A Multi-Dimensional Conceptualization Framework for Personalized Explanations in Recommender Systems

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Abstract

Recommender systems (RS) have become an integral component of our daily lives by helping decision making easier for us. The use of recommendations has, however, increased the demand for explanations that are convincing enough to help users trust the provided recommendations. The recommendations are desired by the users to be understandable as well as personalized to their individual needs and preferences. Research on personalized explainable recommendation has emerged only recently. To help researchers quickly familiarize with this promising research field and recognize future research directions, we present a multi-dimensional conceptualization framework for personalized explanations in RS, based on five dimensions: WHAT to personalize?, TO WHOM to personalize?, WHO does the personalization?, WHY do we personalize?, and HOW to personalize?. Furthermore, we use this framework to systematically analyze and compare studies on personalized explainable recommendation.

Keywords

Recommender systems, Explainable recommendation, Personalized explanation

1. Introduction

Over the past few years, with the increased usage of online services like social media, e-learning, and e-commerce, recommender systems (RS) have become an integral part of our lives. These RS help in shaping the decisions of users and helping them choose what they want based on a number of relevant options presented to them, called recommendations. However, with the increased amount of available recommendations, there is a chance of creating mistrust among users about the presented information. A huge amount of available information creates 'information overload' which might lead to users questioning the validity of the provided content and might think of it as misinformation.

One way to overcome this challenge is to provide personalized recommendations to the users. The content of these recommendations is adapted to users' interests and only relevant items are recommended to them. The goal of personalized recommendations is to predict items considered attractive and interesting by the user. This relevant item prediction is made by either (1) content, i.e., items having similar content with the items already used by the user are recommended or (2) past behavior, i.e., items are recommended based on users' ratings and likes or dislikes, as compared to the items consumed by similar users.

However, the majority of RS still act as a black-box and users have no idea why and how items are being recommended to them. Therefore, it is increasingly important to make RS more intelligible and investigate methods to explain them to end-users. Explaining the reasoning behind a recommendation has become an active area of research in the last few years. Researchers have argued that explanations in RS could be very beneficial [1, 2, 3]. To "explain" means "to make known, to make plain or understandable, to give the reason for or cause of" [4]. An explanation seeks to answer questions such as what, why, how, what if, why not, and how to [5]. Providing the reasoning behind why an item is recommended to the user or how the recommendation process works, as an explanation, adds to the system's transparency [6] and can benefit user experience and trust in the RS [1] .

Explainable RS have traditionally followed a one-size-fits-all model, whereby the same explanation is provided to each user, without taking into consideration an individual user's context, i.e., abilities, goals, needs, or preferences. In the explainable recommendation field, research regarding personalized explanation has emerged only recently, showing that personal characteristics have an impact on the perception of explanations, and that there is potential for the development of personalized explanations in RS [7, 8]. For example, researchers have focused on investigating what specific characteristics may play a role in a user's interaction with an explainable RS [9, 10]. An analysis on existing

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explainable recommendation work focusing on personalized explanation is vital to help researchers quickly familiarize with this promising topic, compare studies in this field, and recognize future research directions. To fill this critical research gap, we present a timely conceptualization framework for personalized explanations in RS and provide an overview of the current state research in this emerging research area. To get at this, we gathered, analyzed, and connected existing concepts related to personalized explanations in the artificial intelligence (AI), machine learning (ML), and RS domains. We then proposed a conceptualization framework that can be used to systematically categorize and compare the literature on personalized explainable recommendation. Based on this framework, we analyzed studies in this research domain.

The paper is structured as follows. We first outline the background for this research (Section 2). We then present the details of the proposed conceptualization framework (Section 3) and use the framework to analyze the literature on personalized explainable recommendation (Section 4). Finally, we summarize the work and outline future research plans (Section 5).

2. Personalized Explanation

In the field of explainable AI (XAI), Mohseni et al. [11] argue that different user groups will have other goals in mind while using such systems. For example, while machine learning experts might prefer highly-detailed visual explanations of deep models to help them optimize and diagnose algorithms, lay-users do not expect fully detailed explanations for every query from a personalized agent. Instead, systems with lay users as target groups aim to enhance the user experience with the system through improving their understanding and trust. In the same direction, Miller [12] argues that providing the exact algorithm which generated the specific decision is not necessarily the best explanation. Therefore, the literature on AI/ML in recent years has emphasized the need for explanations that are tailored to individuals, i.e., personalized explanations. For example, Arya et al. [13] stressed that one explanation does not fit all, as different AI stakeholders present different requirements for explanations and may desire different kinds of explanations (e.g., feature-based, instance-based, language-based). The authors presented an AI toolkit, which contains eight state-of-the-art explainability algorithms that can explain an AI model in different ways to a diverse set of users. Jung and Nardelli [14] pointed out that XAI is challenging since explanations must be tailored (personalized) to individual users with varying backgrounds and proposed an algorithm that allows constructing personalized explanations that are optimal in an information-theoretic sense. Assuming that, based on varying backgrounds like training, domain knowledge and demographic characteristics, individuals have different understandings and hence mental models about the learning algorithm, Kuhl et al. [15] investigated how personalized explanations of learning algorithms affect employees' compliance behavior and task performance. On a conceptual level, Schneider and Handali [16] proposed a conceptualization of personalized explanation in ML based on a framework covering desiderata of personalized explanations, dimensions that can be personalized, what and how information can be obtained from individuals and how this information can be utilized to customize explanations.

In the field of explainable recommendation, research regarding personalized explanation is emerging, recognizing that it is increasingly important not only to explain recommendations to the user but also to personalize these explanations [7, 8]. Studies showed that different users have different reactions to, and expectations from explainable RS [17, 9] and that personal characteristics play a major role in the perception of, and interaction with these systems [10, 18, 19]. However, a comprehensive framework to categorize related work on personalized explanation in the RS field is lacking.

3. A Framework For Personalized Explainable Recommendation

To dive deeper into the understanding of key concepts related to personalized explanation in RS and provide a systematic categorization of the literature in this area, we propose a multi-dimensional conceptualization framework for personalized explanations in RS (see Figure 1). To develop this framework, we gathered, utilized, and adapted ideas, concepts, and methods related to personalized explanations in the RS literature and formulated a succinct and concise framework based on five dimensions: *WHAT to personalize?, TO WHOM to personalize?, WHO does the personalization?, WHY do we personalize?, and HOW to personalize?.* Similar to the conceptualization of personalized explanation in ML presented in [16], we adopted and adapted the framework presented by Fan and Poole [20], and extended it from "what, to whom, and who personalizes?" by adding two more dimensions, namely "why to personalize?" which describes the goals of personalized explanation and "how to personalize?" which describes

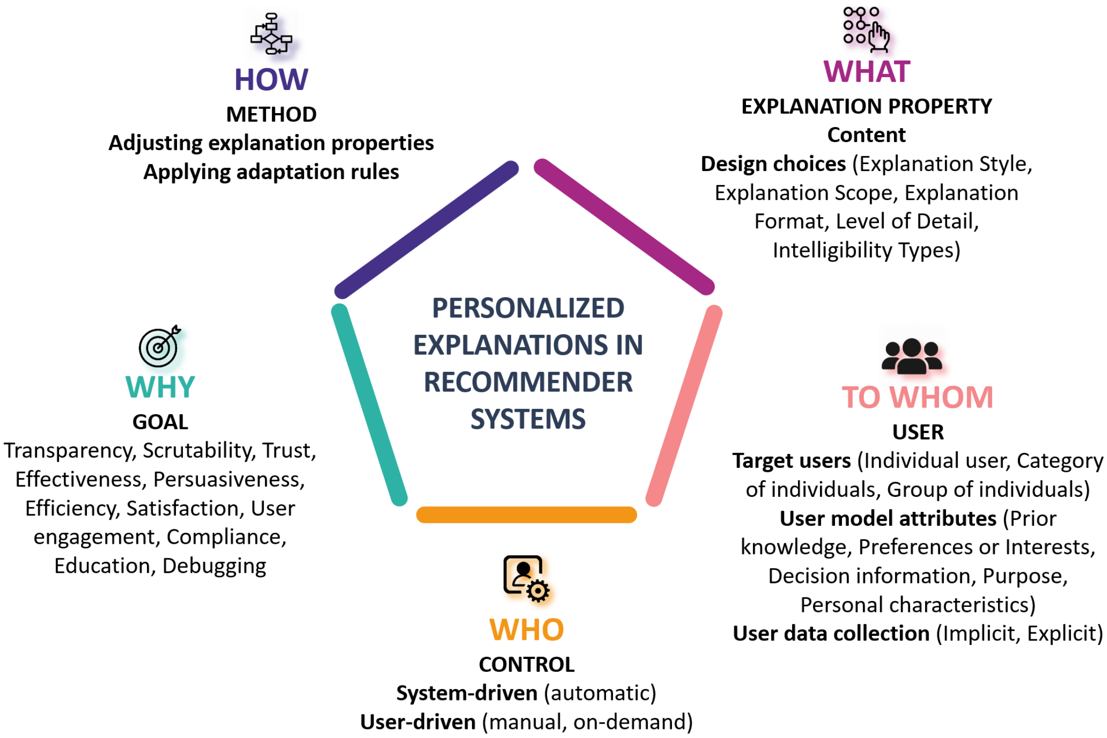

Figure 1: A Conceptualization Framework for Personalized Explainable Recommendation

the methods for personalized explanations. Below, we discuss in detail the five dimensions of our proposed conceptualization framework for personalized explanation in RS.

3.1. WHAT to Personalize?

The "WHAT" dimension refers to the properties of an explanation that can be adjusted to the user profile to provide personalized explanations. We identified two main explanation properties that can be adapted based on explainee (for whom explanations are provided) data, namely *content* and *design choices* of the explanation.

3.1.1. Explanation Content

Content of an explanation refers to the information presented in an explanation. This information represents a description of details related to the recommendation process. These include, for example, user/item attributes contributing to the recommendation, inner workings of background algorithms, information related to the user model used as input to the RS, similarities between users and/or items, and connection between the user profile and recommended item features. To personalize an explanation, its content must be tailored to different user profiles and should be adapted according to the explanation context.

3.1.2. Explanation Design Choices

There is a large design space for explainable RS. Researchers presented different ways to design explainable RS, referred to as explanation design choices [17, 21]. Like the content of an explanation, these design choices represent further characteristics of an explanation that can be customized based on a user profile. Based on the literature on explainable recommendation, we identified five explanation design choices, namely *explanation style*, *explanation scope*, *explanation format*, *level of detail*, and *intelligibility types*.

Explanation Style: The explanation style refers to the model or strategy used for generating explanations [3]. In general, the explanation style is dependent on the recommendation approach used in the RS, e.g., a content-based RS produces content-based explanations [2]. In case of complex RS (e.g., deep learning models), however, the explanation style for a given explanation may not reflect the underlying algorithm by which the recommendations are computed [2, 3]. Personalizing the explanation style means to present explanation in different styles to different users based on their preferences. Explanation styles have been perceived differently in different domains [22, 23]. In this paper, we build on the taxonomy of explanation styles in RS used in [2, 9, 24].

- *User-based Explanations:* Explains similarity with other users having same tastes. For example: User A with whom you share similar tastes, likes item B.
- *Item-based Explanations:* Explains recommended items based on item (rating) similarity. For example: People who like item A in your profile also like item B.
- *Content-based Explanations:* Explains similarity between item features. For example: Item A has similar features as of item B purchased by you.
- *Social-based Explanations:* Explains similarity between users who know each other. For example: Your friend User B likes item A.
- *Knowledge-based Explanations:* Explains the description of user's needs or interests in the context of a recommendation. For example: This destination has higher average temperature, which is better for sunbathing.
- *Demographic-based Explanations:* Explains the use of demographic data and its connection to the recommendations. For example: This movie was recommended to you according to your age.

Explanation Scope: The explanation scope refers to the part of RS that an explanation focuses on, i.e., input, process or output [25]. Explanation focusing on *input* tries to explain the user model which is taken as an input by the RS. Explanation focusing on *process* tries to explain the working and flow of the underlying algorithm used to generate a recommendation. Explanation focusing on *output* tries to explain why an item was recommended. Different users demand explanations with a different scope. Not every user is interested in knowing the details of the user model or the internals of the underlying algorithm [11]. Personalizing the explanation scope means to present explanations that focus on the input, output or process, according to the user's preferences and needs.

Explanation Format: The explanation format refers to how an explanation is displayed to the user. It can either be in form of a text description (textual) or an image, a graph, or a chart (visual). Textual explanations are usually in form of short or long sentences using verbal elements, i.e., words, phrases or natural language describing the reasoning behind a recommendation. Visual explanations are usually in a graphical format using visual elements to explain a generated recommendation. Personalizing the explanation format means to present the explanation in the format preferred by the user.

Level of detail: The level of detail refers to the amount of information exposed in an explanation that should be presented to a user [17, 11]. Users are not always interested in all the information that is produced in an explanation [12]. Different users demand different levels of explanation information and explanations may cause negative effects if an explanation is difficult to understand [26]. Thus, it is important to provide explanations with enough details to allow users to build accurate mental models of how the RS operates without overwhelming them. For example, in an explanation, providing the exact algorithm that was used to generate the explanation may be a good choice for a Machine Learning (ML) expert but not for a lay user [12]. Furthermore, the demand for level of detail in an explanation also varies with the cognitive abilities of the user [26]. Only when the users have enough time to process the information and enough ability to figure out the meaning of the information, a higher level of detail in the explanation will lead to a better understanding. But as soon as the amount of information is beyond the users' comprehension, the explanation could lead to information overload and bring confusion [17].

Intelligibility Types: When user encounters a complex system, she might demand different type of explanatory information based on the system and its context [11]. Lim and Dey [5] identified several queries (called intelligibility types) that a user may ask of a smart system. These include:

- *How Explanations:* demonstrate how the underlying system behind a recommendation works. How explanations are useful when Users are interested in knowing how the system generates certain recommendations. How explanations aim to answer the question: "*How* (under what conditions) does the system do Y?".
- *Why Explanations:* demonstrate why a recommendation is made for a particular user. These explanations cover what was the input to the system (user model) and what logic was used to generate the recommendation. Why questions

are very common by the user hence it is an essential intelligibility requirement. Some users might expect a very informative answer from this why explanation and a simple explanation may not satisfy them [5]. Why explanations aim to answer the question: "*Why* did the system do X?".

- *Why Not Explanations:* (also called Contrastive Explanations) help the users in understanding why a specific item was not recommended to them. Lim et al. [27] argued that these explanations are useful for high-risk circumstances and when user might ask for alternative possibilities from the RS. Why Not explanations aim to answer the question: "*Why* did the system *not* do Y?".
- *What If Explanations:* deal with the manipulation of inputs to the RS. These explanations illustrate how the manipulation of inputs affect the output of the RS, i.e., recommendations. These explanations involve users' interaction with the system when they can change an input to the RS and want to know what will happen as a consequence. What If explanations aim to answer the question: "*What If* there is a change in conditions, what would happen?".
- *What Else Explanations:* demonstrate different examples of the similar inputs to the RS that can produce similar outputs (recommendations). Lim and Dey [5] demonstrated that although the demand for these explanations is low but these are helpful in critical situations when users expect that the RS is doing more than shown to them, to handle a critical situation. What else explanations aim to answer the question: "*What else* the system is doing?".
- *How To Explanations:* (also called Counterfactual Explanations) are basically explanations about what hypothetically needs to change for the desired outcome to happen. How To explanations aim to answer the question: "*How to* make the system recommend X?".

3.2. TO WHOM to Personalize?

The "TO WHOM" dimension focuses on to which user(s) to personalize. A crucial requirement in explainable RS is to build detailed user models that can be used by the system to recommend items or to provide personalized explanations. These user models are based on data collected from the user to generate different attributes.

3.2.1. Target users

The explanations can be personalized for target users at different levels of granularity. A target user for an explanation can be an *individual user, category of individuals* (e.g., experts, lay users), or *group of individuals* (in case of group RS).

3.2.2. User model attributes

To personalize the explanations for a user or a group of users requires to tailor explanation based on user models. Schneider and Handali [16] summarize different user model attributes that can be used to customize an explanation. These include:

- *Prior knowledge:* What an explainee knows, e.g., knowledge about the RS domain, expertise regarding the RS methods to be explained
- *Preferences/Interests:* What an explainee likes and prefers, e.g., preferred presentation format (visual or textual), desired level of detail of the explanation, the time or effort an explainee wants to invest to understand the explanation. User preference and interests are used interchangeably in the literature on RS
- *Decision information:* What information is used by an explainee to make decisions
- *Purpose:* What the explanation is used for

Recent studies on explainable recommendation showed that *personal characteristics* have an effect on the perception of explanations and that it is important to take personal characteristics into account when designing explanations. Examples of personal characteristics that can be used as further user model attributes according to which an explanation can be tailored include the Big Five personality traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism [28, 29, 30, 31, 32], need for cognition (NFC), [33, 10, 9], ease of satisfaction, visualization familiarity, domain experience [9], locus of control, need for cognition, visualisation literacy, visual working memory, tech-savviness [10, 18], and musical sophistication [19].

3.2.3. User data collection

User data collection indicates how data is collected to generate a model of the user for whom an explanation is personalized, in our case the explainee. This could be same as the data used to generate recommendations or different. There are two ways to get explainee data to generate user models:

- *Implicit data collection:* refers to getting explainee data to generate a user model, implicitly through user's past activity, browser search history, mouse clicks, social media information, system usage history, previously consumed items, etc. This requires techniques like preference elicitation and knowledge extraction from raw data.

- *Explicit data collection:* refers to getting explainee data to generate a user model, explicitly by asking the user to write reviews and feedback to items, giving ratings, filling out questionnaires, interviews and surveys, liking and disliking items etc.

3.3. WHO does the Personalization?

The "WHO" dimension focuses on who does the personalization. The literature on personalized systems distinguish between *automatic* personalization by the system providing explanations (i.e., *system-driven* personalized explanation) and *manual* personalization which is done on-demand by the explainee, actively setting the explanation parameters, e.g., choosing the level of detail to be shown in an explanation (i.e., *user-driven* personalized explanation) [20, 17, 16].

3.4. WHY to Personalize?

The "WHY" dimension refers to the intended goals of personalizing an explanation. Different users have different goals when they interact with an explainable RS. Thus, the explanation presented to a specific user should be personalized in a way to achieve the specific goal(s) intended by the user. Prior work on explainable recommendation has presented different explanation goals. For example, Tintarev and Masthoff [2] identified seven goals, as follows:

- *Transparency:* Explain how the system works
- *Scrutability:* Allow users to tell the system it is wrong
- *Trust:* Increase user's confidence in the system
- *Effectiveness:* Help users make good decisions
- *Persuasiveness:* Convince users to try or buy
- *Efficiency:* Help users make faster decisions
- *Satisfaction:* Increase the ease of use or enjoyment

There are possible refinements to these goals. For example, in [1] *satisfaction* is not considered as a single goal, but is split into *ease to use*, *enjoyment*, and *usefulness*. Other explanation goals in RS include *user engagement* resulting from more confidence and transparency in the recommendations [34], *compliance* with legal regulations e.g., European Union's GDPR [7], *education* by allowing users to learn from the system [8], *debugging* to be able to identify wrong or unexpected recommendations and take control to make corrections [8]. This goal is closely related to *scrutability* [1]. The goal might also be seen as obtaining an answer to different intelligibility types of explanations, e.g., what, how and why questions [27, 12].

We consider these goals as also important in relation to personalized explanation and we use them as possible candidates for the "WHY" dimension in our conceptualization.

3.5. HOW to Personalize?

The "HOW" dimension refers to the methods used to generate personalized explanations. In general, personalized explanations can be created using a two-step process, namely (1) *adjusting explanation properties* and (2) *applying adaptation rules*.

3.5.1. Adjusting explanation properties

A personalized explanation can be generated by adjusting explanation properties, i.e., content and design choice, as illustrated in Table 1. A common task in explainable recommendation is to provide explanation based on similarity of items or users. The *content* of an explanation can be personalized by highlighting similarities, e.g., between users (user-based explanation), items related to user's interests (item-based explanation), item features (content-based explanation), and users in a social circle (social-based explanation). The *explanation scope* can be personalized by changing the explanation viewpoint to focus on the RS input, process, or output. The *explanation format* can be personalized by adjusting the presentation (e.g., textual or visual), presentation state (e.g., permanent or on-demand), the visualization idiom (e.g., node-link diagram, bar chart, heatmap, tag cloud), and the interaction method (e.g., select, zoom, filter, brushing and linking, overview+detail) [35]. The *level of detail* of an explanation is personalized by tailoring its soundness and completeness. Soundness refers to telling nothing but the truth, how truthful each element in an explanation is with respect to the underlying system. Completeness refers to telling the whole truth,

Table 1
Exemplary use of different explanation styles and explanation properties to generate personalized explanations

			Explanation Style			
			User-based explanation	Item-based explanation	Content-based explanation	Social-based explanation
Explanation Properties	Content		Similarity with other users	Similarity between items based on users' preferences	Similarity between item features	Similar users in social circle
	Design Choices	Explanation Scope	Choice of explanation scope (input, process, output)			
		Explanation Format	Choice of explanation format (Presentation, Presentation state, Visualization idiom, Interaction method			
		Level of Detail	Choice of level of detail (Soundness, Completeness)			
		Intelligibility Types	Choice of intelligibility type (how, why, why not, what if, what else, how to)			

the extent to which an explanation describes all of the underlying system [36, 37]. The *intelligibility type* can be personalized by adjusting the query that a user can ask from the RS (e.g. how, why, why not, what if, what else, how to). Finally, the choice of the *explanation style*, e.g., user-based, item-based, content-based, social explanation can also be adjusted.

3.5.2. Applying adaptation rules

A system-driven personalized explanation requires to adjust explanation properties by taking into account users' preferences and personal characteristics. Thereby, it is crucial to decide which adaptation to apply and then apply that adaptation [38]. This is a straightforward task in case of personalizing the content as an explanation property, where the adaptation is applied by highlighting similarities between users or preferred items. However, this is a challenging task in case of personalizing design choices as explanation property. The challenge here is to define *adaptation rules* in order to answer the question "which instance of a design choice is good for which user type?". To achieve this, it is important to conduct user studies to evaluate explanations designed for different levels of personal characteristics. The results of these studies would lead to design suggestions and guidelines that help decide which explanation should be provided to which user before adapting the explanation to different users. As examples of adaptation rules, Martijn et al. [19] suggested that (1) for users low in need for cognition, displaying explanations must be optional, (2) provide brief explanations that do not require domain knowledge to support users with low musical sophistication, and (3) provide explanations with a lower number of explanation elements for users with low openness.

4. Categorization of Existing Literature

We used our conceptualization framework to systematically categorize and compare the literature on personalized explainable recommendation. Our aim was not to conduct a systematic literature review, but rather to show how the framework can be applied to analyze studies in the this research area. To identify relevant works, we focused on recent studies that explicitly addressed personalized explanation in RS. The results of the categorization of these studies are summarized in Table 2.

4.1. WHAT to Personalize?

Starting with the "WHAT" dimension of our conceptualization framework, the synthesis of existing literature revealed that in most studies related to personalized explanation, only the *content* of the explanation is personalized by keeping all the design choices (i.e., explanation style, scope, format, level of detail, intelligibility types) constant. The explanation content could be of the form "Because [user] likes [genre]" [34] or "Last.fm's data indicates that [U2] is similar to [Coldplay] that is in your profile" [9]. In these examples, the content of an explanation is personalized by varying the text in the square brackets according to each user's data content. As Schneider and Handali [16] noted, explanations for RS are often inherently personalized due to the nature of the task. For example, users' reviews, tags, or preferred item features, serve as input for the recommendation algorithm as well as explainee data used for explanations. In general, the explanations are personalized by marking certain parts of the recommended item (e.g., item features) which are relevant to the explainee.

All reviewed studies focused on personalizing the content of the provided explanation. For example, Gedikli

Table 2
Categorization of existing literature based on our conceptualization framework. The following abbreviations are used: Ind. (Individual user), Gr. (Group of individuals), I (Implicit data collection), E (Explicit data collection), Pref. (Preferences/Interests), PC (Personal characteristics), UB (User-based explanation), IB (Item-based explanation), CB (Content-based explanation), S (Social-based explanation)

Reference	WHAT						TO WHOM			WHO		WHY	HOW	
		Design Choices												
	Content	Explanation Style	Explanation Scope	Explanation Format	Level of detail	Intelligibility Types	Target users	User model attributes	User data collection	System-driven	User-driven	Goals	Adjusting explanation properties	Applying adaptation rules
Kouki et al. [9]	✓	x	x	x	x	x	Ind.	Pref.	I	✓	x	Satisfaction, Persuasiveness, Transparency, Confidence	Similarity (UB, IB, CB, S)	x
Chang et al. [39]	✓	x	x	x	x	x	Ind.	Pref.	I	✓	x	Satisfaction, Trust, Effectiveness, Efficiency	Similarity (CB)	x
Gedikli et al. [40]	✓	x	x	x	x	x	Ind.	Pref.	E	✓	x	Satisfaction, Persuasiveness, Efficiency Transparency, Effectiveness	Similarity (UB)	x
Lu et al. [41]	✓	x	x	x	x	x	Ind.	Pref.	I	✓	x	x	Similarity (IB)	x
McInerney et al. [34]	✓	x	x	x	x	x	Ind.	Pref.	I	✓	x	Satisfaction, User engagement	Similarity (IB)	x
Musto et al. [42]	✓	x	x	x	x	x	Ind.	Pref.	I	✓	x	Persuasiveness,Trust, Efficiency Transparency, User engagement	Similarity (IB)	x
Svrcek et al. [24]	✓	✓	x	x	x	x	Ind.	Pref.	I	✓	x	Transparency, Trust	Similarity (UB, CB), Choice of explanation style	✓
Millecamp et al. [10]	✓	x	x	x	✓	x	Ind.	Pref.	I	x	✓	Satisfaction, Trust, Confidence	Similarity (IB), Choice of level of detail (Completeness)	x
Chen et al. [43]	✓	x	x	x	x	x	Ind.	Pref.	I	✓	x	x	Similarity (IB)	x
Zhang et al. [6]	✓	x	x	x	x	x	Ind.	Pref.	I	✓	x	x	Similarity (CB)	x
Quijano-Sanchez et al. [44]	✓	x	x	x	x	x	Gr.	Pref., PC	I, E	✓	x	Satisfaction, Persuasiveness	Similarity (S)	x
Tintarev and Masthoff [45]	✓	x	x	x	x	x	Ind.	Pref.	E	✓	x	Effectiveness, Satisfaction	Similarity (CB)	x
Guesmi et al. [17]	✓	x	x	x	✓	x	Ind.	Pref.	I	x	✓	Satisfaction, Transparency, Scrutability	Similarity (CB), Choice of level of detail (Soundness, Completeness)	x

et al. [40] presented and discussed the results of a user study where recommendation systems were provided with different types of explanation. The study revealed that the content-based tag cloud explanations were effective and well accepted by the majority of users. Tintarev and Masthoff [45] focused on personalized feature-based explanations that described item features, tailored to the user's interests. Musto et al. [42] presented a framework for generating personalized natural language explanations of the suggestions produced by a graph-based recommendation model based on the information available in the Linked Open Data (LOD) cloud. Their user study results revealed that their strategy outperformed both a non-personalized explanation baseline and a popularity-based one. McInerney et al. [34] presented a method (Bart) that combines bandits and recommendation explanations. This method is able to jointly learn which explanations each user responds to (personalized explanation), and learn the best content to recommend for each user (personalized recommendation). The conducted experiments revealed that personalizing explanations and recommendations provides a significant increase in estimated user engagement. Lu et al. [41] presented a multi-task learning framework that simultaneously learns to perform rating prediction and generate personalized recommendation explanation. They employed a matrix factorization model for rating prediction, and a sequence-to-sequence learning model for explanation generation by generating personalized reviews for a given recommendation-user pair as they consider user-generated reviews as explanations of the ratings given by users. Inspired by how people explain word-of-mouth recommendations, Chang et al. [39] designed a process, combining crowd-sourcing and computation, that generates personalized natural language explanations. And, Chen et al. [43] provided personalized explanations visually by highlighting different parts of an item based on user preferences.

Considering the design choices (i.e., explanation style, scope, format, level of detail, intelligibility types) which could also be personalized based on user profiles, most of the studies have kept design choices fixed in explanations. Only the work presented in [24] takes the personalized explanation to the *explanation style* design choice level. The authors proposed a hybrid method of personalized explanation of recommendations, which combines basic explanation styles to provide the appropriate type of personalized explanation to each user. Based on this method, each user will be given an explanation adapted to what most impressed her (i.e., explanation style which she prefers). Furthermore, only the works in [10] and [17] reported personalizing the *level of detail* in an explanation depending on how much detail the user prefers to see in an explanation. Millecamp et al. [10] developed a music RS that not only allows users to choose whether or not to see the explanations by using a "Why?" button but also to select the level of detail by clicking on a "More/Hide" button. Guesmi et al. [17] developed a transparent Recommendation and Interest Modeling Application (RIMA) that provides on-demand personalized explanations of both the interest models and the recommendations with three different levels of of detail (i.e., basic, intermediate, advanced).

In all reviewed studies, there was no personalization related to *explanation scope*, *explanation format*, or *intelligibility types.* None of the studies has focused on varying these design choices depending on the user profile. In terms of the *explanation scope* design choice, all reviewed studies have focused only on explaining the output of the RS (i.e., recommendation), none of them has tried to explain the input of the RS (i.e., user model) or the process (i.e., algorithm used used to generate a recommendation). Concerning the *explanation format* design choice, most of the studies have used a textual explanation format by explaining the reasoning behind an explanation in natural language. Only few studies have used a visual explanation format. For example, Kouki et al. [9] have used Venn diagrams and static cluster dendrograms, Gedikli et al. [40] have used tag clouds, and Quijano-Sanchez et al. [44] have used graphical representation of images to present explanations. Finally, none of the studies have worked on personalizing *intelligibility types* of explanations depending on user profile.

In summary, it can be observed that personalizing the content of an explanation to each user's data and personality is dominant in the literature on explainable recommendation. By contrast, personalized explanations that focus on tailoring a certain explanation design choice, such as explanation scope, format, or level of detail are under-explored and deserve more research in the future.

4.2. TO WHOM to Personalize?

Related to the "To WHOM" dimension, which identifies the *target users* of a personalized explanation (i.e., individual user, category of individuals, or group of individuals), it has been observed that almost all the reviewed studies have personalized for individual users. Only the study in [44] provided explanations targeting a group of users. The authors argued that adding a social component to explanations in group recommenders can enhance the impact that explanations have on users' likelihood to follow the recommendations and used explanations like: "Although we have detected that your preference for this item is not very high, your friends X and Y really like it. Besides, we have detected that they usually don't give in".

In terms of *user model attributes* and *user data collection*, most of the studies have focused on user preferences or interests to personalize the explanations and collected data implicitly to generate user models. For example, in the study by Kouki et al. [9], a user model was created based on users' music preferences, Chang et al. [39] generated a user model based on users' preference of movies modeled from their activities with the system. Data was also collected implicitly through users' listening history to generate their music interests in [34], through users' likes to generate their movie preferences [42], through users' interactions, readings, brought and clicked books, to generate user models based on preferences [24]. Furthermore, a user model was created by [10] based on users' music preferences generated implicitly based on listening history. Zhang et al. [6] generated a user model based on user preferences collected implicitly through applying phrase-level sentiment analysis on user reviews and opinions. For visual explanations, Chen et al. [43] used users' attention and users' visual preferences to generate user models, used to personalize visual explanations. Similarly, Gedikli et al. [40] created a used model based on user's preferences of movies, however, users were explicitly asked to provide overall rating for at least 15 items from a collection of 1000 movies, to record their preferences.

Only the work by Quijano-Sanchez et al. [44] generated a user model based on user preferences collected implicitly from users' activities in Facebook as well as personal characteristics (e.g., cooperative, assertive) obtained explicitly through a personality evaluation test to get users' behaviors, and social information related to friends and their preferences to generate personalized explanations where each user will receive a different explanation of the group recommendation presented by the system. In general, it can be observed that there is less focus on personal characteristics as a user model attribute that can be collected (explicitly or implicitly) and used to personalize the explanations. This represents an interesting future research direction.

4.3. WHO does the Personalization?

Related to the "WHO" dimension, we have observed that only the works presented in [10] and [17] have followed a *user-driven* personalized explanation approach by providing on-demand explanations with varying level of details. All the other works have focused on *system-driven* personalized explanation, mainly to automatically adapt the content of the explanation, based on users' preferences. This opens a new avenue of research in the field of explainable recommendation, and researchers should try to fill in this gap. More research is needed to focus on user-driven personalized explanation in RS by having the users in the loop and giving them control to steer the explanation process. Furthermore, there is a need to follow a system-driven personalized explanation approach, that not only focuses on adapting the content of an explanation, but also the design choice.

4.4. WHY to Personalize?

The next dimension is "WHY" to personalize?" which refers to possible goals of providing an explanation. The most common goals evaluated in the reviewed studies are user satisfaction [9, 39, 40, 34, 10, 44, 25, 45], transparency [40, 24, 42, 9, 25], persuasiveness [9, 40, 42, 44], trust [39, 42, 24], effectiveness [39, 40, 42, 45], efficiency [39, 40], confidence [9, 10], and user engagement [34, 42]. Only the study in [25] aimed to provide personalized explanations to achieve scrutability. Moreover, only two studies aimed at comparing personalized and non-personalized variants of an explanation. The study in [40] found that content-based tag cloud explanations were particularly helpful to increase user satisfaction as well as the user-perceived level of transparency thanks to its personalized variant. However, they found that personalization was detrimental to effectiveness. Similarly, Tintarev and Masthoff [45] investigated the impact of personalizing simple feature-based explanations on effectiveness and satisfaction. They also reported that their personalization method hindered effectiveness, but on the other hand increased the satisfaction with the explanations. More studies are needed to investigate the benefits of personalized explanations compared to non-personalized variants related to different goals. Furthermore, only two studies investigated the effects of personal characteristics on the perception of explanations in terms of persuasiveness [9] and confidence [10]. As different design choices will be affected by the user type, more research seems required to understand the interaction effects of design choice and user type on the perception of personalized explainable RS with regard to different explanation goals.

4.5. HOW to Personalize?

In terms of *adjusting explanation properties*, the majority of the reviewed studies only focused on personalizing the explanations by adjusting the content as explanation property. In most cases, a personalized explanation is generated by highlighting the similarities between users (user-based explanation) [40] or items (item-based explanation) [41, 34, 42, 43]. Following a content-based explanation approach, the studies in [39, 10, 6, 17] generated personalized explanations by highlighting feature similarities between items. And, the study in [44] used a social-based explanation approach to explain individual and group recommendations, by highlighting similar users in a social circle. However, only a few studies have worked on personalizing the explanations by adjusting the design choice as explanation property. Among these studies, Svrcek et al. [24] worked on peronalizing explanation style, and Millecamp et al. [10] and Guesmi et al. [17] have personalized level of detail as explanation property, by varying only completeness (show/hide explanation) and both soundness and completeness (basic, intermediate, advanced explanation), respectively.

Referring to *applying adaptation rules*, only few studies have worked on proposing and/or applying adaptation rules to personalize an explanation. In order to assign the appropriate explanation style for the specific user, Svrcek et al. [24] proposed and applied an adaptation rule, following a test-then-train approach that identifies if users prefer a certain explanation style, based on a continuous monitoring of the user clicks on each item explained by different styles. As a result, the users obtain more explanations generated by their preferred style. Kouki et al. [9] and Millecamp et al. [10] also proposed adaptation rules without applying them. In [9], only the content of an explanation is personalized to each user's data and personality, while the explanation styles are kept fixed. The authors, however, investigated the effect of personality on the perception of explanations and found that (1) calm participants (low neuroticism) preferred popularity-based explanations, while anxious participants (high neuroticism) preferred item-based explanations. Likewise, neurotic participants, showed a slight preference for item-based explanations, (2) open participants were persuaded by many explanations, while conscientious participants preferred fewer. The work in [10] did not follow a system-driven explanation approach. The authors, however, investigated the effect of personal characteristics on the perception of explanations and found that participants with a low need for cognition (NFC) were more confident about their playlist when recommendations were explained, as opposed to those with a high NFC. In general, there is a lack of research on adaptation rules to tailor explanations in RS to users with different preferences and personal characteristics. Thus, more user studies need to be conducted on the same lines, to come up with concrete adaptation rules that can be used to personalize system-driven explanations.

5. Conclusion

In this paper, we presented a multi-dimensional conceptualization framework for personalized explanations in recommender systems, based on five dimensions: *WHAT* to personalize in an explanation, *TO WHOM* to personalize, *WHO* does the personalization, *WHY* an explanation should be personalized, and *HOW* to personalize an explanation. Through this work we aimed to (1) provide researchers with a structured way to organize current and future research on personalized explainable recommendation, (2) provide an overview of what has been done in the domain of personalized explanations in RS so that more knowledge can be built on top of it, and (3) identify research gaps in this area. As future work, we will leverage the proposed framework to conduct a thorough systematic literature review to gain more insights into the domain of personalized explanations in recommender systems.

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