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Towards psychology-aware preference construction in recommender systems: Overview and research issues

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Abstract
User preferences are a crucial input needed by recommender systems to determine relevant items. In single-shot recommendation scenarios such as content-based filtering and collaborative filtering, user preferences are represented, for example, as *keywords*, *categories*, and *item ratings*. In conversational recommendation approaches such as constraint-based and critiquing-based recommendation, user preferences are often represented on the semantic level in terms of *item attribute values* and *critiques*. In this article, we provide an overview of preference representations used in different types of recommender systems. In this context, we take into account the fact that *preferences aren't stable* but are rather *constructed* within the scope of a recommendation process. In which way preferences are determined and adapted is influenced by various factors such as *personality traits*, *emotional states*, and *cognitive biases*. We summarize preference construction related research and also discuss aspects of counteracting cognitive biases.

Keywords Preferences · Recommender systems · Cognitive psychology

1 Introduction

Recommender systems help to identify items of relevance for a user (Burke et al., 2011; Felfernig et al., 2018). Knowledge about user preferences is crucial in this context (Jawaheer et al., 2014). Before reasonable recommendations can be determined, the preferences of a user have to be understood as far as possible (De Gemmis et al., 2009). A basic definition of the term *preference* in the context of recommender systems is the following: *something that is in the user's head that determines how he/she will evaluate different alternatives* (see Felfernig & Willemsen, 2018 p. 91). Preferences can be formulated in an *absolute* as well as in a *relative* fashion. Examples of *absolute preferences* are movie ratings on an

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N-point Likert scale (e.g., a 1–5 star rating), likes/dislikes, and attribute values in constraint-based recommendation. *Relative preferences* are of type *I prefer item X over item Y*, for example, *I prefer the movie "The Hobbit" over "Lord of the Rings"*. Relative preferences can also be defined on the attribute level, for example, *I prefer "green salad" over "tomato salad"*. In the following, we will analyze different aspects of preference construction in the context of the recommendation approaches of *collaborative filtering* (Herlocker et al., 2004), *content-based filtering* (Pazzani & Billsus, 1997), *constraint-based recommendation* (Felfernig & Burke, 2008), *critiquing-based recommendation* (Chen & Pu, 2011), and *group recommender systems* (Felfernig et al., 2018).

Content-based (Pazzani & Billsus, 1997) and *collaborative filtering* recommenders (Konstan et al., 1997) are *single-shot* systems that determine recommendations on the basis of information from already completed sessions. For example, when interacting with *amazon.com* recommenders, content-based recommendations are based on information from items previously purchased by the user. Content-based recommendation is based on the idea that items similar to those a user has consumed in the past are considered as recommendation candidates. Collaborative filtering is based on the idea of word-of-mouth promotion where information about users with similar preferences (the nearest neighbors) is exploited to recommend items to the current user. *Constraint-based* (Felfernig & Burke, 2008) and *critiquing-based recommenders* (Chen & Pu, 2011) follow a *conversational approach* where user preferences are constructed in an iterative process within the scope of the current recommendation session. In constraint-based recommendation, recommendation knowledge is represented by constraints (Felfernig et al., 2007). Critiquing-based recommendation exploits similarity metrics to identify items of relevance for the user.

Related overviews The major objective of this article is to provide an overview of the state-of-the-art in preference construction. Basically, recommender systems 1) collect and represent user preferences and 2) predict relevant items (Chen et al., 2013). Related psychological aspects have received much less attention (Shi et al., 2015). Mandl et al. (Mandl et al., 2010) provide an overview of different types of cognitive biases that can occur in recommendation scenarios and discuss different impacts of these effects in decision situations. Cosley et al. (2003) perform an in-depth analysis of the impact of recommender user interfaces and rating scales on the decisions taken by users. A related insight is that, for example, average ratings (i.e., 3 stars) on a 5 stars rating scale are translated to thumbs up on a binary rating scale. Jameson et al. (2015) propose an integrated model of human choice directly related to the mentioned recommendation approaches, for example, following the idea of critiquing-based recommendation, the *trial and error* based choice pattern is used in decision situations where the space of options should be explored starting with a reference solution. Felfernig et al. (2018) provide an overview of different decision biases in the context of group recommendation scenarios, for example, anchoring effects (Jacowitz & Kahneman, 1995) can occur in situations where the preferences of some group members are disclosed too early which can influence the preference construction process of other group members. Finally, Tran et al. (2021) provide an overview of different psychological aspects that play a role when interacting with recommender systems. In their work, the author focus on specific aspects of group decision making. The *major contributions of this article* are the following:

– We provide an overview of preference construction and representation in different recommendation scenarios. In contrast to related research, our work does not focus on specific recommendation approaches such as collaborative filtering (Kostkova et al., 2014)

or group recommenders (Garcia et al., 2012), but provides an integrated overview of preference construction in recommender systems.
- In addition to a summarization of the state-of-the-art in preference construction, we also focus on discussing specific psychological aspects and related contextual factors that have to be taken into account when implementing a recommender system to assure a high quality of decision support.
- In order to show the relevance of the discussed psychological aspects for preference construction, we exemplify the existence of decision biases in software engineering scenarios on the basis of an empirical study. In this context, we also point out ways to counteract these biases.
- With the goal to stimulate further research in preference construction related areas, we provide a discussion of open research issues.

The remainder of this article is organized as follows. In Section 2, we provide an overview of different preference construction and representation concepts used in recommender systems. In Section 3, we discuss psychological aspects of preference construction. The results of an empirical study that focuses on counteracting decision biases (in software requirements engineering) are presented in Section 4. Thereafter, open research issues are discussed in Section 5. This article is concluded with Section 6.

2 Elicitation and construction of preferences: overview

Collecting and adequately interpreting the preferences of users in a way that leads to the recommendation of relevant items is often a very challenging task (De Gemmis et al., 2009). Following the theories of micro-economic models (Grether & Plott, 1979; McFadden, 1999), it should be possible to propose the optimal alternatives if the preferences of a user have been *elicited*. The underlying assumption in this context is that user preferences are fully known at any time of the decision process and also remain *stable*. This strong assumption is associated with the term *preference elicitation* where the primary goal is to “collect” the preferences of the user and to translate these into a representation “understandable” for the recommender system.

The assumption of *preference stability* does not hold in typical real-world scenarios, for example, if a user of an online sales platform wants to purchase a new digital camera, he/she could specify a price limit at the beginning of the decision process. However, there is no guarantee that this preference remains the same over time (Gal & Simonson, 2020). There is a high probability that initial preferences get revised in the face of new relevant features that were not known to the user at the beginning of the decision process (Bettman et al., 1998). For example, a user might not have been aware of the usefulness of *high frame rates* (of *digital cameras*) at the beginning of a decision process. However, since the user wants to use the camera primarily for *sports photography*, the high relevance of this feature becomes obvious within the scope of the recommendation (decision) process.

This clear evidence against the existence of *preference stability* led to the development of alternative decision models (Payne et al., 1993; Pommeranz et al., 2012; Sawyer et al., 1955) and in this context coined the term *preference construction* (Bettman et al., 1998; Lichtenstein & Slovic, 2006) which reflects the idea that people often *construct* their preferences within the scope of a decision process. In this context, decisions are influenced by various factors (Jameson et al., 2015) – we focus on an analysis of influences coming from a.o. a user’s personality, emotions, and cognitive biases.

Preferences can be regarded as something that refers to the taste of a person or the absolute (or relative) utility of an item. Examples thereof are *I like "Lord of the Rings" movies* or *I prefer "Lord of the Rings" over "Harry Potter" movies*. The first example can be regarded as an absolute statement whereas the second one refers to a relative statement between two alternative items. In a more general sense, we can define preferences as *ordering relations* (De Gemmis et al., 2009) between items which help to define which of a given set of alternatives best fits the user. In the line of a utility-based analysis of decision alternatives, Jameson et al. (2015) propose a differentiation between more general and rather specific preferences. An example of *general preferences* is *interest dimensions* in the context of the multi-attribute utility theory (Winterfeldt & Edwards, 1986). For example, a user could state that *the economy of a car is more important compared to security*. An example of more *specific preferences* are *unit critiques* in critiquing-based recommendation scenarios.

There are two basic forms of user preference articulation (De Gemmis et al., 2009; Pommeranz et al., 2012). First, a user can give feedback regarding preferences in an *explicit* fashion. For example, a user provides a star rating for a movie or selects the color of a car (which is a form of *relevance feedback* (De Gemmis et al., 2009)) or provides feedback in terms of critiques on the presented item (Chen & Pu, 2011; Ricci & Nguyen, 2007). Other examples of explicit preference articulation are: the ranking of individual options via the specification of *pairwise preferences* (Kalloori et al., 2016), so-called *choice-based preference elicitation* where users of a collaborative filtering recommender are initially confronted with a diverse item set as a starting point to solve the cold-start problem (Graus & Willemsen, 2015), the *specification of preferred item properties* which is often used in constraint-based recommendation scenarios (Jameson et al., 2004), and the *explicit articulation of emotions* in group recommendation (Chen & Pu, 2012). A major advantage of these forms of explicit methods is that there is a direct link between the "focus property" and the corresponding measured value.

The major disadvantage of explicit preference articulation is that active involvement of users is required. This is the reason why often *implicit feedback* is used to understand the preferences of a user. Such implicit feedback can be collected by observing the purchasing behavior of a user and in this context also to derive preferences from the user navigation behavior when interacting with the purchasing environment. Examples of implicit feedback given in the context of recommendation scenarios are the following: the items purchased by a user (Crossen et al., 2002), the eye tracking related fixations of a user when interacting with a recommender application (Xu et al., 2008), user navigation data (Wang et al., 2019), and information from item-specific chats (Nguyen & Ricci, 2017). A general approach to derive private traits and attributes from records of digital behavior (e.g., data from Facebook) is discussed in Kosinski et al. (2013). The major disadvantage that comes along with these approaches is that there is no direct link between specific item properties ("focus properties") and the measured values. On top of that, preference determination through observations is often not enough and a more in-depth user integration should be supported, for example, in terms of letting users also select the recommendation algorithm (Ekstrand & Willemsen, 2016).

Depending on the used recommendation approach, preference construction is supported differently – a related overview of existing practices is provided in Table 1. Note that *group recommender systems* (Felfernig et al., 2018) often apply preference construction techniques that are also used in single user recommendation settings. Following such an approach, preferences collected from individual group members are then aggregated to

Table 1 Existing basic approaches of explicit and implicit user preference representations depending on the used recommender type (see also Felfernig et al., 2018, Peintner et al., 2008, Pommeranz et al., 2012, Pu & Chen, 2008)

recommender type	explicit preferences	implicit preferences
content-based	item ratings, categories and tags (Pazzani & Billsus, 1997), excluded items (Chao et al., 2005a)	extracted keywords (Pazzani & Billsus, 1997), user behavior sequences (Wang et al., 2019), eye tracking related fixation points (Xu et al., 2008), item reviews (Chen et al., 2015), emotional states (Ayata et al., 2018; Polignano et al., 2021)
collaborative	item ratings (Ekstrand et al., 2011), pairwise preferences (Kalloori et al., 2016), choice-based preference elicitation (Graus & Willemsen, 2015), emotional states (Ho et al., 2006), personality traits (Elahi et al., 2013)	item reviews (Chen et al., 2015), user location data (Levandoski et al., 2012; Qiao et al., 2014), time of item consumption (Wei et al., 2012), emotional states (Ayata et al., 2018)
constraint-based	attribute values (Felfernig et al., 2006), preferences between attribute values (Brafman et al., 2010; Jannach et al., 2010), attribute weights (Felfernig & Burke, 2008; Masthoff, 2003), interest dimensions (Felfernig et al., 2006; Neidhardt et al., 2015)	items selected for comparison, degree of domain knowledge derived from induced conflicts (Felfernig et al., 2006)
critiquing-based	critiques on item features (attributes) (Ricci & Nguyen, 2007), natural language based critiques (Grasch et al., 2013)	information from chats (Nguyen & Ricci, 2017), eye tracking related fixation points (Chen et al., 2016)
group recommender	pro/con arguments (Felfernig et al., 2018), prioritizations (Ninaus et al., 2014), interest dimensions (Stettinger et al., 2015), critiques on item attributes (McCarthy et al., 2006), item ratings (Chao et al., 2005b; DePessemier et al., 2015), emotional states (Chen & Pu, 2014)	persons present at location (Kurdyukova et al., 2012), extracted keywords (Lieberman et al., 1999), item viewing time (Masthoff, 2011)

reflect in one way or another the preferences of the group (Felfernig et al., 2018; Jameson & Smyth, 2007). In the following, we will provide an overview of different existing recommender type specific approaches to preference representation.

Content-based recommendation If experiences from the past are available and can be used in the current decision, content-based recommendation can be used to support the decision process (Jameson et al., 2015). For example, if a user purchased a digital camera from provider x and was completely satisfied with the performance of this camera, there is an increased probability that this experience will be a major influencing factor for his/her preferences regarding a new camera. In this example, the information about the provider is interpreted as one among potentially many decision categories or keywords. In content-based recommender systems (Pazzani & Billsus, 1997), user preferences are often specified *explicitly* in the form of *item evaluations/ratings*, *excluded/disliked items*, or *tags* and *implicitly* in the form of *extracted keywords* (e.g., from item descriptions or user click stream data), *eye tracking related fixation points* of the user, and item-related *reviews*. In this context, reviews are often used to evaluate the overall popularity of items whereas the other mentioned approaches help to understand user-specific preferences regarding individual items. Especially, the analysis of eye tracking fixation points can help to improve the prediction quality of recommendations since it is possible to automatically figure out those aspects of an item with the highest relevance for the user. For example, in a news recommendation scenario, the most relevant subtopics of an article can be determined on the basis of an analysis of a user's eye tracking fixation points. This additional information can be used to give keywords or categories a higher weight that were derived from text segments with a higher associated user focus. Finally, it often makes sense to explicitly take into account *negative preferences* which helps to rule out items completely unacceptable for users, i.e., a negative preference denotes items or item properties a user is not interested in and does not want to be part of a recommendation. For example, in the context of group recommendation scenarios, Chao et al. (2005b) introduce a group recommendation approach based on negative preferences where only songs that are *not disliked* by individual group members are considered as recommendation candidates.

Collaborative filtering If a user is interested in purchasing a new digital camera but does not have the needed domain knowledge, the opinions of friends and family members with the needed experiences are a major preference-influencing factor in the underlying decision process (Jameson et al., 2015). Following this insight, the idea of collaborative filtering is to exploit the preferences of nearest neighbors (users with similar preferences) for determining recommendations. In collaborative filtering, the most often used approach to define user preferences in an *explicit* fashion is to collect user-item ratings (Ekstrand et al., 2011; Xie & Lui, 2014). On the other hand, user preferences can be specified *implicitly*, for example, by analyzing item reviews of users, taking into account a user's location data, and also taking into account the point of time of item consumption (Chen et al., 2015; Qiao et al., 2014; Wei et al., 2012). Item ratings are typically represented in the form of an N-point response scale. For example, MOVIELENS[1] uses a 5-star rating scale with half-star ratings and JESTER[2] (a joke recommendation system) is based on a continuous rating scale between −10 and +10. Already some time ago, NETFLIX[3] switched from a 5-star rating scale to a thumbs up/down based rating scale due to the fact that the simpler rating scale proved to significantly increase the user feedback frequency. A related insight is that the complexity of choice and the related cognitive effort (represented by the rating scale granularity) has an impact on the preparedness of users to provide feedback (Sparling & Sen, 2011). Ratings in the majority of the cases refer to solitary items, however, there also exist approaches that take into account pairwise (relative) preferences (Kalloori et al., 2016) or item list representations (Graus & Willemsen, 2015). Also in the context of collaborative filtering scenarios, preferences can be collected in an *implicit* fashion. For example, the time of an item consumption (potentially also time duration of item consumption) can be exploited to improve the prediction quality of a recommender system (Olaleke et al., 2021). Finally, Lin et al. (2019) show how to take into account the fact that preferences are sometimes compensatory (e.g., high-speed

[1] movielens.org

[2] eigentaste.berkeley.edu

[3] netflix.com

photography vs. time lapse) and sometimes non-compensatory (e.g., the maximum acceptable price of a digital camera). Using a matrix factorization approach (Koren et al., 2009), regularization terms can help to take into account such aspects (Lin et al., 2019).

Constraint-based recommendation More complex items such as apartments, financial services, and digital cameras are often described in terms of attributes (Felfernig & Burke, 2008). For example, attributes of digital cameras are a.o. *price*, *maximum frames per second*, *sensor type*, and *resolution*. In such scenarios, users start to specify their preferences in terms of initial attributes settings. With an increased understanding of the offered items, their preferences might change, which also triggers a change of the initial attribute settings (Jameson et al., 2015). The underlying recommendation process can be considered as iterative where users are specifying their preferences and the recommender system is in charge of finding items that satisfy the preferences and also take into account item domain specific constraints. Constraint-based recommender systems (Felfernig & Burke, 2008) are used in high-involvement item domains where (strict) constraints/dependencies exist between different item attribute values. An example of such a constraint in the digital camera domain is the following: *if your primary application area is sports photography, you have to select a camera with a high frame rate*. Preferences in constraint-based recommendation scenarios are either defined in terms of strict rules/constraints (preferences that have to be taken into account by each recommended item) or preferences that should be taken into account if possible (soft rules/constraints). For the second type of preferences (relaxable preferences), importance weights can be defined that can be used to figure out minimal sets of preferences that can not be fulfilled at the same time (Junker, 2004). These sets are also denoted as *conflict sets* which have to be resolved by the user. An example of such a conflict in the financial services domain is the following: *expected high return rates are incompatible with a low preparedness to take risks*. In this example, a conflict resolution would either require to increase the preparedness to take risks or to reduce the expected return rate. In constraint-based recommendation, preference specification often includes a utility-based evaluation scheme (Winterfeldt & Edwards, 1986), where *interest dimensions* can be used to specify the meta-level preference relationships on items (Felfernig et al., 2006). The aforementioned types of preferences are typically defined in an *explicit* fashion. However, constraint-based recommender systems are sometimes also based on *implicit* preferences. For example, items a user has selected for comparison purposes can be used to infer specific user interests.

Critiquing-based recommendation If an item domain is more or less unknown and users want to develop a better understanding thereof, they often prefer to take a look at example (reference) items to further develop their preferences (Jameson et al., 2015). If a user is interested in purchasing a new camera but is not an expert in the photography domain, he/she can develop a further understanding of the quality of a camera, for example, by taking a look at example photos. On the basis of such new insights, a user can start to "criticize" the reference solution, for example, by simply asking for a higher photo quality. In critiquing-based recommendation (Chen & Pu, 2011), preferences are represented in terms of change requests specified by users on so-called reference items. Critiques are change requests on specific item properties, for example, a user could specify the following critique: *show a digital camera with an overall price below 500 Euros*. Such critiques can refer to single item attributes (so-called *unit critiques*) or to a combination of item attributes (so-called *compound critiques*). An example of a compound critique is the following: *the overall price should be below 500 Euros and the camera should support at least 8 frames per second*. Thus, critiques can be specified via "conventional" user interfaces on predefined item attributes. An example of *implicit* feedback in the context of critiquing-based recommendation is the exploitation of eye tracking information to improve the prediction quality of relevant candidate items (Chen et al., 2016). More advanced approaches to critiquing-based recommendation support critique specification on the basis of natural language statements which help to create more complex critiques thus allowing to significantly reduce the number of needed critiquing cycles (see, e.g., Grasch et al., 2013, Nguyen & Ricci, 2017). In critiquing-based recommendation, combined preference feedback (e.g., critiques combined with natural language feedback) can help to reduce the number of needed critiquing cycles (Grasch et al., 2013; McCarthy et al., 2004).

Group recommender systems In the majority of the cases, preference representation in group recommender systems resembles the representation of preferences in single user recommender systems.[4] For example, in group-based collaborative filtering scenarios, a single user recommender system can be used to predict an item rating for each group member and then aggregate the predicted ratings to achieve a global item rating for the whole group. Consequently, the major difference between single user and group recommendation in this context is the application of different aggregation functions such as *average* or *least misery* (Felfernig et al., 2018). In a similar fashion, group recommender systems based on content-based recommendation aggregate user-individual preferences represented, for example, in terms of keywords, by aggregating keywords of individual user profiles to one keyword-based profile representing the preferences of the whole group (Lieberman et al., 1999). In constraint-based recommendation, either items recommended to individual users can be aggregated into a group recommendation or the preferences of individual users can be aggregated to a group model which is then used for prediction purposes. Similarly, in critiquing-based recommendation, either items recommended to individual users can be aggregated or the union of the individual user critiques is used to determine a group recommendation (McCarthy et al., 2006). Group recommenders can also collect user preferences in terms of *prioritizations*, i.e., group members select their preferred items in terms of a sorted list (prioritization) and the individual user lists are aggregated thereafter. Similar to single user recommendation approaches, extracted keywords and item viewing times are examples of implicit preferences that can also play a role in group recommendation scenarios. If negative preferences (Chao et al., 2005a) are available in a group recommendation setting, these can be applied to rule out alternatives which are completely unacceptable for a subset of the group members (Shafir, 1993). In the context of group recommender systems, it has been shown that multi-dimensional rating scales can help to make ratings more stable. More precisely, multi-dimensional rating scales result in rating processes which are more robust with regard to manipulations by anchoring effects (Stettinger et al., 2015). An analysis of the appropriateness of different preference aggregation strategies depending on the item domain (high-involvement vs. low-involvement items) is provided in Felfernig et al. (Felfernig et al., 2017). In low-involvement item domains (e.g., restaurants), groups tend to apply aggregation strategies that *accept* the misery of individual users to a larger extent (e.g., average voting). In contrast, in high-involvement item domains (e.g., apartments) groups tend to apply least-misery type heuristics.

Consistency preservation of preferences Especially in the context of critiquing-based and constraint-based recommendation, consistency preservation of preferences plays a major

[4] For details on different group recommendation approaches and preference aggregation mechanisms we refer to (Felfernig et al., 2018; Garcia et al., 2012).

role. The reason is that situations can occur where no solutions can be found for the preferences defined by a user. In such situations, it is important for the user to know which preferences are responsible for the inconsistent situation and to understand which alternatives exist to resolve the inconsistency (Falkner et al., 2011). Consistency preservation in preferences can be achieved on the basis of conflict detection (Junker, 2004) and diagnosis (Le et al., 2021; Reiter, 1987) techniques that help to automatically (1) identify minimal sets of preferences responsible for an inconsistency (induced by a set of conflicts) and (2) resolve the identified conflicts (Felfernig et al., 2009; Felfernig et al., 2013; Gupta et al., 2021). Inconsistencies in group-based settings can occur in scenarios where the individual critiques of users are merged to form a group model. Resulting inconsistencies can be resolved by simply omitting elder critiques and keeping only the recent ones in the group model. Alternatively, model-based diagnosis techniques can be applied to resolve such inconsistencies (Felfernig et al., 2012). The application of model-based diagnosis techniques in group decision scenarios is shown in (Felfernig et al., 2016) where aggregation mechanisms from computational social choice (Chevaleyre et al., 2007) are used to rank relaxation alternatives (diagnoses).

3 Psychological aspects of preference construction

Up to now, we have discussed different types of preferences in the context of single user and group-based recommendation scenarios. In this section, we analyze psychological aspects that can have an impact on the preference construction process. Inspired by the categorization of (Felfernig & Willemsen, 2018), we discuss the aspects of *preference visibility* and *choice overload*, and further aspects such as *time*, *personality & emotions*, and *cognitive biases*.

Preference visibility Especially in the context of group decision making, the degree to which preferences of individual group members are made visible to other group members can have a significant impact on the construction of preferences (Stettinger et al., 2015). Group members want to see the preferences of other group members, for example, to have access to the opinions and knowledge of problem-specific experts in the group (effort-saving aspect (Jameson & Smyth, 2007)). Furthermore, knowing the preferences of other group members can also help to streamline the group decision process and avoid inconsistencies in individual preferences. For example, if only one group member is interested in tennis but knows that all other group members are not interested in tennis, the tennis-interested person would not regard this as an important preference for the final group decision – this also helps to avoid conflict situations. The other side of the coin is that the knowledge about the preferences of other group members triggers a.o. *anchoring effects* (Jacowitz & Kahneman, 1995) where group members are focusing on comparing their own preferences with those of other group members and neglect the important aspect of the exchange of decision-relevant knowledge which is a major precondition for being able to take optimal decisions (Stettinger et al., 2015). In addition to anchoring effects, preference visibility can reinforce the effect of *emotional contagion* (Masthoff & Gatt, 2006) where the emotional state of one group member can have an impact on the emotional state of other group members and thus change the perception of individual decision alternatives. Especially in *coherent groups*, preference transparency can lead to the effect of *Groupthink* where group members try to avoid conflicts and therefore agree on already predefined preferences. In all these situations, the postponement of preference disclosure can help to improve the overall quality of a group decision (Stettinger et al., 2015). In the context of (single user) collaborative filtering scenarios, Cosley et al. (2003) show that the visibility of rating predictions can influence the rating behavior of a user. In this context, the authors show, for example, that on the basis of showing the predicted rating, users can even be influenced to move from negative to positive item ratings.

Choice overload The more decision alternatives or possible combinations of item attribute values exist, the higher the effort to analyze the available alternatives and the lower the probability that a decision is made – this is also known as the problem of *choice overload* (Diehl & Poynor, 2010; Huffman & Kahn, 1998; Scheibehenne et al., 2010). The *number of decision alternatives* can be specified, for example, in terms of the number of items shown to a user by a content-based or collaborative filtering recommender or the number of possible attribute value combinations in a constraint-based recommender system. An analysis of choice overload in the context of collaborative filtering recommender systems is provided by Bollen et al. (2012). Related insights are that larger recommendation sets containing only attractive items do not necessarily lead to higher choice satisfaction. Furthermore, choice overload appears more in settings where alternatives are similar (Scheibehenne et al., 2010). An approach to reduce choice overload in constraint-based and critiquing-based recommendation scenarios is to pre-select the next relevant attribute-related question(s), i.e., to avoid situations where a user has to provide feedback on all available attributes. Related approaches support question selection using collaborative filtering (Felfernig & Burke, 2008) or based on measures of information gain (Mahmood & Ricci, 2009). In group decision settings, the tendency of choice deferral is even higher compared to single user decisions (White et al., 2011). Explanations thereof are that on the one hand decision deferral appears to be easier than taking a decision, on the other hand groups are more risk-seeking which is in the line with the behavior of choice deferral.

Nudging As already mentioned, the outcome of a preference construction process heavily depends on different contextual factors (Jameson et al., 2015; Mandl et al., 2010). Already mentioned examples thereof are preference visibility and the number of shown decision alternatives – further factors will be discussed in the following. The goal of *nudging* (Thaler & Sunstein, 2009) is to leverage decision making biases in such a way that users are proactively supported in making better or even optimal decisions (Caraban et al., 2019; Jesse & Jannach, 2021; Yoo et al., 2013). One way of nudging users in the context of recommender systems is introduced in Atas et al. (2017) where it is shown that an increase in recommendation diversity can result in a significantly increased amount of information exchange among users engaged in a group decision process. Since knowledge exchange in group decision processes is crucial for being able to take an optimal decision, increasing recommendation diversity can be regarded as a basic nudging mechanism. On the level of the recommender user interface, Tran et al. (2019) show how an increased transparency regarding user activities in a decision process can reduce the tendency of manipulation efforts and thus can help to increase the decision quality. In the context of software prioritization (Felfernig, 2021) scenarios, Stettinger et al. (2015) show that a delayed disclosure of the preferences of other stakeholders trigger an increased focus on the discussion of the relevance of software requirements and – as a consequence – an increased amount of information exchange which is an extremely relevant aspect to achieve a high-quality or even optimal decision (Mojzisch & Schulz-Hardt, 2010). In Stettinger et al. (2015), the existence *serial position effects* has been analyzed in the context of item descriptions. The authors point out that mentioning the positive properties of an item (e.g., a restaurant) at the beginning and the end of an item description and the negative aspects in the middle of the description text results in significantly higher item ratings compared to versions of item descriptions where the negative aspects are mentioned at the beginning and the end. This aspect should not always be interpreted as nudging, since in the mentioned scenario serial position effects can also be used to *manipulate* (for the worse) the decision behavior of a user.

Time aspects Users experience preference shifts over time, for example, music or movie genres liked in the past become less relevant in the future. Koren (2009) introduces different concepts how to take into account such aspects in collaborative filtering scenarios. The time between item consumption and item evaluation can have an influence on preference construction. For example, the longer the duration between item consumption and item rating, the more there exists a rating tendency towards the middle of the rating scale (Bollen et al., 2012). There also exists a so-called *positivity effect*, i.e., pleasant items are recalled more effectively (Bollen et al., 2012). Especially in the context of group recommender systems, time also plays a role in the context of repetitive decisions. For example, a group of friends meets for dinner once a month. In this context, the group has to decide about which restaurant to visit next. Recommendations should be fair in the sense that the individual preferences of group members should be taken into account in a fair fashion over time (Felfernig et al., 2018). Finally, the chronological ordering in which different decision tasks are completed can have an impact on the outcome of the individual decisions (Tran et al., 2018). The authors also point out that the time spent for taking a decision depends on the positioning of the task in the sequence.

Personality & emotions A definition of *personality* is given in Burger (2010): *consistent behavior pattern and intra-personal processes originating within the individual*. Personality can be regarded as enduring factor that has an influence on human behavior, tastes, and interests. Since personality is a quite predictable and stable factor that determines human behaviors, personality traits are often used to tackle the cold-start problem based on the assumption that people with similar personality traits will have similar interests and behavioral patterns (Zewengel et al., 2017). Personality traits can be determined in an explicit and implicit fashion – a well-known model is the *Five Factor Model (FFM)* (John et al., 2008) which includes the personality traits of *openness*, *conscientiousness*, *extroversion*, *agreeableness*, and *neuroticism*. The inclusion of personality traits may lead to significant improvements of the prediction quality of a recommender system. Interestingly, the recommendation precision due to the integration of personality traits is domain-dependent, for example, higher precision can be achieved in the movie domain compared to the domain of books (Fernández-Tobías et al., 2016). An insight regarding the rating behavior of users is that users with a high degree of agreeableness rate at least 0.5 stars higher compared to users with a low agreeableness (on a rating scale 1..5) (Karumur et al., 2016). Finally, users with different personality traits show different preferences regarding the recommendation properties of *diversity*, *popularity*, and *serendipity* – taking into account this aspect can significantly increase a user's satisfaction with the recommendation output (Nguyen et al., 2018). *Emotions* can be regarded as a feeling such as happiness, anger, or sadness and can have a strong impact on a preference construction process (Picard, 1997). In the context of recommender systems, emotions can be detected (1) in an implicit fashion, for example, on the basis of visual information (Ko, 2018), or (2) in an explicit fashion, i.e., by explicitly reporting about the personal emotional state (Chen & Pu, 2012). The affective state of a user described in terms of inferred emotional states can be regarded as a relevant preference dimension that has to be taken into account when modeling (short-term) user preferences and can help to significantly increase the prediction quality of a recommender system (Polignano et al., 2021).

Cognitive biases An analysis of the role of different cognitive biases and their impact on recommender systems is given in (Mandl et al., 2010). *Serial position effects* can occur in scenarios where items are represented in the form of a list, and – when it comes to item recall – items at the beginning and the end of the list are recalled more often. In such scenarios, item positioning in a list can lead to completely different selection behaviors. The positioning of arguments in item evaluations can have an impact on the overall evaluation of an item (Stettinger et al., 2015). Mentioning the positive aspects at the beginning and the end of an evaluation results in significantly higher item ratings compared to situations where the positive aspects are mentioned in the middle of an evaluation. *Framing effects* (McElroy & Seta, 2003) occur if different (semantically) equivalent descriptions of decision alternatives lead to completely different item selections. In the context of the presentation of recommendation lists, framing effects can occur, if some descriptions of similar or even equivalent items differ in terms of the description style. In the context of group decision scenarios, *hidden profiles* denote decision-relevant information units that need to be known by the whole group in order to be able to take an optimal decision (Schulz-Hardt et al., 2007). In the context of group recommender systems, it has already been shown that different recommender user interfaces trigger different amounts of information exchange among users (Samer et al., 2020). In a similar line of research, (Chen & Pu, 2012) report in the context of a group-based music recommendation scenario that providing feedback on the emotional states of individual group members helps to increase the degree of *mutual awareness*. More specifically, positive emotions can enhance problem solving capabilities with more flexible and efficient cognitive processing (Isen, 2001). Finally, *anchoring effects* (Jacowitz & Kahneman, 1995) can occur in situations where information about the opinions/preferences of other group members can have an impact on the construction of one's own preferences. User ratings appear to be malleable, for example, in the context of collaborative filtering scenarios, recommender-provided ratings represent an anchor and have an influence on the rating behavior of users (Adomavicius et al., 2011; Zhang, 2011). Anchoring effects in the software engineering domain are discussed, for example, in Stettinger et al. (2015).

We want to emphasize that with a few exceptions most of the research on cognitive biases in recommender systems up-to-now focuses on the *analysis of existing biases*. In the following section, we also focus on analyzing such biases but also propose some measures to counteract these. More specifically, we focus on *anchoring effects*, aspects of *hidden profile detection*, and *framing effects* in the specific context of group recommendation (decision) scenarios. For demonstration purposes, we chose the domain of *requirements engineering* which includes group-related decision tasks such as *requirements prioritization* and *release planning* (Felfernig, 2021).

4 Example: Cognitive biases in requirements engineering

The following user study has been conducted within the scope of a university course on *software development processes*. N=623 bachelor-level computer science students (23% female, 77% male) participated in this study. When participating in the study, students were remunerated with bonus points that were then taken into account in the overall course evaluation. The study investigated the existence of different kinds of biases in the context of *requirements engineering* decision making. Study participants were confronted with requirements engineering specific scenario descriptions and were then asked about their preferences. In the following, we introduce the different tasks that had to be completed by students within the scope of our user study and show the relevance of these tasks for recommendation settings. In each task of the study, the number of participants was distributed equally over the given variants. We want to emphasize that the selection of the study participants (computer science students) is a potential thread to validity and we regard the extension of the study participant scope as a major task of our future research.

Anchoring effects Anchoring effects are triggered if the preferences of individual group members are made accessible to other group members too early, i.e., before all group members had the chance to analyze the given alternatives and then make an independent evaluation. *Avoiding anchoring effects in group recommendation scenarios* is extremely important since focusing on evaluations instead of information exchange among group members can easily lead to sub-optimal decision outcomes (Mojzisch & Schulz-Hardt, 2010). In our requirements engineering setting, we were interested whether the information about the preferences of other group members (formulated in terms of the preferences of a single group member as well as in terms of the preferences of a subgroup) can have an impact on the overall evaluation of decision alternatives (see the setting in Table 2). The first hypothesis we wanted to investigate in this context, is the following (H1).

Hypothesis 1 (H1). There is an anchoring effect when performing requirements-specific evaluations. Knowledge about the evaluations of other users (single users and also subgroups) can significantly change the preferences of a user.

Hidden profile detection The detection of hidden profiles is a crucial task in group decision scenarios (Schulz-Hardt et al., 2006). In order to make optimal decisions possible, it is extremely important for a group to make the decision-relevant information (the hidden profile) available to all group members. This information is the basis for the evaluation of individual items and thus is crucial in the support of group decision making. A major challenge in this context is to *foster information exchange* among group members since this can

Table 2 Analyzing *anchoring effects* in preference elicitation: variants 2 and 3 include an anchor (other colleagues who already evaluated the software feature)

Variant	Question
1	Assume, you and four of your project colleagues are in charge of evaluating the following feature: "The new e-learning software should support the automated evaluation of textual answers submitted by the participants of a test." How would you evaluate the relevance of this feature?
2	Assume, you and four of your project colleagues are in charge of evaluating the following feature: "The new e-learning software should support the automated evaluation of textual answers submitted by the participants of a test." *You already know that one colleague evaluated the relevance with 2 stars.* How would you evaluate the relevance of this feature?
3	Assume, you and four of your project colleagues are in charge of evaluating the following feature: "The new e-learning software should support the automated evaluation of textual answers submitted by the participants of a test." *You already know that one colleague evaluated the relevance with 2 stars and another one with 4 stars.* How would you evaluate the relevance of this feature?

The used rating scale was [very low relevance (*) .. very high relevance (*****)]

Table 3 Analyzing *hidden profile detection* in preference elicitation: question variant 1 focuses on relevant evaluation dimensions whereas variant 2 is more open

Variant	Question
1	Assume, you are member of a group of stakeholders who should evaluate the following software feature (F1): "The new e-learning software should support an automated recommendation of learning units for students." *The stakeholders are focusing on finding arguments regarding the aspects of available resources, business relevance, and technical risks*. What are your arguments for (pro) and against (con) F1?
2	Assume, you are member of a group of stakeholders who should evaluate the following software feature (F1): "The new e-learning software should support an automated recommendation of learning units for students." What are your arguments for (pro) and against (con) F1?

increase the probability of also sharing the decision-relevant information. In our requirements engineering setting, we were interested whether a clear focus on decision-relevant dimensions (e.g., business relevance and technical risks in the software engineering context) could increase the degree of information exchange (see the setting in Table 3). In our user study, we have tested the degree of information exchange in terms of pro- and counter-arguments for/against a specific alternative. The hypothesis we wanted to investigate in this context, is the following (H2).

Hypothesis 2 (H2). Clearly defined evaluation criteria (in contrast to unspecified evaluation criteria) help to increase the amount of exchanged arguments.

Framing effects Depending on the way an alternative is characterized, it could be evaluated differently. In this context, we were interested to which extent framed alternatives could lead to a change in alternatives perception and - as a consequence – in the selection behavior of group members (within the scope of a group decision process). In our requirements engineering setting, we were interested to which extent the framing of requirements has an impact on the overall risk estimation related to the requirement (see the setting in Table 4). The hypothesis we wanted to investigate in this context, is the following (H3).

Hypothesis 3 (H3). There exist framing effects in the context of risk estimation which can lead to significantly different overall risk estimates.

Study results The results of our user study can be summarized as follows (see Table 5). Regarding Hypothesis 1 (H1), there are significant anchoring effects in the context of the

Table 4 Analyzing *framing effects* in preference elicitation: question variant 1 is positively framed (80% chance of success) whereas variant 2 is negatively framed (20% chance of failure)

Variant	Question
1	Assume, you are engaged in a software project that has *an 80% chance of being successfully completed without exceeding the original budget of 100.000 Euros*. If the budget gets exceeded, how high (on an average) would be the exceeding from your point of view (0-250k €)?
2	Assume, you are engaged in a software project that has *a 20% chance of not being successfully completed without exceeding the original budget of 100.000 Euros*. If the budget gets exceeded, how high (on an average) would be the exceeding from your point of view (0-250k €)?

Table 5 Summary of study results

Hypothesis	Result	Significance
H1	Existence of anchoring effects triggered by early preference disclosure of individuals as well as subgroups.	$p<0.05$ (*Variant 1 vs. Variant 2*: Independent t-test, $p=0.0027$; *Variant 1 vs. Variant 3*: Independent t-test, $p=0.0095$)
H2	Increased knowledge exchange (in terms of the length of specified arguments) if evaluation criteria have be defined in terms of concrete evaluation dimensions.	$p<0.05$ (*Pro-arguments*: Independent t-test, $p=0.0021$; *Con-arguments*: Independent t-test, $p=0.00075$)
H3	Negative framing leads to more risk-aware (conservative) evaluations compared to scenarios with a positive framing.	$p<0.05$ (Independent t-test, $p=0.0128$)

setting shown in Table 2. The average evaluation of the requirement (feature) in *Variant 1* was 3.6 whereas the average evaluation in *Version 2* was 3.0 and 3.2 in *Variant 3*. In both settings (Variant 2 and Variant 3), the additional information about existing evaluations of other stakeholders had an impact on the evaluation of the current user. On a descriptive level, the negative evaluation of a single user had a more negative impact than the negative evaluation of one user combined with a more optimistic one of a third user. Consequently, an insight to be taken into account is that *preferences of stakeholders in group decision processes should not be shared too early. In this context, deferred preference disclosure can help to counteract anchoring effects and thus help to improve decision quality* (Stettinger et al., 2015).

In the context of H2, we could identify significant differences in terms of the number of identified pro- and con-arguments depending on the underlying variant. In *Variant 1*, significantly more arguments for and against the proposed feature have been defined by study participants (on an average, 1.737 pro-arguments and 1.752 con-arguments per study participant). In *Variant 2*, 1.224 pro-arguments and 1.075 con-arguments have been specified. Consequently, an important insight is that *clearly defined evaluation criteria trigger an increased degree of decision-relevant information exchange which can help to counteract infrequent information exchange in decision scenarios (which is a major source of suboptimal decisions)* (Schulz-Hardt et al., 2007).

In the context of H3, we could observe a significant increase of the perceived risk level (specified in terms of the estimated consequential costs). The framing *unsuccessful completion* lead to an average estimate of 37.21k € whereas in the case of a positive framing (successful completion) 30.22k €. Consequently, *negative framing leads to more risk-avoiding item evaluations (compared to positive framing) and thus can help to counteract risky decision behavior*.

5 Research issues

There exist a couple of research issues related to the support of preference construction processes in recommender systems. To further advance the related state-of-the-art, we now discuss different open research issues.

User interfaces for preference construction Existing recommender user interfaces are in the majority of the cases based on standard interface elements supporting, for example, preference articulation and item selection. Related work on the integration of natural language processing into recommendation processes (e.g., Grasch et al., 2013) has clearly shown the potential of natural language interfaces to make the interaction with recommender systems more flexible. Further related developments are needed that help to extend the applicability of natural language processing, for example, to constraint-based recommendation scenarios where users are in the need of support in situations where no solution can be identified. Furthermore, preferences can be extracted on the basis of the results of an eye tracking analysis – a knowledge source that is rarely used in real-world scenarios to improve the prediction quality of recommender systems. When taking a look at Table 1, it becomes clear that not every preference type has been analyzed in the context of every possible type of recommender system. For example, eye tracking information can also be relevant in the context of constraint-based recommendation scenarios (e.g., in terms of an analysis of attribute views) and can thus be regarded as a relevant issue for future work.

Counteracting decision biases From the requirements engineering related user study presented in this article we know that anchoring effects can be reduced, for example, by not sharing preference knowledge of other group members too early in a decision process. Furthermore, we are able to increase the quality of decision processes (and related decisions) by fostering information exchange among group members, for example, through the definition of evaluation criteria for decision alternatives. Such criteria help to more easily develop multiple views on existing decision alternatives which can then also be communicated to other group members. Cognitive biases such as anchoring are often the reason for sub-optimal decisions. A major issue for future work is to analyze in detail cognitive biases discussed in the literature (see, e.g., Thomas, 2018) and to develop approaches on the algorithmic and the user interface level to counteract these biases.

Nudging and preference construction In this article, we have already discussed a couple of scenarios where nudging is applied to improve the quality of decision processes. Due to a plethora of cognitive biases that are documented in the psychological and managerial literature (Thomas, 2018), there is a huge playground for studies that focus on the analysis of exploitation potentials of these biases to improve the overall quality of decision processes, on the level of single user decisions as well as group decisions. Future research also has to analyze dependencies between personality traits and emotional factors and the corresponding susceptibility for nudging mechanisms. For example, a corresponding study could first try to figure out personality aspects and then analyze which types of nudging mechanisms appear to have more impact.

Negotiation mechanisms for preference construction in groups Especially in the context of group decision scenarios, negotiation mechanisms have to be developed to support groups in achieving goals such as consensus and fairness (Sonboli et al., 2021). Existing approaches to group recommendation are primarily based on different kinds of functions that are used to aggregate the preferences of individual group members. In the context of constraint-based and critiquing-based recommenders, conflict and diagnosis approaches can be used to resolve inconsistencies. However, future group recommender systems should go a step further and support negotiation processes to be able to achieve high-quality decisions.

Avoiding manipulations of group preferences Group recommender systems can be attacked in such a way that the preferred options / alternatives of some group members are pushed whereas the preferences of other group members get neglected. The avoidance of manipulations is an important issue to assure high-quality group decisions. One possibility to achieve this goal is to develop manipulation-immune aggregation functions. A simple example thereof are median-based aggregations that avoid the influence of extreme high or low evaluations (Jameson, 2004). An alternative is to include explanations (Tran et al., 2019) that present the current status of the decision process and the decision-related activities of individual users. Related research results are reported in Tran et al. (2019).

6 Conclusions

Preferences are a major input for a recommender system to be able to determine items of relevance for a user. In this article, we provide an overview of different approaches to represent preferences depending on the underlying recommendation approach where we differentiate between the explicit and implicit specification of preferences. Furthermore, we discuss different psychological aspects of importance in the context of preference construction processes. As an example, we show the existence of decision biases in the specific domain of software requirements engineering and discuss measures to counteract these biases. In order to stimulate further related work, we discuss different future research topics related to psychological aspects of preference construction.

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