Draft of User Modelling - Short Review

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1 User Modelling

This chapter describes different definitions associated to user modelling which includes main characteristics and techniques existing in the literature. In the end of the chapter, we look at existing proposals and the work developed over the last years related to user modelling.

1.1 User Characteristics

A user model is composed by a set of characteristics that adjust the content, presentation and navigation to each user. These characteristics can be domain-dependent and domain-independent and are related with beliefs about the user, which include preferences, knowledge and attributes, or are an explicit representation of properties of individual users and user classes.

Domain Dependent Data (DDD).
Domain dependent data is related with system responses tailored according to the domain knowledge of a user [2]. For this, it is necessary to perceive user current state and knowledge regarding concepts and relations inherent to the domain, predict how the user will interpret system responses, understand the many different goals and plans of each user, predict and respond to different mistakes while the user is using the system and identify the most adequate way to present information to each user. Different methods can be used to measure user knowledge and expertise regarding the domain: Direct Dialogue and Indirect Acquisition.

Direct Dialogue.
This type of interaction is performed directly with the user in order to assess his/her expertise regarding the domain. For this, the system should incorporate features to allow users to input and share their knowledge (for example, using questionnaires or forms) and mechanisms to process the inserted data to correctly measure user knowledge regarding the domain.

Indirect Acquisition.
Indirect acquisition method allows the system to assess user knowledge indirectly according to how the user performs different actions. Depending on this assessment the

user knowledge regarding the domain is classified in different levels which in turn are updated over time as the user works with the system.

Domain Independent Data (DID).

Domain independent data is not related with user expertise regarding the domain but to his/her cognitive abilities which indicates how the user perceives, thinks, remembers, behaves and solves different problems[2]. In other words, domain-independent knowledge can corresponds to the phycological characteristics of the user. There are many different psychological models and tests that can be used to assess user personality such as the Myer-Briggs Type Indicator, the Eysenck's Pen Model and the Big Five Model.

Myer-Briggs Type Indicator.

Myer-Brigg Type Indicator model [3] is a model used to identify personal characteristics and preferences. This model considers four different areas of personality based on the Carl Jung's Psychological Types [4] and which are perception, judgment, extraversion and orientation. These four areas combined result in sixteen different types and the scores on each dimension represent the strength of each dimension.

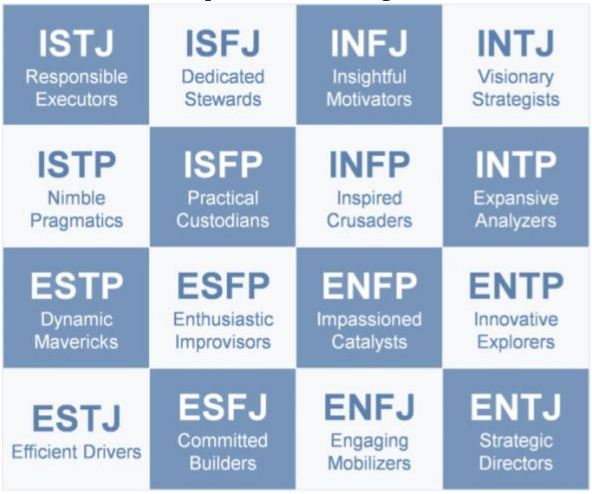

Fig. 1. Myer-Briggs Type Indicator

Eysenck's Pen Model.

In 1950 [5], Eysenck proposed the PEN model using three dimensions to describe different personalities. These dimensions are: extraversion-introversion; Neuroticism versus Emotional Stability; and psychoticism versus impulse control. According to Eysenck, individuals with high levels of extraversion are more social, talkative and outgoing, while individuals with high levels of introversion are more quiet, shy and less social. Individuals with high levels of neuroticism experience more stress and anxiety, while individuals with low levels of neuroticism experience more stable emotional levels. Individuals with high levels of psychoticism are more likely to show impulsive, irresponsible and miscalculated behaviour while individuals with low levels of psychoticism tend to be more controlled and organized.

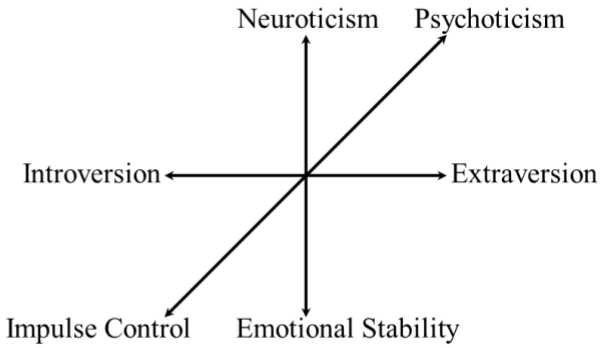

Fig. 2. Eysenck's Pen Model

The Big Five Model.

The Big Five Model, also known as the OCEAN model has been proposed and developed over the last century by different researchers such as [6-9] and considers the existence of five main traits of personality which are extraversion, agreeableness, openness, conscientiousness, and neuroticism.

Openness – Trait associated to characteristics such as imagination and insight. People who have high openness tend to have a broad range of different interests about the world and other people and are willing to learn new things and enjoy new experiences.

Conscientiousness – Trait associated to characteristics such as thoughtfulness, good impulse control, and goal-directed behaviour. People who have high conscientiousness tend to be organized and mindful of details.

Extraversion – Trait associated to characteristics such as excitability, sociability, talkativeness, assertiveness, and emotional expressiveness. People who have high extraversion tend to be outgoing and value social interactions.

Agreeableness – Trait associated to characteristics such as trust, altruism, kindness, affection, and other prosocial behaviours. People who have high agreeableness tend to value cooperation.

Neuroticism – Trait associated to characteristics such as sadness, moodiness, and emotional instability. People who have high neuroticism tend to experience mood swings, anxiety, irritability, and sadness.

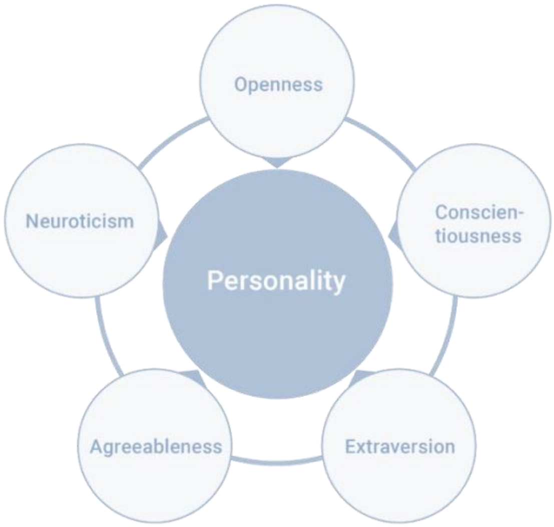

Fig. 3. Five Traits of Personality

Common Characteristics

In Table 1, it is presented common characteristics for user modelling considering the definitions presented in previous sections.

Table 1. Common characteristics in user modelling

Model	Profile	Characteristics	Descriptions/Examples
Domain Independent Data	**Generic Profile**	Personal Information	Name, email, password, etc.
		Demographic Data	Age, Gender, etc.
		Patient Background	Smoker, Pregnant, etc.
		Allergies	Allergies which the patient may have
		Deficiencies: visual or others	Sees well, uses eyeglasses, etc.
		Domain of application	Localization of the user, etc.
		Inheritance of the characteristics	Creation of stereotypes that allow to classify the user
		Knowledge (Background Knowledge)	A collection of knowledge translated in concepts. Possibility of a qualitative, quantitative or probabilistic indication of concepts and knowledge acquired for the user
	Psychological Profile	Cognitive Capacities	
		Traits of Personality	Psychological profile (introvert, extrovert, etc.)

		Personal Preferences	Likes and Dislikes
		Inheritance of characteristics	Creation of stereotypes that allow to classify the user
Domain Dependent Data		Objectives	Questionnaires to determine user objectives
		Complete description of the navigation	Kept register of each page accessed
		Knowledge acquired	A collection of knowledge translated in concepts.
		Medication Intake	Data related to patient intake of medication
		Context model	Data related with the environment of the user
		Aptitude	Definition of the capacity to use the system
		Task Preferences	Definition of the individual preferences with the objectives to adapt the navigation and contents

Techniques for User Modelling

After identifying the data related to each user characteristics, it is then possible to define the algorithms that will process this data and in turn affect the computational environment. These algorithms are mainly defined using statistical and non-statistical techniques.

Statistical Techniques.

Linear Modelling.

Linear Modelling is a technique which takes the weighted sum of known values and predicts the value of an unknown quantity [10]. These models are usually very inexpensive and easy to learn and understand. Furthermore, these models can be also extended and generalized without much effort. Two examples could be using a linear model to predict user's ratings of different activities suggested by the system or using linear model to assess the association between total cholesterol and body mass index.

Beta Distribution

The Beta Distribution is a predictive model which considers the number of correct predictions and the number of incorrect predictions and then generates both and estimate and a confidence level [11]. It is easy and cheap to calculate since it only requires two numbers (the number of hits and misses) to measure both estimate and confidence level. An example could be using a Beta Distribution model to track users' preferences by the number of likes and dislikes they provide to system for any suggested activity.

Markov Model.

A Markov Model follows a structure very similar to a Linear Model and consists of a set of states, a set of probabilities which determine the likelihood of transition between these states and, for each state, a set of observation/probability pairs [10]. For example, a Markov Model could be used to predict user most frequent actions while using the system by looking at his past performed actions.

Bayesian Networks

A Bayesian Network is a directed acyclic graph where nodes denote variables and the arcs connecting nodes represent causal links from parent nodes to child nodes [10]. Each node is associated with a conditional probability distribution which assigns a probability to each possible value of this node for each combination of values of its parent nodes. These models are usually very flexible as they can provide a compact representation of any probability distribution, they can explicitly represent causal relations and they allow predictions regarding more than one variable (unlike many other statistical models which only considers a single variable). Examples of Bayesian Network models could be to predict the most adequate type of suggestions for a user according to the type of action being performed, or to predict error rates while the user is using the application.

Rule Induction Model.

Rule Induction Model consists of learning sets of rules that predict the class of an observation from its attributes [10]. These models can represent rules directly or represent rules as decision trees or in terms of conditional probabilities. A rule itself is not considered a model and therefore, this type of models always considers a set of rules which collectively define a prediction model, or the knowledge base.

Non-Statistical Techniques

Overlay Model.

An overlay model assumes that the user's knowledge is a subset of the domain knowledge. An overlay user model can thus be thought of as a template that is "laid over" the domain knowledge base. Domain concepts can then be marked as "known" or "not known" (or with some other method, such as an evidential scheme), reflecting beliefs inferred about the user. Overlay modelling is a very attractive technique because it is easy to implement and can be very effective. Unfortunately, the underlying assumption of an overlay model, that the user's knowledge is a subset of the domain knowledge of the system, is quite wrong. An overlay model cannot account for users who organize their knowledge of the domain in a structure different from that used in the domain model, nor can it account for misconceptions users may hold about knowledge in the knowledge base [12].

The overlay model consists of (a subset of) the concepts from the underlying domain model. For each concept, the overlay model contains data that represents (an estimation of) the individual user's knowledge about or interest in this concept (or some other relationship with this concept)[1].

In this method, the user knowledge is related, layer to layer, to the Domain Model, producing the user knowledge model [13]. The expression of the knowledge level of each concept is dependent on the Domain Model itself: this value can be binary (knows or ignores), qualitative (good, average, weak, etc.) or quantitative (the probability of knowing or not, a real value between 0 and 1, etc.).

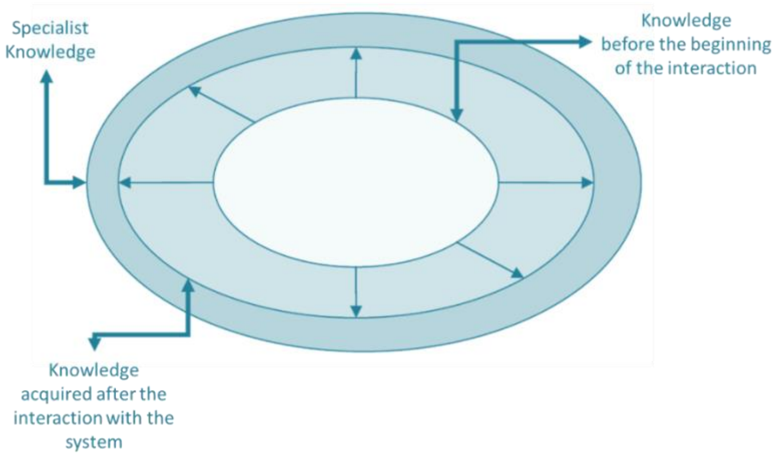

Fig. 4. Representation of the Overlay Model, adapted from [13]

Perturbation Model.

The perturbation model can represent user beliefs that the overlay model cannot handle. A perturbation user model assumes that the beliefs held by the user are similar to the knowledge the system has, although the user may hold beliefs that differ from the system's in some areas. These differences in the user model can be viewed as perturbations of the knowledge in the domain knowledge base. Thus, the perturbation user model is still built with respect to the domain model but allows for some deviation in the structure of that knowledge [12].

Perturbation model represents learners as the subset of expert's knowledge plus their mal-knowledge [14].

This method considers that the knowledge and the student aptitudes are a perturbation of the specialist knowledge, and not a subset of his knowledge (as in the previous model) [13]. This method can be used to represent knowledge that is beyond the Domain Model defined by the specialist.

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1 https://www.eelcoherder.com/images/teaching/usermodeling/03_user_modeling_techniques.pdf

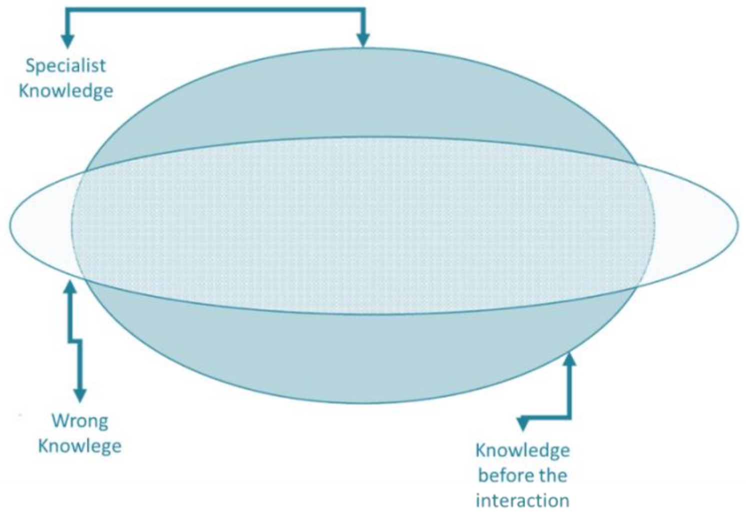

Fig. 5. Representation of the Perturbation Model, adapted from [13]

Knowledge Modelling.

Process of creating a computer interpretable model of knowledge or standard specifications about a kind of process and/or about a kind of facility or product. The resulting knowledge model can only be computer interpretable when it is expressed in some knowledge representation language or data structure that enables the knowledge to be interpreted by software and to be stored in a database or data exchange file.

Behaviour-Based Model.

A very common approach to gather requirements for developing a system is to interview and observe the behaviours of users from the intended user population. System design requirements typically characterize the user as one entity with a single set of behaviours, namely expert, novice, or a composite of all the users [15]. The goal of this type of models is to develop a system that can accommodates the great diversity of the user population and improve the users' performance. For this, system users can be categorized into different groups, and then it should be described and modelled each group's behaviours, and finally, this information should be included in both design and operational processes. Users can be categorized based upon similar behavioural characteristics that are important to system interface design and use. User modelling should then describe how users within a specific user group behave in certain situations or perform certain functions.

Rule-Based Model.

Rule-Based Models can be automatically defined using learning algorithms to identify useful rules (also known as Rule-based Machine Learning Modelling) or can depend on expert-crafted knowledge bases to make inferences about users (traditional Rule-Based Modelling). Examples of this type of models could be using a Rule-Based

Model to model user's current abilities, or to predict actions and errors performed by the user. Other examples include using a Rule-Based Model to identify irregular monitoring values captured by the application regarding current user health condition and alert the healthcare professional.

Stereotypes.

One of the easiest and most common techniques for building models of other people is the evocation of stereotypes. Stereotypes were first introduced in the literature related to User modelling by Elaine Rich in 1979 [16], and it was brought with the necessity to define a "useful mechanism for building models of individual users on the basis of a small amount of information about them". According to the author, in order to correctly define and use stereotypes it is necessary to collect and use two kinds of information. The first required information is related to the stereotypes themselves which includes the information of different collections of clusters of characteristics or facets. These facets depend on the domain and purpose of the system but may also include information related to the level of expertise while using the system or specific concepts and tasks dealt with by the system. These different facets will result and describe different groups of users. The second kind of information is related to the use of triggers which correspond to the occurrence of different events and that in turn will activate appropriate stereotypes. For example, if a user performs an advanced task while using the system, an "expert user" trigger could be activated. Table 2 shows an example on how to build different stereotypes related to practicing exercise and eating habits.

Table 2. Examples of Stereotypes

	Trigger	**Cluster/Stereotype**	**People who like**	**Will like**
Direct Domain	$exercise$ $food$	ExercisePractitioner FoodEater FoodForExercise	$exercise_1$ $food_1$ $exercise_1$	$exercise_2$ $food_2$ $food_1$
Domain Attributes	$food$	FoodNutrient	$attribute_1$ in $food$	$food_2$
User Attributes	$user$	UserExerciser	**People who have**	**Will like**
			$attribute_2$	$exercise_2$

Ontologies.

Nowadays, there is a great necessity to develop systems which can reuse and share knowledge and information for all sort of areas and applications including healthcare. To support such kind of systems, new tools are being developed, also known as Ontologies. On of the most common definitions comes from Gruber which refer to ontologies as "an explicit specification of a conceptualization" [17]. Although it seems a very simple definition, it is widely accepted in the Artificial Intelligence domain. To sum up, an ontology describes a data model, represents concepts and relationships existing in a certain domain. These relationships should allow inferring about all different instances related to the domain. The information represented by an ontology should include individuals (or instances), classes (concepts or types of instances), attributes (concepts' properties which can be mandatory or nor) and relationships (how concepts are related with each other). Some of the most used languages to define and instantiate ontologies are the RDF and RDFS [18] and OWL [19], with the last one being recognized as a standard by the W3C Consortium[2]. There are several advantages associated to the use of ontologies which are:

- Possibility to reuse existing ontologies, considering possible adaptations or extensions of knowledge bass which can promote a significant gain in terms of efforts and investments. Furthermore, this type of structure offers a great availability and possibility to be extended and complemented with concepts of different specific domains and to create an hierarchy/taxonomy.
- Easy access to ontological information, capacity to store thousands of examples, classes, attributes, relationships serving as an efficient search tool and preserve the integrity and share of knowledge between different communities while providing a uniform vocabulary.
- Use Linked Data practices, establishing a global association network between data and different domains.

User Ontologies.

A user ontology classifies all the relevant characteristics and associated partitions of users into classes with corresponding associated information. In other words, a user ontology includes all the characteristics that can describe the user as a person [20]. Using sharable data structures containing user's features and preferences will enable personalized interactions with different devices for the benefit of the users [21]. A user ontology can be defined using OWL description language which contains the following elements: C – a set of concepts (entities and instances in user ontology); R – the relationship between classes or instances in the user ontology; I – a set of instances and A – a set of rules and restrictions [22]. Several works have been proposed in the literature regarding the definition and use of user ontologies. For example, in [23] it is proposed a Person Profile Ontology model which is responsible for modelling the profile of the user using five main classes: Person (can be either the assisted person, doctor, relative, etc,), Habit (daily activities performed by the assisted person), Impairment (visual, mobility, speech and other impairments associated to the assisted person), Contact Profile (email, phone number and other mechanisms to contact the assisted person) and Preference (preferences of the assisted person such as device preferences).

[2] The World Wide Web Consortium: https://www.w3.org/

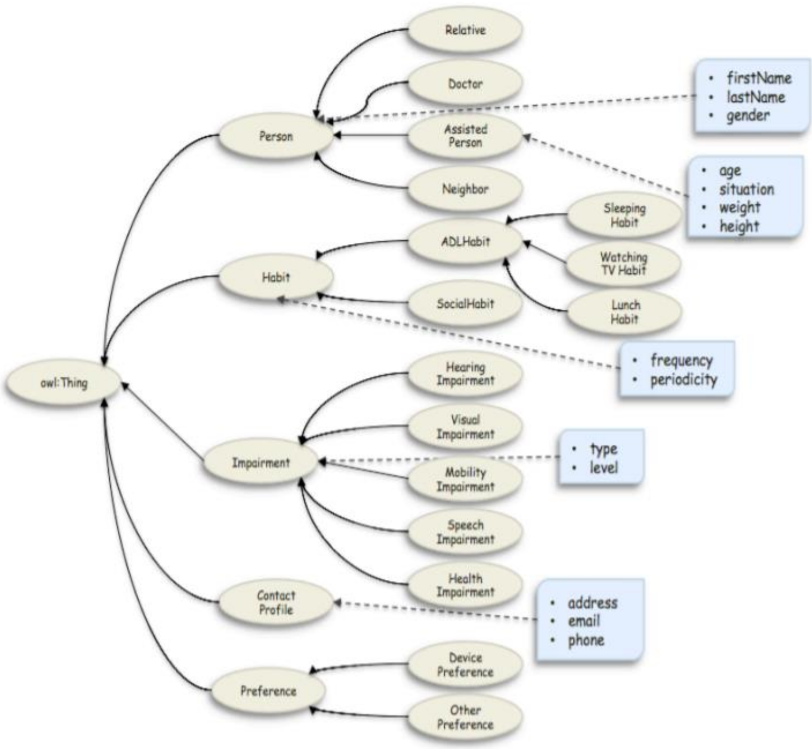

Fig. 6. Person Profile Ontology, adapted from [23]

In [24], it is proposed a user ontology to model information of users using smart home applications. They divided the user ontology in two main components, one component related to static information of the user (such as name and age) and the role of the user (whether the user is a resident or a visitor) and another component related to the profile data of the user (such as heart rate recorded) and preferences (preferred activities).

In [25], it is proposed a ontology-based context modelling approach for a home care assistance scenario where it is defined a Patient Personal Domain Ontology where it is identified different relevant context items related to patient physical data (such as biomedical acquired values), location and activity. These data is then used to automatically infer patient current health status and detect and alert problematic or dangerous situations and events.

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