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SCIENCE DIRECT
Interacting with Computers 18 (2006) 432–456
Interacting with Computers
www.elsevier.com/locate/intcom

Goal-based structuring in recommender systems

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Available online 20 December 2005

Abstract

Recommender systems help people to find information that is interesting to them. However, current recommendation techniques only address the user's short-term and long-term interests, not their immediate interests. This paper describes a method to structure information (with or without using recommendations) taking into account the users' immediate interests: a goal-based structuring method. Goal-based structuring is based on the fact that people experience certain gratifications from using information, which should match with their goals. An experiment using an electronic TV guide shows that structuring information using a goal-based structure makes it easier for users to find interesting information, especially if the goals are used explicitly; this is independent of whether recommendations are used or not. It also shows that goal-based structuring has more influence on how easy it is for users to find interesting information than recommendations.

Keywords: Goal-based structuring; Recommender systems; Uses and gratification theory; Decision theory; Personalisation

1. Introduction

Intelligent systems that support people in easily and quickly finding interesting items, such as papers, books, music and TV programs, are one of the key solutions to overcome information overload. A lot of research focuses on selecting interesting items (e.g. information, products or other people) for a user by predicting what the expected interest of an item will be to the user, e.g. Konstan (2004); Smyth and Cotter (2000); Burke (2002);

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0953-5438/$ - see front matter
doi:10.1016/j.intcom.2005.11.005

van Setten et al. (2004); so-called recommender systems or recommenders (Resnick and Varian, 1997). Recommender systems can use a variety of algorithms to predict an interest value (predicted rating) for a user for an item, e.g. collaborative filtering (Shardanand and Maes, 1995), case-based reasoning (Smyth and Cotter, 1995) and information filtering (Billsus and Pazzani, 1999), or use a combination of algorithms; so-called hybrid recommender systems (Burke, 2002). A recommender selects and recommends the most interesting items based on the predicted ratings. However, selection is not the only way to support users in finding interesting items; structuring items into meaningful groups and presenting them to the user in a manner that suits the user should also be part of the solution. This paper addresses structuring items; we address the presentation of items with predictions in van Barneveld and van Setten (2004).

Current recommendations algorithms only address the user's short-term and long-term interests, not the user's interests at the moment he is looking for information: immediate interests. In this paper, a structuring method is introduced that provides support for users in finding interesting items taking into account their immediate interests: a goal-based structuring method. This structuring method is based on ideas from decision theory and the uses and gratifications theory (Section 2). An experiment with goal-based structuring and recommendations in an electronic TV program guides shows that structuring information according to goals is even more helpful to users than using recommendations in finding interesting information. The design of this experiment is discussed in Section 3, while Section 4 describes the sample of the experiment. Section 5 shows how helpful different combinations of goal-based structuring and recommendations are to users in finding interesting TV programs. The effort it takes users to use and learn goal-based structuring and recommendations and what they gain from them is examined in Section 6. Finally, consequences of our findings are discussed in Section 7.

2. Using goals in recommender systems

Recommender systems can be regarded as a decision process: for each item a decision is made whether it is interesting enough for the user or not. Most decision-making theories agree that people try to achieve goals when making a decision (Selten, 2001, page 13–14) (Scott, 2000, page 127) (Reynolds and Olson, 2001). Kass and Finin (1988) define a goal as some state of affairs a user wishes to achieve. The differences between various decision-making theories lies in the way they perceive how people make decisions in order to reach their goals, not the fact that people try to achieve goals.

This means that for items recommended by recommender systems, people also have goals they want to achieve. One might argue that not every selection of items is goal-directed; e.g. one may decide to just sit on the couch and watch TV by skimming through channels; this hardly seems goal-directed. However, research has shown that even this behaviour addresses a goal: the goal to pass some time (Lee and Lee, 1995) (Weaver III, 2003); i.e. people are not always explicitly aware of their goals. Our main premise is that if a recommender is aware of these goals, it can use this knowledge to better help users in finding interesting items.

Conversational or knowledge-based recommenders (Burke, 2000) allow a user to find an item that meets his goals by retrieving an item and allowing the user to tweak or critique the item; users indicate which attribute or combination of attributes needs to be changed to better suit his needs; e.g. less expensive, more luxurious, larger display. Based on such tweaks, an item that is similar to the previously suggested item and which adheres the most to the specified tweaks is then retrieved; this process is repeated until either a satisfactory item is found or the user breaks of the process. Knowledge-based recommenders are especially suitable for helping users choose one item in a complex information space that the user is not familiar with and where the user has enough time to go into a dialogue with the recommender; e.g. buying a new camera. Knowledge-based recommenders are less suitable for day–day recommendations; e.g. finding TV programs to watch or e-mails and news articles to read. This research focuses on the latter type of recommender systems.

2.1. Determining the user's current goal

Determining a user's current goal can be accomplished in three ways depending on where the decision effort is placed. On the one extreme, a recommender can ask a user to specify his current goal(s) and recommend items belonging to that goal; this puts all the effort on the user. This assumes that people are capable of and willing to make their goal(s) explicit and that they are capable of articulating these goals; this is not always the case (Kass and Finin, 1988). For these reasons, this option is not been examined any further.

On the other end, the recommender can try to predict the user's current goal(s). This is comparable to predicting how interesting an item is; all the effort to make this decision is put on the recommender. This requires more knowledge about a user and his context than is currently possible to acquire; e.g. in the TV domain, factors such as the emotional and physiological state are important indicators for a user's goal when watching TV (Zillmann and Bryant, 1986). Although recommenders can certainly benefit from the acquisition of such detailed user and context knowledge, we leave this open for future research and first focus on investigating if using goals will actually help users in finding interesting items.

Finally, a combination of predicting and specifying can be used, where the effort is shared between the user and the recommender: the recommender structures the items into different groups that correspond to the different possible goals users may have. The user then picks that group that best matches his current goal. Structuring recommendations according to the possible goals does not require knowledge about the current goals of the user, it only requires that a recommender knows the possible goals users may have in the domain in which the recommender operates and determine which of these goals each item would achieve for the user; e.g. in the TV domain it is necessary to know the possible goals people have for watching TV and what goal(s) each TV program will help a specific user to achieve. Goal-based structuring allows a recommender to support the user by using goals, while leaving the final decision about the user's current goal(s) to the user; the user is able to navigate through the items, meanwhile adjusting and/or refining his goal(s) based on the items presented using a goal-based structure.

Determining the possible goals people can have in a certain domain is a topic that is also being researched in the mass-communication domain using the uses and gratification theory.

2.2. Uses and gratification theory

The uses and gratification theory can help to determine the goals of people when accessing information. In 1959, Elihu Katz first introduced the uses and gratifications theory (Severin and Tankard, 2001, page 293). This theory states that people choose the types of media (TV, newspapers, radio, etc.) that they will expose themselves to based on certain gratifications or some sense of personal satisfaction that they expect to receive; this has later been extended to choosing content within and over media; i.e. individuals actively seek out media and content that provide them with useful information or psychological gratifications, such as entertainment or emotional comfort, and avoid media or content with displeasing characteristics (Cooper et al., 2000).

According to the uses and gratification theory, “communication behaviour, including the selection and use of the media, is goal-directed, purposive, and motivated” (Severin and Tankard, 2001, page 527). Furthermore, “people initiate the selection and use of communication vehicles” (Severin and Tankard, 2001, page 527) and “a host of social and psychological factors guide, filter, or mediate communication behaviour” (Severin and Tankard, 2001, page 528); i.e. individuals decide upon which media and content to access based on their personal goals and social and psychological factors. Recommender systems can support people in the process of selecting media and content, but in the end it is the user who chooses what media and content he will access, not the recommender.

Uses and gratification theory helps to determine the gratifications people expect to receive from using certain content. However, gratifications are not the same as goals. Gratifications are what the user experiences after using content; goals are what the user would like to achieve using content. In an ideal situation, the experienced gratifications are sufficient to meet the goal(s) of the user (see Fig. 1).

Knowing the possible gratifications users may receive from using content or items within a domain is not enough for a recommender to structure items according to goals; recommenders must also be able to determine which goal(s) can be achieved for a user by a specific item. A decision-making theory called the means-end approach provides useful insights into the relationship between items and achieving goals.

2.3. Means-end approach

Decisions made by users about what information to access are similar to decisions made by consumers when buying products or services. In both cases, people have to

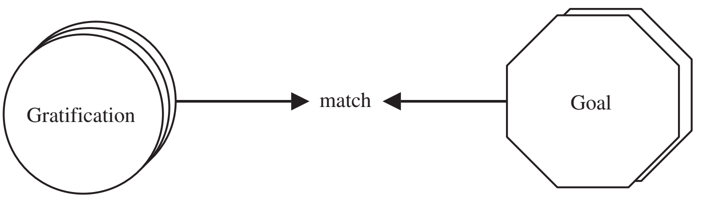

Fig. 1. Gratifications received from using content should match the goal(s) of the user.

make a choice between alternatives; between different products or services or between different information items. Reynolds and Olson (2001) describe a conceptual framework, called the means-end approach, for understanding how consumers use choice criteria in their decisions between alternatives. The basic assumption is that people decide between alternatives based on the anticipated consequences of each alternative and not on the direct attributes of an alternative. “Attributes, taken alone, have no consequences, and thus have no relevance. Consequences only occur when the consumer buys and consumes (or uses) the product and thereby experiences the consequences of use” (Olson and Reynolds, 2001, page 15). In recommender systems, the “attributes” concept of the means-end approach is equivalent with the content and its metadata for which a prediction must be made.

The most basic means-end model consists of attributes that lead to consequences when the product is used; these consequences contribute to the values or goals of the user: attributes → consequences → values/goals. Consequences of accessing information depend on the item itself and the person who accesses the item. The concept of consequences is similar to the concept of gratifications in the uses and gratification theory.

The means-end approach indicates that people make decisions based on the consequences of using items, not on the attributes of items and also not explicitly on the goals they want to achieve. The goals to achieve are implicit in the decision process, the consequences or gratifications are explicit; hence, goal-based structuring methods can better employ the explicit consequences or gratifications than the implicit goals: goal-based structuring should be done on gratifications not on goals. This results in a means-end model for goal-based structuring of information that describes how item attributes lead to one or more gratifications by using an item; these gratifications should match the goal(s) the user wants to achieve (see Fig. 2). E.g. a TV program with attributes like ‘Comedy’ and ‘American’, will lead for some people to the gratification ‘mood improvement’ when watched, while for others a TV program with attributes like ‘Comedy’ and ‘British’ would lead to that gratification. Depending on the person, either the first or the latter program should be watched when the goal is to improve his or her mood.

The next sections validate this model, focusing on whether using goal-based structuring actually helps users in finding interesting items and how this compares to the help users get from using recommendations in the form of predictions.

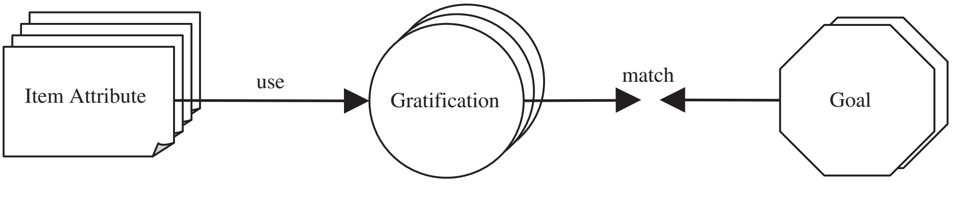

Fig. 2. Means-end model for goal-based structuring.

3. Validation of goal-based structuring

3.1. Hypotheses

Our main hypothesis is that using recommendations in the form of predictions and goal-based structuring both help users in finding interesting items; predictions are the predicted ratings that are calculated by a recommender system to reflect the anticipated interest of a user in an item. This hypothesis has been refined in a set of five hypotheses that are tested in the experiment:

Hypothesis 1. Using predictions for items makes it easier for users to find interesting items than using no predictions.

Hypothesis 2. Structuring items based on the user's goals makes it easier for users to find interesting items than using structures that are not based on the user's goals.

When assuming that goal-based structuring and the use of predictions enhance each other, one can derive from these hypotheses that:

Hypothesis 3. Using both predictions and structuring items based on the user's goals makes it easier for users to find interesting items than using no predictions and no structures that are based on the user's goals.

Hypothesis 4. Using both predictions and structuring items based on the user's goals makes it easier for users to find interesting items than using only predictions.

Hypothesis 5. Using both predictions and structuring items based on the user's goals makes it easier for users to find interesting items than using only structures that are based on the user's goals.

These five hypotheses are tested in the domain of electronic program guides (EPG) for TV. According to the means-end model for goal-based structuring, TV viewers do not choose programs based on the attributes of the program, but on the anticipated gratifications of watching a TV program; the attributes are used to determine these anticipated gratifications.

To test these hypotheses, it is first necessary to make "how easy it is for people to find interesting TV programs" measurable.

3.2. Measuring

"How easy it is to find interesting TV programs" is a complex construct that can be interpreted in several ways, such as the speed in which interesting programs are found, the ease-of-use and how helpful the EPG was in finding interesting programs. Several studies have researched ways to measure how helpful technology is to its users, including aspects such as speed, ease-of-use, and usefulness. Venkatesh et al. (2003) compared various studies and integrated them into a unified theory of user acceptance of information technology; this theory measures the success of information technology by measuring the intention that users will actually use new information technology after deployment.

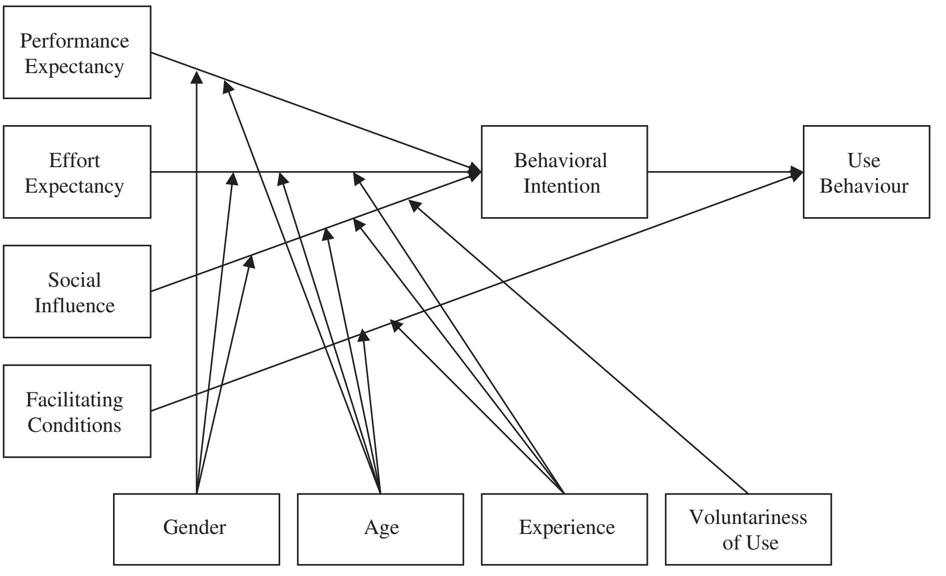

Fig. 3. Unified theory of acceptance and use of technology.

Intention is measured, not real usage, as in most cases one wants to determine the probable success of new technology before introduction; this is also the case in this experiment; the system is only experimental and not available to the general public.

The intention users have for using a certain type of EPG is an indication of how good that EPG is in helping them find interesting TV programs. The intention to use an EPG that does not help users in finding interesting programs easily will be lower than the intention to use an EPG that does help users in finding interesting programs easily. For this reason, in our experiment we will measure the intention that users will use an EPG.

Venkatesh et al. (2003) examined eight different models that try to explain those factors that influence the acceptance by users of information technology. Based on these eight models they formulated and empirically validated a unified model that integrates elements across these eight models. Their unified model, called the unified theory of acceptance and use of technology (UTAUT), is shown in Fig. 3.

This model describes the four core determinants of intention and usage of new information technology:

1. Performance expectancy: “the degree to which an individual believes that using the system will help him or her attain gains in job performance” (Venkatesh et al., 2003, page 447).
2. Effort expectancy: “the degree of ease associated with the use of the system” (Venkatesh et al., 2003, page 450).
3. Social influence: “the degree to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003, page 451).

4. Facilitating conditions: “the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system” (Venkatesh et al., 2003, page 453).

As “facilitating conditions will not have a significant influence on behavioural intention [...] [but] do have a direct influence on usage ...” (Venkatesh et al., 2003, page 454) it is not necessary to measure the facilitating conditions in this experiment, as only the intention to use a certain type of EPG is measured, not the actual usage after the experiment.

There are four moderators that influence the relationship between the four core determinants and the intention and usage: gender, age, experience and voluntariness of use. Regarding the voluntariness of use, Venkatesh et al. notice that “none of the social influence constructs are significant in voluntary contexts” (Venkatesh et al., 2003, page 451). Since the use of the EPG is voluntary, the social influence determination is not relevant for this experiment. The gender and age moderators are of influence on the relationship between performance expectancy and intention (Venkatesh et al., 2003, page 450). The gender, age and experience moderators are of influence on the relationship between effort expectancy and intention (Venkatesh et al., 2003, page 450).

As it is not necessary to take into account social influence and facilitating conditions in this experiment, a limited model of factors that influence the acceptance by users of the various EPGs can be used (see Fig. 4).

The result of using this limited UTAUT model is that “how easy it is for users to find interesting TV programs” is measured by behavioural intention. To be able to explain and understand the reasons behind the intention of participants in the experiment, it is also necessary to measure performance expectancy, effort expectancy, gender, age and experience with using EPGs.

As UTAUT and the studies it has been based on all focused on professional environments, it is necessary to translate the concrete measures of UTAUT to the home environment where concepts like tasks and job performance have little meaning; these have been translated to concepts like “finding interesting and fun TV programs” and

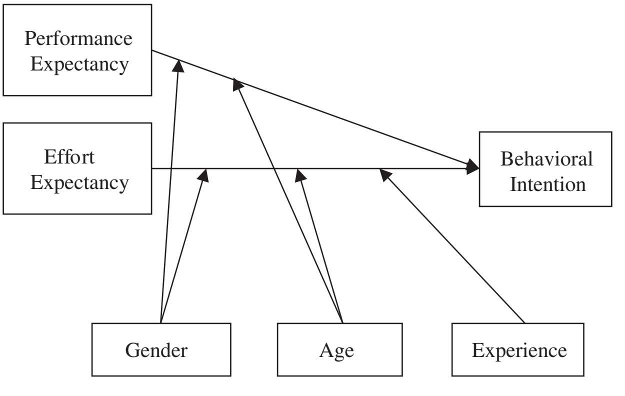

Fig. 4. Limited UTAUT model for the EPG experiment.

"increased chances of a fun and interesting evening". UTAUT uses four statements to measure performance expectancy (Venkatesh et al., 2003, page 460); translated to the home environment they are:

- The EPG helps me to find interesting and fun TV programs.
- Due to the EPG, I can find interesting and fun TV programs faster.
- Due to the EPG, I watch less TV programs that disappoint me than without this online EPG.
- Using the EPG increased my chances of a fun and interesting evening of watching TV.

UTAUT also uses four statements to measure effort expectancy (Venkatesh et al., 2003, page 460); the translated four statements are:

- It is easy to learn the possibilities of the EPG.
- The use of the EPG is clear and understandable.
- The EPG is easy to use.
- Learning to use the EPG is simple.

Intent is measured using the following translated statement:

- If the EPG would become available as a real system, I intend to use the EPG.

UTAUT measures intention, performance expectancy and effort expectancy using a seven point scale that measures the level of agreement to the statements with 1 being the negative end and seven being the positive end of the scale (Venkatesh et al., 2003, page 438). Davis (1989) labels these seven points as extremely unlikely, quite unlikely, slightly unlikely, neither, slightly likely, quite likely and extremely likely; making the scale non-parametric. One could argue that the measurement scale is parametric; however, parametric tests show similar results as the non-parametric tests discussed in this paper.

For all tests a 95% confidence level is used to determine if differences are statistically significant. As the five hypotheses are one-sided—the expectation is that using predictions and/or goal-based structuring increases the intent to use an EPG—all significance values for hypothesis testing are based on one-tailed probabilities. As no hypotheses have been defined concerning performance expectancy and effort expectancy, significant differences for these measures are tested with two-tailed probabilities.

3.3. Gratifications for watching TV

Several investigations have been made to discover gratifications of media use; some tried to identify high-level gratifications that describe an averaged attitude, also called orientations; e.g. Rubin (2002) describes two main orientations: ritualized use, using a medium more habitually to consume time and for diversion, and instrumental use, seeking certain content for informational reasons. Others have investigated need gratifications in specific domains such as TV (Lee and Lee, 1995) (Weaver III, 2003) and websites (Eighmey and McCord, 1998). For our experiment, the study of Lee and Lee (1995) is the most relevant. Results from this study have the highest level of detail of all TV gratification studies and the results encompass results of other TV gratification studies. This study started with 18 focus groups, followed by a quantitative survey of a national probability sample of 1872 television viewers in the US resulting in the identification of six gratification factors for watching TV. We gave more goal-oriented labels to these gratifications before presenting them to users in order to make them easier to understand; these labels are listed between brackets:

1. Committed/ritualized viewing: planning an evening filled with favoured programs provides people with the enjoyment of anticipation (programs to keep up with).
2. Mood improvement: by watching TV, people can relax, relieve stress and escape everyday troubles, which improves their moods (improving my mood).
3. Informational/cognitive benefit: TV also keeps people up-to-date on events going on in the world (both locally as globally) and it provides people with a source for self-education and "food for thought" (to be kept up to date; learning new things).
4. Social learning: watching TV can also be used for self-examination and guidance through identification with people and situations on TV that are similar to ones own life (learning from others).
5. Social grease: TV also has a role to smooth interpersonal relations. People that have seen the same programs have a topic to discuss, something to talk about (watching what my friends watch).
6. An engrossing different world (escapism): instead of being drawn by the similarities with ones own life, some TV programs allow people to "escape" to a different world in which they experience things they never would experience in the real world (to lose myself in a program).

In our experiment, the informational/cognitive benefit gratification has been divided into two separate gratifications as we believe that there is a difference between being informed about events and learning new things; learning something new does not necessarily include recent events that took place in the world, while being informed about events does not imply that something is learned from those events.

3.4. Alternative structuring methods

Traditional paper TV guides group their programs by the channels on which they are broadcast. Grouping programs on channel is also used in almost every existing EPG. For this reason, channel-based grouping is used in our experiment as the structuring method that represents the situation in which a structure is used that does not reflect user goals; one may argue that some channels are inherently goal-based due to their programming; e.g. documentary channels and news channels. However, as channel-based structuring is the most widely known and used form of structuring, it is the best structuring method to use as the basis situation (control group) to which other structuring methods are compared.

Although the means-end approach indicates that people choose programs based on anticipated consequences instead of attributes of a TV program, it might be possible that making these consequences explicit is too unfamiliar to people. To anticipate this possibility, another way of structuring is also used, namely one using an attribute that is not a gratification in itself, but one that gives a indication of what gratifications to expect: the main genre of a TV program (see Section 3.6 for details about the relationship between genres and gratifications). Genres are a way of implicitly structuring on goals.

3.5. Experimental design

To determine the effect of using goal-based structuring and/or predictions in an EPG on how easy it is for people to find interesting TV programs, we need to manipulate the independent variables "type of structuring" and "using predictions" in order to create different EPGs and measure our dependent variable "how easy it is for people to find interesting TV programs" in each of these EPGs. "using predictions" is a binary variable: predictions are used or predictions are not used (also refered to as personalised versus non-personalised). As mentioned in the previous section, three types of structures are compared in this experiment: non goal-oriented structuring (channel-based), implicitly structuring on goals using an attribute that gives a good indication of what gratifications to expect (the main genre) and explicitly structuring on goals using gratifications (goal-based).

The two independent variables, "using predictions (yes/no)" and "type of structuring (channel/genre/goal)" result in a 2×3 factorial design (see Table 1) for which a between-subjects approach is used. Of the three moderators that can influence intention (gender, age and experience), especially experience can be of great influence; the intention of people who never used an EPG to use a specific type of EPG will contain both their intention towards that specific EPG and their intention towards using EPGs in general; for people who already use EPGs their intention will only consist of the intention to use that specific type of EPG. For this reason, experience is used as a classificatory variable; people are assigned to experimental groups taking into account their experience with using EPGs. To keep the experiment manageable, gender and age are not included as classificatory variables, but their values will be acquired for checking their influence afterwards.

3.6. Experimental system

An experimental EPG has been developed to validate the five hypotheses. This EPG encompasses six types of guides conforming to the six experimental groups. The look and feel and how users have to interact with the EPG is the same for all six guides, except for functionality that is specific to using predictions or a certain type of structuring; e.g. presentation of predictions and functionality to provide ratings are only present in personalised guides. Even for non-personalised EPGs, the recommender is instructed to

Table 1
Factorial design: six experimental groups

		Using prediction	
		No	Yes
Structuring	Channel	1	4
	Genre	2	5
	Goal	3	6

generate predictions in order to keep the processing time for all types of EPG similar, even though these predictions are never presented to the user. An overview and screenshots of the six guides is given in Fig. 5.

The experimental system uses two methods to assign gratifications to TV programs. For new users and for TV programs that a user has not seen before, a gratification is

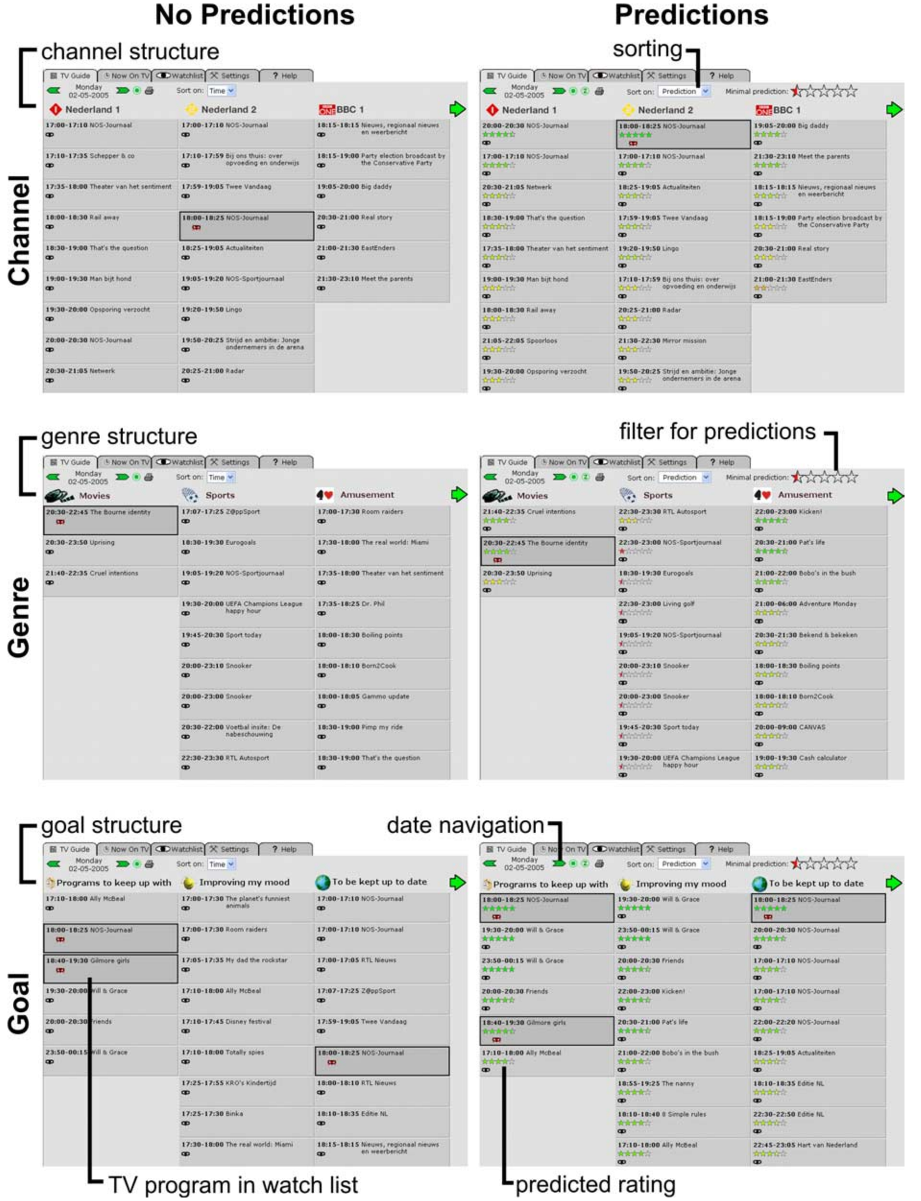

Fig. 5. The six TV guides used in the experiment.

determined based on the main genre of the TV program, using the following mapping:

- amusement, children, animation, comedy, music → mood improvement
- current affairs, sports → informational
- nature, informative, documentary, science, other → cognitive benefit
- religious, art/culture → social learning
- crime, serial/soap, movie, erotic → escapism
- combined watch lists of a user's buddies → social grease
- only explicitly assigned TV programs → committed/ritualized viewing

If a user does not agree with these assigned gratifications, he can assign one or more other gratifications to that TV program, which is consequently stored in the user's profile. The next time that that TV program (or other episodes of that TV program) appears in the EPG, those explicitly assigned gratifications will be used instead of the gratifications derived from the main genre.

The only exceptions to the genre-based assignment of gratifications are the committed/ritualized viewing gratification and the social grease gratification. A TV program is only assigned to the committed/ritualized gratification if the user has explicitly assigned that program to this gratification. The social grease gratification is filled with programs by combining all the watch lists of the user's buddies (independent of whether buddies use the same type of EPG); users can invite other people to take part in the experiment and become their buddies. A watch list is a list of TV programs that a user has selected from the whole TV guide which he or she intents to watch.

The next sections describe the participants that took part in the experiment and the results of testing the five hypotheses.

4. Sampling

4.1. The sample

In the three and a half months that the EPG was online, 320 people created an account. These participants have been randomly assigned to one of the six experimental groups taking into account their experience in using EPGs. A special group has been used for colleagues and friends of the researchers and others whom already knew about the purpose of the experiment; the results of this group (consisting of 18 people) have not been used to test the hypotheses and are not included in the 320 accounts. Participation was voluntary; the only incentive for participants was that they were able to win a gift certificate of 50 euro.

After the three and a half months, all participants were asked to complete a survey in which their intention to keep using the EPG was measured (including performance and effort expectancy); 114 participants completed the survey. Even though this is a high dropout rate, the dropout rate is fairly distributed over the six experimental groups according to a chi-square test: group 1: 67%, group 2: 58%, group 3: 69%, group 4: 66%,

Table 2
Distribution of participants over the six experimental groups

Experimental group	Frequency	Percentage (%)
1	17	15.6
2	22	20.2
3	16	14.7
4	19	17.4
5	18	16.5
6	17	15.6
Total	109	100

group 5: 67%, group 6: 68% ($\chi^2=1.067$; df=5; $p=0.9570$ two-tailed). Although it is not possible to know the real reason for this high dropout rate, it does not influence the results as the type of guide did not influence the dropout rates.

While examining these 114 surveys, we discovered that five participants indicated that they were never able to use or had never used the EPG at all. As the opinions of these users were not based on usage of the EPG, these five surveys have been excluded from analysis, resulting in 109 valid surveys. These 109 participants are fairly distributed over the six experimental groups as described in Table 2 ($\chi^2=1.257$; df=5; $p=0.939$ two-tailed).

As the survey results from the six groups are to be compared, it is important that participants are well distributed over the six groups according to their gender, age and experience in using EPGs. If distribution is not fair for one of these moderators, it is not possible to compare the six groups without explicitly taking these moderators into account; if distribution is fair, the six groups can be compared directly. A chi-square test shows that participants are fairly distributed over the six experimental groups according to their gender ($\chi^2=2.179$; df=5; $p=0.824$ two-tailed), their age ($\chi^2=4.845$; df=10; $p=0.901$ two-tailed) and their experience in using EPGs ($\chi^2=3.656$; df=5; $p=0.600$ two-tailed). As all three moderators, gender, age and experience, are fairly distributed over the six experimental groups, the results of these six groups can be compared without explicitly taking any of these moderators into account.

4.2. Generalizability

Multiple acquisition methods have been used to acquire participants in order to get a representative sample of TV guide users in the Netherlands, making it possible to generalize the results of the sample to the whole population: a banner in the online TV guide of the public broadcasting companies, flyers distributed in several major cities, mouth-on-mouth advertising and an invitation to a diverse group of Internet users from the Kenniswijk project in the city of Eindhoven. This way of sampling allowed us to find a representative group of participants including people with and without experience in using EPGs.

Even though there was a high dropout rate (as shown in the previous section), comparing the sample of 109 participants who completed the survey to all 320 people who registered to use the EPG shows that the sample of 109 is a good representative of all registered accounts as far as the three moderators are concerned (gender $\chi^2=3.730$; df=1;

$p = 0.053$ two-tailed, age $\chi^2 = 0.1017$; df = 2; $p = 0.950$ two-tailed, experience $\chi^2 = 0.0446$; df = 1; $p = 0.833$ two-tailed); this makes the final sample of 109 participants just as representative as the group of all 320 registered participants.

4.3. Weighting the cases

When testing the five hypotheses and examining performance expectancy and effort expectancy, cases will be weighted using the number of times a participants has used the EPG. There are two reasons to weigh cases using the number of logins:

1. Users are better capable to determine if the EPG helped them in finding interesting TV programs when they used the EPG frequently than users who only used the EPG a few times.
2. Due to the limited number of valid surveys some statistical tests will not be able to find any significant differences, even if there are any; e.g. a chi-square test between the six experimental groups and intent shows that 100% of the cells in the cross-table for this test have an expected count of less than 5; i.e. there is not enough data to successfully apply the chi-square test. Weighing the cases can solve this issue, but only if a meaningful weight is assigned, otherwise the gained significance will be meaningless.

Frequency of use is measured by the number of times a participant logged into the EPG. The usage logs of the experiment show that some participants used the EPG more than others. As there are a few extreme outliers in the number of times people logged into the EPG (see Fig. 6), the number of logins have been mapped onto six groups, were the group number is used as a weight for opinions of participants in that group:

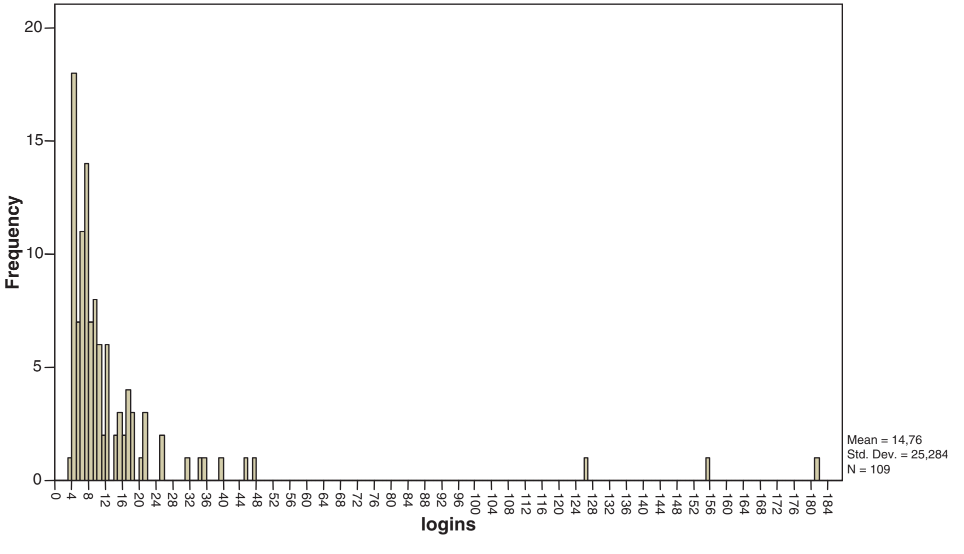

Fig. 6. Histogram of the number of logins.

1. number of logins ≤ 5
2. number of logins > 6 and ≤ 10
3. number of logins > 10 and ≤ 15
4. number of logins > 15 and ≤ 20
5. number of logins > 20 and ≤ 25
6. number of logins > 25

Without this mapping, the three extreme outliers would have dominated the results too much. The histogram of the number of login groups (nlogins) is shown in Fig. 7, which has a similar shape to the non-grouped frequency of use, without having extreme outliers.

It is only allowed to use the number of login groups if there is no relationship between the intent of people to use the EPG and the number of logins; if such a relationship would exist, e.g. people who used the EPG more often have a higher intent to use the EPG than people who used the TV only a few times, it would bias the results. A chi-square test shows that the number of login groups (nlogins) is fairly distributed over the six experimental groups ($\chi^2 = 19657$; df$=25$; $p = 0.765$ two-tailed). As the number of login groups are fairly distributed over the six experimental groups, it is safe to use the number of logins to weigh the survey cases when testing hypotheses and examining performance expectancy and effort expectancy.

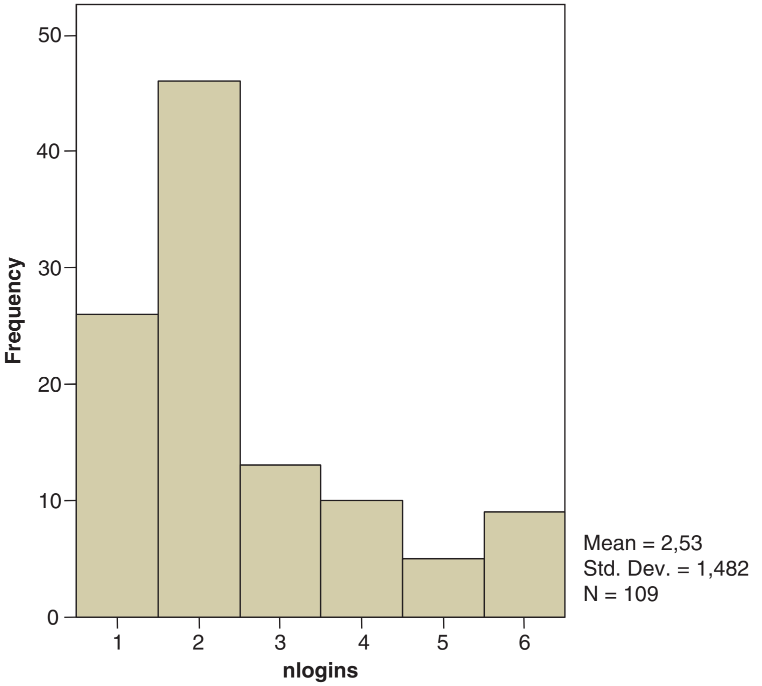

Fig. 7. Histogram of the number of login groups.

5. Analysis of intent

The responses concerning intent have been summarized in Table 3. A first observation shows that the intent of participants to use the assigned EPG varies a lot within each group.

In order to test the five hypotheses, it is necessary to determine whether there are significant shifts in intention between the various types of EPG. We use Mann–Whitney tests to examine these shifts.

5.1. Hypothesis 1: predictions

The first hypothesis states that using predictions for items makes it easier for users to find interesting items than using no predictions. To test this hypothesis, a comparison is made between the intention of users of non-personalised EPGs (independent of the type of structuring), in which no predictions are used, and the intention of users of personalised EPGs (also independent of the type of structuring), in which predictions are used.

The Mann–Whitney test shows that participants who used an EPG with predictions have a significantly ($U=7632.5$; $p=0.002$ one tailed) higher intent (mean rank = 152.19) to use that EPG than those who used an EPG without predictions (mean rank = 124.81). This supports the hypothesis that using predictions for items makes it easier for users to find interesting items than using no predictions.

5.2. Hypothesis 2: goal-based structuring

The second hypothesis states that structuring items based on the user's goals makes it easier for users to find interesting items than using structures that do not match the user's goals. To test this hypothesis, a comparison is made between the intention of users of channel-based EPGs, genre-based EPGs (implicit goals) and goal-based EPGs (explicit goals) independently of whether predictions are used or not. Another interesting test is to determine if the use of explicit goals (goal-based guide) has a significant influence on intent compared to using implicit goals (genre-based guide).

Table 3
Cross-tab of intent and experimental group (weighted with nlogins)

		Experimental group						Total
		Without predictions			With predictions			
		Channel Group 1	Genre Group 2	Goal Group 3	Channel Group 4	Genre Group 5	Goal Group 6	
Intent	1	13	11	3	3	7	2	39
	2	14	6	2	13	4	5	44
	3	2	7	5	6	8	4	32
	4	0	1	10	3	1	7	22
	5	2	9	17	10	6	1	45
	6	8	16	2	13	15	3	57
	7	7	0	3	5	6	16	37
Total		46	50	42	53	47	38	276

The first Mann–Whitney test between channel-based guides and genre-based guides shows that although the mean rank of intent of the genre-based guides (mean rank = 101.36) is higher than the mean rank of the channel-based guides (mean rank = 95.7) this difference is not statistically significant ($U = 4524.5$; $p = 0.239$ one-tailed); i.e. implicit goal-based structuring does not significantly increase the intent to use an EPG over traditional channel-based structuring.

The second Mann–Whitney test between channel-based guides and goal-based guides shows that there is a significant difference between the two types of guide ($U = 3128.5$; $p = 0.0075$ one-tailed). As the mean rank of intent of the goal-based guides (mean rank = 100.39) is higher than the mean rank of the channel-based guides (mean rank = 81.60), there is a significantly higher intent to use goal-based guides than channel-based guides; i.e. explicit goal-based structuring does significantly increase the intent to use an EPG over traditional channel-based structuring.

The third Mann–Whitney test between genre-based guides and goal-based guides shows that although the mean rank of intent of the goal-based guides (mean rank = 95.28) is higher than the mean rank of the genre-based guides (mean rank = 83.82), this difference is not statistically significant ($U = 3378.0$; $p = 0.067$ one-tailed); indicating that the intent to use genre-based guides is not significantly higher than channel-based guides. As there is a significant difference between channel-based guides and goal-based guides but not between channel-based and genre-based guides and between genre-based and goal-based guides, implicit goal-based structuring using genres seems to be situated in between using no goal-based structuring and explicit goal-based structuring.

These results confirm the second hypothesis under a condition: structuring items based on the user's goals indeed makes it easier for users to find interesting items than using structures that are not based on the user's goals, but only when goals are used explicitly.

5.3. Hypothesis 3: predictions and goal-based structuring

The third hypothesis states that using both predictions and structuring items based on the user's goals makes it easier for users to find interesting items than using no predictions and no structures that are based on the user's goals. In this situation, non-personalised channel-based guides are compared with personalised goal-based guides; i.e. comparing experimental group 1 with experimental group 5 (implicit goals) and experimental group 6 (explicit goals).

A Mann–Whitney test between experimental group 1 and experimental group 5 shows that the increase in intent from experimental group 1 (mean rank = 41.40) to experimental group 5 (mean rank = 52.48) is significant ($U = 823.5$; $p = 0.022$ one-tailed). A Mann–Whitney test between experimental group 1 and experimental group 6 shows that the increase in intent from experimental group 1 (mean rank = 34.48) to experimental group 6 (mean rank = 52.21) is also significant ($U = 505.0$; $p = 0.0005$ one-tailed). These tests confirm the hypothesis that using both predictions and structuring items based on the user's goals (both implicit and explicit goal-based structuring) makes it easier for users to find interesting items than using no predictions and no structures that are based on the user's goals.

5.4. Hypothesis 4: goal-based structuring over predictions

The fourth hypothesis states that using both predictions and structuring items based on the user's goals makes it easier for users to find interesting items than using only predictions. In this situation, personalised channel-based guides are compared with personalised goal-based guides; i.e. comparing experimental group 4 with experimental group 5 (implicit goals) and experimental group 6 (explicit goals).

A Mann–Whitney test between experimental group 4 and experimental group 5 shows that there is no significant increase in intent from personalised channel-based guides (mean rank = 48.92) to personalised genre-based guides (mean rank = 52.29) ($U = 1161.5$; $p = 0.278$ one-sided). However, a Mann–Whitney test between experimental group 4 and experimental group 6 shows that there is a significant increase in intent from personalised channel-based guides (mean rank = 41.35) to personalised goal-based guides (mean rank = 52.49) ($U = 760.5$; $p = 0.022$ one-tailed).

These results confirm the hypothesis that using predictions and structuring items based on the user's goals makes it easier for users to find interesting items than using only predictions, but only when goals are used explicitly.

5.5. Hypothesis 5: predictions over goal-based structuring

The fifth hypothesis states that using both predictions and structuring items based on the user's goals makes it easier for users to find interesting items than using only structures that are based on the user's goals. For this hypothesis, non-personalised genre-based and goal-based guides are compared with personalised genre-based and goal-based guides; i.e. comparing experimental group 2 with experimental group 5 (implicit goals) and experimental group 3 with experimental group 6 (explicit goals).

A Mann–Whitney test between experimental group 2 and experimental group 5 shows that there is no significant increase in intent from non-personalised genre-based guides (mean rank = 44.70) to personalised genre-based guides (mean rank = 53.57) ($U = 960.0$; $p = 0.056$ one-sided). A Mann–Whitney test between experimental group 3 and experimental group 6 shows that the increase in intent from non-personalised goal-based guides (mean rank = 36.92) to personalised goal-based guides (mean rank = 44.46) is also not significant ($U = 647.5$; $p = 0.070$ one-sided).

These results show that adding predictions to an implicit goal-based guide or explicit goal-based guide does not significantly increase the intention of usage. As adding explicit goal-based structuring to both non personalised and personalised channel-based guides does increase the intention of usage significantly (see Sections 5.3 and 5.4), it can be concluded that adding goal-based structuring to a EPG has a greater influence on the intention of usage than adding personalisation. Only adding personalisation to a non-personalised channel-based guide significantly increases the intent of usage ($U = 936.0$; $p = 0.0215$ one-tailed).

This rejects the hypothesis that using both predictions and structuring items based on the user's goals makes it easier for users to find interesting items than using only structures that are based on the user's goals.

6. Effort expectancy and performance expectancy

Intention has been used to measure "how easy it is to find interesting TV programs", which is based on the unified theory of user acceptance of information technology. This theory also states that performance expectancy and effort expectancy influence the intention of accepting technology (see Section 3.2). In order to provide more insights in the gains and efforts people expect from predictions and goal-based structuring, responses concerning performance expectancy and effort expectancy are analyzed in this section.

6.1. Performance expectancy

The first statement concerning performance expectancy is the most related to the five hypotheses as it directly asks how people think that the EPG helps them in finding interesting TV programs. When examining the influence of the three types of structuring on how people think that the EPG helps them in finding interesting TV programs, there is only a significant (U=3080.0; p=0.009 two-tailed) increase between the channel-based guides (mean rank=81.11) and goal-based guides (mean rank=101.00), not between the channel-based and genre-based guides or between the genre-based and goal-based guides.

When examining the influence of using predictions on how people think that the EPG helps them in finding interesting TV programs, there is no significant difference between using predictions and using no predictions.

A detailed analysis between the experimental groups shows that the increase in intent between experimental group 1 (mean rank=36.21) and experimental group 6 (mean rank=50.12) is significant (U=584.5; p=0.007 two-tailed). Similar results are found between experimental group 4 (mean rank=41.32) and experimental group 6 (mean rank=52.53) (U=759.0; p=0.037 two-tailed); i.e. personalised goal-based guides help people better to find interesting TV programs than non-personalised and personalised channel-based guides.

When examining the other three statements concerning performance expectancy, no significant influences of structuring or using predictions on performance expectancy are found. For the second statement, this indicates that although people do believe that goal-based structuring helps them in finding interesting or fun TV programs, they do not believe that this will help them find these programs any faster. Notice, this statement measured expected and subjective speed, which is something different than objective speed; measuring objective speed requires controlled laboratory experiments, which is subject for future research. The final two statements used to measure performance expectancy both measure an indirect consequence of using an EPG, namely TV watching experience, i.e. watching less disappointing programs and having a fun time watching TV. No significant differences have been found for these statements, which might be attributed to the fact that TV watching experience is influenced by more factors than the EPG only, e.g. a TV has to be shared with other family members, other activities influence what is actually watched and how much it is enjoyed.

These results show that people do believe that goal-based structuring helps them in finding interesting or fun TV programs (especially when combined with personalisation) but they do not believe that this will help them find these interesting or fun programs any faster or that it will actually influence their TV watching experience.

6.2. Effort expectancy

The first and fourth statement concerning effort expectancy is both about learning: learning the possibilities and learning to use an EPG. As both statements show similar results, only the results of the first statement are reported. When examining the influence of the three types of structuring on how much effort people believe it will take them to learn the possibilities of the EPG, there is no significant difference between channel-based and genre-based guides. A Mann–Whitney test shows that the decrease in effort expectancy between channel-based (mean rank = 100.33) and goal-based guides (mean rank = 77.21) is significant (U = 2937.0; p = 0.002 two-tailed). A Mann–Whitney test between genre-based (mean rank = 97.71) and goal-based guides (mean rank = 78.44) shows that this decrease in effort expectancy is also significant (U = 3035.0; p = 0.010 two-tailed). These results show that explicit goal-based structuring takes more effort to learn than non goal-based structuring or implicit goal-based structuring.

When examining the influence of using predictions on how much effort people believe it will take them to learn the possibilities of the EPG, there is no significant difference between personalised and non-personalised guides; i.e. it is does not take more effort to learn personalised guides than non-personalised guides.

The observation that goal-based structuring takes more effort to learn and that using predictions does not influence the learning effort is also confirmed when examining the differences in effort expectancy between the six experimental groups separately. Between the experimental groups there are significant differences between experimental group 1 (mean rank = 49.93) and experimental group 6 (mean rank = 33.50) (U = 532.0; p = 0.001 two-tailed), between experimental group 2 (mean rank = 51.45) and experimental group 6 (mean rank = 35.36) (U = 602.5; p = 0.003 two-tailed), between experimental group 4 (mean rank = 53.39) and experimental group 6 (mean rank = 35.70) (U = 615.5; p = 0.001 two-tailed) and between experimental group 5 (mean rank = 48.89) and experimental group 6 (mean rank = 35.71) (U = 616.0; p = 0.011 two-tailed). These results confirm that personalised goal-based guides take more effort to learn than other personalised and non-personalised guides (except for a non-personalised goal-based guide). It does not confirm that a non-personalised goal-based guide is significantly more difficult to learn than other non-personalised guides.

The second statement for effort expectancy measures whether people believe that the interaction with the EPG is clear and understandable. There is no significant difference between any of the structuring types, i.e. the type of structuring does not influence how clear and understandable an EPG is.

When investigating the influence of using predictions on whether the interaction with the EPG is clear and understandable, a Mann–Whitney test shows that there is a significant difference between non-personalised (mean rank = 127.70) and personalised EPGs (mean rank = 149.30) (U = 8031.0; p = 0.021 two-tailed); i.e. people believe that the interaction with personalised EPGs is clearer and better to understand than with non-personalised EPGs.

When examining the differences between the experimental groups in detail, an interaction can be observed between using predictions and goal-based structuring. A personalised goal-based EPG (experimental group 6, mean rank = 39.62) is significantly less clear and understandable than a personalised channel-based EPG (experimental group 4, mean rank = 50.58) (U = 764.5; p = 0.042 two-tailed); i.e. although using predictions does make the interaction clearer and better to understand, goal-based structuring combined with predictions makes the interaction less clear and more difficult to understand.

The final aspect of effort expectancy is ease-of-use. All tests show that there is no significant difference between the different types of structuring, between personalised and non-personalised guides or between any of the experimental groups. There is only a significant difference between experimental group 3 (non-personalised goal-based guide, mean rank = 39.30) and experimental group 5 (personalised genre-based guide, mean rank = 50.10) (U = 747.5; p = 0.043 two-tailed); however, these two have no direct relation concerning structuring or personalisation; i.e. neither structuring nor using predictions has any effect on the ease-of-use of EPGs.

The results for effort expectancy show that people believe it takes more effort to learn explicitly goal-based structured EPGs than channel or implicitly goal-based EPGs independently of whether predictions are used or not. However, people believe that using predictions makes the interaction clearer and better to understand, except when explicit goal-based structuring is combined with predictions, which makes the interaction less clear and more difficult to understand; we believe that this can be attributed to the higher learning curve of explicit goal-based guides. People also believe that neither the various types of structuring nor using predictions has any effect on the ease-of-use of an EPG.

7. Conclusions

From this experiment, we conclude that structuring EPGs using a goal-based structuring method makes it easier for users to find interesting items, especially if the goals are used explicitly; this is independent of whether predictions are used or not. Predictions on its own will only make it easier for people to find interesting items when they are added to a channel-based non-personalised EPG; however, adding predictions to goal-based EPGs (either implicitly or explicitly goal-based) will not make it more difficult for users to find interesting items.

The analysis of the effect of using predictions and goal-based structuring on performance expectancy and effort expectancy shows that goal-based structuring helps people to better find interesting and fun TV programs to watch, but it will not influence how fast people expect to find these items nor will it influence people's TV watching experience. Goal-based structuring has a higher learning curve than non goal-based structures. We believe this can be attributed to the fact that people are forced to make their goals for watching TV explicit, which is something that most people are not used to. Furthermore, the interaction with personalised EPGs is clearer and better to understand than non-personalised EPGs, except when combined with goal-based structuring, which can be contributed to the learning curve of goal-based structuring. Goal-based structuring and predictions have no effect on the ease-of-use of EPGs. These conclusions are under the condition that people are willing to learn to use new types of EPGs.

However, due to the large diversity in opinions about the intent to use each of the different types of EPGs with or without predictions, we believe that it is wise to give people a choice in what structuring method to use (or allow them to switch between methods) and whether to use predictions or not. This allows people to use that type of structuring that best suites their personal preferences and needs and allows people to get used to goal-based structuring and predictions at their own pace.

The results of the experiment also support our model that combines the means-end approach and the uses and gratification theory. The explicit use of gratifications in EPGs resulted in a higher intention to use the EPG than using attributes of TV programs such as channel and genre; i.e. people indeed make decisions based upon the expected gratifications of watching a TV program and how these gratifications match their goals. By making these gratifications explicit, people are better supported in finding those TV programs that are of interest to them. The results even show that structuring on gratifications has a greater effect on helping people to find interesting items than using recommendations in the form of predictions.

As the results support our model that combines the means-end approach and the uses and gratification theory, we expect that the usage of goal-based structuring, perhaps combined with the use of predictions, will also better support people in finding interesting items in other domains, even though the results of the experiment can only be directly generalized towards electronic TV guides.

As the mapping from an attribute of a TV program (the main genre) to gratifications formed the basis to assign TV programs to gratifications, and structuring on gratifications resulted in a higher intent to use the EPG, the stated linkage between attributes and consequences in the means-end approach is also confirmed. We believe that future research in recommender systems should focus more on understanding the linkage between item attributes and the gratifications they have for a user than trying to optimize algorithms that try to predict how interesting an item will be for a user based on their short- and long term interests in the form of predicted ratings; people are better supported by a recommender that is capable of successfully determining what gratifications a certain item will give to an individual user. As the assignment of goals to a TV program is subjective, EPG providers who want to use goal-based structuring can no longer provide one EPG for all its users; for each user, the EPG either needs to be adapted on the servers of the provider or special hardware and/or software is required at the user's side that can adapt the EPG; e.g. a component in a digital TV receiver.

One way to implement goal-based recommender systems would be to use intelligent agents; each agent is assigned to one user and one gratification; the goal of such an agent is to find items for its user that belong to the assigned gratification; to fulfil this, the agent has to learn the linkage between items and the assigned gratification for its user. Various strategies can be employed to learn this linkage; e.g. agents can work together by finding agents of similar users to learn which items they believe belong to the gratification or learn from feedback of the user about items suggested by the agent; i.e. techniques that are similar to the now used techniques to predict ratings (such as collaborative filtering and case-based reasoning) might also be usable to learn the linkage between items and gratifications; however, some alterations to these techniques are necessary as they now need to predict classes (gratifications) instead of values (ratings); this is a topic for further research.

Understanding the linkage can also help recommenders with explaining their recommendations (Herlocker et al., 2000). Current explanation methods try to translate algorithmic aspects into user understandable explanations, e.g. "there are 75 users with a similar taste in TV programs who also liked this item" or "this TV program is similar to program x and z that you also liked". Understanding the linkage between attributes and gratifications may provide additional support in explaining recommendations, e.g. "This TV program will improve your mood as it is an American comedy; furthermore there were 75 users with a similar taste who also liked this TV program."

Based on this research, we conclude that using goal-based structuring is extremely important in supporting users in finding interesting items, even more important than recommendations in the form of predictions.

Acknowledgements

This work is part of the MultimediaN program (http://www.multimedian.nl) and the PhD project Duine (http://duine.telin.nl) at the Telematica Instituut (http://www.telin.nl). MultimediaN is sponsored by the Dutch government under contract BSIK 03031. The authors would like to thank omroep.nl for providing TV guide data, Kenniswijk Eindhoven for giving us access to their user base, all people who helped us with inviting participants and all participants.

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