Explaining User Models with Different Levels of Detail for Transparent Recommendation: A User Study

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In this paper, we shed light on explaining user models for transparent recommendation while considering user personal characteristics. To this end, we developed a transparent Recommendation and Interest Modeling Application (RIMA) that provides interactive, layered explanations of the user model with three levels of detail (basic, intermediate, advanced) to meet the demands of different types of end-users. We conducted a within-subject study (N=31) to investigate the relationship between personal characteristics and the explanation level of detail, and the effects of these two variables on the perception of the explainable recommender system with regard to different explanation goals. Based on the study results, we provided some suggestions to support the effective design of user model explanations for transparent recommendation.

CCS Concepts: • **Human-centered computing → Interactive systems and tools**; • **Computing methodologies → Artificial intelligence**.

Additional Key Words and Phrases: intelligent explanation interfaces; recommender systems; explainable recommendation; explainable user modeling, personal characteristics

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1 INTRODUCTION

Recommender systems (RS) are one of many adaptive systems that leverage user models to deliver relevant content to their end-users. User models have been enriched with various features such as *openness*, *scrutability*, and *explainability*. These features are the most investigated ones by researchers in view of their significant impact on the user's perception of adaptive systems and their outcomes [7, 21]. Opening the user model means allowing users to see how the system is perceiving them in a human-understandable form, which will lead to several benefits such as improving the accuracy of the model [12]. Scrutinizing the user model is a concept built on top of openness and is related to user control in a sense that, in addition to letting the users inspect their models, they can interact with them (e.g., edit the content, provide more information) [12]. Explaining the user model consists of providing explanations about how these models were generated [19]. Recently, research on explainable recommendations started to focus on explaining the user models (i.e., explaining the recommendation input) as an alternative to revealing the inner working of the system (i.e., explaining the recommendation process) or justifying the recommended items (i.e., explaining the recommendation output) [8, 21].

In addition to the explanation scope (i.e., input, process, output), another crucial design choice in explainable recommendation relates to the level of explanation detail that should be provided to the end-user [2]. Users may not be interested in all the information that the explanation can produce [38]. Different users have different needs for explanation and explanations may cause negative effects (e.g., high cognitive load, confusion, lack of trust) if they are difficult to understand [18, 27, 30, 52, 53]. The majority of current designs of explainable recommendation still follow a one-size-fits-all approach that does not attempt to identify and address the needs and preferences of different users, with different personal characteristics. The effect of individual user differences and human factors on behaviors with explainable RS has only been studied very recently. These studies showed that personal characteristics may have an impact on the perception of explanations [24, 29, 35, 37, 44]. However, studies investigating the effects of personal characteristics on the perception of the user model explanation with different levels of detail are scarce in the literature on explainable recommendation.

In this work, we are particularly interested in explaining black-box user interest models with different levels of detail to provide transparent recommendation for users with different personal characteristics. Recognizing that it is generally insufficient to take the explanation level of detail and user's personal characteristics separately, we conducted a user study where we investigated the dependencies between these two factors and their effects on the user perception of different explanation goals (transparency, scrutability, trust, effectiveness, persuasiveness, efficiency, satisfaction) [49]. To conduct this study, we developed a transparent Recommendation and Interest Modeling Application (RIMA) that provides layered explanations of the user interest model with three different levels of detail (basic, intermediate, advanced). The objective of the study was to answer the following research question: *How do personal characteristics impact user perception of the user model explanations in terms of different explanation goals?*

The main contribution of this paper is twofold: First, we focus on explaining the RS input (i.e., user model) with varying level of details. Second, in this context, we provide evidence for a dependency relation between explanation goal, personal characteristics, and explanation level of detail.

2 RELATED WORK

2.1 User model explanation

The rise of distrust and skepticism related to the collection and use of personal data, and privacy concerns in general has led to an increased interest in transparency of black-box user models, used to provide recommendations [43] by *opening*, *scrutinizing*, and *explaining* these models [7, 21]. Several recommendation tools have represented and exposed the user model behind the recommendation mechanism [4, 9, 10, 17]. However, scrutability is lacking in these tools. The interest in providing scrutable user models has increased in the last decade and various studies have been conducted in this direction, presenting systems that provide user control on the RS input, by allowing users to correct their models when they disagree with (parts of) it or modify their models in order to adjust the recommendation results according to their needs and preferences [5, 16, 20, 25, 26, 33, 41, 42, 51, 54]. Explaining user models goes beyond just exposing and manipulating the user model to provide concrete explanations of how the user model was inferred. One of the benefits of explaining the user model is that it facilitates users' self-actualization [19, 43]. Moreover, it helps users build a more accurate mental model of the RS as well as it can help detect biases which is crucial to producing fair recommendations, thus leading to increased transparency and trust in the system [21]. Very few works followed this approach and provided explanations of the user model to make the RS transparent [7, 21–23, 43].

2.2 Explanation with different levels of details

In this work, the level of detail refers to the amount of information exposed in an explanation. Generally, in the explainable AI (XAI) domain, different users will have different goals in mind while using such systems. For example, Mohseni et al. [39] point out that while machine learning experts might prefer highly-detailed visual explanations of deep models to help them optimize and diagnose algorithms, systems with lay-users as target groups aim instead to enhance the user experience with the system through improving their trust and understanding. In the same direction, Miller [38] argue that providing the exact algorithm which generated the specific recommendation is not necessarily the best explanation. People tend not to judge the quality of explanations based on how they were generated, but instead around their usefulness. Aside from the goals of the users, another crucial aspect that will influence their understanding of explanations are their cognitive capabilities [53].

Different levels of explanation detail would lead to different levels of RS transparency. Here, it is necessary to differentiate between objective transparency and user-perceived transparency. On the one hand, Objective transparency means that the RS reveals the underlying algorithm of the recommendations either by explaining it or justify it in case of high complexity of the algorithm. On the other hand, user-perceived transparency is thus based on the users' subjective opinion about how good the system is capable of explaining its recommendations [18]. In general, it can be assumed that a higher level of explanation detail increases the system's objective transparency but is also associated with a risk of reducing the user-perceived transparency, depending on the users' background knowledge.

Providing explanations with different levels of detail remains rare in the literature on explainable recommendations. To the best of our knowledge, only Millecamp et al. [37] followed this approach while developing a music RS. The authors suggest that users should have the option to decide whether or not to see explanations, and explanation components should be able to present varying level of details to the users depending on their preferences. Consequently, their system allows users to choose whether or not to see the explanations by using a "Why?" button and also enables them to select the level of detail by clicking on a "More/Hide" button.

2.3 Effects of personal characteristics

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 [24, 29, 35, 37, 44]. These studies investigated the effect of human factors, such as Big Five traits, need for cognition, and visualization familiarity and confirmed that users with specific personal characteristics will perceive and interact in different ways with an explainable RS. In particular, prior research investigated the effects of personal characteristics on the perception of different explanation styles (e.g., user-based, item-based, content-based, social) [29] and different explanation formats (textual, visual) [24, 44]. However, the effects of personal characteristics on the perception of user models explanations with different levels of detail are under-explored in explainable recommendation research.

3 RIMA: RECOMMENDATION AND INTEREST MODELING APPLICATION

To address the limitations outlined above, we focus in this work on explaining black-box user interest models with different levels of detail to provide transparent recommendation for users with different personal characteristics. To this end, we developed the transparent Recommendation and Interest Modeling Application (RIMA) with the goal of providing explanation of the user interest models used as input for providing recommendations. RIMA is a content-based RS for scientific publications that produces content-based explanations [21]. It follows a user-driven personalized explanation approach by providing explanations with different levels of detail and empowering users to steer the explanation process the way they see fit [22]. The application provides on-demand explanations, that is, the users can decide whether or not to see the explanation and they can also choose which level of explanation detail they want to see [23]. In this work, we focus on inferring and explaining the user interest model, and leveraging explanatory visualizations to provide explanations with different levels of detail.

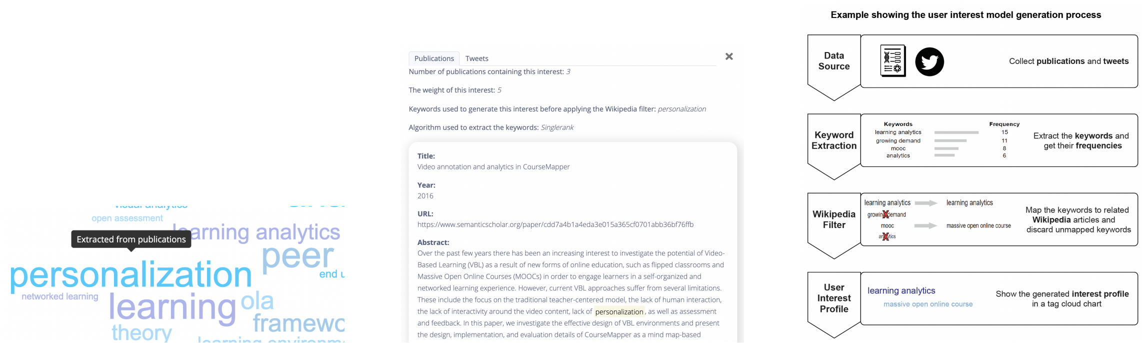
3.1 Interest model inference

The user interest models represent the input part of RIMA. These interest models are generated from users' publications. The application uses Semantic Scholar IDs provided by users to gather their publications. It applies unsupervised keyphrase extraction algorithms on the collected publications to generate keyphrase-based interests. First, our proposed approach starts with extracting candidate interest keywords from user's pubications using various unsupervised keyword extraction algorithms, including TextRank, SingleRank, TopicRank, TopicalPageRank, PositionRank, MultipartitieRak, Rake, and YAKE!. Inspired by the fact that an interest is often a well-defined concept (article) in Wikipedia, we use a method of interest modeling that mixes unsupervised keyword extraction algorithms and Wikipedia as a knowledge base to generate semantically-enriched interest models that we called Wikipedia-based interests. Leveraging Wikipedia to infer interest models has the potential to address different semantic-related issues: (a) synonym interests can be merged (b) acronym interests can be reduced, and (c) noise coming from non-relevant keywords can be filtered out. As a result, Wikipedia-based interest models would be more representative and more accurate than keyword-based ones. Further, Wikipedia is used to find the categories of Wikipedia-based interests and generate Wikipedia category-based interests. Enriching an interest model with Wikipedia categories might lead to unexpected but still relevant interests, which can be important to achieve serendipitous recommendations. The main steps of the interest model inference process are described in detail in [14].

3.2 Explanation design

Our approach to explaining scientific publication recommendations is based on explaining the underlying user interest models that are used to provide the recommendations. The aim of explaining the interest model in RIMA is to foster user's *awareness* of the raw data (publications) and the derived data (interest model) that the RS uses as an input to generate recommendations, in order to increase *transparency* and improve end-users *trust* in the RS. Moreover, this may let users become aware of system errors and consequently help them give feedback and correction in order to improve future recommendations (*scrutability*).

The current explanation design was mainly the result of several brainstorming sessions involving the authors and students from the local university. It was inspired by popular explanation visualizations used in the literature on explainable RS, such as word clouds and flowcharts [18]. RIMA provides three layered explanations (i.e., basic, intermediate, advanced) that the users can choose from, depending on whether they want more or less information. The intermediate and advanced explanations are hidden by default, but users are able to view these explanations through interacting with the interface.



(a) Basic explanation (b) Intermediate explanation (c) Advanced explanation

Fig. 1. Explaining the interest model with three levels of details

3.2.1 Basic explanation. Due to its wide use in the literature of explanatory visualization and its relevance to our context of visualizing text data along with its importance, a word cloud was selected to present the inferred interest model to the user. Moreover, it serves the purpose of the word-frequency analysis across the user interests. The user can hover over an interest in the word cloud to see its source (i.e., either from user's publications or manually added) as a *basic explanation* (Figure 1a). Disclosing the interest source to the user may result in increasing transparency and present a simple answer to the question "Why this interest?", without going deep into detail.

3.2.2 Intermediate explanation. In addition to hovering over an interest, another interaction is provided to the word cloud, where users can click on a specific interest. This interaction will lead users to the second level of explanation, which is the *intermediate explanation*. This explanation provides more information through a pop-up window, such as the publications from which an interest was extracted, highlighting the selected interest in the title/abstract of these publications, and disclosing the name of the extraction algorithm (Figure 1b). This explanation presents a more detailed answer to the question "Why this interest?", including some technical details.

3.2.3 Advanced explanation. The next level of detail is provided in the *advanced explanation* which provides a static explanation by example to show in detail the logic of the algorithm used to infer the interest model (Figure 1c). The algorithm is explained visually through a flowchart revealing the different steps of inferring the interest model, starting from extracting the keywords along with their weights, passing by semantically enriching them, ending with visualizing the resulted set of interest using a word cloud chart. This explanation is hidden per default. The user can access to this explanation by clicking on "How?" button, located on left side of the word cloud.

4 EMPIRICAL STUDY

4.1 Participants

To obtain a diverse sample, the study included participants from different countries, educational levels, and study backgrounds. A total of 36 participants completed the study. We ensured the data quality through the examination of redundant answering patterns (e.g., consistent selection of only one answering option) and attention checks (i.e., "Please answer 'disagree' on this question"). Accordingly, five participants were excluded. The final sample consisted of $N = 31$ participants (14 males, 17 females) with an average age of 32 years. Out of the 31 participants, 19 (61.3%) reported to live in Germany, where 12 (38.7%) were international users from eight different countries. All participants had sufficient English language skills to participate in the study. The highest level of education reported by most participants was *master's degree* (61.3%). The majority of participants (38.7%) had a study background in *Computer Science*.

4.2 Study procedure

While the study was originally planned as a laboratory experiment, due to the COVID-19 pandemic and its restrictions, we decided to conduct an online study. Each session was accompanied by a research assistant for technical support. The ethics motion to conduct the user study was approved by the Ethics Committee of the Department of Computer Science and Applied Cognitive Science of the Faculty of Engineering at the University of Duisburg-Essen on February 10, 2021. All participants gave informed consent to study participation. The target group of our study was researchers who have at least one scientific publication. Participants were recruited via e-mail, word-of-mouth, and groups in social media networks and had to fulfill two participation requirements: they had to have at least one scientific publication and a Semantic Scholar ID.

Participants first answered a questionnaire in SosciSurvey[1] which asks for their Semantic Scholar ID and included questions about their demographics and personal characteristics. Next, participants were given a short demo video on how to use the RIMA application. Afterwards, participants were asked to (1) create an account using their Semantic Scholar ID, (2) explore the system and find matching recommendations to their interests, and (3) take a close look at each explanation provided by the system. After that, participants were asked to evaluate each of the three explanations in terms of seven explanation goals (transparency, scrutability, trust, effectiveness, persuasiveness, efficiency, and satisfaction [49]). All participants evaluated the explanations in an iterative approach, by answering the same set of questions for each explanation. To avoid any order-related biases, the order in which participants rated the explanations was randomized. They needed on average 48.09 minutes to complete the questionnaire ($SD = 9.40$, range = 24.08-65.23). At the end of the session, participants were debriefed and compensated with the possibility to win one of five Amazon vouchers.

4.3 Measurements

4.3.1 Personal Characteristics. Our study included measurements of six personal characteristics, namely: need for cognition (NFC), visualization familiarity (VF), personal innovativeness (PI), trust propensity (TP), domain knowledge (DK), and technical expertise (TE). For each personal characteristic, answers were given on a 5-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Table 1 shows the definitions and example items for each of the six measured personal characteristics.

4.3.2 Explanation Goals. The measurements for the seven explanation goals were adopted from different previous works [6, 29, 46–48, 50, 53]. The first six explanation goals were measured using a 5-point Likert-scale, while satisfaction was measured using a 7-point Likert-scale. An overview of used questionnaire items is shown in Table 2. Besides quantitatively measuring the explanation goals, participants could provide qualitative feedback to each explanation and the overall RS by answering a set of open-ended questions.

[1] https://www.soscisurvey.de

Personal characteristics (PC)	**Definition**	**Example item**	**Source**
Need for Cognition (NFC)	Tendency for an individual to engage in and enjoy effortful cognitive activities [13]	I would prefer complex to simple problems.	[34]
Visualization Familiarity (VF)	Extent to which users have experience with analyzing and graphing data visualizations	I frequently analyze data visualizations.	[29]
Personal Innovativeness (PI)	Confidence or optimism regarding adoption of new technologies [1]	I like to explore new Web sites.	[36]
Trust Propensity (TP)	Level of intensity of an individual's natural inclination to trust other parties in general [28]	It is easy for me to trust a person/thing.	[32]
Domain Knowledge (DK)	Knowledge about or experience with the type of recommended items	I am knowledgeable about Twitter.	[3]
Technical Expertise (TE)	Knowledge about artificial intelligence and recommender systems	In the past I learned about how recommender systems work.	[31]

Table 1. Measurement of personal characteristics

Metric	**Statement** This explanation ...	**Source**
Transparency	helps me to understand what the recommendations are based on.	[6]
Scrutability	allows me to give feedback on how well my preferences have been understood.	[6]
Trust (Competence)	shows me that the system has the expertise to understand my needs and preferences.	[50]
Trust (Benevolence)	shows me that the system keeps my interests in mind.	[50]
Trust (Integrity)	shows me that the system is honest.	[50]
Effectiveness	helps me to determine how well the recommendations match my interests.	[47]
Persuasiveness	is convincing.	[29]
Efficiency	helps me to determine faster how well the recommendations match my interests.	[47]
Satisfaction	**Question** How good do you think this explanation is?	[46, 48]

Table 2. An overview of questionnaire items used for the evaluation of explanations

5 RESULTS

5.1 Descriptive data

The RIMA application explains the interest model with three different levels of detail (basic, intermediate, advanced). Following a within-subjects design, participants rated the three explanations in terms of the seven explanation goals (i.e., transparency, scrutability, trust, effectiveness, efficiency, persuasiveness, and satisfaction). We calculated scores of the measured personal characteristics as the average of the values reported for the corresponding items. Further, we calculated the evaluation score for trust as the average of the individual values reported for the three trusting beliefs (i.e., competence, benevolence, and integrity).

5.2 Interaction effects

To address our research question, we performed seven repeated measures ANCOVA analyses, where the evaluation scores of the seven explanation goals were included as dependent variables (DV), the explanation level (basic, intermediate, advanced) as independent variable (IV), and the personal characteristics scores as covariates. To visualize the significant interaction effects, we performed a median split for each personal characteristics dividing the participants in a low and high group for each of them.

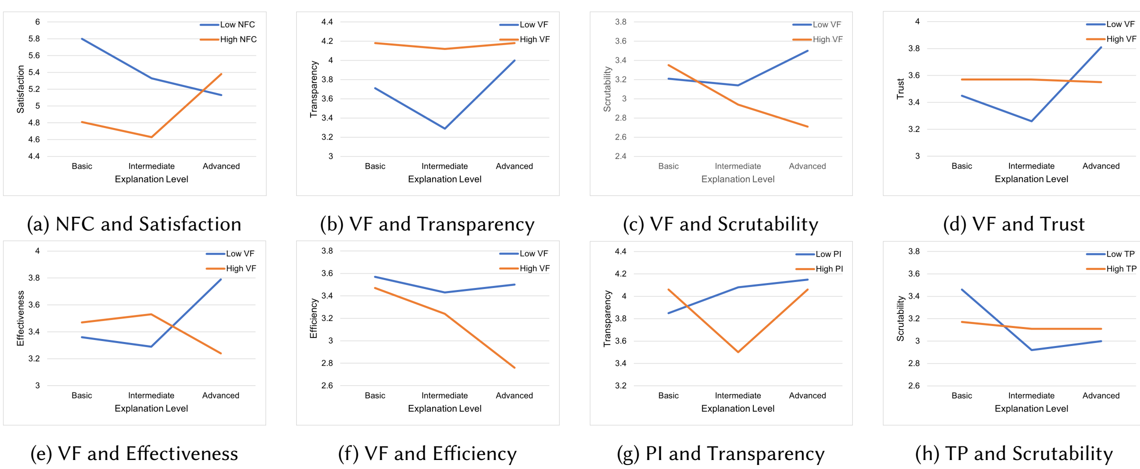
Need for Cognition: A significant interaction was found between NFC and explanation level regarding *satisfaction* (F(2,48) = 3.557, p =.036, f = .38). The effect size corresponds to a moderate effect [15]. Figure 2a shows that the overall average satisfaction of users with low NFC was higher for the basic explanation than the advanced explanation, while it is the other way around for users with high NFC. There were no significant interactions between NFC and explanation level regarding the other explanation goals.

Visualization Familiarity: Significant interactions were found between VF and explanation level concerning *transparency* (F(2,48) = 4.400, p = .018, f = .42), *scrutability* (F(2,48) = 3.760, p = .030, f = .40), *trust* (F(2,48) = 4.569, p = .015, f = .44), *effectiveness* (F(2,48) = 3.831, p = .029, f = .40), and *efficiency* (F(2,48) = 3.336, p = .044, f = .37). The effects are strong for transparency, scrutability, trust, and effectiveness, and moderate for efficiency [15]. Figure 2b shows that users with low VF had lower perceptions of transparency than users with high VF. The interaction plots in Figure 2c, 2d, 2e and 2f show that the overall average scrutability, trust, effectiveness, and efficiency of the advanced explanation was higher for users with low VF than users with high VF. We found no significant interactions between VF and explanation level in terms of persuasiveness or satisfaction.

Personal Innovativeness: A significant interaction was found between PI and explanation level in terms of *transparency* (F(2,48) = 7.702, p = .001, f = .57). The effect size corresponds to a strong effect [15]. Figure 2g shows that the perception of transparency increased for users with low PI, while the intermediate explanation had the lowest average perceived transparency for users with high PI. There were no significant interactions between PI and explanation level in terms of the other explanation goals.

Trust Propensity: A significant interaction was found between TP and explanation level in terms of *scrutability* (F(2,48) = 4.673, p = .014, f = .44). The effect size corresponds to a strong effect [15]. Figure 2h shows that users with low TP had the highest overall perception of scrutability in the basic explanation, while the intermediate and advanced explanation were perceived as less scrutable. There were no significant interactions between TP and explanation level in terms of transparency, trust, effectiveness, efficiency, persuasiveness, or satisfaction.

Finally, there were no significant interactions between both **Domain Knowledge** and **Technical Expertise** and explanation level in terms of the seven explanation goals.



(a) NFC and Satisfaction (b) VF and Transparency (c) VF and Scrutability (d) VF and Trust

(e) VF and Effectiveness (f) VF and Efficiency (g) PI and Transparency (h) TP and Scrutability

Fig. 2. The interaction effects between personal characteristics and explanation levels in terms of explanation goals

5.3 Qualitative analysis

Besides our quantitative analysis, we also conducted a qualitative analysis of the open-ended questions to gain further insights into the reasons behind the individual differences in the perception of explanations. We followed the instruction proposed by Braun and Clarke [11]. To do so, we started by familiarizing ourselves with the depth and breadth of the qualitative data. Next, we worked systematically through the data set and coded each answer to identify patterns in the data set. Then, we organized the codes into meaningful groups. The analysis was rather deductive as we aimed to find additional explanations for the findings of our quantitative analysis.

5.3.1 Need for Cognition. As expected, the majority of users with high NFC (12 of 15) were more satisfied with the detailed advanced explanation of their interest model. Nevertheless, three participants with high NFC disliked that the advanced explanation is *"static"* (P22) and *"just about the algorithm"* (P26), so it *"does not differ from user to user"* (P9). Overall, it seems that users with high NFC wanted to explore the explanation in detail, but were disappointed when they realized that it shows example values.

5.3.2 Visualization Familiarity. The quantitative analysis revealed a number of surprising findings with regard to users' VF. Firstly, we found that users with low VF perceived each of the three explanations of their interest model, especially the intermediate one, as less transparent than users with high VF. However, this finding is contradictory to their answers to the open-ended questions: we observed that participants with low VF reported that the explanation is easy to understand and *"very helpful"* (P4). We also observed that one participant with low VF perceived the intermediate explanation as an *"easy algorithm to understand my interests"* (P17). As the intermediate explanation shows the user's publications, we believe that users might have perceived it as a general explanation of their interests and could not understand how it relates to their recommendations, thus had lower perceptions of transparency (i.e., understand how the RS works). In contrast, users with high VF might have leveraged their knowledge about visualization to create a mental model about how the system works (i.e., understand the interplay between the recommendation input and output). This assumption, however, requires further investigation.

Secondly, the quantitative analysis revealed that participants with high VF had lower perceptions of scrutability, trust, effectiveness, and efficiency of the advanced explanation of the interest model than users with low VF. When analyzing their answers, we found that out of the six participants reporting negatively about the advanced explanation, five have a high VF. For instance, P22 reported *"the advanced one is static, i.e. not adapted to my data"*. Their answers show that, like users with high NFC, users with high VF also disliked the static appearance of the advanced explanation. However, there is not enough evidence in the qualitative data to conclude that this has negatively impacted trust or scrutability, as we found that three users with high VF also reported positively about the advanced explanation: *"it is most trustworthy"* (P31), *" establishes trust for the user"* (P10), and *"shows me why the system might have erred in identifying my interests"* (P15). One possible explanation for the reduced efficiency is that users with more knowledge about data visualization spent more time to explore the explanation in detail. We plan to test this hypothesis in future studies by measuring users' interaction time.

5.3.3 Personal Innovativeness. We found that users with high PI perceived the intermediate explanation of the interest model to be the least transparent. After analyzing their answers, we observed that a number of participants with high PI disliked the general appearance of the explanation and suggested that *"this one needs better UX"* (P16). As a high PI is related to higher interest in testing new websites, these users might have paid more attention to the general design and usability of the explanations and spent less effort in trying to understand how the system works. However, we also observed that a number of participants with high PI encountered technical issues with the extraction of their publications: P6 reported *"my indexed study did not show the true study which I have done, it seems to be inaccurate"*. Overall, we assume that users with high PI had lower perceptions of transparency of the intermediate explanation as they detected design and technical issues.

5.3.4 Trust Propensity. We found that users with low TP had the highest perception of scrutability of the basic explanation of the interest model, while the intermediate and advanced explanation reduced their perceived scrutability. The qualitative analysis revealed that half of participants with low TP reported to prefer the basic explanation as it is *"more fun and interactive"* (P12). One participant with low PI also reported to be familiar with this interaction component: *"It's simple and I get used to other tools similar to this one"* (P16). As the intermediate explanation shows the weight of an interest, one participant with low TP reported *"I do not know how the number is calculated"* (P6). Thus, as the basic explanation is easy to use and understand, it might have improved users' perception of scrutability.

6 DISCUSSION

We discuss the findings of our study in relation to our research question: *"How do personal characteristics impact user perception of the user model explanations in terms of different explanation goals?"*. Our results show that the perception of the user model explanations with different levels of detail is affected to different degrees by the explanation goal and user type. These effects are summarized in Table 3 and discussed below.

6.1 Satisfaction

One main finding is that NFC influenced satisfaction with the explanations of the interest model. Users with a low NFC were more satisfied with the basic explanation, while users with high NFC preferred the highly detailed advanced explanation. This is in line with the findings in [13]. However, users were dissatisfied with the static appearance of the advanced explanation as they expected to see their actual interests in the user model inference process. Overall, the results indicate that users with high NFC are more satisfied with detailed explanations that are personalized to their own data. We suggest:

S1: *To increase satisfaction with the system, provide explanations of the user model with low level of detail to users with low NFC, and explanations with high level of detail to users with high NFC.*

S2: *To increase satisfaction with the system, provide explanations that address the users' actual interests.*

6.2 Scrutability

Our analysis also indicated that the basic explanation of the interest model led to higher perception of scrutability for users with low TP. The answers of participants with low TP indicate that these users perceived the basic explanation as more scrutable because they already know this kind of interaction component from other websites. As distrusting users may have doubt against how the system processes their data, the other two explanations could have been unfamiliar to them and created feelings of uncertainty about how the system understands their interests. Further, we believe that detailed information about the algorithm or wrong assumptions made by the system have a greater negative impact for these users. For instance, if users with low TP cannot understand why the system calculated a wrong weight for a specific interest, they might not be able to estimate if the system correctly understands their interests. Thus,

S3: *For users with low TP, provide familiar visual explanations to achieve scrutability.*

6.3 Efficiency

Our analysis showed that the explanation level of detail influenced the perceived efficiency of explanations. In general, independent from the personal characteristics, the basic explanation of the interest model was rated as most efficient, which indicates that increasing the explanation level of detail resulted in lowered perceptions of efficiency. Overall, our result is in line with previous findings that some explanations help users determine the quality of a recommendation more quickly than others [18]. Our finding also confirms the warnings of researchers that highly detailed information about the system's inner logic reduces efficiency [40, 45, 53] and that simple explanations are often better [38]. In fact, explanations with a high level of detail reduce efficiency as users need more time and cognitive effort to interpret the provided information, which limits the ability of explanations to help users make decisions faster [47]. This suggest that simple explanations are more suitable to increase the efficiency of an explanation facility, regardless of whether the explanation is performed at the input or output level. Therefore, we propose the following design suggestion for explainable RS:

S4: *If an explanation facility should be optimized for efficiency, use explanations with a low level of detail.*

Goal	PC	Level of detail	Like (+) / Dislike (-)
Satisfaction	low NFC	Basic	simple (+), easy to understand (+)
Satisfaction	high NFC	Advanced	detailed (+), static (-)
Scrutability	low TP	Basic	familiar (+)
Efficiency	low VF	Basic	
Efficiency	high VF	Basic	

Table 3. Relationships between goal, personal characteristics (PC), and level of detail

7 LIMITATIONS

Our study did not go without limitations. Firstly, due to the small sample size of the participants, the results of the study cannot be generalized. Secondly, some explanation goals could have been measured using objective instead of subjective measurements. Thirdly, there were some technical issues that some participants have encountered during the study, which may have negatively influenced their perception of the provided explanations. Finally, the results of this study could have been different if we had designed and presented other explanations (e.g., personalized advanced explanation instead of just static explanation by example).

8 CONCLUSION AND FUTURE WORK

In this paper, we aimed to shed light on an aspect that remains under-researched in the literature on explainable recommendation, namely the effects of personal characteristics and level of detail on the perception of user model explanations in a recommender system (RS). To this end, we developed and evaluated a transparent Recommendation and Interest Modeling Application (RIMA) that explains the inferred interest models with three different levels of detail (basic, intermediate, advanced). The results of our study demonstrated the interaction effects of personal characteristics and level of detail on the perception of explainable RS that focus on explaining the user model. In future work We will explore other possible visualizations to provide explanations at the three levels of detail. In particular, we will develop and evaluate advanced explanations that are tailored to user data.

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