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User Ontology for Intelligent Decision Support Based on User Digital Life

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Abstract

The research is aimed at the development of an ontology that classifies the users into user types based on which personalized decisions are recommended. A user type represents a category of users distinguished by common preferences and decision-making behaviours. The ontology is intended to be used in a decision support system implemented following an earlier proposed conceptual framework of intelligent decision support based on user digital life. The paper briefly introduces this framework and provides the formalization for main framework components. The major research result is a multi-aspect user ontology that models a user via three aspects: user profile, user segment, and user digital life model. Users' digital traces is the framework's component that provides information about the users to determine their types. Suggestions on ontology usage for intelligent decision recommendation are provided.

1 Introduction

The present reality supposes intensive online human activities during which users leave hundreds of digital traces. Each trace is a source of data/information/knowledge. Among other things, the traces contain user-specific information. For intelligent decision support systems, such information is a valuable resource to provide decisions personalized regarding user preferences and decision-making behaviour. This motivated the usage of digital traces for the identification in them user-specific information based on that context-aware decisions can be recommended. A conceptual framework of intelligent decision support based on a model of user digital life [1] embodies this idea. The framework is purposed to recommend to the user a decision that the users sharing their preferences and decision-making behaviour with this user would make in the user context.

The goal of the present paper is the development of an ontology that classifies the users into types. A user type represents a category of users distinguished by common preferences and decision-making behaviour. The apparatus of multi-aspect ontologies [2] is used to develop a user ontology. This ontology models a user from three perspectives: a user profile aspect, a user segment aspect, and an aspect of user digital life model. The source of the information about the users and their contexts is user digital traces. The ontology supports a context-sensitive classification, that is the same user in different contexts can belong to different user types.

The rest of the paper is structured as follows. Section 2 provides an overview of related research. Section 3 introduces the conceptual framework and provides the formalization for its components. Section 4 is devoted to the multi-aspect user ontology, the place of that in the conceptual framework is briefly described in Section 5. The main research results and drawbacks are discussed in the Conclusion.

2 Related Research

Approaches to multi-aspect user modelling have been developing for a long time. The core idea of those models is based on the assumption that differences in some user characteristics affect the usefulness of the services or information provided to the users. Thus if a system's behaviour is tailored according to such characteristics, its value to the users will be increased [3].

Various approaches model the users from multiple perspectives. For instance, personalized education systems use three aspects to model the students: knowledge, beliefs, and background [4]. Interests and preferences are two user characteristics that adaptive search engines, including recommenders, typically distinguish as the most important [5]. Modelling users' goals, plans, and information needs has been widely exploited in intelligent dialog systems [6]. With the advent of context aware systems and personalised ubiquitous computing, much attention has been paid to the users' context modelling [7]. One of the most widely used aspect in this field is demographic [8]. MYRROR platform [9] models a user through multiple aspects to create a comprehensive representation of the user. In this platform, a user model encodes different aspects of people's life, such as demographic data, interests, affect values, social relations, activities and physical states.

In relation to the research described in this paper, it is necessary to put attention on the stereotype-based user modelling in that typical categories of users that use the system in a similar way, expect from it similar outcomes and can be described by similar sets of features are identified [10]. As a rule, stereotypes are the result of user clustering regarding behavioural variables [11]. Stereotype-based user modelling is at the heart of various recommender systems (e.g., [12]).

The users' digital traces as a source of information to user modelling are used in a toolset for user profiling in the cybersecurity domain [13], a tool for assessing employee competencies [14], research on user modeling and personalization in the microblogging sphere [15], a method for personality prediction based on an analysis of users' activities in social networks [16], and in other approaches.

3 Conceptual Framework for Intelligent Decision Support Based on User Digital Life

The conceptual framework for intelligent decision support based on user digital life (Figure 1) is intended to recommend decisions that the user would made in the current situation (context). The main components of this framework are user digital traces, user profile, user digital life model, user segment, user ontology, and context [1].

User profile is a set user characteristics that can be used to create a descriptive portrait of an individual and to identify one. *User digital life model* is a structured representation of a part of the content of user digital traces, which carries information related to the decision-making process of the user. *User segment* is a group of users with common needs and behavioural reactions when making decisions. *User digital traces* is a set of records fixing information on the user activity including decision-making; it is a source of information to user profiling, user segmentation, and user digital life

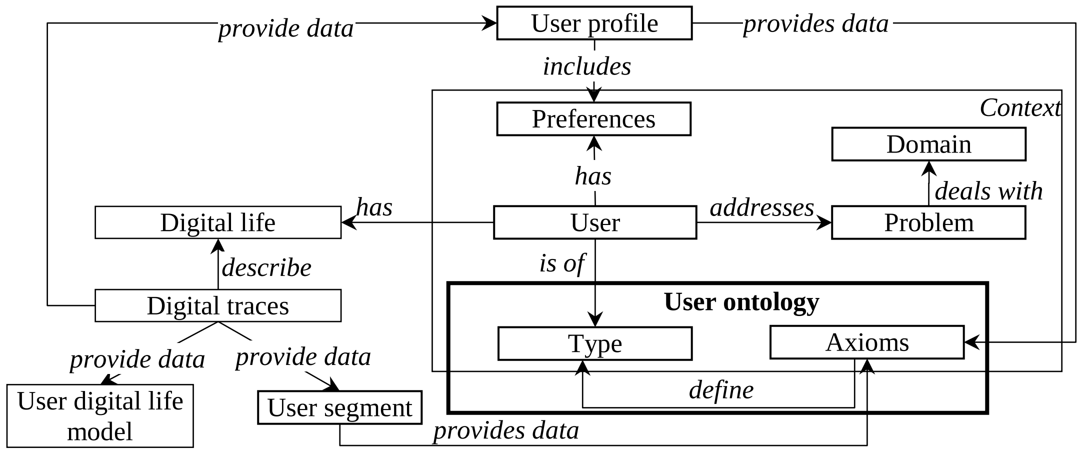

Figure 1: Conceptual framework for intelligent decision support based on user digital life model [1]

modelling. *User ontology* is a multi-aspect user model, which formalizes knowledge to classify a user into a user type, i.e. into a category of users distinguished by common preferences and decision-making behaviour. *Context* is any information that characterizes the user when making a decision. In the conceptual framework, context comprises the user identifying information and information on the user preferences, the user type, the problem requiring a decision, and the knowledge domain that this problem deals with.

The decision support according to the conceptual framework is as follows. When a user faces a problem requiring a decision, the information on this problem and the domain is introduced to the context model. The source of this information is the user digital life model. The contextual values of user characteristics from the user profile and user segment are introduced to the user ontology. Based on these values the ontology infers the user type and introduces this type to the context model. The instantiated context model is the basis to recommend a decision. This decision takes into account the specifics of the decisions that the users of the same type as the active user would make in the context of this user.

Digital traces is the framework's component that provides information about the users and their activities, i.e. the information that can be used to determine user types. This component is an unstructured information source. User profile, user segment, user digital life model, and context organize the information from the digital traces into meaningful structures. Below, a set-theoretic formalization for these components is given [17].

User profile (*UP*):

$$UP = (User\_ID,\ P\_out, P\_in(C)),\ P\_in(C) = DM\_Type(C) \bigcup P_c(C) \bigcup Pr(C)\ , \tag{1}$$

where $User\_ID$ is the unique user identifier, P_out is the set of context-independent user characteristics; P_in is the set of context-sensitive user characteristics in the context $C(T)$; $DM\_Type(C)$ is the user type in the context $C(T)$; $Pr(C)$ is the set of user preferences in the context $C(T)$; $P_c(C)$ is the set of context-sensitive user characteristics other than the user type and the user preferences (e.g., the user location, local time, etc.); T is the period of existence of the context C.

User digital life model (DL):

$$DL = \left(User\_ID, Problem(t_0, t_n), Domain, \left\{Action\left(t_a^-, t_a^+\right)\right\}, Decision(t_n), R_1, R_2, R_3\right),$$

$$R_1 \in Problem \times Domain,\ R_2 \in Problem \times Decision\ ,\ R_3 \in Action\left(t_a^-, t_a^+\right) \times Problem(t_0, t_n)\ , \tag{2}$$

where $Problem$ is the kind of the problem requiring a decision; t_0 is the time instant when the user starts decision-making; t_n is the time instant when the user has made a decision; $Domain$ is the knowledge domain that the problem deals with; $Action\left(t_a^-, t_a^+\right)$ is the action carried out on the interval t_a^-, t_a^+ $\left(t_0 \le t_a^-, t_a^- < t_a^+, t_a^+ < t_n\right)$; $Decision$ is the decision made.

User segment (*S*):

$$S = \left(Domain, Behaviour\_Type, Var, R_4, R_5\right),\ R_4 \in Domain \times Var,\ R_5 \in Var \times Behaviour\_Type, \quad (3)$$

where $Behaviour\_Type$ is the behavioural model of the users that belong to the segment S, Var is the set of behavioural variables providing data to the behavioural model.

User ontology (O_U):

$$O_U = \left(Cl, Rel, A\right),\ Cl = Cl_o \bigcup Type,\ A = A_o \bigcup A_{DM\_Type},$$

where Cl is the set of ontology classes, Rel is the set of class relationships ($Rel \to Cl \times Cl$), $Type$ is the class that represents the user types, $Cl_o = Cl \setminus Type$, A is the set of ontology axioms, A_{DM_Type} is the set of axioms that define the membership of the class $Type$ by a user, $A_o = A \setminus A_{DM\_Type}$.

Context (C):

$$C(T) = \left(user\_ID, user\_type(T), domain(T), problem(T), Pr_u(T), R_6\right), \quad (4)$$

$$user\_ID \to User\_ID,\ user\_type(T) = \left(dm\_type, s\right),\ dm\_type \to DM\_Type,\ s \to S,$$

$$domain(T) \to Domain,\ problem(T) \to Problem,\ Pr_u(T) \subseteq Pr,\ R_6 \in domain(T) \times Pr,$$

where $user\_ID$ is the unique user identifier, $user\_type(T)$ is the user type in the context $C(T)$, $problem(T)$ is the problem for which the user is making a decision in the context $C(T)$, $domain(T)$ is the domain of knowledge that the problem $problem(T)$ deals with, $Pr_u(T)$ is the set of user preferences in the context $C(T)$, $T = (t_0, t_n)$.

4 Multi-Aspect User Ontology

The apparatus of multi-aspect ontologies [2] is used to model a user of the intelligent decision support system implemented based on the conceptual framework (Figure 1). Three aspects corresponding to three framework's components are proposed to represent a user in the user ontology: a user profile, a user digital life model, and a user segment. The set-theoretic formalization of these components fits well with most ontology formalizations. The aspects are developed independently of each other. Generally, the representation formalisms of these aspects can be different. The mechanism of multi-aspect ontologies enables the aspects to be integrated. This mechanism supports heterogeneous aspect representations by alignment of structural elements of the aspect representation models. In this paper, means of aspect representations are limited by the constructions of the Web ontology language – OWL [18]. Consequently, the aspects below are described in the OWL terminology.

4.1 User Profile Aspect

The user profile aspect (Figure 2) comprises context-independent and context-sensitive user's descriptions in user profile (1). The classes corresponding to these descriptions represent the context-independent user characteristics (P_out) (e.g., unique identifier, name, occupations, field of interest, etc.) and the context-sensitive characteristics that are included in the context model C (4), that is, the

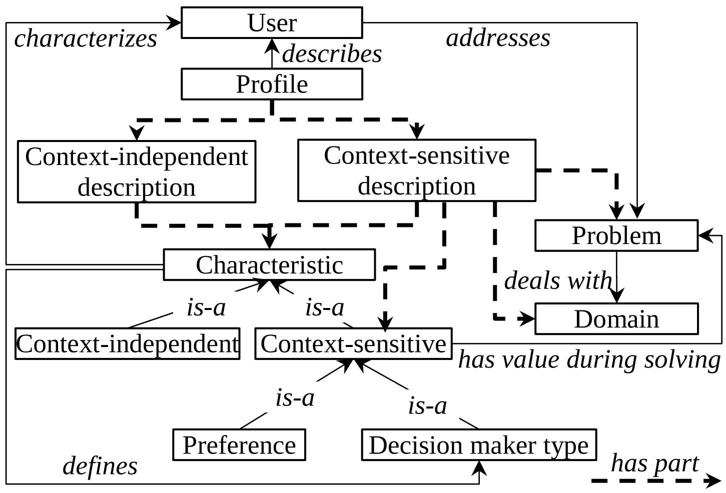

Figure 2: User profile aspect

user preferences $Pr(C)$ and the user type as a decision maker $(DM\_Type(C))$ in the context *C*. Corresponding classes represent the above characteristics. Besides the user characteristics, the context sensitive user's description comprises the kind of the problem (for example, searching, planning, diagnostics, etc.) that the user addresses in the context *C*, and the knowledge domain that this problem deals with. Classes *Problem* and *Domain* represent this knowledge, respectively.

Types of decision makers specified in the aspect (hidden in the class *Decision maker type* and not shown in the figure) are adopted from the project management domain. These types are based on decision-making styles distinguished in the management decisions. Each type corresponds to one of the styles. Spontaneous, rational, inert, risky, and cautious decision makers are subclasses of the class *Decision maker type*. Addressing this classification is because it is based on an analysis of the processes of evaluating and selecting alternatives by decision makers in any domain. A decision-making style reflects personality traits of the decision maker [19].

The spontaneous decision makers instantly select a decision from available alternatives. This style is characterized by making rapid, hasty, and impulsive decisions and is considered a feature of intuition [20]. As a rule, this style is typical for self-confident people with high self-esteem. They do not need a lot of additional information to make a decision. In some cases, they may turn to someone for advice, but they should know this person – a spontaneous decision maker will not waste time looking for a "good" consultant. Since in the spontaneous decision-making there are almost no procedures of searching for information, a comprehensive analysis of alternatives, and decision coordination, and, thus, little time is required for decision-making, the decision-making procedure is considered as simple. When selecting an alternative a decision maker of this type focuses on how quickly the decision will bring benefits.

The rational decision makers carefully and critically analyse and evaluate alternatives, weighing all the pros and cons. They consider important information search and special assistance. They often consult with specialists. For the rational decision makers, the complexity of their decision-making procedure and the decision-making time are estimated as medium compared to other decision maker types. The rational decision makers aim at making high-quality and effective decisions.

For the inert decision makers, forms and procedures are critical. They spend considerable time searching for missing and clarifying information to comprehensively analyse and evaluate alternatives. Due to such decision-makers subject any idea to careful analysis, harsh criticism and endless clarifications, it is more comfortable for them to work alone or in a small team in order to reduce the number of incoming alternatives. This decision-making style is typical for extremely insecure people. Decision-making is slow, takes a lot of time and the decision-making procedure is complex. The peculiarities of the nature of the inert decision makers dictate the main criterion is compliance with the formal procedure of analysis and evaluation of alternatives; at the same time, this analysis is aimed at making a qualitative and effective decision.

The decision makers of the risky type do not do a scrupulous analysis of alternatives and their weighing, as they are self-confident, not afraid of potential dangers, and ready to take risks. Their analysis is aimed at identifying the advantages of alternatives (ignoring the disadvantages) and the expected benefit or gain. At the same time, possible losses and associated risks are underestimated. It has not been revealed what kind of work, collective or individual, the risky decision makers are prone to. The complexity of the decision-making procedure for this type of decision makers and the decision-making time estimated as medium.

The cautious decision makers carefully and supercritical analyse and evaluate alternatives. They make great efforts to collect the necessary information. As a rule, they are insecure people, afraid of wrong decisions, and tend to consult with others. It takes a lot of time for them to make a decision, and the decision-making procedure is complex. Decision-making of a cautious decision maker is associated with the fear of making a bad decision, which forces them to try to minimize losses, just not to mistake.

The descriptions of the decision maker types above allowed us to find out the factors that can be identified in digital traces and based on values of which the type of a decision maker can be determined (Table 1).

Factor	Decision maker type				
	Spontaneous	Rational	Inert	Risky	Cautious
Decision-making time	low	medium	high	medium	high
The number of decision makers	one-two	group	one-two	one/group	group
Confidence degree	high	medium	low	high	low
Decision-making procedure	simple	medium	complex	medium	complex
Criterion	maximizing rapidity of getting benefit	maximizing effectiveness of problem resolving	maximizing effectiveness of problem resolving	maximizing benefits	minimization of losses

Table 1: Characteristics of decision maker types

The distinguished factors are:

- the number of decision makers to express a preference for an individual or collective decision-making style; in digital traces, it is represented by the number of recipients to whom the user sent requests during the decision-making, and the information on the initiation of groups for exchanging opinions or accepting invitations to such groups;
- the decision making time to express the thoroughness of the analysis and evaluation of alternatives (this time includes the time of searching for information); in digital traces, it is represented by search requests, the time spent to analyse the request results, and the time spent on selecting an alternative;
- kinds and number of knowledge sources used (including the number of decision makers) to express the degree of the decision maker's confidence in his/her knowledge and assessments. For instance, a decision maker that does not use any knowledge sources, i.e. relies only on own knowledge, is characterized by an extreme (high) degree of confidence. The other extreme is an uncertain decision maker with a low degree of confidence. Such a decision maker looks through large volumes of irrelevant information and contacts other individuals for help. A decision maker with a medium degree of confidence combines the analysis of specialized knowledge sources, the usage of appropriate applications and software services, and expert advises. The described examples of the confidence assessment are not full-fledged methods and given here just to illustrate the main ideas;

- kinds and the number of knowledge sources used, and the decision-making time to determine the degree of the decision-making procedure complexity that can be simple, medium, or complex. All the information revealed to determine values of the factors above is used to assess the complexity of this procedure. Since the present research does not suppose a development of an assessment methodology, the main evaluation principles are presented only. If the decision is made quickly (the decision-making time is low) and no additionally approved, then the procedure is evaluated as simple. If the decision-making time is high and the decision is not additionally approved, then the procedure is evaluated as complex. If the decision is made in a reasonable (medium) time with comprehensive coordination, then the procedure is evaluated as medium. If the decision-making time is high and the decision is comprehensively coordinated, then the procedure is assessed as complex. A quick decision with comprehensive approval is not considered, as it is thought unlikely;
- the decisions made to determine the preference criterion that a decision maker uses explicitly or implicitly; in this research, the source of information about the decisions made is the user digital life model (the information about the made decisions represented in this model is revealed from digital traces).

4.2 Aspect "User Digital Life Model"

The aspect that represents the user digital life model (2) comprises classes of *User*, *Problem*, *Domain*, *Action*, *Alternative*, *Decision*, and a set of classes describing temporal properties defined in (2) (Figure 3). *User* is a person who addresses a *Problem* and intends to resolve it as a decision support problem. *Problem* is a kind of problem that the user addresses. *Domain* is a knowledge domain that the *Problem* deals with. *Action* is a traceable digital activity that the user performs during decision-making. *Alternative* is an optional problem solution. *Decision* is an agreement to adopt an *Alternative* to resolve the *Problem*. In the figure, the set of actions is represented by one individual *Make,* since it is this action that determines the end of the decision-making process. In fact, the user digital life model contains a set of actions that the user performs making a decision on the time interval represented by the class *Interval*.

Additionally, the aspect represents classes that are under consideration by the W3C consortium as a recommendation for time modelling (Time Ontology in OWL) [21]. The class *Beginning* defines the time instant when the user faces the *Problem*; the class *End* captures the time instant when the *Decision* is made; the class *Interval* models the time interval that the user takes on the decision-making.

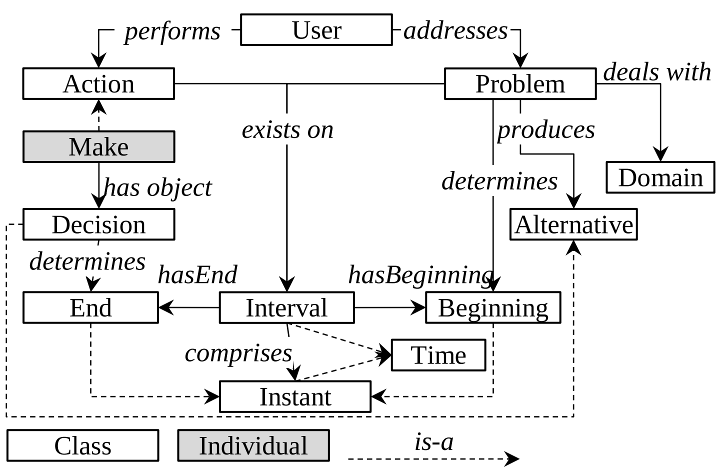

Figure 3: Aspect of user digital life model

4.3 User Segment Aspect

User segment is a group of users with common needs and behavioural reactions when making decisions. The main application area of the segmentation strategy is marketing. There, the users (consumers) are segmented to effective organize sales of products and services. In this paper, it is proposed to consider the users as consumers of Internet services, where the Internet service is a recommended decision, and the users express their behaviours when making it.

The user segment aspect comprises classes of *User*, *Behavioural variable*, *Behaviour model*, *Segment*, and *Domain* (Figure 4). *User* is a consumer of the recommendations. *Behavioural variable* is a user characteristic that affects his/her behaviour while decision-making. The behavioural variables provide data to building behavioural models. *Behaviour model* is an ordered sequence of user actions in the decision-making process. Behavioural segmentation divides consumers into *segments* according to these models. *Domain* is a field of activity for that the segmentation is carried out (with reference to decision support the domain corresponds to the area for that the recommendations are provided).

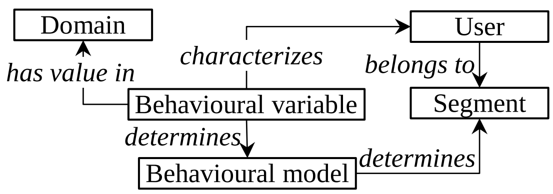

Figure 4: User segment aspect

The class *Segment* represents kinds of segments that specialists of McKinsey & Company identified in the research on online banking behavioral segmentation in the banking domain. They distinguished five segments: progressives, consolidators, always-hurrying, traditionalists, and security-concerned [22]. These segments seem to be quite suitable for the segmentation of Internet service consumers.

Progressives are good at the Internet, spend more than two hours each day browsing it, often consult others; use the Internet to search for information, make purchases, and communicate on social networks. Such users demonstrate a low level of loyalty to various institutions and brands and, as a rule, choose the most profitable offer for themselves after carefully studying the market. They are actively interested in innovations and are happy to use new services offered by providers.

Consolidators are interested in new technologies, but for them the benefits obtained with their help are more important. As well, an easy and fast access to the service is of a much priority for them. Such users spend at least one and a half hours a day online. They are active customers of online shops, participants of social networks, bloggers, but, compared to the progressives, they are less involved in the Internet. The consolidators prefer convenience to innovations and fashion. For example, they prefer e-commerce Websites that enable them to make multiple purchases at once. Their loyalty to institutions and brands is higher than that of the progressives.

Always-hurrying spend around an hour and a half a day online and prefer traditional services and reliable online shops. Like the consolidators, they appreciate convenience. These users are neither participants of social networks nor bloggers. They are sure that the Internet will help them save personal time and find the right solution on favorable terms. The always-hurrying users prefer written communications to speech.

Traditionalists are relatively new at the Internet and spend about an hour there. They visit sites that they are used to do systematically, and almost do not spend time searching for new sites or services. As a rule, they are loyal enough to their service providers and trust them. They see no reason to search for innovative products until they are convinced of their actual usefulness.

Security-concerned are not much different from the traditionalists, but they are much less likely to consume new services and rarely use online shops. About half of these users most often use the Internet only to view information about the status of their accounts and to check the balance. They are concerned that hackers may attack them. Comparing to the representatives of the other four segments, the security-concerned users more often ring up to the service providers to confirm transactions. Many preferences of such users come from the desire to protect themselves and their savings.

Based on the descriptions of the user segments above, behavioural variables are identified, values for that can be found in digital traces (Table 2). All the variables are fall into context-sensitive and context-independent. Namely, the values of variables such as the time spent online and the degree of involvement in social networks do not depend on the context, while some variables as, e.g., activity of the users accessing the bank's services or their attitude to innovative products offered by the bank are domain-dependent. Thus, in different domains, the same user may belong to different segments.

Variable	User segment				
	Progressives	Consolidators	Always-hurrying	Traditionalists	Security-concerned
Time spent in the Internet	much	moderate	moderate	little	little
Degree of involvement in social networks	medium	high	n/a	low	low
Degree of Internet services consuming	high	high	medium	low	low
Degree of interest to innovations	high	medium	low	low	low
Loyalty level	low	medium	high	high	medium
Preferable communication means	no preferences	no preferences	written	voice	voice
Criterion	maximizing own benefits	maximizing benefits of other users	maximizing own benefits, minimizing the time	utility maximization	minimizing losses

Table 2: Behavioural variables to user segmentation

Digital traces' content that provides values for the behavioural variables is following:

- time values represented in any record of the digital traces to determine the time spent by the user browsing the Internet;
- time values contained in digital traces produced by the social interactions to determine the degree of the involvement of the users in social networks;
- digital trace records that represent kinds of services that the users use, on the basis of which number of hits to these services is evaluated to determine the degree of the Internet-services consuming;
- digital trace records that represent the time when the users hit a service, which is compared with the time of the service release to assess the degree of the users' interest to innovations;
- records on searches for services that are the same as offered by a specific site; records containing information about the use of such services on other sites; and records containing information about the use of services (not necessarily those available on the given site) offered by competitors, to determine the level of the user loyalty;
- records containing information about phone calls or written messages when the users interact with the site, on the basis of which the frequency of both is calculated and the preferred means of communication is determined;
- decisions made to determine the user preference criterion expressed explicitly or implicitly (in this research, the source of the decisions is the user digital life model).

4.4 User Ontology

Integration of the aspects above produces the user ontology. The general ontology level is built to support the integration. For this, the methodology of the development of multi-aspect ontologies [2] is followed, which developed co-authored with the authors of the present paper. The schema of the general level creation is as follows. First, an aspect ontology level is constructed. This level comprises fragments of aspect ontologies, which represent classes shared by more than one aspect. Then, classes shared by more than one fragment of the aspect level are captured. These classes organize the general level. Necessary relationships are introduced to relate these classes appropriately. The aspect level represents possible kinds of the relationships. Corresponding classes of the aspect ontologies, classes represented by the fragments of the aspect level, and classes of the general level are aligned.

Regarding the aspects of user profile, user digital life model, and user segment, the following classes are shared by more than one aspect: *User, Problem, Domain,* and *Characteristic* or *Behavioural variable*. The ontology developers identified the classes *Characteristic* and *Behavioural variable* as identical, that is the individuals represented by these classes are members of a common class. This class has been referred to as *Characteristic.* At the aspect level, all the listed classes occur more than in one fragment and therefore are general level classes. Additionally, the developers introduced the class *Action* as a class of the general level to specify that digital trace records representing the user actions provide the values of the characteristics (Figure 5).

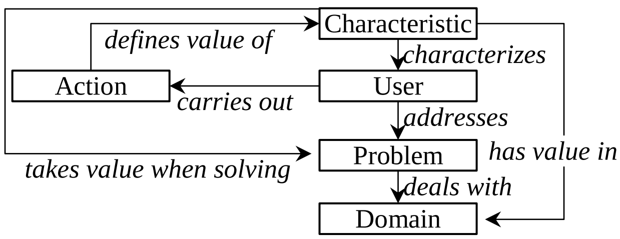

Figure 5: User ontology: general level

The general level proposes the following conceptualization. When the *User* addresses a *Problem* that uses knowledge from some *Domain* this user is carrying out *Actions* towards solving this problem. Performing the actions, the user demonstrates his/her personality traits (*Characteristics*). The characteristics' values depend on the kind of the *Problem* being solved and the *Domain*.

The user ontology infers a user type based on the values for the user characteristics. The set of relationships below that specify alignments between aspects' classes show that two aspects represent user characteristics: the user profile aspect and the user segment aspect.

Rel_1 = *GL*:Characteristic → *A_PU*:Characteristic;

Rel_2 = *GL*:Characteristic → *A_S*:Behavioural variable,

where *GL* – the general level of the user ontology; *A_PU* – user profile aspect; *A_S* – user segment aspect.

The user profile aspect contains the individual characteristics defining the user as a decision maker, such as preferences. The user segment aspect provides information on the decision-making behaviour of the user. In this regard, a user type is represented as a compound one: $Type = \{DM\_Type, DM\_S\}$, where DM_S is the user segment ($DM\_S \rightarrow S$).

Relationships Rel_1, Rel_2, Rel_3, Rel_4, and Rel_5 illustrate the aspect interrelations when the user ontology solves the problem of user classification.

Rel_3 = *GL*:Action → *A_DL*:Action;

Rel_4 = *GL*:Problem → *A_DL*:Problem;

Rel_5 = *GL*:Domain → *A_S*:Domain,

where *A_DL* – aspect of user digital life model.

Based on the relationships Rel_1, Rel_3, and Rel_4 the ontology determines the decision maker type of the user. The relationship Rel_4 defines that to determine values of the user characteristics the actions of this user represented in the digital traces at the interval (t_0, t_n) are analyzed. The aspect of user digital life model represents this fact through the the time instant when the user faces the problem and the time instant when the decision is made. Based on the relationships Rel_2, Rel_3, and Rel_5 the ontology determines the user segment in the problem domain.

5 User Ontology in the Conceptual Framework

In the conceptual framework for intelligent decision support based on user digital life, the user ontology serves to classify the users into user types based on their characteristics identified in the user digital traces in the context *C*. The user type is the basis to recommend a personalized decision on the problem that the user addresses in the considered context. The element of the user type that represents the user type as a decision maker provides information on the user preferences (see Table 1, row "Criterion"). The element of the user type that represents the user segment provides information on the decision-making behaviour of the user.

The distinctive features of the decisions that the users from different segments make usually are given in Table 3. In this table, integrated decisions represent the idea of one decision for several problems. An example of such a decision is a single website for registration at a conference, purchasing a ticket to travel to the conference venue, and hotel booking.

User segment	Decisions
Progressives	Innovative
Consolidators	Integrated
Always-hurrying	Quickly implementable
Traditionalists	Accustomed
Security-concerned	Known with feedback

Table 3: Features of decisions that users from different segments make

Usage of the user ontology in a decision support system that implements the conceptual framework can be illustrated by an example of a user that the ontology classifies as an always-hurrying. If this user also is classified as a spontaneous decision maker then this user if offered a decision that does not require much time for the implementation and brings benefits as quickly as possible. On the contrary, if this user is identified as a cautious decision maker, then he/she is offered a decision that does not require much time for the implementation and promises the least losses.

6 Conclusion

The paper proposes a multi-aspect user ontology that comprises three aspects: user profile, user segment, and user digital life model. The ontology is intended to be used in the intelligent decision support systems that recommend context-aware decisions. The ontology is aimed at a context-aware classification of the users into user types in order to offer them recommendations that other users of the same type would make in the context of the active users. User preferences and decision-making behaviour define a user type. The sources of information about the users (their personal and behavioural characteristics) and their contexts are the users' digital traces. The main research specific is the combination of user characteristics commonly used in decision support systems and user behavioral features identified by segmentation techniques to describe the type of a user as a decision maker.

The proposed decision support mechanism recommends decisions comfortable for given types of users. Speaking about efficiency of these decisions, they may not be such. As a compromise, the decisions recommended for the users whose type differs from the rational one can be offered to compare with the decision that would be supposed to make a decision maker of rational type in the same context.

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