# Meta-Intents in Conversational Recommender Systems

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**Abstract**

We present a study investigating the psychological characteristics of users and their conversation-related preferences in a conversational recommender system (CRS). We collected data from 260 participants on Prolific, using questionnaire responses concerning decision-making style, conversation-related feature preferences in the smartphone domain, and a set of *meta-intents*, a concept we propose to represent high-level user preferences related to the interaction and decision-making in CRS. We investigated the relationship between users' decision-making style, meta-intents and feature preferences through Structural Equation Modeling. We find that decision-making style has a significant influence on meta-intents as well as on feature preferences, however, meta-intents do not have a mediating effect between these two factors, indicating that meta-intents are independent of item feature preferences and may thus be generalizable, domain-independent concepts. Our results provide evidence that the proposed meta-intents are linked to the general decision-making style of a user and can thus be instrumental in translating general decision-making factors into more concrete design guidance for CRS and their potential personalization. As meta-intents seem to be domain-independent factors, we assume meta-intents do not affect users' various interests in concrete product features and mainly reflect users' general decision-support needs and interaction preferences in CRS.

**Keywords**

Decision-making style, Meta intents, Conversational UI design, Conversational recommender systems

## 1. Introduction

Conversational recommender systems (CRS[1]) have been gaining increased attention in research and industry in recent years [2, 3]. Generally, conversational techniques can provide users with strong guidance to achieve their goals combined with a high level of flexibility in expressing their needs. Jannach et al. [4] distinguish between natural language-based, form-based, and critiquing approaches. Due to the advances in NLP techniques in recent years, natural language-based CRS have become subject of extensive research. Fu et al. [5] summarized NLP-based CRS into 3 paradigms: System is Active, User is Passive (SAUP), System is Active, User Engages (SAUE), System is Active, User is Active (SAUA). SAUA is a user-initiated paradigm of CRS, which provides the user with the greatest degree of flexibility, allowing the user and the system to lead the conversation, and be able to give appropriate feedback to the user's questions. The appropriate feedback means answering user questions in a user-friendly style, but different users should have different preferences, e.g. preferring long sentences or short sentences, involving more technical details or not. These are challenges for user-initiated CRS.

SAUE and SAUP are system-initiated paradigms of CRS, in which the system guides the dialog and the user answers, the difference is that SAUP requires the user to answer the question directly, while SAUE allows the user to not answer the question directly, instead providing another preference or chit-chat. There are also lots of challenges for system-initiated CRS, e.g. questions from CRS need to be formulated at an appropriate level of abstraction, for example, asking either about the intended use of the product or about some specific technical features. Question relevant GUI widgets need to show a suitable number of options. Dialog flow should follow the user's likely mental decision process, providing sufficient flexibility without becoming overly complex, and recommendations should be presented in appropriate numbers and with an appropriate level of detail.

To address these challenges for CRS, a thorough understanding of user needs and their decision-making style is needed. Little research, however, has investigated the influence of psychological user characteristics and general, dialog-related preferences, in the context of CRS thus far [6]. In this paper, we explore psychological characteristics of CRS users under two different objectives. First, we aim at obtaining a deeper understanding of psychological characteristics of CRS users, based on responses from questionnaire instruments. Here, we distinguish between stable individual traits including personality factors [7] and decision-making style [8], and, second, task-oriented characteristics that represent general user preferences when interacting with a CRS, such as obtaining detailed information about items or comparing products. We call the latter characteristics *meta-intentions* (or meta-intents for short) since they describe user goals that are more

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general and high-level than the search goals typically extracted through intent detection methods in CRS. Psychological factors are an important resource underutilized by current CRS. We therefore propose an initial framework that includes the psychological factors in CRS design, and also describes our core research target, the meta-intents in it (Figure 1). As a second objective, we investigate the relations between psychological user characteristics and users' interests in product topics in a conversational scenario.

In this paper, we describe a study analyzing these questions and present its results. Our contribution is: we provide insights about CRS users' decision-making style (rational vs. intuitive) and its influence on the different meta-intents that we propose, as well as about the relation between decision style, meta-intents, and users' interest in product-specific features/topics. For this purpose we present an analysis using Structural Equation Modeling.

## 2. Related work

Conversational Recommender Systems (CRS) have become a rapidly growing and popular research area because they provide a flexible, human-like multi-turn dialog for preference elicitation, which is essential for generating personalized recommendations [9]. Jannach et al. [4] distinguish three types of CRS, differing in the style and structure of the interaction used: natural language-based, form-based, and critiquing-based.

**NLP-based CRS** have received considerable interest recently due to the advancements in natural language processing. They typically use a question-answer format Zhang et al. [10]. As the mainstream, it has developed vigorously in recent years, e.g. Sun and Zhang [1] import the end-to-end reinforcement learning model to CRS, Zhang et al. [11] combine contextual bandits method to improve preference elicitation and recommendation performance. Zhou et al. [12] utilize knowledge graph-based as an external knowledge to enhance CRS, Li et al. [13] unifying items and features in same arm space, use bandits method to facilitate cold-start problem in CRS, Zhou et al. [14] extract topic threads from their dataset and leverage it to increase utility and user acceptability of CRS. NLP-based CRS provides the greatest freedom, allowing users to express freely, while misunderstandings can also usually happen and lead to user frustration.

**Form-based CRS** present questions and answer in a GUI style, leading users through a predefined dialog structure. This type of CRS has many advantages as they provide guidance to the users, avoid errors, and can incorporate domain knowledge. Especially usage-related questions are important for users who have only limited knowledge about technical item properties [15]. The disadvantage is that the question sequences/paths are hand-crafted, not enough freedom, and a lower-level personalization.

**Critiquing-based CRS** will first recommend options and then elicit users' feedback in the form of critiques [16], It help users to efficiently refine their preference by providing more options, but on the other hand, it can be frustrating for novice users because they are overwhelmed by so many parameter options without really understanding what those parameters really mean. Ma et al. [17] proposed mixing language, GUI elements to improve user experience in CRS. However, it poses a greater challenge to the design of the CRS as well.

Currently, very limited research has as yet studied users' psychological influence in CRS and related design questions. For example, Papenmeier et al. [18] investigated human advisory dialogs, identifying some recurring strategies such as funneling to successively narrow down the space of potential items. Kleemann et al. [19] investigated user behavior and personal characteristics when using a advisor in combination with other decision aids, and studied various supporting methods' (chatbot, advisor, filter, recommendation) popularity, utilization, and switching rate between each other [20]. Atas et al. [21] summarize that preferences are determined and adapted is influenced by various factors such as personality traits, emotional states, and cognitive biases.

To provide design guidance for CRS and to potentially adapt them to the individual user, a deeper understanding of the psychological factors influencing users' decision making and interaction behavior in CRS is required. For recommender systems in general, the influence of psychological characteristics on users' preference construction and decision making has been shown repeatedly [21]. Lex et al. [22] distinguish between factors related to cognition, personality, and emotion. The influence of psychological characteristics such as the Big Five personality factors (e.g. [23, 24]), Need for Cognition [25], or cognitive biases [26] has been studied in several works. However, these studies mostly aim at better understanding user preferences with respect to the recommended items and at improving their accuracy. In contrast, the relationship between psychological factors and the design of advisory dialogs in CRS remains an underexplored area. Especially theories related to human decision-making styles appear to be promising points of departure for studying this relation. The distinction between rational and intuitive decision-making styles [27] or cognitive styles such as the need for cognition may influence users' assessment of CRS. More domain-specific theories such as Shopping Orientation [28, 29], distinguishing between task-focused and experiential shopping are also of interest. However, none of these approaches has yet been applied to CRS.

User goals and preferences when interacting with a CRS may be located on different levels of abstraction.

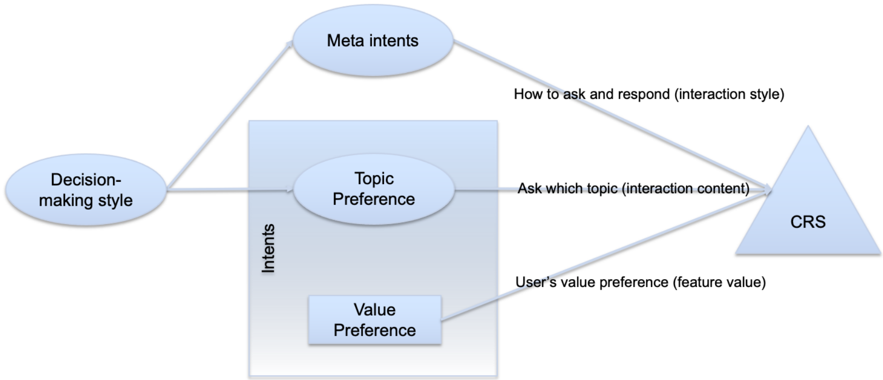


**Figure 1:** CRS framework that combines psychological factors (Decision-making style and meta-intents ) and conventional CRS

Low-level preferences refer to concrete properties of the desired item (often called *intents* in CRS, specifically *Add Details* [30]). Jameson et al. [31] suggest high-level factors (such as economy and safety) but these factors are related to the product itself, not to the way users prefer to interact with a CRS. On a more abstract level, meta-level preferences that relate to the conversation and type of questions in a CRS have, to our knowledge, not been studied yet.

## 3. User characteristics and meta-intents

To investigate differences in CRS users' psychological properties, we hypothesized that decision-making style might influence users' usage and interaction in CPA. Accordingly, we applied instruments to measure these properties, using the Decision Styles Scale (DSS) [27] for distinguishing rational and intuitive decision-making.

While general decision-making styles, e.g. rational and intuitive, apply to arbitrary decision contexts, we also aimed at capturing users' preferences at a more specific, yet still abstract level. These *meta-intents* should bridge the gap between item-level intents and general decision-making style, and should also relate to the design and question-asking style in CRS. They might also be relevant for more general recommendation scenarios. We postulated the following set of meta-intents (with sample questionnaire items in parentheses), partly related to general usage factors such as efficiency, effectiveness, and user guidance. We see this list as a first step towards defining factors relevant for users' decision-making process in CRS which is neither complete nor final.

- **Efficiency orientation** (For me, finding a suitable product quickly is more important than exploring all options.)
- **Diversity orientation** (When shopping online, I tend to explore a diverse range of products that might interest me.)
- **Goal focus** (I usually have a clear idea of what I want before visiting an online shop. I often only make up my mind once I see the available choices.)
- **Openness for guidance** (I appreciate it if a shop recommends products I might like.)
- **Interest in detail** (I usually gather as much information as possible about products that I want to buy. I am interested in detailed information about products.)
- **Human-like** (I would like a human-like conversation with an advisor system such as a chatbot.)
- **Comparison orientation** (Comparing the features of different candidate products is important for me.)
- **Scope of choice** (When the system recommends products, I rather like to see a longer list rather than a short one.)

The CRS framework we propose incorporates psychological level factors and preferences that relate to the items and their properties (topic preferences and value preferences) as shown in Figure 1. We first introduce what each part represents. The decision style shown on the left side as main characteristic factors that might influence meta-intents and users' feature preferences which are in the middle part of the figure. Here we use the term *topics* instead of *features* to emphasize that in the CRS, the user's preference is not only about product features but also the user experience, usage, and other higher abstract level topics. For example, asking user questions about the resolution of the main camera (feature level), or taking good pictures (usage level), or the quality of the main camera (assessment level) all belong to *topic* preference elicitation. Users' interest in product features/topics is abbreviated as *topic preference* below.

The right part of the Figure 1 refers to a conventional CRS model which can be, for example, CRM model [1] or EAR model [32] (which are 2 popular CRS models that include conversation function and recommendation function and utilized deep neural networks). The top element of the middle part is *meta-intents* which solves the problem *how to ask and respond* and can be used to guide the interaction style of CRS. *Topic preference* is related to the interactive content (*ask which topic*) and can be used to improve the preference elicitation process. *Value preference* which stands for the users' personalized preference value for one specific feature/topic. The middle part, *topic preference* and *value preference* are also known as *intents detection* which is an active area of research in NLP-based CRS. We decouple *intents detection* into two elements here for studying the impact of decision-making style on it. Our framework proposes that psychological characteristics can be treated as additional knowledge to improve CRS design, so in this paper, we apply SEM to analyze how does psychological characteristic impact these factors and our research can be boiled down to two questions:

- Does decision-making style significantly influence users' meta-intents and topic preference?
- Do meta-intents have a mediation effect between decision-making style and topic preference?

# 4. Study

To investigate CRS users' psychological characteristics, both at the level of decision-making style and meta-intentions, as well as possible relations with their topic preference, we conducted an online survey in which participants were presented a scenario involving the purchase of a new smartphone and answered questionnaires concerning their product-related preferences as well as their psychological characteristics. We hypothesized that general traits (decision-making style) significantly influence meta-intents and topic preference. We also assumed that meta-intents might have a mediating effect between decision-making style and users' topic preference .

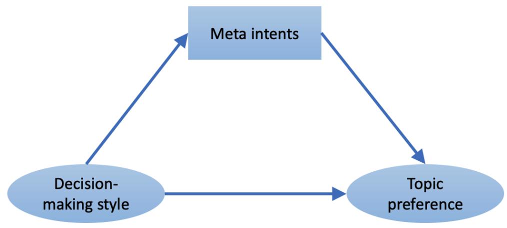


**Figure 2:** Our structural equation model that includes 3 parts, stable psychological traits (decision-making style), the proposed psychological traits (meta-intents) and topic preference (smartphone domain).

## 4.1. Method

We first presented participants with a scenario in which they were supposed to buy a new smartphone, and then started our questionnaire. The smartphone domain was chosen because it requires a sufficiently complex decision process, involving a variety of decision criteria. For most people it is also a well-known, real-life task that requires understanding the product features at least to a certain extent. Furthermore, it has a large number of feature options. To measure psychological characteristics, we applied the existing Decision Style Scale (DSS) questionnaire [27] as well as a self-developed questionnaire on meta-intents (Section 3), both with 5-point Likert scales. To measure topic preference, we collected a total of 27 topics in the smartphone domain, including 4 different levels: usage-level, general-level, technical-level, and professional-level, as shown in Table 1. There were short descriptions for some less well-known topics in our questionnaire, e.g. network sensitivity (signal strength, how easy is it to connect to a mobile network). We asked participants to rate each topic on a 5-point Likert scale according to their interest (1: don't care, 5: very interested in), along with an *unknown* option, in case participants did not understand the topic's meaning.

## 4.2. Participants

We recruited 278 participants using Prolific[1], a tool commonly used for academic surveys [33], of whom 275 finished the study. In our analysis, we only considered participants who passed 3 inner attention test questions (e.g. , It's an attention test, please select strongly agree), leaving us with 260 participants. 143 of the 260 participants were female. Their age ranged from 19 to 75 ($M$=38.42, $SD$=12.60). We pre-selected Prolific users based on the following criteria to maximize quality: (1) participants should be fluent in English; (2) their success rate should

[1]https://www.prolific.co

**Table 1**
The collection of total 27 user-interested topics in smartphone domain and 4 categories.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Usage** | smartphone game | taking photo and video | taking selfies | watching videos and documents | multi apps | | | |
| **General** | price performance ratio | network sensitivity | brand | color | size weight | robustness | voice quality | |
| **Technical** | latest technology | headphone jack 35 | good front camera | number of main cameras | battery life and charging speed | biometric unlock | 5G | dual SIM |
| **Professional** | screen resolution | main camera resolution | operating system | RAM | ROM | localization | CPU and GPU | |

be greater than 95 %. The average duration of the survey was 5.56 minutes ($SD = 2.48$) and each participant received compensation of 0.75£ if they successfully completed the survey.

# 5. Results

We applied Structural Equation Modeling (SEM) to our dataset for estimating and testing the causal effects of three main variables: Decision-making style, meta-intents and topic preference. Since DSS is a well-established, validated questionnaire and meta-intents are captured with single-items (each factor has only one question), we could directly incorporate both in our proposed model (see Figure 2). Concerning topic preference, on the other hand, a total of 27 topics (items) with assumed commonalities have been asked, e.g. *taking photo video* (usage), *number of main cameras* (technical) and *main camera resolution* (professional) should involve correlated rating patterns, hence presumably loading onto the same factor. Therefore, we do not treat all 27 topics as single independent variables but apply Exploratory Factor Analysis (EFA) to extract conjoint latent variables that can subsequently be fed into our proposed SEM model.

## 5.1. EFA on topic preference

The scores for topic preference are derived from a set of 260 valid participants' ratings of 27 smartphone topics. 63 of them tagged at least one topic as unknown (see Figure 3). Thereby, we found that the more technical the topic, the fewer people could grasp its meaning. Finally, only 197 participants' data could be used for the EFA analysis.

First, we performed prerequisite tests for EFA, the Kaiser-Meyer-Olkin (KMO) value is .796 ($> 0.7$) and Bartlett's test is significant ($< .001$), which both indicate that our data meets the requirements for performing EFA. Next, we used Principal Component Analysis (PCA) to extract factors, with Varimax rotation and Kaiser Normalization, taking *eigenvalue > 1* as the threshold to determine the number of factors. We ran the EFA recursively such that after the first epoch, resulting in dropping one item, a second run finally met the requirements. We filtered out seven topics in total: *screen resolution* (factor loadings < 0.4), *price performance ratio* (single item factor), *biometric unlock* (single item factor), *multi apps* (factor loadings < 0.4), *headset jack 35* (single item factor), *take photo and video* and *smartphone game* (*Cronbach's α* < 0.6). Finally, we extracted six factors from 22 topics. We name these factors according to the topics they represent: camera, reliability, novelty, design, memory storage, and technical. The cumulative variance of 6 factors is 66.35 %, all of them having a factor loading over 0.4, commonality over 0.49, *Cronbach's α* over 0.60. Details are shown in Table 2.

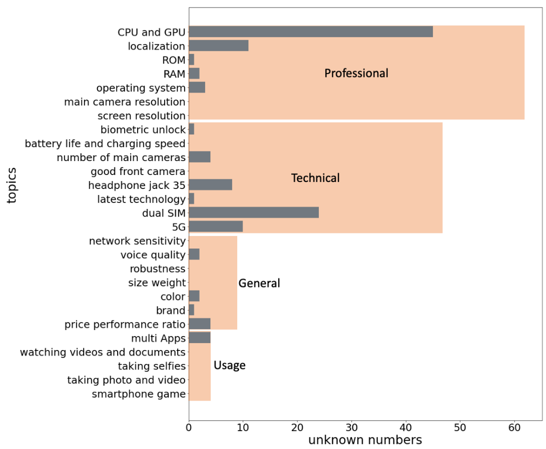


**Figure 3:** Unknown number of user-interested topics. X-axis stands for the unknown number, Y-axis stands for user-interested topics. Orange bar indicates the unknown number of 4 categories.

**Table 2**
Final EFA results of total 27 topics (*df*=197). The first column represents the kept topics in the smartphone domain and *Cronbach's α* values of factors. The first column represents communities of topics and the founded latent factors. The bold font indicates the values are greater than 0.5.

| | | Factors | | | | | |
|---|---|---|---|---|---|---|---|
| Topics | Commonalities | camera | reliability | novelty | design | memory storage | technical |
| taking photo and video | .74 | **.85** | -.01 | .01 | -.06 | .10 | .04 |
| good front camera | .74 | **.79** | .23 | -.04 | .02 | .08 | .07 |
| main camera resolution | .58 | **.75** | .10 | .04 | .03 | .32 | -.03 |
| taking selfies | .49 | **.71** | .13 | .11 | .20 | .01 | .03 |
| number of main cameras | .55 | **.64** | .06 | .33 | .27 | .08 | .16 |
| network sensitivity | .66 | .17 | **.76** | -.02 | -.09 | .21 | .07 |
| robustness | .61 | .14 | **.69** | .10 | .19 | -.04 | .13 |
| voice quality | .77 | .05 | **.64** | .30 | .05 | -.10 | .17 |
| battery life and charging speed | .65 | .10 | **.60** | -.23 | .11 | .35 | -.18 |
| 5G | .56 | .08 | .11 | **.75** | .06 | .15 | .08 |
| dual SIM | .65 | .03 | -.06 | **.71** | .19 | .13 | .03 |
| latest technology | .56 | .26 | .28 | **.56** | .30 | -.01 | .04 |
| color | .68 | .05 | .05 | .17 | **.85** | .04 | .04 |
| brand | .69 | .21 | -.02 | .06 | **.68** | -.06 | .27 |
| size and weight | .65 | .01 | .23 | .22 | **.64** | .26 | -.01 |
| ROM | .67 | .24 | .15 | .14 | .09 | **.83** | .03 |
| RAM | .71 | .15 | -.01 | .22 | .02 | **.77** | .23 |
| operating system | .76 | .02 | .02 | -.08 | .16 | .08 | **.85** |
| localization | .72 | .26 | .27 | .35 | .12 | .09 | **.60** |
| CPU and GPU | .81 | .02 | .25 | .47 | .01 | .22 | **.58** |
| *Cronbach's α* | | .83 | .60 | .66 | .64 | .80 | .68 |

## 5.2. SEM on decision-making style, meta-intents, topic preference

Finally, based on our data, we constructed a SEM, which contains decision-making style, meta-intents and topic preference, as shown in Figure 4. Decision-making style (ovals) and topic preference (ovals) are estimated from several directly measurable questionnaire items. In order to display the relationships between our main factors as clearly as possible, we leave out the factor loadings of concrete questionnaire items. Decision-making style and meta-intents are latent variables in this framework, however, since the meta-intents are measured by a single question, we use rectangles to represent them. The arrows indicate significant influences, with the value above depicting standardized regression coefficients, while non-significant connections have been removed for clarity. As the entire SEM is quite large, in order to analyze it methodically, we split it into two parts with the green rounded rectangle representing Part A, and the yellow rounded rectangle representing Part B respectively.

### 5.2.1. Part A: decision-making style and meta-intents

Part A focuses on the influence of decision-making style on meta-intents. After removing non-significant effects, five of eight meta-intents factors remain. We found the factor rationality having significant influences on five meta-intents factors with the greatest impact on *interest in details* (0.61) and *comparison oriented* (0.47). Besides these relationships, rationality also has positive influences on *diversity orientation* (0.22) and *scope of choice* (0.26), but a negative influence on *efficiency orientation* (-0.29). In contrast, for the intuitiveness factor only a single significant (positive) effect on *efficiency orientation* (0.34) could be identified.

### 5.2.2. Part B: decision-making style and topic preference

Part B focuses on the influence of decision-making style on topic preference. After cleaning the non-significant effects, four of six topic preference factors remain. We found the rationality has positive and significant influences on *camera* (0.27), *memory storage* (0.31), and *technical* (0.26). The intuitiveness has positive and significant influences on *camera* (0.46), *reliability* (0.34), *memory* *storage* (0.21), and *technical* (0.29). While decision style showed opposite effects at the MI level (for efficiency-orientation), here they did not show this pattern, only differing in the impact coefficient. The biggest difference was observed for the *camera* factor, for which the intuitiveness has a larger standardized regression coefficient (0.46) than the rationality (0.27).

From these results, we can answer the first research question posed earlier: decision-making style has a significant influence on some meta-intents and topic preference factors.

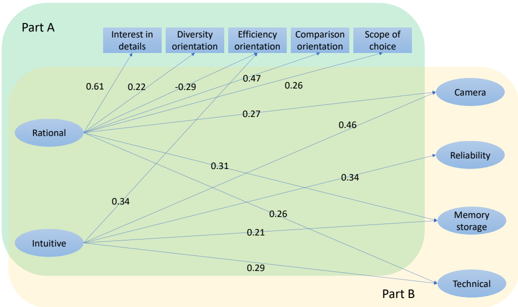


**Figure 4:** Structural equation model including 3 parts, stable psychological traits (Decision-making style), proposed psychological traits (meta-intents) and user interested topics (smartphone domain).

### 5.2.3. Overall model

The overall model fit is shown in Table 3. The subsection 5.2.1 and 5.2.2 claim that decision-making style significantly impacts both meta-intents and topic preference, which meet the prerequisite for testing mediating effects (meta-intents as mediator). However, we found no significant influence of meta-intents on topic preference. Applying Bootstrap testing (2000 iterations) for indirect effects (decision-making style ⟶ meta-intents ⟶ topic preference) yielded no significant indirect effect, preventing further mediation analysis and answering the second research question: meta-intents do not act as mediators between decision-making style and topic preference. This finding provides some indication that meta-intents are independent of the specific product domain, in this case smartphones.

**Table 3**
The overall fitness indices of the proposed structural equation model.

| | $\chi^2/df$ | GFI | AGFI | TLI | NFI | CFI | RMSEA |
|---|---|---|---|---|---|---|---|
| **evaluation standard** | 1< & <3 | >0.8 | >0.8 | >0.9 | >0.9 | >0.9 | <0.08 |
| **proposed SEM** | 1.809 | .846 | .794 | .849 | .768 | .877 | .064 |

## 6. Discussion

### 6.1. Part A: decision-making style and meta-intents

We found that *rationality* has more significant influences on meta-intents than *intuitiveness*, and that both have opposite effects on *efficiency orientation.* This implies that the more rational people are, the less they seem to care about efficiency. At the user interaction level in CRS, efficiency may be determined by interaction time as well as the number of clicks and keystrokes needed for typing text. In personalized CRS design, this factor has a guiding role for the length of the dialogue, the amount of information displayed per output, and when to display the recommended products. Rationality also has positive influence on *diversity orientation*, *interest in details*, *comparison orientation*, and *scope of choice. Diversity orientation* indicates that the user would like to see a diverse range of items in the recommendation list. *Interest in details* provides insights into how much content should be shown when displaying product features and other information, such as customer comments. *Comparison orientation* suggests that users would like to see products, their features and customer assessments side by side, e.g. in a comparison function, to take a decision. *Scope of choice* can inform us about choosing an appropriate length of the recommendation list and probably also the length of features lists shown for a product. In sum, these findings provide some insights for the design of CRS with respect to dialog structure, design of questions and answers, and the presentation of recommendations. If data on the user's decision style were available, e.g. through classifying their interactive behavior, the findings can also provide a basis for personalizing the CRS.

### 6.2. Part B: decision-making style and topic preference

Concerning Part B, we notice that the intuitiveness has larger standardized regression coefficients (0.46) on *camera* than the rationality (0.27) implying that intuitive people are more interested in camera functionality than rational people. This gives us some pointers for CRS design in this specific domain. When eliciting preferences (or detecting intents), *camera* is a topic of interest to the user with high intuition. From a more general point of view, the discrepancies between rational and intuitive decision makers suggest that the former are more focused on the low-level technical specifics of a product domain (such as the CPU which is installed in a smartphone), while the latter are more attracted to information about immediately experiential properties (such as the quality of a shot photo).

Our findings provide insights into intent detection for

CRS in preference elicitation. Supposing data on users' decision-making styles are available, the survey results can provide a basis for personalizing the preference elicitation process, e.g. to help choosing which features to ask and the order in which they are asked. At the same time, we want to point out a limitation here. Unlike the high abstract level of meta-intents which can be applied to various fields, the findings here are based on a specific field (smartphone). Still, we provide an idea for utilizing decision-making knowledge to enhance the preference elicitation process of CRS in a specific domain.

### 6.3. Overall model

After applying SEM to the overall model, we found that the meta-intents factors do not significantly impact topic preference, which means our proposed meta-intents seem to be independent of product features and topics, and do not have mediating effects between decision-making style and topic preference. Meta-intents appear to be independent of our concrete product domain, but whether it is truly domain-independent remains to be verified by multi-domain research.

We believe our results provide some initial valuable insights that can help be better designe and possibly personalize CRS. In particular, we would like to point out that experiences with a CRS should be viewed from multiple perspectives. Differences in individual decision behavior seem to be related not only to attitudes toward specific product features, but also to expectations of the interaction process as a whole. When designing a CRS, therefore, consideration should be given not only to personalizing the recommended products, but also to adapting the agent's mode of communication. If both aspects are taken into account in an appropriate manner, it can be assumed that positive transfer effects could arise which, taken together, enrich the user's overall experience.

## 7. Conclusion

In this paper, we propose a set of meta-intents factors, which can be seen as a bridge between classic psychological factors (decision-making style) and item-level intents, and which can be used as indicators of personalized UI design for CRS. We also propose a CRS framework that incorporates decision-making style, meta-intents factors, and conventional CRS models. This work uses SEM to validate the significant influence of decision-making style on meta-intents and topic preference. We also found that meta-intents seem to be domain-independent, dialog-specific factors that do not have a mediating effect on topic preference. Our results provide evidence that the proposed meta-intents are linked to the general decision-making style of a user and can thus be instrumental in translating general decision-making factors into more concrete design guidance for CRS and their potential personalization. At the same time, we also point out three limitations of this experiment: 1. Meta-intents is a new concept for which we used only one or two questionnaire items per intent. We plan to develop the instrument further and validate the meta-intents with a larger number of questions. 2. The domain of this experiment is limited to smartphones, and comparative experiments in several fields will be necessary in the future. 3. The integration of meta-intents into specific CRS models and the real impact of MI on user interaction needs to be explored in future work.

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