Context-aware Personalized Decision Support based on User Digital Life Model

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Abstract: Digital traces is a source of information about the users and their actions while the online activities. A structured part of this source, which represents information related to the decision-making process of a user, is proposed to be formalized in the form of user digital life model. The decision support system addresses this model for information to recognize user types and recommend personalized decisions. A user type is characterized with common personality traits of the users as decision makers and common decision-making behaviours of these users as consumers. A user ontology represents a priori knowledge on the user types and supports the user classification into them. The paper considers kinds of factors influencing decision-making styles and consequently personality traits of decision makers as well as behaviour variables determining decision-making behaviour. The user digital life model provides information to score these factors and instantiate the variables. A decision support scenario is described and its application to a search problem is demonstrated.

1 INTRODUCTION

Personalized decision support based on information from user digital traces has recently gained popularity as a result of the success of the efforts on personality prediction from these traces (Stachl, Pargent, et al., 2020). Digital traces are beneficial for obtaining users' personality traits without burdensome questionnaires. Decision support systems (DSSs) and recommendation systems add the personality information in the processes of decision support and recommendation.

One of the problems of using information from digital traces is their weakly structured and poorly curated content that complicates its analysis in a context-aware meaningful way (Breiter & Hepp, 2018). Information from the digital traces represented in a well-structured way would simplify its analysis to predict personality.

Context-aware integration of information describing personality traits and online behaviour that the user manifest while decision-making to predict or recognize personality would increase the efficiency of DSSs.

The paper proposes a conceptual framework of personalized decision support based on user digital life model, in which such a model systematizes the content of digital traces and represents information related to the decision-making process of a user. This model is used as an information source to recognize user types and recommend personalized decisions. A user type groups users with common personality traits of them as decision makers and common decision-making behaviours as consumers. A user ontology represents a priori knowledge on the user types and supports the user classification into these types. The types are context-sensitive, i.e. the same user in different contexts can be classified into different user types. A DSS that implements the conceptual framework infers the user type and recommends a decision based on the knowledge about the kinds of decisions customary for the users of this type.

The rest of paper is as follows. Section 2 outlines related research. Section 3 introduces a conceptual framework of personalized decision support based on

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user digital life model. Section 4 presents the user ontology and provides ideas of user classification. Section 5 describes a scenario of personalized decision support according to the conceptual framework. Section 6 demonstrates the scenario applied to a book search problem. Section VII discusses main concluding remarks.

2 RELATED RESEARCH

Many studies have concluded that personalities influence human decision making process and interests (Rentfrow & Gosling, 2003).

The most commonly, research on personality prediction from user digital traces analyses traces from social media platforms. Such approaches include integrating information from Twitter on self-language usage, avatar, emoticon, and responsive patterns (Wei et al., 2017) or on profile attributes and language (Sumner et al., 2012); integrating text, image, and users' meta features from Twitter and Instagram (Skowron et al., 2016); integrating demographic features, social network activities, and language extracted from Facebook, Twitter, and YouTube (Farnadi et al., 2016); analysing text and pictures contained in traces left in multiple public and private social media platforms (Azucar et al., 2018).

Researchers agree that personality traits and individual behaviour patterns are strongly related (Augstein et al., 2019). In this direction, approaches integrate information on networks-related behaviour and personal traits (Lee & Kim, 2017; Zhao & Zhu, 2019); personal traits and emotions as a behaviour regulating factor (Lerner et al., 2015; Tkalčič, 2020); personal traits and behaviour activities of smart-phone users (Stachl, Au, et al., 2020), and others.

Various personalized DSSs and recommendation systems exploit digital traces as a resource of personality information (e.g., (Courtin & Tomasena, 2016; Narducci et al., 2019)). Comprehensive reviews of personality-based recommendation systems that use information on personality traits extracted from digital traces and combine it with user behaviour can be found in (Augstein et al., 2019; Suhaim & Berri, 2021).

Multiple personalized and adaptive systems rely upon user types (or stereotypes) characterized with common personal features. Researches that support prediction of user types through classification include a classification of social media users into types that reflect the level of their engagement in the media usage (Lee & Kim, 2017), personality classification based on Twitter text (Pratama & Sarno, 2015), and others. Ontologies, which provide classification service, support a user categorization based on personality traits, facets, culture, and age in relation to specific tasks (El Bolock et al., 2020); personality traits and facets recognized in different tests (Garcia-Velez et al., 2018); textual data contained in the digital traces (Alamsyah et al., 2021); combinations of text and social behavioural aspects of user on multiple social media (Sewwandi et al., 2017), and many others.

The present research relies upon a user digital life model as a collection of user-specific information. This model is a structured representation of a part of the content of user digital traces. Personality is recognized through ontology-based classification. A user ontology represents a priori knowledge on user types. It infers a user type based on the type definitions and information from the user digital life model. The information used concerns the user traits and online behaviour that this user manifest while decision-making.

3 CONCEPTUAL FRAMEWORK

The conceptual framework of personalized decision support based on user digital life model (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 (Smirnov & Levashova, 2020). The user digital life model is the main source of information for the rest of the components.

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 traces* is a set of records fixing information on the user activities including decision-making. *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 ontology* is a user model, which formalizes knowledge to classify a user into a user type, i.e. into a category of users distinguished by common personality traits of these users as decision makers and common decision-making behaviour. *Context* is any information that characterizes the situation of the user in the decision-making process. In the conceptual framework, context comprises the user identifying information and the information on the user preferences, the user type, the problem requiring

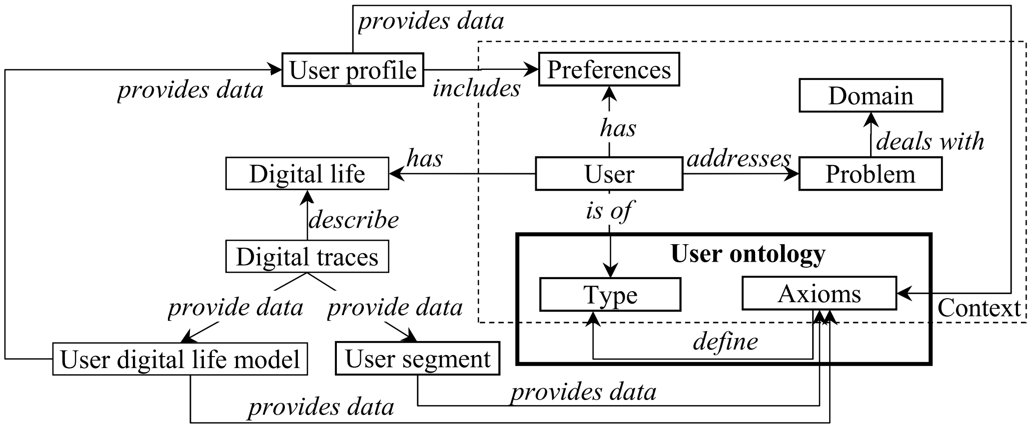

Figure 1: Conceptual framework for personalized decision support based on user digital life model.

a decision, and the knowledge domain that this problem deals with.

When the user requests the DSS with a problem requiring a decision, or when the DSS finds out that the user needs a recommendation, the system infers the user type and recommends a decision based on the knowledge about the kinds of decisions customary for the users of this type.

The framework components are modelled using the set-theoretic approach.

User profile (*UP*):

$UP = (User\_ID, P\_out, P\_in(C))$,

$P\_in(C) = DM\_Type(C) \cup P_c(C) \cup Pr(C)$,

where $User\_ID$ is the unique user identifier, P_out is the set of context-independent user characteristics; $P\_in(C)$ 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):

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

$R_1 \in Problem \times Domain$, $R_2 \in Problem \times Decision$, $R_3 \in Action(t_a^-, t_a^+) \times Problem$,

where $Problem$ is the kind of the decision-making problem ($Problem(t_0, t_n)$ means that the user addresses the problem $Problem$ in the interval (t_0, t_n)); 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 $Problem$ deals with ($Domain(t_0, t_n)$ means that the domain knowledge is dealt with in the interval (t_0, t_n)); $Action(t_a^-, t_a^+)$ is the action carried out in the interval (t_a^-, t_a^+) $(t_0 \le t_a^-, t_a^- < t_a^+, t_a^+ < t_n)$; $Decision(t_n)$ is the decision made at the time instant t_n.

User segment (*S*):

$S = (Domain, Consumer\_Type, Var, R_4, R_5)$, $R_4 \in Domain \times Var$, $R_5 \in Var \times Consumer\_Type$,

where $Consumer\_Type$ is the type of users sharing a common behavioural pattern when choosing a decision, Var is the set of behavioural variables providing data to the behavioural pattern.

User ontology (O_U):

$O_U = (Cl, Rel, A)$,

$Cl = Cl_O \cup Type$, $A = A_O \cup A_{DM\_Type}$,

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, $Cl_O = Cl \backslash Type$, 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, $A_O = A \backslash A_{DM\_Type}$.

Context (C):

$$C(T) = (user\_ID, user\_type(T), domain(T), problem(T), Pr_u(T), R_6), \quad (1)$$

$user\_ID \subset User\_ID$, $user\_type(T) = (dm, consumer)$, $dm \subset DM\_Type$, $consumer \subset Consumer\_Type$, $domain(T) \subset Domain$, $problem(T) \subset Problem$, $Pr_u(T) \subseteq Pr$, $R_6 \in domain(T) \times Pr$,

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 that the user is making a decision in the context $C(T)$; $domain(T)$ is the knowledge domain 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 USER ONTOLOGY

The user ontology represents a priori knowledge on user types and supports the user classification.

4.1 User Types

A user type is compound. It combines the type of users as decision makers and the type of users as online consumers. Two direct subclasses of the class *Type*, that are *DM_Type* and *Consumer_Type*, represent these subtypes, respectively. The user types are context-sensitive.

The class *DM_Type* represents types of the users depending on their decision-making styles and class axioms that specify user characteristics influencing these styles. A decision-making style affects personality traits of a decision maker (El Othman et al., 2020), preferences for the selection of an alternative (Sharma & Pillai, 1996), and eventually the decision. Kinds of the decision-making styles are adopted from the management domain. According to them, decision makers can be spontaneous, rational, inert, risky, and cautious.

Detailed descriptions of the decision-making styles (Allen, 2017; Bavol'ár & Orosová, 2015; Sharma & Pillai, 1996) allowed us to find out factors that influence decision making and that can be scored based on information from digital traces (Table 1).

Number of decision makers expresses a preference for an individual or collective decision-making.

Decision making time expresses the thoroughness of the analysis and evaluation of the alternatives (this time includes the time of searching for information). It is scored as low, medium, or high.

Confidence degree scores the confidence of the user in his/her knowledge and assessments in the scale of low, medium, and high.

Complexity of decision-making procedure is the complexity of the process thought that the user has to go to reach the final decision (searching for information, analysing and evaluating the alternatives, consulting, and decision coordinating). This procedure is proposed to be assessed as simple, medium, or complex.

Criterion is the preference criterion (latent or explicit) that the user applies to evaluate the alternatives.

The class *Consumer_Type* classifies the users as consumers of the recommended decisions based on the behavioural variables (*Var*). The classification used has come from the customer behaviour segmentation, which focuses on the division of the users into groups based on common online behaviour patterns. In the paper, it is supposed that the users play the role of Internet service consumers, the DSS is an online service that recommends decisions, and the users' behavioural patterns when they are thinking of either accept a decision or do not reflect the online behavioural patterns of these users as consumers. Progressives, consolidators, always-hurrying, traditionalists, and security-concerned consumers are represented in the class *Consumer_Type*.

Based on detailed descriptions of the consumer types, behavioural variables are identified, values for that can be found in digital traces (

Table 2). The meanings of these variables are intuitively clear; therefore, they are not described unlike the factors.

4.2 User Digital Life Model

Actions and decisions specified in the model of user's digital life are analysed to identify the information that can be used to score the factors (Table 3) and variable values (Table 4).

Actions on information search (information search requests) and communicating actions provide information to score the number of decision makers (f1) and to score the user confidence degree (f3) (a decision maker that relies only on own knowledge, is characterized by an extreme (high) degree of confidence and opposite, a decision maker that looks through large volumes of irrelevant information and

Table 1: Factors influencing decision making allocated to decision maker types.

Factor	Decision Maker Type				
	Spontaneous	Rational	Inert	Risky	Cautious
f1. Number of decision makers	one-two	group	one-two	one/group	group
f2. Decision-making time	low	medium	high	medium	high
f3. Confidence degree	high	medium	low	high	low
f4. Complexity of decision-making procedure	simple	medium	complex	medium	complex
f5. Criterion	maximizing rapidity of getting benefit	maximizing effectiveness of problem resolving	maximizing effectiveness of problem resolving	maximizing benefits	minimizing losses

Table 2: Behavioural variables influencing consumer type.

Variable	Consumer Type				
	Progressives	Consolidators	Always-hurrying	Traditionalists	Security-concerned
v1. Time spent in the Internet	much	moderate	moderate	little	little
v2. Degree of involvement in social networks	medium	high	do not use, usually	low	low
v3. Degree of Internet services consuming	high	high	medium	low	low
v4. Degree of interest to innovations	high	medium	low	low	low
v5. Loyalty level	low	medium	high	high	medium
v6. Preferable communication means	no preferences	no preferences	written	voice	voice
v7. Criterion	maximizing own benefits	maximizing benefits of other users	maximizing own benefits, minimizing time	utility maximization	minimizing losses

contacts other individuals for help is characterized by a low degree of confidence). Time values fixed for the actions on information search and on the interactions of the user with the DSS are used to calculate how much time the user gathers and analyses information, and evaluates the recommendation in order to either accept or decline it (f2). All kinds of actions used to score factors f1–f3 are used to score complexity of the decision-making procedure (f4) (if the decision is made quickly (the decision-making time is low) then the procedure is assessed as simple; if the decision-making time is high then the procedure is evaluated as complex). The result of an analysis of the user decisions is the criterion (f5), which expresses explicit or latent preferences of the user.

Table 3: Digital life model as source for factor scores.

Factor	Information from digital life model
f1	Number of individual recipients or groups to which the user sent requests
f2	Time taken to analyze the request results, and to evaluate the recommendation
f3	Kinds, number, and relevance of the knowledge sources used
f4	All the above
f5	Decision

Table 4 provides information from the user digital model that can be analysed to instantiate the behaviour variables. Durations calculated based on the time values fixed for the corresponding actions instantiate the time behaviour variables (the first three rows in the table). The degree of the Internet-services consuming is calculated as the ratio of the number of the kinds of the services used to the number of hits normalized to low, medium, or high. The loyalty level is determined by the information showing the user interest to similar services offered by different organizations. Communication activities provide information about phone calls or written messages of a user, on the basis of which the frequency of both is calculated and the preferred means of communication is determined. The criterion is determined based on the information about the decisions that the user digital life model specifies.

Table 4: Digital life model as source for variable values.

Variable	Information from digital life model
v1	Time fixed for the on-line activities
v2	Time fixed for the social networks activities
v4	Time fixed for service hints comparing with time of the service releases
v3	Kinds of services used, service hits
v5	• Activities on searching for the services that are the same as offered by a specific site • Activities on the usage of services that are the same as offered by a specific site services on other sites • Activities on the usage of services offered by competitors
v6	Communication activities
v7	Decision

5 PERSONALIZED DECISION SUPPORT SCENARIO

The scenario of personalized decision support based on user digital life model implements the general idea of the conceptual framework and leaves aside cases when the user does not accept the recommendation. Such cases create a reason to a refinement of user types and system learning, but they are out of research scope so far. The scenario considers situations that the DSS addresses on the interval from the time instant when the user starts decision-making until a recommendation has been provided (Figure 2).

A problem that the user faces (the decision-making problem) initiates the scenario. The information on the unique user identifier $user\_ID$, the time *t* when the user performs the actions causing the system reaction, these actions $action(t^-, t^+)$, $action(t^-, t^+) \subseteq Action(t_a^-, t_a^+)$ (the very first action in time is $action(t_0, t^+)$), the decision-making problem *problem(t)*, and the domain $domain(t)$ is identified in the user digital traces and becomes represented in the user digital life model.

A formal problem model is built. The DSS uses this model to solve the problem $problem(t)$ as a decision support problem. The function *M*: *problem(t)* → *PM* assigns the problem its formal model.

Scores for the factors determining decision-making styles and values for the behaviour variables are assessed based on the user characteristics

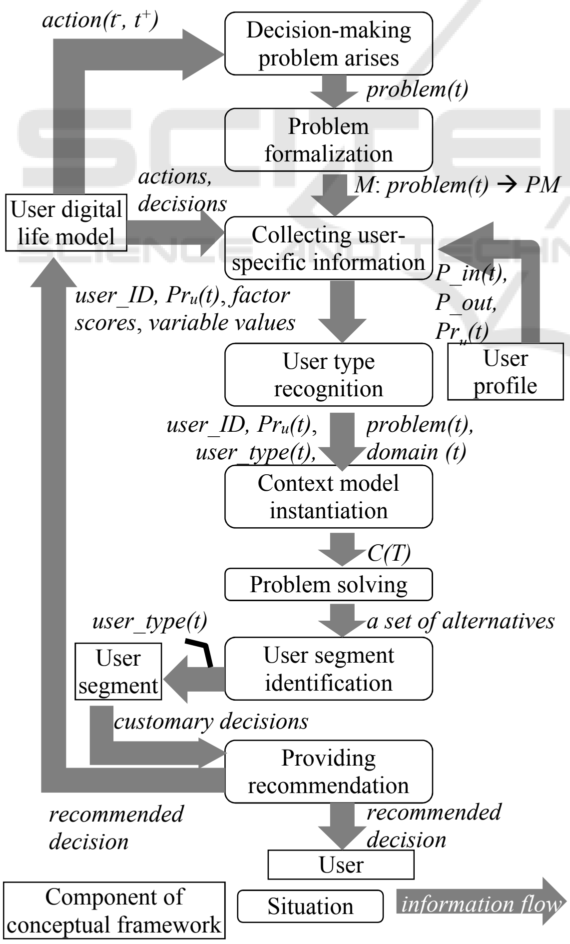

Figure 2: Scenario of personalized decision support.

contained in the user profile and the information from the user digital life model. These scores and values fully or partly instantiate the ontology axioms and rules that define the user types. The fully instantiated axioms and rules become assertions (axioms and rules describing individuals (Glimm et al., 2012)).

Based on the set of the assertions, the ontology solves the classification problem and derives the user type (*user_type(t)*) made up of the user type as decision maker and the user type as consumer.

The information on the user identifier (*user_ID*), the user type (*user_type(t)*), the kind of the problem that the user addresses (*problem(t)*), the knowledge domain (*domain(t)*), and the set of user preferences ($Pr_u(t)$) instantiates the context model *C(T)* (1).

Using the model (*PM*), the DSS solves the problem *problem(t)* as a decision support problem. The result of problem solving is a set of alternatives.

In accordance with the user type as consumer, the segment of the users of this type is distinguished and the kind of decisions customary to the users of this segment is identified. Based on this kind of decisions a recommended decision from the set of alternatives is selected. The recommended decision is delivered to the user, appears in the user digital traces, and saved in the user digital life model:

$$DL(t_n) = (User\_ID, problem(T), domain(T), \{action\ (t_n)\}, decision\ (t_n)).$$

6 USE CASE

The scenario above is demonstrated by an example of decision support for the user that searches a book on programming in Java in a library.

The user name is Alex; the part of the digital life model built for Alex based on his digital traces for the problem in question is as follows:

$$DL_{Alex}(t_0, t^+) =$$
$$= (Alex, Search(t_0), Library(t_0), \{action(t_0, t^+)\})$$
$$t_0 = 2020\text{–}11\text{–}19\ 19{:}55{:}16.057\ \ ,\ \ \{action(t_0, t^+)\} =$$
$$= \begin{Bmatrix} Press.MenuItem.Search(\text{2020-11-19 19: 55: 17.0648, 2020-11-19 19: 55: 17.926}) \\ Chose.Option.Title(\text{2020-22-19 19: 55: 16.057, 2020-11-19 19: 55: 18.873}) \\ Enter.Title.\text{Programming in Java}(\text{2020-11-19 19: 55: 19.203, 2020-11-19 19: 55: 19.936}) \end{Bmatrix}.$$

The model above specifies that the user identified as Alex ($user\_ID$ = Alex) addresses the problem of searching ($problem(t)$ = $Search(t_0)$) a book entitled "Programming in Java" in the library ($domain(t)$ = $Library(t_0)$).

The preferences of Alex coming from his profile for the problem of book searching declare that the preferable language for Alex is English. Based on the scores for the factors influencing decision-making styles and values for the behaviour variables, the user ontology classifies Alex as a spontaneous decision maker and as an always-hurrying consumer. The scores are obtained as results of an analysis of the actions and decisions represented in Alex's digital life model. All the actions and decisions that concern the problem of books searching are analysed, not just those for the given time (for the time interval $[t_0, t^+]$ this model does not contain a decision).

Below, the instantiated context model (1) is given.

$$C(T_c) = (Alex, SA(T_c), Library(T_c), Search(T_c), language\text{:English}(T_c)),$$

SA = (spontaneous, always-hurrying), $T_c = [t_0, t_c)$, t_c – the moment of the context model instantiation.

A set of available in the library books in English devoted to programming in Java is the result of problem solving. The DSS uses the information that the always-hurrying users prefer quickly implementable decisions to select a recommendation from this set.

Among various options that the library suggests are benefits for its subscribers. The DSS checks in the Alex's profile that he is a library subscriber and recommends the book: "Herbert Schildt, Java: The Complete Reference, Ninth Edition, McGraw-Hill Education – Europe, 2014, 1312 p. (English, Paperback), ISBN: 9780071808552." This book is digitalized and the library can provide access to a digital copy of the book immediately after the request of a subscriber. Alex accepts the recommendation by ordering the book from the library.

Alex's digital life model is updated with the recommended decision:

$$DL_{Alex} = (Alex, Search(t_0, t_n), Library(t_0, t_n), \{action\ (t_0, t_n)\}, \text{"9780071808552"}), (decision(t_n) = 9780071808552).$$

7 CONCLUSIONS

Personalized decision support needs user-specific information. Digital traces is a valuable resource of such information. The paper proposes a conceptual framework of personalized decision support in which the core source of information about user specifics is user digital life model. This model systematizes and contextualizes the content of digital traces that can be used to recognize personal user characteristics. Based on these characteristics the user ontology infers a user type. The DSS implementing the proposed framework refers to the user type to recommend a decision customary for the users of this type.

The novelties of the presented research are that it proposes a user digital life model, which offers a new means for organizing weakly structured content of digital traces; suggests a way to recognise context-sensitive user types from their digital traces, and gives idea of a system dealing with context-sensitive user types to provide personalized recommendation.

Future research can address the development of decision support scenarios for the cases when the user does not accept the recommendation.

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