Contextual personalization

TPB in user modeling

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##### Theory of planned behavior in user modeling: motivation, procedure and applicational example

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The aim of this study was to investigate the use and the potential of the psychological theory of human behavior modeling, called the theory of planned behavior (TPB), in a user modeling domain. We performed a user experiment involving a well studied problem of user modeling: recommender system (RS) for movies. As a part of the TPB, a survey to estimate behavioral, normative and control beliefs regarding movie selection was designed. Using participantsâ€™ responses, Ajzen model for movie genres was built and evaluated. Existing public dataset for context-aware movie recommendation CoMoDa was used to evaluate the proposed method. Results had shown that the TPB approach lead to an accurate prediction of selected movie genres. Among others, the potential applications of TPB in recommender systems and what is the architecture of such RS were addressed. Questions of what are potential applications of TPB in user modeling domain and what are limitations and drawbacks of it were discussed. Theory of planned behavior, Ajzen model, Recommender system

## 1 Introduction

User modeling and user adaptation techniques have received much attention in recent decades as the way how to tackle the problem of human computer interaction in broad range of communication services. Recommender systems as a part of this user modeling are today a part of most services that involve content or service selection made by end users. A tremendous amount of academic, industrial research and development was dedicated to develop more efficient user modeling techniques. Many user adaptation tasks can be seen as a problem of effective recommendation of predefined set of entities. Several different directions of algorithm are under development due to the fact that effective user adaptation is very much dependent on the domain of recommendations. However, several drawbacks of existing user modeling techniques are only partially solved such as the problem intrusive end user data acquisition, end user privacy protection, the problem of diversity of RS, etc.

One direction of addressing these issues is to predict end user behavior while he is interacting with the service and utilize such prediction in user adaptation. Human behavior modeling is an intensive research field in psychology for several decades . The theory of planned behavior [29] is particularly appealing in user modeling and adaptation for several reasons. First, the behavior model it assumes is relatively easily interpreted in several domains in the way that the available adaptation domain knowledge can be utilized. Second, The next reason is the procedure of building the Ajzen model for a given domain is a well defined procedure (we present it in Sec. 2). Third, , the prediction model is not predefined but can be selected according to the domain knowledge. Fourth, there is a large amount of modeling cases providing rich past experiences resulting in effective modeling guidelines.

We present the procedure of Ajzen model building including how to select predefined behaviors and demonstrate the model on a real users dataset. We discuss the potential of this type of psychological modeling of human behavior in user adaptation procedures. Discussion also addresses constrains and issues of further development in regard to implementation of TPB into RS.

### 1.1 Related work

#### 1.1.1 Recommender systems

The main goal of RSs is to predict the ratings for the items that the user has not consumed yet. Based on the predicted ratings, the suitable items (those with high predicted ratings) are selected and provided as the recommendations. Content-based (**CB**) recommender systems [23] analyse the itemsâ€™ descriptions in order to learn the user's preference for specific types of items. The prediction for the unseen item is based on the ratings for similar items by the same user. There are many limitations of CB systems: the system depends on the metadata which has to be explicitly associated with each item; overspecialisation due to the item-similarity paradigm; the users are not given serendipitous recommendations and the user is held in the so-called "filter bubble" [22]. In Collaborative Filtering (**CF**) strategies the prediction for the unseen item is based on the opinion from users with similar tastes [25]. This approach ignores the items' metadata so cross-domain recommendations are possible (e.g., books, movies, music, etc.) by employing cross-domain techniques [13]. After the Netflix prize competition [7], matrix factorization has become a popular CF technique [18, 17]. When a substantial amount of ratings are present in the system, these techniques tend to outperform other approaches. However, according to [5], for the user whose tastes are unusual compared to the population, the similarity to other users will be poor, hence resulting in poor recommendations for such a user. Knowledge-Based (**KB**) systems use knowledge from the domain expert in order to prepare meaningful recommendations [26]. However, pure KB systems are not popular and widely used, since they are expensive due to the required input from the domain expert. In order to overcome the different problems with the CF and CB strategies, they are sometimes combined into the Hybrid RS [9]. Furthermore, some context-aware techniques actually fall into the hybrid-system strategies, since the basic rating prediction can be made in one way and later adapted by the contextualization, e.g., post-filtering contextualization [1].

This kind of model construction has a number of constrains. One way to adddress these issues is to gain additional knowledge in regard to One such model is Lazy User Theory [Lazy User Theory: A Dynamic Model to Understand User Selection of Products and Services]. Authors developed a theory that a user will most often choose the solution that will fulfill her information needs with the least effort. Such assumption allows us to explain selection factors using multivariate statistics but it also assumes that a user has a clear defined goal in while seeking information. However, it seems this simple and strong hypothesis is not valid in many situations of user interaction with information systems due to the fact that modern users uses these systems with no specific goal. A different theory, TPB seems more promissing in this context. The theory and the rationals for applying it in the RS context are provided below.

#### 1.1.2 Theory of planned behavior (TPB)

A pioneer work on theory of planned was carried out by Icek Ajzen [3] and model suggested by TPB is usually called Ajzen model.

Ajzen model was introduced as a complete model for explaining human behavior and is based on a large number of behavior studies. According to TPB, human behaviors are influenced by attitudes towards the behavior, by subjective norms regarding the behavior and perceived behavior control [3], see Fig. 1. Behavior is domain specific; in this study we selected the behavior as a selection of a movie with a given genre. Attitudes are beliefs that one person has about the outcomes of the behavior (seeing the selecting movie) and are divided into cognitive, emotional and behavioral. Subjective norms are related to beliefs about the expectations of others and the wish to comply them. Behavior control relates to the ability one can perform the preselected behavior and this directly affect the decision about the behavior.

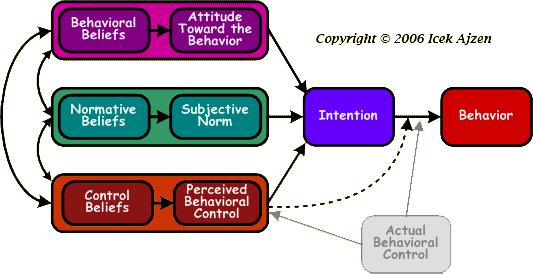


Figure 1: A diagram of Theory of planned behavior, reproduced from [29].

There are several areas where human decision making is of key importance exhaustively studied by TPB models such as outdoor recreation activities [11], decisions related to high school studies [12], public transportations habits [6], health related behavior [2], consumer attitudes and behavior [4], employers' hiring intentions [14] and job satisfaction [15], adoption of wireless sensor network service in households [21], factors Influencing the intention to watch online video advertising [20] and mobile phone usage while car driving [27],[28].

The common goal of these studies is not only to be able to predict human decision but also to understand the underlying mechanism of these decisions. These explanations are then used to create a new theory or to modify existing ones in order to provide a further insights of the targeted domain.

Extensive tutorials of how to effectively build and apply models of TPB in practice are available online [29]. A guide for conducting statistical analyses in a reasoned action context is given in [8]. Further research directions related to TPB and Ajzen model are surveyed in [16].

### 1.2 Problem statement

The goal of this papers is to provide a rational for using the Theory of planned behavior (TPB) in user modeling applications. We present the background of the TPB and outline the procedures for the acquisition of the TPB parameters. As a proof-of-concept we present the results of an experiment where we used in TPB model in recommender system for movies.

## 2 The procedure of model building

We list the below given procedure of TPB building to collect the most relevant guidelines and potential errors for the UM community. There are two reasons why a crucial step of the model building is the selection (definition) of behaviors. The first one is the fact that the quality of the model is mainly limited by the selection of behaviors, details are given at step 1. below. The next one is that selected behaviors also defines the role of the modeling itself. These roles can vary from predicting groups of items to the explanation of the specific aspect of the decision making process. We elevate on this in section 5.

1.  *Define a set of behaviors.* As indicated above, this is the most important step of the whole modeling task. Prior to it the reason why we apply the TPB must be clarified. In this paper given example the reason was to further understand mechanisms of movie selection. Preliminary results showed that there are high variabilities among users regarding genres of movies they select. So we conclude that understanding reasons for these variabilities would provide the insight that we can utilize to improve the accuracy of user model in move recommender. If we defined behaviors as selection content item (each movie was associated to one behavior) we would gain no explanation. Besides, the model quality would be very low due to the lack of separability of behaviors. This observation leads to the second guideline which is related to the quality of model fitting. The behaviors are required to be discriminable by the reasonable user data. This means that the survey (see step 2.) used to acquired user data is feasible, that is short enough and clear enough. Also, it is clear that two behaviors that are the same in most of end user situations can not be discriminable. For example, if two genres are both either present either not not present in almost all movies selected by users, these associated behaviors can not be discriminable. To summarize, the behavior definition should relay on a end user data analysis and on the clear goal of the modeling itself.

2.  *TPB questionnaire construction.* The next step is to design a questionnaire for end users in order to estimate parameters of the model. It must meet the requirements set by TPB. We group them into three groups regarding Behavioral beliefs (about consequences of the behavior), normative beliefs (about expectations of others) and control beliefs (about factors that affect the performance of the behavior). Therefore, this construction requires deep domain knowledge of the selected behaviors. The base of all questions are the defined behaviors (see step 1.). The next issue addressed is the specification of end user population. Five to six questions are then formulated to assess each of the constructs (attitude, norms, control and intention). For each question, the type of answers is selected. As usual, the next phase is administering a pilot questionnaire, its evaluation on a small population following by a standard questionnaire construction.

3.  *Select and build the prediction model.* According to the constructed questionnaire and a set of predefined behaviors, a prediction model is selected. First, the criteria variable indicating the true behavior is constructed. In our example of movie genre selection, for the first the criteria variable is computed from the past movie selection of the targeted end users (see Sub. 4.1). For the second model, the criteria variable is the simply genre indicator of the most likely selected genre by this end user. Next, the model itself is selected. Typically, the first option considered is linear regression model if predictor and criteria variables fits the requirements. Options are also linear discriminant analysis, logit regression model, canonical regression, stuctual equations modelling etc. In general, there is no limitation from the TPB imposed on the model selection. For example, one could apply neuron network to model the relationship among predictor and criteria variables. However, the explanation power of the selected model also matters since the interpretation of the fitted model may provide useful hints for further improvement of user adaptation procedure.

4.  *Interpret the model.* Interpretation of models are based on standard interpretation of selected models. For instance, linear regression model is interpreted according to the sign and magnitude of the estimated normalized model coefficients etc. Again, the main aim of the mdel is 1) to gain additional insight into the mecanisms behind mocvies selections, and 2) to improve the performance of RS.

## 3 Materials and Methods

### 3.1 Participants

In our experiment we had 28 subjects aged between 17 and 38 years old (18 males and 10 females). Each of the subjects filled-in a TPB questionnaire using GDrive forms. Users were selected from contributors of movie ratings in contextual movie dataset CoMoDa [19].

### 3.2 Instruments

The constructed TPB questionnaire consists of 49 questions related to beliefs regarding move selection and consumption according to TPB and is available on-line. The filling time was 10 to 12 minutes. Most of the answers were level Likert scales Not important - Important (38), some were binary (2) and No - yes (7) and some required free text answer (3).

## 4 Results

As already indicated, the selected behaviors we model are selection of three movie genres drama, action and comedy. In this section we list and briefly explain results of TPB models fitting of user data acquired by the designed questionnaire. We first explain procedures undertaken to measure behaviour; following we explain how and why we used TPB variables for modelling the behaviour.

### 4.1 Construction of criteria

We describe the ground truth user behavior by two criteria variables determined from known users past movie selections and ratings they provided for the dataset CoMoDa [19]. Each of the rated movie in the dataset has three genres assigned to it. The first one is genres scores denoted by where is user and is the movie genre. It is defined as a ration between the number of movies selected having genre and the number of all genre (movie) selections. For example, if a user has rated drama movies and provide ratings to the database, we have since every movie selection means a selection of three genres.

The next criteria variable we introduce is genre membership where . Indexes of genres (also behaviors in our case) are , and . is defined as the index of users preferred genre for which users expected rating is the highest. These expected scores are computed from users past genre ratings. Here we assume that users has rated mostly movies with genres he prefers since the rating in the dataset are collected for movies the user selected to see by his preference and not by our recommendation. For example, if a user has rated drama movies and his average rating for these movies is while average ratings for action and comedy are lower, we set .

### 4.2 Construction of predictor variables

To allow the explanation of contributions of the three beliefs (behavioral, normative and control, see Sec ??) of TPB, we decided for the hierarchical model. As depicted at Fig. 2, we fit the following models:

1. Each of three beliefs is regressed to score showing the contribution of each beliefs to the selection of behavior (movie with a given genre). The criteria variable used is and this Yields to a nine models. In these models, predictor variables are answers to questions assigns to the modeled belief;

2. Hierarchical model: Prediction of scores of each of three beliefs obtained (previous step) are used as predictor variables model the selected behavior.

The regression model we selected depend on the criteria variables used. For genre scores we selected linear regression and for genre membership we used linear discriminant analysis.

Figure 2: Hierarchical model of genre selection.

### 4.3 Testing models

#### 4.3.1 Multivariate linear regression model

In this subsection, we list and explain multivariate linear regression model.

Table 1: Multivariate regression coefficients of cognitive attitude toward the behavior predictors, .

Table 2: Multivariate regression coefficients of emotive attitude toward the behavior predictors, .

Table 3: Multivariate regression coefficients of behavioral attitude toward the behavior predictors, , .

Table 4: Multivariate regression coefficients of emotive attitude toward the behavior predictors, .

Table 5: Multivariate regression coefficients of emotive attitude toward the behavior predictors, .

#### 4.3.2 Linear discriminant model

In this subsection, we list and explain multivariate linear discriminant model.

Table 6: Linear discriminant regression coefficients of cognitive attitude toward the behavior predictors.

Table 7: Linear discriminant regression coefficients of emotive attitude toward the behavior predictors.

Table 8: Linear discriminant regression coefficients of behavioral attitude toward the behavior predictors.

Table 9: Linear discriminant regression coefficients of emotive attitude toward the behavior predictors.

Table 10: Linear discriminant regression coefficients of emotive attitude toward the behavior predictors.

## 5 Discussion

the main goal of this paper was to introduce the theory of planned behavior into a user modeling; the results suggested that introduction of TPB is likely to increase accuracy of RS. Below, we discuss most relevant issues ergarding advanages, limitations, and futher development RS backing with psychology based research.

tukaj naj bodo vsi boldirano podnaslovi napisani v obliki vprašanj, ker se mi zdi, da je to zelo učinkovito; spremenil bi tudi vrstni red teh vprašanj/razdelkov

1 What are the benefits of implementing TPB to RS?

2

3

4 **What are the problems of TPB user data aquisition?.** The theory and practice of TPB shows that the surveys required to fit the TPB model accurately enough are relatively long and they also demand a considerable effort of the respondent (end user) to provide relevant answers. In the context of user modeling, this means that the user data acquisition is relatively intrusive. On the other hand, since users' attributes, norms and beliefs are changing very slowly time it is enough for the user to fill the survey once a year only. However, the sampling period may vary significantly according to the domain and also according to an individual user's practice. In our example, attributes, norms and beliefs toward movie genre selection may change faster for those users who sees more films in given amount of time.

5  **Does TPB allows cross-domain user modeling?** Cross-domain of user adaptation techniques are of great interest. The question is can TPB models, in particular Ajzen model assure cross-domain capabilities in terms that the attributes, norms and beliefs of the end user estimated in one domain (for example movie selection) are at least in part valid for the other domain (for example tourist destination selection). Unfortunately, in general the answer is no. The reason for this is simply the fact that she survey used to estimate these attributes, norms and beliefs must be very specifically related to the domain of behaviors. For instance, the relevance of certain factors is asked for movies or for tourist destinations and not about some general user opinion common to both domains. However, the research on life - styles indicates that there are strong relations among human behaviors in different domains.

(**) misim, da to ni ključno!**

**(**) mislim, da tudi to ni klučno, ker se nanapa na samo TPB, mi pa hočemo argumentirati njeno uporabo pri RS; jaz bi dal to ven

## 6 Conclusion and further work

The work present in this paper aims at establishing the relevance of psychological human decision modeling theory of planned behavior (TPB) into the field of user modeling. The study contributes to the models applicable in user modeling, in particular to the explanation of these models.

Our results show that the application of TPB in the area of recommender systems allows further insight into the underlying process of user's decision making, i.e. into factors that affect these decisions. These insights can be used to address several issues such as effective user data acquisition, understanding and mitigating reasons for unacceptable recommendations etc. As an important part of this research performed by an interdisciplinary team including engeneers, mathematicians, and psychologists are the guidelines for the future applications of TPB in different areas of user modeling. They include behavior selection, user questionnaire construction, criteria variable construction, regression model selection and fitting, and the explanation of obtained results.

Despite limitations of the proposed modeling, our study showed that such modeling improve the understanding of user adaptation process. It is not meant as a replacement of existing user modeling models (for example Matrix factorization in movie recommendations) but as a predictor of end user behaviors that affects the whole process. Such behaviors the selection of the device he use to consume the recommended service etc. Furthermore, in the discussion section we addressed several issues relevant for the application of TPB into the user modeling domain.

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