopting a human-centered approach to user modeling, it is vital to consider these traits. Accordingly, we enumerate different perspectives that can be utilized in user modeling to capture human qualities: cognitive, affective, and personality traits. This list is not exhaustive, rather, it serves as a starting point to exemplify the multiple (and sometimes complementary) viewpoints that can be taken into consideration when constructing UMs to more accurately represent humans, as opposed to “merely users.”

### *4.1 Cognitive Factors*

Cognition refers to mental processes via which individuals analyze and interpret the world around them, their thoughts, and their actions [274]. Given this broad definition, the lack of consensus on what constitutes cognitive factors is unsurprising. Therefore, in line with Savolainen [230], we describe these factors based on the perspectives considered for their definition.

From a cognitive *science* viewpoint, the main subdomains of study are human intelligent behaviors or actions; human propositional attitudes; human knowledge representation and use; and human cognitive capacities whose exercise is sensitive to the subject’s goal and general knowledge [274, pp. 58–95]. Cognitive *psychology* is similarly concerned with factors such as attention, memory, learning, language use, problem-solving, and decision-making [230, 242, 250]—all aspects that impact how individuals interact with intelligent solutions related to, for instance, recommender systems, tutoring systems, and information seeking. From a cognitive *style* standpoint, cognitive factors have been associated with tendencies displayed by individuals to adopt a particular type of information processing strategy [89].

The literature on theories of the cognitive process, and how these theories guide the modeling of cognitive factors, is rich. Following the taxonomy proposed by Lex et al. [148], we discuss prominent methods that can be used to model cognition[5]; along with relevant examples applying different theories to produce UMs.

*Empirical* approaches often involve gathering and analyzing behavioral data using statistical models derived from mathematical psychology [2, 94]. These models leverage parameters that represent cognitive constructs. For instance, Papanikolaou et al. [197] conducted empirical studies on two educational systems, Flexi-OLM and INSPIRE. They did so to examine users’ learning and cognitive styles, as well as preferences during their interaction with these systems. *Cognitive-computational* approaches, on the other hand, specify cognitive assumptions and use computable models to simulate specific aspects of the human mind [78]. As an illustration within the domain of web search we find SINF-ACT [93, 208], which simulates the mental or physical steps that enable users to follow information scent cues, guiding them to locate desired information [92].

*Memory* is another factor intricately linked to human cognition. Memory directly impacts goal-directed interactions with the physical and social environment [231]. Modeling approaches based on memory models have been broadly applied. Com-

[5] For an in-depth discussion of cognitive process theories, along with an overview of the applicability of computational cognitive models to improve intelligent systems, please refer to [148].

mon examples include utilizing the Ebbinghaus forgetting curve to better support knowledge acquisition and retention of school subjects in a mobile game environment [48], in addition to learning and tracking the drifting of the users' interests, thereby influencing the quality of generated recommendations [287].

*Attention*, a mechanism to "selectively process information in an environment in the face of distraction" [148], is central to triggering any human cognition model. Most research leveraging attention mechanisms is more commonly associated with deep learning-based models [275, 290]. Still, Wood et al. [282] spotlight the challenges of modeling this dynamic and multi-faceted phenomenon, whereas Ma et al. [159] propose an architecture to model user attention based on visual, linguistic, and aural lenses, which they apply to the personalization of video summarization.

Other examples that showcase the use of different theories to guide the design of UMs for intelligent systems include the work by Huang et al. [110], who rely on cognitive factors to explore the continued use of information systems. While Ravi et al. [215] introduce a cognitive user preference model to improve the recommendation process, Contreras and Salamo [60] leverage long- and short-term cognitive behavior to improve location recommendation. Cognitive modeling is also known to support decision-making in the finance and education domains [101, 125, 252].

## 4.2 Affective Factors

Affective aspects play a major role in human-centered approaches to producing UMs. In their survey, Julien et al. [120] discuss the importance of the affective dimension (e.g., emotion or confidence) in human information behavior. They advocated for the research community to explicitly include affective dimensions in their studies. Emotions, viewed as one of these affective dimensions, can be defined as "an integrated feeling state involving physiological changes, motor-preparedness, cognitions about action, and inner experiences that emerge from an appraisal of the self or situation" [164].

Emotions impact how users engage and interact with intelligent solutions. Their influence can be observed, for instance, in the choice of strategy users employ to engage with information systems or how far and deep the searchers will browse the list of results in a Search Engine Result Page (SERP) [240]. When confronted with a new search task, users experience feelings of uncertainty, confusion, and frustration, which are often accompanied by negative emotions like sadness, fear, and anger [209]. Searchers experience anxiety about being unable to fulfill their information needs and consequentially fear not accomplishing the task at hand. On the other hand, successful search outcomes elicit positive feelings while dealing with failure at the end of a session engaging with an intelligent system that can prompt reflections on the overall system usability, as discussed in [17]. In particular, through analysis of textual feedback provided by searchers after they had successfully performed their tasks, Barifah and Landoni [17] acknowledged the presence of trust, joy, and anticipation.

Instead, participants reporting failed searches expressed anger and sadness in their feedback.

The duration of a search process has been linked to subjective feelings of being lost in web searches, as demonstrated by a study conducted by Gwizdka and Spence [105]. In a more recent investigation by Kazai et al. [129], the authors discuss the role of emotions in SERPs and how searchers tend to explore more snippets charged with positive emotions. Along similar lines, Landoni et al. [147] investigated the search behavior of primary school children in relation to positive and negative emotions in SERPs. Similar to adults, children were attracted by results conveying positive emotions, but interestingly, they were even more compelled to concentrate on searches with results that had a negative tone. Their will to "fix things" made them keener to engage in longer search sessions and go deeper in the exploration of retrieved results. Examining the broader impact of the search experience on children's emotional state, Bilal [24] observed that children were negatively affected by the lack of matches and difficulty in finding the answer. In this respect, the work by Nahl [184] and her definition of affective load theory (ALT) illuminate how different search behaviors can be influenced by the presence of affective coping skills (e.g., self-efficacy and optimism) and how these skills could compensate for lower cognitive skills. A more comprehensive study by Lopatovska [155] considered primary and secondary emotions in participants and their moods during searches. Primary emotions, derived from the analysis of facial expressions, proved to be directly linked with search actions, indicating a reciprocal relationship. On the other hand, there was no evidence of a link between secondary emotions (gathered through post-search interviews) and participants' evaluations of their search experience. Moods appeared to remain stable and unaffected by the search experience, and vice versa.

Kazai et al. [129] describe how lexica such as SentiWordNet and EmoLexData—commonly used to detect the presence of sentiments (positive, negative, or objective) and emotions (such as being afraid, amused, angry, annoyed, don't care, happy, inspired)—roughly associate to the eight elements of Plutchik's Wheel of Emotions. Similarly, Landoni et al. [147] highlight that in a study involving children, young searchers were drawn to content expressing positive sentiments and joyful emotions. Unlike adults, children tended to become more involved in the search activity when faced with unpleasant stimuli generating negative emotions like fear and sadness. This gives a unique perspective on how to more accurately model children's behavior, level of engagement, motivation, and expectations when interacting with (intelligent) search and recommendation systems.

A wide range of UMs that incorporate different affective factors have found applications in diverse domains, including educational recommender systems [227, 229], personalization of news suggestions [170], and many other intelligent solutions involving decision-making [210].

### 4.3 Personality Factors

Personality traits have long been considered as a mean to better understand users and in turn improve personalization and adaptation of intelligent systems [67, 190]. Their impact on user modeling is well documented.

Regarding models of personality, the Big 5 model [98] is the most popular [79]. It describes personality based on five traits: extraversion, agreeableness, openness, conscientiousness, and neuroticism. As presented by Fehrer and Vernon [79], however, many other dimensions can be accounted for when modeling personality. Following the taxonomy introduced in [79], we outline some of the more prominent models beyond the Big 5.

Looking into alternative models of personality, we find HEXACO [10], which accounts for six personality factors: Honesty-humility, Emotionality, Extraversion, Agreeableness, and Openness to Experience. Given its predictive power of criteria like psycophantic traits, egoism, and phobic tendencies, it is not surprising that it has been used to model users in intelligent applications involving decision-making [281]. Supernumerary models of personality traits, like Supernumerary Personality Inventory [201], look into conventionality, seductiveness, manipulativeness, thriftiness, humorousness, integrity, femininity, religiosity, risk-taking, and egotism. The Psychobiological model [57] focuses instead on aspects reflecting temperament and character traits. Focusing on the so-called narrow personality traits, we should mention Dark Tetrad [200] (accounting for psychopathy, narcissism, sadism, and Machiavellianism), Self-defeating personality style [1] (which measures insecure attachment, undeserving self-image, and self-sacrificing nature), and emotional intelligence [206] (encompassing expressing emotions, perceiving emotions, regulating emotion, social abilities, etc.).

Personality-based UMs in the context of intelligent systems encompass a range of applications. Examples include intelligent technologies that leverage personality traits to improve users' well-being [131], introduce diversity among choices [283], support tourism recommendations [44], provide personalized explanations [142], and aid education [45].

## 5 A Holistic Perspective

The landscape of user modeling has undergone significant transformations in recent years, shaped by the constant evolution of the digital environment. The proliferation of mobile and social web platforms enhances our capacity to access information and communicate with others on a global scale, while wearable and ubiquitous technologies expand the scope of digital integration in our daily lives. The quantity and variety of data attainable regarding users, which can be utilized for UM development, has increased exponentially. The integration of diverse datasets covering different facets of individuals' daily lives holds the potential to enrich UMs, essentially creating a comprehensive "digital twin" of the user [254]. The aforementioned alterations give rise to novel research inquiries regarding the potential services that may be offered, the efficacious means of communicating innovative forms of personalization and adaptation, and the necessary modifications to be made to conventional user modeling to capitalize on this potential to provide personalized services.

The concept of a *holistic user model* (**HUM**) was born in this context [41, 43, 180]. A HUM is a comprehensive profile that encapsulates all the information about a user's interests, feelings, psychological states, health, social connections, and behavior in a single profile. Creating such a profile requires collecting information from different places like social networks, smartphones, wearable devices, and environmental sensors, which will be ultimately used to populate the different facets of the profile.

Although the concept of HUMs shares a connection with Generic User Modeling and User Modeling Servers [136], which gained popularity in the early 2000s (see Sect. 2.2), the current user modeling landscape is completely different, i.e., background in the area has evolved to support the recent spread of this family of approaches. In recent years, two main phenomena have notably influenced user modeling:

- The evolution of the web 2.0 [165] facilitated a paradigm shift from traditional passive consumption of information by web users to an active role as information producers. This transformation enabled the rise and expansion of various collaborative platforms exemplified by Wikipedia, alongside the production and adoption of social networking applications like Twitter, Facebook, and YouTube.
- The growth of the Internet of Things [280] has been a contributing factor to the emergence and growth of the Quantified Self and Personal Informatics movement [157]. Consequently, contemporary and cost-effective instruments using advanced sensing and technological mechanisms are currently available for acquiring and retaining data about an individual's routine activities.

The convergence of both trends mentioned above has resulted in an escalated and unregulated proliferation of data, exacerbating the issue [76]. Undoubtedly, users demand a heightened level of assistance to navigate the copious amounts of information that they are required to handle. Personalized search engines [236], recommender systems [217], and intelligent personal assistants [63] can be used to support the users. At the same time, as the quantity of available data increases, it becomes necessary to have methods and tools to efficiently process and store these data to create a model.

Most of the approaches for building UM suffer from two issues:

- Online platforms generally use one type of information, even though there is a lot of different data available. For instance, some websites only look at the information users leave on the Internet, not what their phone or smartwatch can tell them about their health, where they have been, or what they have been doing.
- The vast majority of individual data is maintained and leveraged by a singular platform that refrains from conversing with comparable systems concerning the data

it retains. The issue, commonly known as the data silo problem, has a detrimental impact on the resultant profiles.

The goal of a HUM should be to assist users in their decision-making processes across various, even complex, domains. We posit that such a comprehensive user representation is core to human-centered intelligent technologies, as they are the means to better capture humans—who are ultimately the users of the technology—and thereby enhance the overall performance of the technology.

An area where we see progress toward incorporating HUMs is in recommender system research by using cross-domain recommenders [35]. These recommenders use what a user likes in one area to try and figure out what they might like in another area and make suggestions accordingly [149, 195]. However, these systems do not fully capitalize on information integration. In other words, they do not exploit *together* the different kinds of information on the user's life, which may potentially influence the recommendation process. Instead, the idea here is to simultaneously exploit diverse kinds of information about the user's life [43].

## 5.1 Facets of a Holistic User Model

A HUM is a comprehensive representation of the individual that is constructed using heterogeneous traces spread by the users in both their online activities (e.g., generated content, purchases, social connections, and search histories) and real-world behavior (such as localization, daily activities, and physical data). A similar concept in the learning domain is the Lifelong UM [278], which aims to produce a complete picture of the user by merging various aspects of their life in a unified space. HUM, however, differs in that it strives to be domain-independent and applicable across several scenarios.

Inspired by the conceptualization introduced by Cena et al. [41], where real-world data from environmental and wearable sensors are used for modeling, a HUM should also integrate information from the web (social connections, posts, comments, tags, and interactions) to create a more comprehensive profile of the individual. In particular, a HUM can be divided into different facets, each describing a specific aspect of the person: demographics, interests, knowledge and skills, affects, psychological traits, behaviors, social connections, and physical states. Table 1 summarizes the (groups of) *short-term* and *long-term* features that could be ideally encoded in a HUM.

*Demographics*. These features regard the demographic information about the user (age, gender, city of birth, and so on). This set of attributes is generally not domain-specific and exhibits minimal to negligible variability.

*Interests*. This accounts for the user's preferences about some domain objects. This feature is the building block of intelligent systems [115] like recommender systems that mainly rely on ratings to produce suggestions, both in collaborative and content-based filtering [153]. Such a feature is typically domain-dependent.

**Table 1** Features that can be accounted for by a holistic user model; Adapted from [41]

| User data | Short term | Long term |
|---|---|---|
| Demographics | Address, Job, Marital status, etc. | Name, Date of birth, etc. |
| Knowledge and skills | Particular skills | General capabilities |
| Preferences | Opinions short-term interests | Believes long-term interests |
| Affects | Emotions, Moods | Emotional disorder |
| Psychological traits | Cognitive states (level of attention, etc.) | Cognitive skills (orientation, etc.) personality traits |
| Behavior | Tasks, Activities | Habits |
| Physical states | Physiological parameters (blood pressure, etc.) | Chronic diseases |
| Social connections | Encounters | User's social network |

*Affective aspects*. This deals with users' feelings, emotions, and moods. It can be domain-independent and context-dependent and can vary greatly. As shown in the literature, mood and emotions are fundamental for modeling a user [264].

*Psychological aspects*. This includes information about users' personality traits and other psychological aspects such as Locus of Control [223], Self-efficacy [16], Need for Cognition [33], as well as the level of empathy [61]. These aspects are more stable than affective aspects, and they are domain- and context-independent. The importance of these aspects for UMs has been shown in several studies [11, 257, 263].

*Behaviors*. This comprises all the tasks, actions, and activities the users engage with, in principle both online and in the real world. It can contain for example data about users' physical activities, such as when they are walking or running, where, and for how long. This type of data can be collected by the sensors in smartphones and wearable devices. Inference in user's actions can lead to learning their habits.

*Physical states*. This aspect regards physiological and physical data about the user, including physical parameters like heart rate, blood pressure, and temperature. They are short-term and domain-independent information that can be directly gathered by the means of sensors in wearable devices [214]. By applying some form of reasoning to these data, it is possible to derive more complex user dimensions, such as chronic diseases, or stress and anxiety.

*Connections*. The social connections and the relationships of the user are key aspects of user modeling. They provide valuable insights into predicting user behavior. In research areas like social recommender systems [104], the information derived from a user's social connections plays a crucial role. More recently, methods employing graph neural networks have been proposed, leveraging the user's personal network for improved modeling [77].

The list of features presented thus far includes some highly sensitive information. Given the potential privacy concerns for users, it becomes crucial to design and implement robust privacy policies [42]. Respecting user privacy is a paramount consideration, and any approach undertaken to develop HUMs should align with ethical standards and legal regulations, ensuring the safeguarding of sensitive information.

## *5.2 Building a Holistic User Model*

The construction of a HUM involves two main steps: (i) collecting raw data about an individual from sources like social networks, smartphones, and wearable devices; and (ii) processing this data using natural language processing and machine learning techniques to populate the facets that constitute a HUM.

To support this vision, some tools have been implemented over the years [43]. An example of such a tool is Myrror [180], a platform that allows user to connect their digital identities to acquire personal data and process them to generate holistic user profiles. Myrror is organized by following the typical layered architecture consisting of a data acquisition layer, a data processing and enrichment layer, a holistic profile builder, and a final layer for data visualization and data exposure.

The typical workflow carried out by Myrror is captured in Fig. 1. The construction of a holistic user profile begins with the data acquisition phase, where raw data are extracted from social networks and combined with information extracted from personal devices and the Internet of Things (i.e., smart bands and smartwatches). Next, the collected data undergoes a processing and enrichment phase, involving aggregation and processing through mapping and reasoning mechanisms. These mechanisms facilitate the inference of high-level features from the raw data. As an example, user preferences can be inferred by mining entities mentioned in the user's posts, mood can be deduced from the sentiment of recent posts, and GPS sensor data can contribute to inferring recent activities. Finally, once the data is processed, a holistic user profile is constructed by mapping the learned features to the facets defined for the holistic user profile. The resulting user profiles are made available to the user, either through a classical web interface or REST APIs. An advanced version of Myrror, known as MyrrorBot [182], allows querying user profiles in natural language and utilizing personalized services based on holistic user profiles.

## *5.3 Exploiting Holistic User Models*

When individuals interact with intelligent solutions, particularly those involving decision-making and information seeking, they commonly focus on (and are influenced by) different aspects, on the domain of the choice and even other (apparently unrelated) domains [113]. Here, we explore a context and user groups to emphasize—in practice, not just theory—the importance and need for a HUM to effectively represent and cater to users in human-centered intelligent technologies.

### 5.3.1 Food Recommendation

When a person is deciding *what to eat*, various factors can influence the decision-making process. While most people may first consider their preferences in the food domain (“*I’d like cake*”), other aspects might also play a role [181]. This concerns contextual factors related to how an individual thinks and feels, such as a user’s current mood (“*I feel sad*”), their past experiences (“*When I feel sad usually sweets help me*”), constraints related to their health condition (“*But I have to control my glucose intake*”), long-term goals (“*I’d like to lose weight for the summer*”), contextual factors (“*there are no good pastry shops nearby and I have no time to search for other places*”), and social acceptability (“*maybe my boyfriend would be disappointed if I don’t eat with him*”). Much of this information may be compatible (e.g., mood and sugar intakes), or at odds with each other (e.g., the momentary desire of eating sweets and its long-term consequences). Hence, some kind of cost-benefit evaluation among these aspects needs to be performed by the user [213], even when decisions are unconscious and thus users are not aware of the underlying process [69, 152].

Recommendation algorithms in the food domain consider more than preference optimization, as evidenced by the adoption of knowledge-based recommendation strategies [181, 249]. These strategies should simultaneously take into account the user’s food preferences, health data (e.g., overweight with a heart condition), current mood (e.g., the user is sad, and sweets might turn the day for the better), how much physical activity has been done (e.g., ran for 1 hour), and general goals (e.g., lose weight). This multi-faceted information can also be of use to support healthier decision-making.

In multiple studies, Musto et al. [181, 183] examine how natural language justifications contribute to promoting healthier food choices. These justifications are based on user characteristics, recipe features, and the relevant relationship between them.

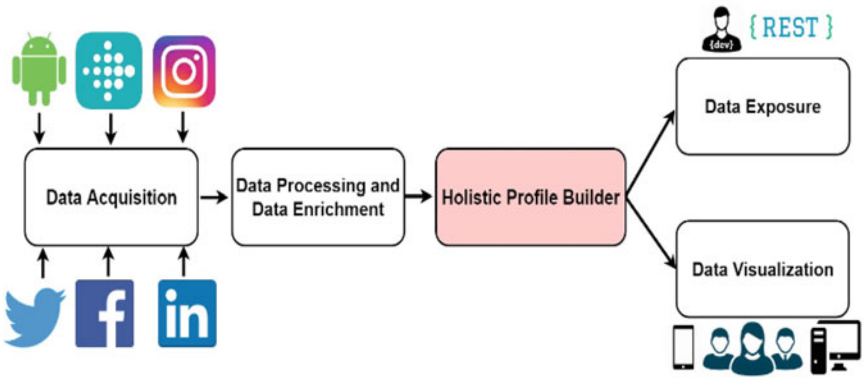


**Fig. 1** Sample workflow for producing Holistic User Models. Inspired by Myrror [180], building holistic user profiles starts by gathering data from a multitude of online sources and culminates with comprehensive profiles that users can access

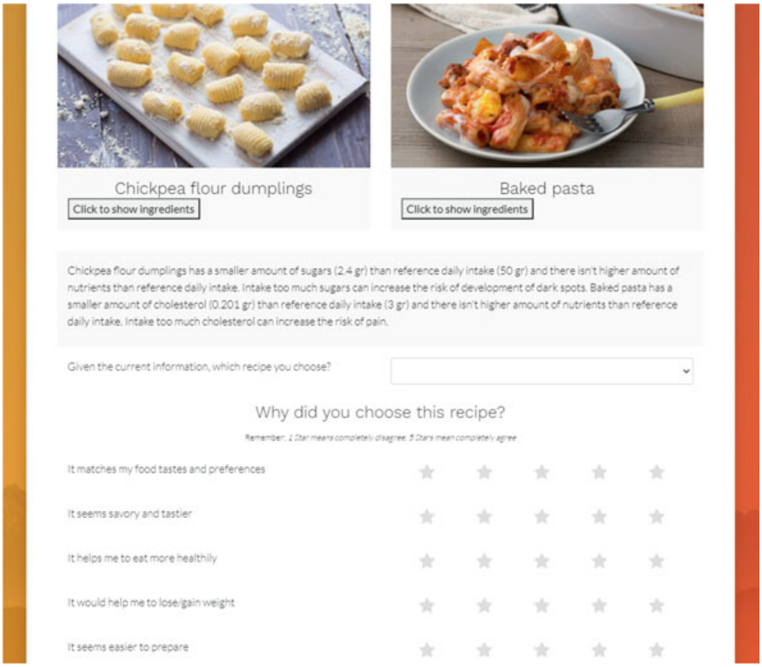


**Fig. 2** An overview of a food recommender system with holistic user modeling. Depicted are two recipes with a "single-style" justification from Musto et al. [183]. Justifications differed across participants to examine which ones would support the healthiest recipe choices

By presenting pairs of recipes (one healthy, one popular) along with different justifications, the authors demonstrate that justifications influence preferences toward the healthier recipe. A sample experimental pair is presented in Fig. 2, where a justification related to food features is presented, this is because justifications that make nutritional information transparent are identified as the most effective in supporting healthier choices [183].

Musto et al. [183] argue their justifications tap into different user motivations. Some justifications are rather context-rich and "immediate," such as those that describe different cooking times and difficulties for recipes. Others are more related to health and long-term effects, describing for instance the relation between fat and cardiovascular disease or sugar and diabetes. Different responses to these can be explained by construal level theory, which describes the perceived psychological distance of individuals toward (attitudinal) objects [266]. Justifications focusing on health hazards in the long term might not resonate with users who have no prior history of food-related illnesses and therefore have no long-term perspective on decision-making.

In the end, the studies leverage a pipeline for holistic user modeling. As illustrated in Fig. 3, the pipeline consists of (i) the Profiler module that collects user charac-

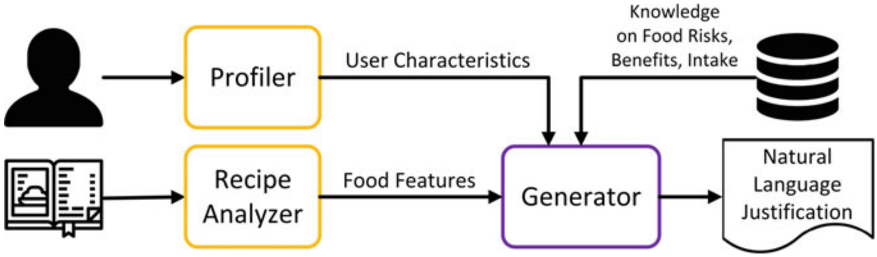


**Fig. 3** Schematic workflow that is used to generate natural language justifications. The justifications are based on user and recipe features, which are paired based on inserted food knowledge. These factors are also used for knowledge-based food recommendations

teristics, which are based on a holistic user profile. This leverages different types of characteristics, including contextual constraints (e.g., time to cook), demographics (i.e., age, BMI), but also affect (e.g., a user's current mood), and a user's self-reported health status and goals (e.g., lifestyle self-evaluation, weight-loss goals); (ii) the Recipe Analyzer extracts the food features of the recipes in the database. These include the nutritional content of food, such as fats and fibers, as well as an aggregate FSA recipe health score (cf. [248] for computational details), and (iii) the Generator outputs a justification, which is based on the relationship between user input, recipe features, and information about possible relevant health effects, e.g., the justification may highlight that eating a recipe that contains a lot of fat may lead to a higher risk of cardiovascular disease.

### 5.3.2 Personalized Support for Vulnerable User Groups

Individuals who are considered to be part of vulnerable user groups (such as people with cognitive problems or neurodiversity, children, and the elderly) are critical use cases for holistic user modeling for various reasons. For illustration purposes, we bring attention to use cases in the realm of search and recommendation tasks that could be enabled by intelligent technologies.

Because of their condition, individuals with cognitive issues often encounter serious difficulties in their daily lives and therefore need support. This assistance extends beyond and is far more complex than single-domain recommendations. For example, suggesting what to do in case of a problem during a move requires much more user information compared to providing a suggestion about which movie to see or book to read. In this case, a broader and more diverse set of information is essential, encompassing not only "traditional" details about preferences but also aversions, habits, cognitive skills, and abilities, aligning with the HUM perspective.

Individuals with autism spectrum disorder (ASD) tend to adhere to rigid routines and experience anxiety in unfamiliar situations [238]. Moreover, they are usually overloaded by environmental sensory stimuli that do not usually cause any problems to neurotypical individuals [256]. These aversions are usually idiosyncratic, varying from person to person. Therefore, to alleviate stress and discomfort, individuals with ASD benefit from personalized support [187]. For instance, they could receive suggestions for safe places to visit when experiencing anxiety. Such spatial support should be tailored based on the user's preferences (such as recommending a comic bookshop if the user likes comics), aversions (by suggesting a less crowded route or one avoiding places with sensory features that might not annoy other users [163]), habits (by suggesting an activity that the user is used to do), and current emotional state (by calling a caregiver if the user is in a state of panic).

Children, as another vulnerable user group with developing cognitive skills and abilities, spotlight the vital role of HUMs in guiding search and recommender systems tailored to this population. In this context, a traditional UM produced based on user-system interactions and/or user preferences is not sufficient. Instead, a more comprehensive counterpart that captures not only user interests but also individuals' (cognitive) skills would be more advantageous [12, 147]. Affect is another important factor that impacts children's engagement with the completion of a search task [147]. Further, when it comes to online resources, children must be provided with suitable materials they can comprehend. Still, children's reading skills are very much in development, and suitability is also something that gradually changes as children grow; making text complexity and topic alignment crucial factors to model [12, 161, 168, 169, 174, 187].

While not exhaustive, it is clear from the aforementioned examples that HUM should contain factors that capture both short-term and long-term information: Cognitive status and skills, personality traits, spatial activities, habits, affects, along with interests and aversion.

## 6 Concluding Remarks

The purpose of this chapter was to highlight the significance and diversity of human factors that anchor the design, development, and deployment of intelligent systems that prioritize humans, rather than just considering them as mere users. Specifically, we presented key concepts, theories, and methodologies integral to human-centered user modeling. While not exhaustive, they are meant to serve as a foundation and provide understanding regarding: *What is a UM?*, *What are human factors?*, *How to collect data to enable user modeling? (and which type of data?)*, and *How to produce UMs driven by human factors?*

The examples and overall discussion presented in this chapter not only evidence the critical role of human factors but also emphasize the need for adopting a holistic view to producing UMs. This comprehensive perspective is essential for enabling adaptation and personalization in the context of intelligent solutions for a wide range of users with different needs, abilities, and expectations.

Given the focus on human-centered user modeling, we cannot but urge researchers and industry practitioners alike to reflect on the privacy, ethical, and broader societal implications of the data directly elicited, indirectly gathered (and their source), or used to infer human factors for user modeling. Moreover, as Artificial Intelligence (AI) continues to advance, there is a pressing need for further research to explore and expand upon the strategies and perspectives discussed in this chapter. This is particularly crucial in harnessing the potential of AI to keep users in the loop and integrated at different stages of intelligent system development.

## References


1. Ambler K, Petrides KV, Vernon PA (2023) Relations between a self-defeating interpersonal style and trait emotional intelligence. Pers Individ Differ 203:112026 (2023)
2. Anderson JR, Matessa M, Lebiere C (1997) Act-r: a theory of higher level cognition and its relation to visual attention. Human–Comput Interact 12(4):439–462
3. Antle AN (2006) Child-personas: fact or fiction? In: Proceedings of the 6th conference on designing interactive systems, pp 22–30
4. Antunes C (2008) Acquiring background knowledge for intelligent tutoring systems. In: Educational data mining
5. Ardissono L, Sestero D (1995) Using dynamic user models in the recognition of the plans of the user. User Model User-Adap 5(3):157–190. https://doi.org/10.1007/BF01099760
6. Ardissono L, Torasso P et al (2000) Dynamic user modeling in a web store shell. In: ECAI, pp 621–625
7. Ardissono L, Brna P, Mitrovic A (eds) (2005) Proceedings of the 10th international conference on user modeling, UM 2005, volume 3538 of Lecture Notes Computer Science. Springer, The Netherlands
8. Ariely D, Jones S (2008) Predictably irrational. Harper Collins, USA
9. Armstrong R, Freitag D, Joachims T, Mitchell T (1995) WebWatcher: a learning apprentice for the world wide web. In: AAAI spring symposium on information gathering, pp 6–12
10. Ashton MC, Lee K (2008) The hexaco model of personality structure and the importance of the h factor. Soc Pers Psychol Compass 2(5):1952–1962
11. Atas M, Felfernig A, Polat-Erdeniz S, Popescu A, Tran TNT, Uta M (2021) Towards psychology-aware preference construction in recommender systems: overview and research issues. J Intell Inf Syst 57:467–489
12. Azpiazu IM, Dragovic N, Pera MS, Fails JA (2017) Online searching and learning: Yum and other search tools for children and teachers. Inf Retrieval J 20:524–545
13. Bachrach Y, Kosinski M, Graepel T, Kohli P, Stillwell D (2012) Personality and patterns of facebook usage. In: Contractor NS, Uzzi B, Macy MW, Nejdl W (eds) Proceedings of the web science 2012, WebSci 2012. ACM, USA, pp 24–32. ISBN 978-1-4503-1228-8. https://doi.org/10.1145/2380718.2380722
14. Bai X, White D, Sundaram D (2012) Contextual adaptive knowledge visualization environments. Electron J Knowl Manag 10(1):1–14
15. Bai X, White D, Sundaram D (2011) Adaptive knowledge visualization systems: a proposal and implementation. Int J e-Educ, e-Bus, e-Manag e-Learn 1(3):193
16. Bandura A (1986) Social foundations of thought and action: a social cognitive theory. Prentice Hall, Englewood Cliffs, NJ
17. Barifah M, Landoni M (2020) Emotions associated with failed searches in a digital library. In: *Proceedings of ISIC, the information behaviour conference*, p 4
18. Basu K (1994) The traveler's dilemma: paradoxes of rationality in game theory. Am Econ Rev 84(2):391–395
19. Berkovsky S (2006) Decentralized mediation of user models for a better personalization. In: Wade VP, Ashman H, Smyth B (eds) AH, volume 4018 of Lecture notes computer science. Springer, The Netherlands, pp 404–408. ISBN 3-540-34696-1

20. Berkovsky S, Kufliki T, Ricci F (2009) Cross-representation mediation of user models. User Model User-Adap 19(1–2):35–63
21. Berners-Lee T, Hendler J, Lassila O (2001) The semantic web. Sci Am 284(5):34–43
22. Bettman JR, Luce MF, Payne JW (1998) Constructive consumer choice processes. J Consum Res 25(3):187–217
23. Bhattacharya P, Zafar MB, Ganguly N, Ghosh S, Gummadi KP (2014) Inferring user interests in the twitter social network. In: Proceedings of the 8th ACM conference on recommender systems, RecSys '14. ACM, New York, NY, USA, pp 357–360. ISBN 978-1-4503-2668-1. https://doi.org/10.1145/2645710.2645765
24. Bilal D (2000) Children's use of the yahooligans! web search engine: I. cognitive, physical, and affective behaviors on fact-based search tasks. J Am Soc Inf Sci 51(7):646–665
25. Brajnik G, Tasso C (1994) A shell for developing nonmonotonic user modeling systems. Int J Hum-Comput St 40(1):31–62
26. Brooks CA, Winter M, Greer JE, McCalla GI (2004) The massive user modelling system (MUMS). In: Proceedings of the 7tth international conference on intelligent tutoring systems, pp 635–645
27. Brusilovsky P, Pesin L (1998) Adaptive navigation support in educational hypermedia: an evaluation of the ISIS-Tutor. J Comput Inf Technol 6(1):27–38
28. Brusilovsky P (1996) Methods and techniques of adaptive hypermedia. User Model User-Adap 6(2–3):87–129
29. Brusilovsky P (2004) Knowledge tree: a distributed architecture for adaptive e-learning. In: Feldman SI, Uretsky M, Najork M, Wills CE (eds) WWW, International world wide web conferences. ACM, USA, pp 104–113. ISBN 1-58113-912-8
30. Brusilovsky P, Millán E, User models for adaptive hypermedia and adaptive educational systems. In: Brusilovsky et al. [32], pp 3–53
31. Brusilovsky P, Millán E (2007b) User models for adaptive hypermedia and adaptive educational systems. *The adaptive web: methods and strategies of web personalization*, pp 3–53
32. Brusilovsky P, Kobsa A, Nejdl W (eds) The adaptive web, methods and strategies of web personalization, volume 4321 of Lecture notes computer science. Springer, The Netherlands
33. Cacioppo J, Petty R (1982) The need for cognition. J Pers Soc Psychol 42:116–131. https://doi.org/10.1037/0022-3514.42.1.116
34. Caglayan AK, Snorrason M, Jacoby J, Mazzu J, Jones R, Kumar K (1997) Learn sesame, a learning agent engine. Appl. Artif. Intell. 11(5):393–412. ISSN 0883-9514
35. Cantador I, Fernández-Tobías I, Berkovsky S, Cremonesi P (2015) Cross-domain recommender systems. In: Recommender systems handbook. Springer, The Netherlands, pp 919–959
36. Carmagnola F, Dimitrova V (2008) An evidence-based approach to handle semantic heterogeneity in interoperable distributed user models. In: Nejdl W, Kay J, Pu P, Herder E (eds) Proceedings of the 5th international conference on adaptive hypermedia and adaptive web-based systems, AH 2008, volume 5149 of Lecture notes computer science. Springer, The Netherlands, pp 73–82. ISBN 978-3-540-70984-8
37. Carmagnola F, Cena F, Cortassa O, Gena C, Torre I (2007) Towards a tag-based user model: how can user model benefit from tags? In: User modeling 2007: 11th international conference, UM 2007, Proceedings, vol 11. Springer, Corfu, Greece, pp 445–449
38. Carmagnola F, Cena F, Console L, Cortassa O, Gena C, Goy A, Torre I, Toso A, Vernero F (2008) Tag-based user modeling for social multi-device adaptive guides. User Model User-Adap 18(5):497–538
39. Cena F, Furnari R (2009) A model for feature-based user model interoperability on the web. In: Kuflik I, Berkovsky S, Carmagnola F, Heckmann D, Krüger A (eds) Advances in ubiquitous user modelling, revised selected papers, volume 5830 of Lecture notes computer science. Springer, The Netherlands, pp 37–54
40. Cena F, Console L, Gena C, Goy A, Levi G, Modeo S, Torre I (2006) Integrating heterogeneous adaptation techniques to build a flexible and usable mobile tourist guide. AI Commun. 19(4):369–384. ISSN 0921-7126

41. Cena F, Likavec S, Rapp A (2019) Real world user model: Evolution of user modeling triggered by advances in wearable and ubiquitous computing: State of the art and future directions. Inf Syst Front 21:1085–1110
42. Cena F, Pensa RG, Rapp A (2019b) Privacy issues in holistic recommendations. In: Papadopoulos GA, Samaras G, Weibelzahl S, Jannach D, Santos OC (eds) Adjunct publication of the 27th conference on user modeling, adaptation and personalization, UMAP 2019, Larnaca, Cyprus. ACM, pp 263–265. https://doi.org/10.1145/3314183.3323461
43. Cena F, Rapp A, Musto C, Semeraro G (2020) Generating recommendations from multiple data sources: a methodological framework for system design and its application. IEEE Access 8:183430–183447
44. Cena F, Console L, Likavec S, Micheli M, Vernero F (2023) How personality traits can be used to shape itinerary factors in recommender systems for young travellers. IEEE Access
45. Chaffar S, Frasson C (2004) Inducing optimal emotional state for learning in intelligent tutoring systems. In: Intelligent tutoring systems: 7th international conference, ITS 2004, Proceedings, vol 7. Springer, Maceió, Alagoas, Brazil, pp 45–54
46. Chaiken S, Trope Y (1999) Dual-process theories in social psychology. Guilford Press, London
47. Chang A (2020) The role of artificial intelligence in digital health. In: Digital health entrepreneurship, pp 71–81
48. Chao CW, Chang L, Cheng A-C, Wu T-T (2016) Exploration on the effectiveness of learning, interest, and attitude of the integration of review system of history based on mobile game and forgetting curve. In: Emerging technologies for education: first international symposium, SETE 2016, Held in conjunction with ICWL 2016, Revised Selected Papers 1. Springer, Rome, Italy, pp 34–42
49. Chen J, Nairn R, Nelson L, Bernstein M, Chi E (2010) Short and tweet: experiments on recommending content from information streams. In: Proceedings of the SIGCHI conference on human factors in computing systems, CHI 2010. ACM, USA, pp 1185–1194. ISBN 978-1-60558-929-9. https://doi.org/10.1145/1753326.1753503
50. Chen L, Pu P (2012) Critiquing-based recommenders: survey and emerging trends. User Model User Adapt Interact 22(1–2):125–150
51. Chen L, Yang Y, Wang N, Yang K, Yuan Q (2019) How serendipity improves user satisfaction with recommendations? a large-scale user evaluation. In: The world wide web conference, pp 240–250
52. Chen M, Herrera F, Hwang K (2018) Cognitive computing: architecture, technologies and intelligent applications. IEEE Access 6:19774–19783
53. Chen Y, Elenee Argentinis JD, Weber G (2016) Ibm watson: how cognitive computing can be applied to big data challenges in life sciences research. Clin Ther 38(4):688–701
54. Chen Z, Lin F, Liu H, Liu Y, Ma W-Y, Wenyin L (2002) User intention modeling in web applications using data mining. World Wide Web 5(3):181–191. ISSN 1386-145X. https://doi.org/10.1023/A:1020980528899
55. Cheung CM, Sia CL, Kuan KK (2012) Is this review believable? a study of factors affecting the credibility of online consumer reviews from an elm perspective. J Assoc Inf Syst 13(8):2
56. De Choudhury M, Gamon M, Counts S, Horvitz E (2013) Predicting depression via social media. In: Kiciman E, Ellison NB, Hogan B, Resnick P, Soboroff I (eds) *Proceedings of the 7th international conference on weblogs and social media, ICWSM*. The AAAI Press, USA. ISBN 978-1-57735-610-3
57. Cloninger CR, Svrakic DM, Przybeck TR (1993) A psychobiological model of temperament and character. Arch General Psychiatry 50(12):975–990
58. Cohen P, Perrault C (1979) Elements of a plan-based theory of speech acts. Cognitive Sci 3(3):177–212
59. Colman AM (2003) Cooperation, psychological game theory, and limitations of rationality in social interaction. Behav Brain Sci 26(2):139–153
60. Contreras D, Salamó M (2020) A cognitively inspired clustering approach for critique-based recommenders. Cognitive Comput 12(2):428–441

61. Cuff BM, Brown SJ, Taylor L, Howat DJ (2016) Empathy: a review of the concept. Emot Rev 8(2):144–153
62. Daoud M, Tamine L, Boughanem M, Chebaro B (2007) Learning implicit user interests using ontology and search history for personalization. In: *Proceedings of the 2007 international conference on web information systems engineering*, WISE'07. Springer, Berlin, pp 325–336. ISBN 3-540-77009-7, 978-3-540-77009-1
63. de Barcelos Silva A, Gomes MM, da Costa CA, da Rosa Righi R, Barbosa JL, Pessin G, De Doncker G, Federizzi G (2020) Intelligent personal assistants: a systematic literature review. In: Expert systems with applications, pp 113–193
64. De Bra P, Houben GJ, Wu H (1999) Aham: a dexter-based reference model for adaptive hypermedia. In: Proceedings of the 10th ACM conference on hypertext and hypermedia: returning to our diverse roots, HYPERTEXT '99. ACM, USA, pp 147–156. ISBN 1-58113-064-3. https://doi.org/10.1145/294469.294508
65. De Bra P, Aerts A, Berden B, De Lange B, Rousseau B, Santic T, Smits D, Stash N (2003) Aha! the adaptive hypermedia architecture. In: Proceedings of the fourteenth ACM conference on Hypertext and hypermedia, pp 81–84
66. Deniz M (2011) An investigation of decision making styles and the five-factor personality traits with respect to attachment styles. Educ Sci: Theory Pract 11(1):105–113
67. Dhelim S, Aung N, Ning H (2020) Mining user interest based on personality-aware hybrid filtering in social networks. Knowl-Based Syst 206:106227
68. Díaz A, Gervás P (2004) Dynamic user modeling in a system for personalization of web contents. In: Current topics in artificial intelligence: 10th conference of the spanish association for artificial intelligence, CAEPIA 2003, and 5th conference on technology transfer, TTIA 2003. Revised Selected Papers. Springer, San Sebastian, Spain, pp 281–290
69. Dijksterhuis A (2004) Think different: the merits of unconscious thought in preference development and decision making. J Pers Soc Psychol 87(5):586
70. Divya Vani L, Suneetha D (2015) Mood classification of social media text. Int J Comput Sci Commun Netw 5(5):299–302
71. Dobelli R (2013) The art of thinking clearly: better thinking, better decisions. Hachette, UK
72. Dolog P, Vassileva J (2005) Decentralized, agent based and social approaches to user modelling. In: Proceedings of the workshop on decentralized, agent based and social approaches to user modelling DASUM-05 at UM 2005
73. Dolog P, Schäfer M, A framework for browsing, manipulating and maintaining interoperable learner profiles. In: Ardissono et al. (ed) [7], pp 397–401
74. Ekstrand MD, Willemsen MC (2016) Behaviorism is not enough: better recommendations through listening to users. In: Proceedings of the 10th ACM conference on recommender systems, pp 221–224
75. El Majjodi A, Starke AD, and Christoph Trattner. Nudging towards health? examining the merits of nutrition labels and personalization in a recipe recommender system. In: *Proceedings of the 30th ACM conference on user modeling, adaptation and personalization*, pp 48–56
76. Eppler MJ, Mengis J (2004) The concept of information overload: a review of literature from organization science, accounting, marketing, mis, and related disciplines. Inf Soc 20(5):325–344
77. Fan W, Ma Y, Li Q, He Y, Zhao E, Tang J, Yin D (2019) Graph neural networks for social recommendation. In: The world wide web conference, pp 417–426
78. Farrell S, Lewandowsky S (2018) Computational modeling of cognition and behavior. Cambridge University Press, USA
79. Feher A, Vernon PA (2021) Looking beyond the big five: a selective review of alternatives to the big five model of personality. Pers Individ Differ 169:110002
80. Ferguson MJ, Bargh JA (2004) How social perception can automatically influence behavior. Trends Cognitive Sci 8(1):33–39
81. Fernandez A, Insfran E, Abrahão S (2011) Usability evaluation methods for the web: A systematic mapping study. Inf Softw Tech 53(8):789–817. ISSN 0950-5849. https://doi.org/10.1016/j.infsof.2011.02.007

82. Fink J, Kobsa A (2000) A review and analysis of commercial user modeling servers for personalization on the world wide web. User Model User-Adap 10(2–3):209–249
83. Fink J, Kobsa A, Nill A (1998) Adaptable and adaptive information provision for all users, including disabled and elderly people. New Rev Hypermedia Multimed 4:163–188. https://doi.org/10.1080/13614569808914700
84. Fink JV (2003) User modeling servers—requirements, design and evaluation. PhD thesis, University of Duisburg-Essen
85. Fischer G (2001) User modeling in human-computer interaction. User Model User-Adap 11(1–2):65–86
86. Fleming MN (2021) Considerations for the ethical implementation of psychological assessment through social media via machine learning. Ethics Behav 31(3):181–192
87. Flock E (2023) As stephen hawking turns 70, six life lessons you should learn from him
88. Fogg BJ (2002) Persuasive technology: using computers to change what we think and do. Ubiquity 2
89. Ford N (2004) Towards a model of learning for educational informatics. J Documentation 60(2):183–225
90. Franciosi R, Kujal P, Michelitsch R, Smith V, Deng G (1996) Experimental tests of the endowment effect. J Econ Behav Organ 30(2):213–226
91. Francis JC (2021) Reformulating prospect theory to become a von neumann-morgenstern theory. Rev Quant Financ Account 56(3):965–985
92. Fu WT (2020) How cognitive computational models can improve information search. In: Understanding and improving information search: a cognitive approach, pp 29–45
93. Fu W-T, Pirolli P (2007) Snif-act: a cognitive model of user navigation on the world wide web. Human-Comput Interact 22(4):355–412
94. Fum D, Del Missier F, Stocco A et al (2007) The cognitive modeling of human behavior: why a model is (sometimes) better than 10,000 words. Cognitive Syst Res 8(3):135–142
95. Gigerenzer G (2004) Fast and frugal heuristics: the tools of bounded rationality. Blackwell Handb Judgment Decis Making 62:88
96. Gigerenzer G, Brighton H (2009) Homo heuristicus: why biased minds make better inferences. Top Cognitive Sci 1(1):107–143
97. Golbeck J, Robles C, Edmondson M, Turner K (2011) Predicting personality from twitter. In: PASSAT/SocialCom 2011, privacy, security, risk and trust (PASSAT), 2011 IEEE 3rd international conference on social computing (SocialCom). IEEE, USA, pp 149–156. ISBN 978-1-4577-1931-8. https://doi.org/10.1109/PASSAT/SocialCom.2011.33
98. Goldberg LR (1990) An alternative description of personality: the big-five factor structure. J Pers Soc Psychol 59(6):1216
99. Golemati M, Halatsis C, Vassilakis C, Katifori A, Peloponnese UO (2006) A context-based adaptive visualization environment. In: Proceedings of the 10th international conference on information visualisation, IV 2006, pp 62–67. https://doi.org/10.1109/IV.2006.5
100. Gomez-Uribe CA, Hunt N (2015) The netflix recommender system: algorithms, business value, and innovation. ACM Trans Manag Inf Syst (TMIS) 6(4):1–19
101. Gorelova G, Badwan N (2019) Cognitive modeling for the intellectual system of supporting decision making on regulating reproduction and accumulation of financial capital. Int Res J Financ Econ 175:70–82
102. Graus MP (2018) From behavior-centered to user-centered: incorporating psychological knowledge and user feedback in personalization
103. Güell M, Salamo M, Contreras D, Boratto L (2020) Integrating a cognitive assistant within a critique-based recommender system. Cognitive Syst Res 64:1–14
104. Guy I, Carmel D (2011) Social recommender systems. In: Proceedings of the 20th international conference companion on World wide web, pp 283–284
105. Gwizdka J, Spence I (2007) Implicit measures of lostness and success in web navigation. Interact Comput 19(3):357–369

106. Haggerty A, White RW, Jose JM (2003) NewsFlash: adaptive TV news delivery on the web. In: Nürnberger A, Detyniecki M (eds) Proceedings of the 1st international workshop on adaptive multimedia retrieval AMR, volume 3094 of Lecture notes computer science. Springer, Berlin, pp 72–86. https://doi.org/10.1007/978-3-540-25981-7_5
107. Hanani U, Shapira B, Shoval P (2001) Information filtering: overview of issues, research and systems. User Model User-Adap Interact 11:203–259
108. Heckmann D (2005) Ubiquitous user modeling. PhD thesis, Department of Computer Science Saarbrucken, Saarland University
109. Heckmann D, Schwartz T, Brandherm B, Schmitz M, von Wilamowitz-Moellendorff M, Gumo—The general user model ontology. In: Ardissono et al (ed) [7], pp 428–432
110. Huang C-C (2017) Cognitive factors in predicting continued use of information systems with technology adoption models. Inf Res Int Electron J 22(2):n2
111. Iana A, Alam M, Paulheim H (2022) A survey on knowledge-aware news recommender systems. Semantic Web (Preprint):1–62
112. Jameson A, Smyth B (2007) Recommendation to groups. In: The adaptive web: methods and strategies of web personalization, pp 596–627
113. Jameson A, Berendt B, Gabrielli S, Cena F, Gena C, Vernero F, Reinecke K (2014) Choice architecture for human-computer interaction. Found Trends Human-Comput Interact 7(1–2):1–235
114. Janarthanam S, Lemon O (2014) Adaptive generation in dialogue systems using dynamic user modeling. Comput Linguist 40(4):883–920. ISSN 0891-2017. https://doi.org/10.1162/COLI_a_00203
115. Jannach D, Zanker M, Felfernig A, Friedrich G (2010) Recommender systems: an introduction. Cambridge University Press, USA
116. Jannach D, Manzoor A, Cai W, Chen L (2022) A survey on conversational recommender systems. ACM Comput Surv 54(5):105:1–105:36. https://doi.org/10.1145/3453154
117. Johnson EJ, Goldstein D (2003) Do defaults save lives?
118. Johnson EJ, Shu SB, Dellaert BGC, Fox C, Goldstein DG, Häubl G, Larrick RP, Payne JW, Peters E, Schkade D et al (2012) Beyond nudges: tools of a choice architecture. Market Lett 23:87–504
119. Joshi A, Krishnapuram R (2000) On mining web access logs. In: Proceedings of th ACM SIGMOD workshop on research issues in data mining and knowledge discovery, pp 63–69
120. Julien H, McKechnie LEF, Hart S (2005) Affective issues in library and information science systems work: a content analysis. Lib Inf Sci Res 27(4):453–466
121. Kahneman D (2003) Maps of bounded rationality: psychology for behavioral economics. Am Econ Rev 93(5):1449–1475
122. Kahneman D (2011) *Thinking, fast and slow*. Macmillan, USA
123. Kahneman D, Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47(2):263–292
124. Kahneman D, Knetsch JL, Thaler RH (1990) Experimental tests of the endowment effect and the coase theorem. J Polit Econ 98(6):1325–1348
125. Katz S, Albacete P, Chounta IA, Jordan P, McLaren BM, Zapata-Rivera D (2021) Linking dialogue with student modelling to create an adaptive tutoring system for conceptual physics. Int J Artif Intell Educ 31(3):397–445
126. Kay J (1995) The um toolkit for reusable, long term user models. User Model User-Adap 4:149–196
127. Kay J, Kummerfeld B (2013) Creating personalized systems that people can scrutinize and control: Drivers, principles and experience. ACM Trans Interact Intell Syst 2(4):24:1–24:42. ISSN 2160-6455
128. Kay J, Kummerfeld B, Lauder P (2002) Personis: a server for user models. In: De Bra P, Brusilovsky P, Conejo R (eds) Proceedings of the 2nd international conference on adaptive hypermedia and adaptive web-based systems, AH 2002, volume 2347 of Lecture Notes Computer Science. Springer, The Netherlands, pp 203–212

129. Kazai G, Thomas P, Craswell N (2019) The emotion profile of web search. In: Proceedings of the 42nd international ACM SIGIR conference on research and development in information retrieval, pp 1097–1100
130. Kelly D, Teevan J (2003) Implicit feedback for inferring user preference: a bibliography. SIGIR Forum 37(2):18–28. ISSN 0163-5840. https://doi.org/10.1145/959258.959260
131. Khwaja M, Ferrer M, Iglesias JO, Faisal AA, Matic A (2019) Aligning daily activities with personality: towards a recommender system for improving wellbeing. In: Proceedings of the 13th acm conference on recommender systems, pp 368–372
132. Kim HR, Chan PK (2003) Learning implicit user interest hierarchy for context in personalization. In: Proceedings of the 8th international conference on intelligent user interfaces, IUI 2003. ACM, USA, New York, pp 101–108. ISBN 1-58113-586-6. https://doi.org/10.1145/604045.604064
133. Knijnenburg BP, Kobsa A (2013) Making decisions about privacy: information disclosure in context-aware recommender systems. ACM Trans Interact Intell Syst (TiiS) 3(3):1–23
134. Knijnenburg BP, Willemsen MC (2009) Understanding the effect of adaptive preference elicitation methods on user satisfaction of a recommender system. In: Proceedings of the third ACM conference on Recommender systems, pp 381–384
135. Knijnenburg BP, Willemsen MC (2010) The effect of preference elicitation methods on the user experience of a recommender system. In: CHI'10 extended abstracts on human factors in computing systems, pp 3457–3462
136. Kobsa A (2001) Generic user modeling systems. User Model User-Adap 11:49–63
137. Kobsa A, Fink J (2006) An LDAP-based user modeling server and its evaluation. User Model User-Adap 16(2):129–169
138. Kobsa A, Koenemann J, Pohl W (2001) Personalized hypermedia presentation techniques for improving online customer relationship. Knowl Eng Rev 16(2):111–155
139. Kobsa A, Generic user modeling systems. In: Brusilovsky et al (ed) [32], pp 136–154
140. Kobsa A, Pohl W (1995) The user modeling shell system BGP-MS. User Model User-Adap 4(2):59–106
141. Konstan Joseph A, Miller Bradley N, David Maltz, Herlocker Jonathan L, Gordon Lee R, John Riedl (1997) Grouplens: applying collaborative filtering to usenet news. Commun ACM 40(3):77–87
142. Kouki P, Schaffer J, Pujara J, O'Donovan J, Getoor L (2019) Personalized explanations for hybrid recommender systems. In: Proceedings of the 24th international conference on intelligent user interfaces, pp 379–390
143. Krulwich B (1997) Lifestyle finder: intelligent user profiling using large-scale demographic data. AI Mag 18(2):37–45
144. Kunda Z (1990) The case for motivated reasoning. Psychol Bull 108(3):480
145. Lagun D, Agichtein E (2015) Inferring searcher attention by jointly modeling user interactions and content salience. In: Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval, SIGIR 2015. ACM, New York, NY, USA, pp 483–492. ISBN 978-1-4503-3621-5, https://doi.org/10.1145/2766462.2767745
146. Lai H-J, Liang T-P, Ku Y-C (2003) Customized internet news services based on customer profiles. In: Sadeh NM, Dively MJ, Kauffman RJ, Labrou Y, Shehory O, Telang R, Cranor LF (eds) Proceedings of the 5th international conference on electronic commerce, ICEC, volume 50 of ACM international conference proceeding series. ACM, USA, pp 225–229. https://doi.org/10.1145/948005.948035
147. Landoni M, Pera MS, Murgia E, Huibers T (2020) Inside out: Exploring the emotional side of search engines in the classroom. In: Proceedings of the 28th ACM conference on user modeling, adaptation and personalization, pp 136–144
148. Lex E, Kowald D, Seitlinger P, Tran TNT, Felfernig A, Schedl M et al (2021) Psychology-informed recommender systems. Found Trends® Inf Retrieval 15(2):134–242
149. Li B, Yang Q, Xue X (2009) Can movies and books collaborate?: cross-domain collaborative filtering for sparsity reduction. In: Proceedings of the 21st international jont conference on artifical intelligence, IJCAI'09. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, pp 2052–2057. http://dl.acm.org/citation.cfm?id=1661445.1661773

150. Li C, Yoo J (2006) Modeling student online learning using clustering. In: Proceedings of the 44th annual southeast regional conference. ACM, pp 186–191
151. Liang Y, Willemsen MC (2021) The role of preference consistency, defaults and musical expertise in users' exploration behavior in a genre exploration recommender. In: Proceedings of the 15th ACM conference on recommender systems, pp 230–240
152. Libet B (1985) Unconscious cerebral initiative and the role of conscious will in voluntary action. Behav Brain Sci 8(4):529–539
153. Linden G, Smith B, York J (2003) Amazon.com recommendations: Item-to-item collaborative filtering. IEEE Internet Comput 7(1):76–80. https://doi.org/10.1109/MIC.2003.1167344
154. Liu F, Yu C, Meng W (2004) Personalized web search for improving retrieval effectiveness. IEEE T Knowl Data En 16(1):28–40. ISSN 1041-4347. https://doi.org/10.1109/TKDE.2004.1264820
155. Lopatovska I (2014) Toward a model of emotions and mood in the online information search process. J Assoc Inf Sci Technol 65(9):1775–1793
156. Lorenz A, Agent-based ubiquitous user modeling. In: Ardissono et al (ed) [7], pp 512–514
157. Lupton D (2016) The quantified self. Wiley, New York
158. Zemirli N, Tamine-Lechani L, Boughanem M (2006) Inferring the user interests using the search history. In: Proceedings of the workshop on information retrieval, learning, knowledge and adaptability, LWA 2006, pp 108–110. ISBN 978-1-4503-2668-1
159. Ma Y-F, Hua X-S, Lu L, Zhang H-J (2005) A generic framework of user attention model and its application in video summarization. IEEE Trans Multimed 7(5):907–919
160. Machado I, Martins A, Paiva A (1999) One for all and all in one: a learner modelling server in a multi-agent platform. In: Proceedings of the 7th international conference on user modeling, UM 1999. Springer, New York, pp 211–221. ISBN 3-211-83151-7
161. Madrazo Azpiazu I, Dragovic N, Pera MS (2016) Finding, understanding and learning: Making information discovery tasks useful for children and teachers. In: CEUR workshop proceedings, vol 1647. CEUR-WS
162. Martina AF, Musto C, Iovine A, de Gemmis M, Narducci F, Semeraro G (2022) A virtual assistant for the movie domain exploiting natural language preference elicitation strategies. In: Adjunct proceedings of the 30th ACM conference on user modeling, adaptation and personalization, pp 7–12
163. Mauro N, Ardissono L, Cena F (2022) Supporting people with autism spectrum disorders in the exploration of pois: an inclusive recommender system. Commun ACM 65(2):101–109
164. Mayer JD, Roberts RD, Barsade SG (2008) Human abilities: emotional intelligence. Annu Rev Psychol 59:507–536
165. Mayfield A (2008) What is social media
166. Mehta B, Niederée C, Stewart A, Degemmis M, Lops P, Semeraro G (2005) Ontologically-enriched unified user modeling for cross-system personalization. In: User modeling, pp 119–123
167. Miller BN, Albert I, Lam SK, Konstan JA, Riedl J (2003) Movielens unplugged: experiences with an occasionally connected recommender system. In: *Proceedings of the 8th international conference on intelligent user interfaces*, IUI '03. ACM, USA, pp 263–266. ISBN 1-58113-586-6. https://doi.org/10.1145/604045.604094
168. Milton A, Pera MS (2023) Into the unknown: exploration of search engines' responses to users with depression and anxiety. ACM Trans Web 17(4):1–29
169. Milton A, Anuya O, Spear L, Wright KL, Pera MS (2020) A ranking strategy to promote resources supporting the classroom environment. In: 2020 IEEE/WIC/acm international joint conference on web intelligence and intelligent agent technology (WI-IAT). IEEE, pp 121–128
170. Mizgajski J, Morzy M (2019) Affective recommender systems in online news industry: how emotions influence reading choices. User Model User-Adap Interact 29(2):345–379
171. Mobasher B (2007) Data mining for web personalization. The adaptive web: methods and strategies of web personalization, pp 90–135
172. Mobasher B, Cooley R, Srivastava J (2000) Automatic personalization based on web usage mining. Commun ACM 43(8):142–151. ISSN 0001-0782. https://doi.org/10.1145/345124.345169

173. Moser C, Fuchsberger V, Neureiter K, Sellner W, Tscheligi M (2012) Revisiting personas: the making-of for special user groups. In: CHI'12 extended abstracts on human factors in computing systems, pp 453–468
174. Murgia E, Landoni M, Huibers T, Fails JA, Pera MS (2019) The seven layers of complexity of recommender systems for children in educational contexts. In: ComplexRec workshop-co-located with ACM RecSys
175. Musa DL, de Oliveira JPM (2005) Sharing learner information through a web services-based learning architecture. J Web Eng 4(3):263–278
176. Mushtaq S, Kumar N (2022) Text-based automatic personality recognition: Recent developments. In: Proceedings of third international conference on computing, communications, and cyber-security: IC4S 2021. Springer, Berlin, pp 537–549
177. Musto C (2010) Enhanced vector space models for content-based recommender systems. In: Proceedings of the 4th ACM conference on recommender systems, RecSys 2010, ACM, USA, pp 361–364. ISBN 978-1-60558-906-0. https://doi.org/10.1145/1864708.1864791
178. Musto C, Basile P, Lops P, De Gemmis M, Semeraro G (2014) Linked open data-enabled strategies for top-n recommendations. In: CBRecSys@ RecSys, pp 49–56
179. Musto C, Greco C, Suglia A, Semeraro G (2016) A content-based recommender system based on recurrent neural networks. In: IIR, Ask me any rating
180. Musto C, Polignano M, Semeraro G, de Gemmis M, Lops P (2020) Myrror: a platform for holistic user modeling: Merging data from social networks, smartphones and wearable devices. User Model User-Adap Interact 30:477–511
181. Musto C, Trattner C, Starke A, Semeraro G (2020b) Towards a knowledge-aware food recommender system exploiting holistic user models. In: Proceedings of the 28th ACM conference on user modeling, adaptation and personalization, pp 333–337
182. Musto C, Narducci F, Polignano M, De Gemmis M, Lops P, Semeraro G (2021) Myrrorbot: a digital assistant based on holistic user models for personalized access to online services. ACM Trans Inf Syst (TOIS) 39(4):1–34
183. Musto C, Starke AD, Trattner C, Rapp A, Semeraro G (2021b) Exploring the effects of natural language justifications in food recommender systems. In: *Proceedings of the 29th ACM conference on user modeling, adaptation and personalization*, pp 147–157
184. Nahl D (2005) Affective and cognitive information behavior: interaction effects in internet use. Proc Am Soc Inf Sci Technol 42(1)
185. Nasoz F, Lisetti CL (2007) Affective user modeling for adaptive intelligent user interfaces. In: Human-computer interaction. HCI intelligent multimodal interaction environments: 12th international conference, HCI international, Proceedings, Part III 12. Springer, Heidelberg, pp 421–430
186. Nazemi K, Stab C, Kuijper A (2011) A reference model for adaptive visualization systems. In: Jacko JA (ed) Proceedings of the 14th international conference on human-computer interaction, HCI international 2011, design and development approaches, Part I, volume 6761 of Lecture notes computer science. Springer, Berlin, pp 480–489. https://doi.org/10.1007/978-3-642-21602-2_52
187. Ng Y-K, Pera MS (2018) Recommending social-interactive games for adults with autism spectrum disorders (asd). In: Proceedings of the 12th ACM conference on recommender systems, pp 209–213
188. Niederée C, Stewart A, Mehta B, Hemmje M (2004) A multi-dimensional, unified user model for cross-system personalization. In: Workshop on environments for personalized information access, pp 34–54
189. Nielsen L (2013) Personas-user focused design, vol 1373. Springer, Berlin
190. Ning H, Dhelim S, Aung N (2019) Personet: Friend recommendation system based on big-five personality traits and hybrid filtering. IEEE Trans Comput Soc Syst 6(3):394–402
191. Niu X, McCalla GI, Vassileva J (2003) Purpose-based user modelling in a multi-agent portfolio management system. In: Brusilovsky P, Corbett AT, de Rosis F (eds) Proceedings of the 9th international conference on user modeling, UM 2003, volume 2702 of Lecture notes computer science. Springer, Berlin, pp 398–402. ISBN 3-540-40381-7

192. Di Noia T, Ostuni VC (2015) Recommender systems and linked open data. In: Faber W, Paschke A (eds) Reasoning Web Web Logic Rules—11th international summer school 2015, tutorial lectures, volume 9203 of Lecture notes computer science. Springer, Switzerland, pp 88–113. ISBN 978-3-319-21767-3, https://doi.org/10.1007/978-3-319-21768-0_4
193. Orwant J (1995) Heterogeneous learning in the doppelgänger user modeling system. User Model User-Adap 4(2):107–130
194. Ana P, Self John A (1995) TAGUS—a user and leamer modeling workbench. Lect Notes Comput Sci 4(3):197–226
195. Pan W, Xiang EW, Liu Nathan N, Yang Q (2010) Transfer learning in collaborative filtering for sparsity reduction. In: Proceedings of the 24th AAAI conference on artificial intelligence. AAAI Press, AAAI, USA, pp 210–235
196. Pang B, Lee L, Vaithyanathan S (2002) Thumbs up?: sentiment classification using machine learning techniques. In: Proceedings of the ACL-02 conference on empirical methods in natural language processing, EMNLP 2002, vol 10. Association for Computational Linguistics, Stroudsburg, PA, USA, pp 79–86. https://doi.org/10.3115/1118693.1118704
197. Papanikolaou KA, Grigoriadou M, Kornilakis H, Magoulas GD (2003) Personalizing the interaction in a web-based educational hypermedia system: the case of inspire. User Model User-Adap Interact 13:213–267
198. Paramythis A, Weibelzahl S, Masthoff J (2010) Layered evaluation of interactive adaptive systems: Framework and formative methods. User Model. User-Adap. 20(5):383–453. ISSN 0924-1868. https://doi.org/10.1007/s11257-010-9082-4
199. Parker AM, De Bruin WB, Fischhoff B (2007) Maximizers versus satisficers: Decision-making styles, competence, and outcomes. Judgment Decis Making 2(6):342–350
200. Paulhus DL, Curtis SR, Jones DN (2018) Aggression as a trait: the dark tetrad alternative. Curr Opin Psychol 1(19):88-92
201. Paunonen SV (2002) Design and construction of the supernumerary personality inventory. Res Bull 763
202. Pearl J (1984) Heuristics: intelligent search strategies for computer problem solving. Addison-Wesley Longman Publishing Co., Inc., USA
203. Raymond Perrault C, Allen JF, Cohen PR (1978) Speech acts as a basis for understanding dialogue coherence. In: Proceedings of the 1978 workshop on theoretical issues in natural language processing, TINLAP 1978. Association for Computational Linguistics, Stroudsburg, PA, USA, pp 125–132. https://doi.org/10.3115/980262.980282
204. Persky J (1995) Retrospectives: the ethology of homo economicus. J Econ Perspect 9(2):221–231
205. Petrelli D, De Angeli A, Convertino G (1999) A user-centered approach to user modeling. In: Kay J (ed) 7th international conference on user modeling, UM 1999, volume 407 of CISM international centre for mechanical sciences, courses and lectures. Springer, New York, pp 255–264. ISBN 978-3-211-83151-9, https://doi.org/10.1007/978-3-7091-2490-1_25
206. Petrides KV (2010) Trait emotional intelligence theory. Ind Organ Psychol 3(2):136–139
207. Petty RE, Cacioppo JT, Petty RE, Cacioppo JT (1986) The elaboration likelihood model of persuasion. Springer, USA
208. Pirolli P, Fu W-T (2003) Snif-act: a model of information foraging on the world wide web. In: International conference on user modeling. Springer, Berlin, pp 45–54
209. Poddar A, Ruthven I (2010) The emotional impact of search tasks. In: Proceedings of the third symposium on Information interaction in context, pp 35–44
210. Polignano M, Narducci F, de Gemmis M, Semeraro G (2021) Towards emotion-aware recommender systems: an affective coherence model based on emotion-driven behaviors. Expert Syst Appl 170:114382
211. Polignano M, Narducci F, de Gemmis M, Semeraro G (2023) Helena: an intelligent digital assistant based on a lifelong health user model. Inf Process Manag 60(1):103124
212. Pruitt J, Grudin J (2003) Personas: practice and theory. In: Proceedings of the 2003 conference on designing for user experiences, pp 1–15
213. Quah E, Haldane JBS (2007) Cost-benefit analysis. Routledge, London

214. Rapp A, Cena F, Gena C, Marcengo A, Console L (2016) Using game mechanics for field evaluation of prototype social applications: a novel methodology. Behav IT 35(3):184–195. https://doi.org/10.1080/0144929X.2015.1046931
215. Ravi L, Devarajan M, Vijayakumar V, Sangaiah AK, Wang L, Subramaniyaswamy V (2021) An intelligent location recommender system utilising multi-agent induced cognitive behavioural model. Enterp Inf Syst 15(10):1376–1394
216. Razmerita L (2007) Ontology-based user modeling. In: Sharman R, Kishore R, Ramesh R (eds) Ontologies: a handbook of principles, concepts and applications in information systems, pages 635–664, USA, 2007. Springer. ISBN 978-0-387-37022-4. https://doi.org/10.1007/978-0-387-37022-4_23
217. Resnick P, Varian HR (1997) Recommender systems. Commune ACM 40(3):56–58
218. Resnick P, Iacovou N, Suchak M, Bergstrom P, Riedl J (1994) Grouplens: an open architecture for collaborative filtering of netnews. In: Smith JB, Donelson Smith F, Malone TW (eds) Proceedings of the conference on computer supported cooperative work, CSCW. ACM, USA, pp 175–186. https://doi.org/10.1145/192844.192905
219. Ricci F, Rokach L, Shapira B, Kantor PB (2010) Recommender systems handbook, 1st edn. Springer, New York, NY, USA, pp 0387858199, 9780387858197
220. Rich E (1979) Readings in intelligent user interfaces. chapter User Modeling via Stereotypes. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, pp 329–342. ISBN 1-55860-444-8
221. Rieger A, Bredius F, Tintarev N, Pera MS (2023a) Searching for the whole truth: Harnessing the power of intellectual humility to boost better search on debated topics. In: Extended abstracts of the 2023 CHI conference on human factors in computing systems, pp 1–8
222. Rieger A, Draws T, Theune M, Tintarev N (2023b) Nudges to mitigate confirmation bias during web search on debated topics: Support versus manipulation. ACM Trans Web. ISSN 1559-1131. https://doi.org/10.1145/3635034
223. Rotter Julian B (1966) Generalized expectancies for internal versus external control of reinforcement. Psychol Monogr 80(1):1–28
224. Rowe JP, Lester JC (2010) Modeling user knowledge with dynamic bayesian networks in interactive narrative environments. In: Proceedings of the 6th AAAI conference on artificial intelligence and interactive digital entertainment, AIIDE 2010
225. Ruvini J-D (2003) Adapting to the user's internet search strategy. In: Brusilovsky P, Corbett AT, de Rosis F (eds) 9th international conference on user modeling, UM 2003, volume 2702 of Lecture notes computer science. Springer, Berlin, pp 55–64. https://doi.org/10.1007/3-540-44963-9_9
226. Sadilek A, Homan C, Lasecki WS, Silenzio V, Kautz H (2014) Modeling fine-grained dynamics of mood at scale. In: Carterette B, Diaz F, Castillo C, Metzler D (eds) Proceedings of the 7th ACM international conference on web search and data mining, WSDM. ACM, USA. ISBN 978-1-4503-2351-2
227. Salazar C, Aguilar J, Monsalve-Pulido J, Montoya E (2021) Affective recommender systems in the educational field. a systematic literature review. Comput Sci Rev 40:100377
228. Samuelson W, Zeckhauser R (1988) Status quo bias in decision making. J Risk Uncertainty 1:7–59
229. Santos OC, Boticario JG, Manjarrés-Riesco Á (2014) An approach for an affective educational recommendation model. In: *Recommender systems for technology enhanced learning: research trends and applications*, pp 123–143
230. Savolainen R (2015) The interplay of affective and cognitive factors in information seeking and use: Comparing kuhlthau's and nahl's models. J Documentation
231. Seitlinger P, Ley T (2016) Reconceptualizing imitation in social tagging: a reflective search model of human web interaction. In: Proceedings of the 8th ACM conference on web science, pp 146–155
232. Sen AK (1977) Rational fools: a critique of the behavioral foundations of economic theory. Philo Public Affairs 317–344

233. Shafto P, Nasraoui O (2016) Human-recommender systems: from benchmark data to benchmark cognitive models. In: Proceedings of the 10th ACM conference on recommender systems, pp 127–130
234. Shapira B, Rokach L, Freilikhman S (2013) Facebook single and cross domain data for recommendation systems. User Model User-Adap 23(2–3):211–247. https://doi.org/10.1007/s11257-012-9128-x
235. Sharma A, Cosley D (2013) Do social explanations work? studying and modeling the effects of social explanations in recommender systems. In: Proceedings of the 22nd international conference on World Wide Web, pp 1133–1144
236. Shen X, Tan B, Zhai C (2005) Implicit user modeling for personalized search. In: Proceedings of the 14th ACM international conference on information and knowledge management, CIKM '05. ACM, New York, pp 824–831. ISBN 1-59593-140-6, https://doi.org/10.1145/1099554.1099747
237. Shuai H-H, Shen C-Y, Yang D-N, Lan Y-F, Lee W-C, Yu PS, Chen M-S (2016) Mining online social data for detecting social network mental disorders. In: Proceedings of the 25th international conference on world wide web, WWW. Republic and Canton of Geneva, Switzerland, International World Wide Web Conferences Steering Committee, pp 275–285. ISBN 978-1-4503-4143-1. https://doi.org/10.1145/2872427.2882996
238. Simm W, Ferrario MA, Gradinar A, Smith MT, Forshaw S, Smith I, Whittle J (2016) Anxiety and autism: towards personalized digital health. In: Proceedings of the 2016 CHI conference on human factors in computing systems, pp 1270–1281
239. Simon HA (1955) A behavioral model of rational choice. Q J Econ 99–118
240. Sinclair RC, Mark MM (1995) The effects of mood state on judgemental accuracy: Processing strategy as a mechanism. Cognition Emotion 9(5):417–438
241. Singh MP (1994) Multiagent systems. Springer, Berlin
242. Smith AD, Kelly A (2015) Cognitive processes. The encyclopedia of adulthood and aging, pp 1–4
243. Smyth B, Cotter P (2002) Personalized adaptive navigation for mobile portals. In: van Harmelen F (ed) Proceedings of the 15th Eureopean conference on artificial intelligence, ECAI 2002. IOS Press, The Netherlands, pp 608–612
244. Stanovich KE (1999) Who is rational?: studies of individual differences in reasoning. Psychology Press, London
245. Starke A, Willemsen M, Snijders C (2017) Effective user interface designs to increase energy-efficient behavior in a rasch-based energy recommender system. In: Proceedings of the eleventh ACM conference on recommender systems, pp 65–73
246. Starke A, Willemsen M, Snijders C (2021) Promoting energy-efficient behavior by depicting social norms in a recommender interface. ACM Trans Interact Intell Syst (TiiS) 11(3–4):1–32
247. Starke AD, Willemsen MC, Snijders C (2021b) Using explanations as energy-saving frames: a user-centric recommender study. In: Adjunct proceedings of the 29th ACM conference on user modeling, adaptation and personalization, pp 229–237
248. Starke AD, Willemsen MC, Trattner C (2021c) Nudging healthy choices in food search through visual attractiveness. Front Artif Intell 4:621743
249. Starke AD, Asotic E, Trattner C, Van Loo EJ (2023) Examining the user evaluation of multi-list recommender interfaces in the context of healthy recipe choices. ACM Trans Recommender Syst
250. Sternberg RJ (1996) Cognitive psychology. Harcourt Brace College Publishers, USA
251. Su X, Khoshgoftaar TM (2009) A survey of collaborative filtering techniques. Adv Artif Intell 421425:1–421425:19. https://doi.org/10.1155/2009/421425
252. Sweta S, Sweta S (2021) Recommender system to enhancing efficacy of e-learning system. In: Modern approach to educational data mining and its applications, pp 87–93
253. Tang TY, McCalla G (2002) Student modeling for a web-based learning environment: a data mining approach. In: AAAI/IAAI, pp 967–968
254. Tao F, Xiao B, Qi Q, Cheng J, Ji P (2022) Digital twin modeling. J Manuf Syst 64:372–389

255. Taramigkou M, Bothos E, Apostolou D, Mentzas G (2013) Fostering serendipity in online information systems. In: 2013 international conference on engineering, technology and innovation (ICE) and IEEE international technology management conference. IEEE, pp 1–10
256. Tavassoli T, Miller LJ, Schoen SA, Nielsen DM, Baron-Cohen SB (2014) Sensory over-responsivity in adults with autism spectrum conditions. Autism 18(4):428–432
257. Teppan EC (2008ions of psychological phenomenons for recommender systems. In: Proceedings of the 2008 ACM conference on Recommender systems, pp 323–326
258. Thaler R (1980) Toward a positive theory of consumer choice. J Econ BehavOrgan 1(1):39–60
259. Thaler RH (2016) Behavioral economics: past, present, and future. Am Econ Rev 106(7):1577–1600
260. Thaler RH, Sunstein CR (2003) Libertarian paternalism. Am Econ Rev 93(2):175–179
261. Thaler RH, Sunstein CR (2008) Nudge: improving decisions about health, wealth, and happiness
262. Thaler RH, Sunstein CR (2009) Nudge: improving decisions about health, wealth, and happiness. Penguin
263. Tkalcic M, Chen L (2015) Personality and recommender systems. Recommender systems handbook, pp 715–739
264. Tkalcic M, Kosir A, Tasic J (2011) Affective recommender systems: the role of emotions in recommender systems. In: Proceedings the RecSys 2011 workshop on human decision making in recommender systems, pp 9–13
265. Trella M, Conejo R, Guzmán E, Bueno D (2003) An educational component based framework for web its development. In: Lovelle JMC, Rodríguez BMG, Aguilar LJ, Gayo JEL, del Puerto Paule Ruíz M (eds) Proceedings of international conference on web engineering, ICWE 2003, volume 2722 of Lecture notes computer science. Springer, The Netherlands, pp 134–143
266. Trope Y, Liberman N (2010) Construal-level theory of psychological distance. Psychol Rev 117(2):440
267. Tversky A, Kahneman D (1991) Loss aversion in riskless choice: a reference-dependent model. Q J Econ 106(4):1039–1061
268. Vaisey S (2009) Motivation and justification: a dual-process model of culture in action. Am J Soc 114(6):1675–1715
269. Van Der Sluijs K, Houben GJ (2006) A generic component for exchanging user models between web-based systems. Int J Continuing Eng Educ Life-Long Learn (IJCEELL) 16(1–2):64–76
270. van Gemert-Pijnen LJ, Kelders SM, Beerlage-de Jong N, Oinas-Kukkonen H (2018) Persuasive health technology. In: eHealth research, theory and development. Routledge, London, pp 228–246
271. Van Lange PA, Higgins ET, Kruglanski AW (2011) Handbook of theories of social psychology. In: Handbook of theories of social psychology, pp 1–568
272. Vassileva J (2001) Distributed user modelling for universal information access. In: Stephanidis C (ed) Proceedings of the 4th international conference on universal access in human-computer interaction, pp 122–126
273. Volkova S, Bachrach Y, Armstrong M, Sharma V (2015) Inferring latent user properties from texts published in social media. In: Proceedings of the 29th AAAI conference on artificial intelligence, AAAI 2015. AAAI Press, USA, pp 4296–4297. ISBN 0-262-51129-0
274. Von Eckardt B (1995) What is cognitive science? MIT press, England
275. Wang R, Wu Z, Lou J, Jiang Y (2022) Attention-based dynamic user modeling and deep collaborative filtering recommendation. Expert Syst Appl 188:116036
276. Wang X, Wang D, Xu C, He X, Cao Y, Chua T-S (2019) Explainable reasoning over knowledge graphs for recommendation. Proc AAAI Conf Artif Intell 33:5329–5336
277. Wang Y, Aroyo LM, Stash N, Rutledge L (2007) Interactive user modeling for personalized access to museum collections: the rijksmuseum case study. In: Conati C, McCoy KF, Paliouras G (eds) User modeling, volume 4511 of Lecture notes computer science. Springer, Berlin, pp 385–389. ISBN 978-3-540-73077-4
278. Warburton S (2012) Digital identity and social media. IGI Global, USA

279. Weber G, Specht M (1997) User modeling and adaptive navigation support in WWW-based tutoring systems. In: *User modeling*. Springer, Berlin, pp 289–300
280. Weber RH, Weber R (2010) *Internet of things*, vol 12. Springer, The Netherlands
281. Weller JA, Tikir A (2011) Predicting domain-specific risk taking with the hexaco personality structure. J Behav Decis Making 24(2):180–201
282. Wood S, Cox R, Cheng P (2006) Attention design: eight issues to consider. Comput Human Behav 22(4):588–602
283. Wu W, Chen L, He L (2013) Using personality to adjust diversity in recommender systems. In: Proceedings of the 24th ACM conference on hypertext and social media, pp 225–229
284. Wyer Jr RS, Clore GL, Isbell LM (1999) Affect and information processing. In: Advances in experimental social psychology, vol 31. Elsevier, USA, pp 1–77
285. Xian Y, Fu Z, Zhao H, Ge Y, Chen X, Huang Q, Geng S, Qin Z, De Melo G, Muthukrishnan S et al (2020) Cafe: Coarse-to-fine neural symbolic reasoning for explainable recommendation. In: Proceedings of the 29th ACM international conference on information and knowledge management, pp 1645–1654
286. Yang P, Song Y, Ji Y (2015) Tag-based user interest discovery though keywords extraction in social network. In: Wang Y, Xiong H, Argamon S, Li X, Li J (eds) Proceedings of the 1st international big data computing and communications: conference, BigCom 2015. Springer International Publishing, pp 363–372. ISBN 978-3-319-22047-5, https://doi.org/10.1007/978-3-319-22047-5_29
287. Yu H, Li Z (2010) A collaborative filtering method based on the forgetting curve. In *2010 international conference on web information systems and mining*, vol 1. IEEE, pp 183–187
288. Zhang F, Song Z, Zhang H (2006) Web service based architecture and ontology based user model for cross-system personalization. In: Proceedings of the 2006 IEEE/WIC/ACM international conference on web intelligence, WI 2006. IEEE Computer Society, IEEE, Washington, DC, USA, pp 849–852. ISBN 0769527477
289. Zhang J (2011) The perils of behavior-based personalization. Market Sci 30(1):170–186
290. Zhou C, Bai J, Song J, Liu X, Zhao Z, Chen X, Gao J (2018) Atrank: an attention-based user behavior modeling framework for recommendation. In: Proceedings of the AAAI conference on artificial intelligence, vol 32
291. Zhu T, Greiner R, Häubl G (2003) Learning a model of a web user's interests. In: Brusilovsky P, Corbett AT, de Rosis F (eds) Proceedings of the 9th international conference on user modeling, UM 2003, volume 2702 of Lecture notes computer science. Springer, Berlin, pp 65–75. ISBN 3-540-40381-7, https://doi.org/10.1007/3-540-44963-9_10
292. Zimmerman J, Kurapati K (2002) Exposing profiles to build trust in a recommender. In: Terveen LG, Wixon DR (eds) Extended abstracts of the 2002 conference on human factors in computing systems, CHI 2002. ACM, USA, pp 608–609. https://doi.org/10.1145/506443.506507