Modeling User Interaction at the Convergence of Filtering Mechanisms, Recommender Algorithms and Advisory Components

Timm Kleemann
University of Duisburg-Essen
Duisburg, Germany
timm.kleemann@uni-due.de

Magdalena Wagner
University of Duisburg-Essen
Duisburg, Germany
magdalena.wagner.96@outlook.com

Benedikt Loepp
University of Duisburg-Essen
Duisburg, Germany
benedikt.loepp@uni-due.de

Jürgen Ziegler
University of Duisburg-Essen
Duisburg, Germany
juergen.ziegler@uni-due.de

ABSTRACT

A variety of methods is used nowadays to reduce the complexity of product search on e-commerce platforms, allowing users, for example, to specify exactly the features a product should have, but also, just to follow the recommendations automatically generated by the system. While such decision aids are popular with system providers, research to date has mostly focused on individual methods rather than their combination. To close this gap, we propose to support users in choosing the right method for the current situation. As a first step, we report in this paper a user study with a fictitious online shop in which users were able to flexibly use filter mechanisms, rely on recommendations, or follow the guidance of a dialog-based product advisor. We show that from the analysis of the interaction behavior, a model can be derived that allows predicting which of these decision aids is most useful depending on the user's situation, and how this is affected by demographics and personality.

CCS CONCEPTS

• **Human-centered computing** → **HCI theory, concepts and models**; • **Information systems** → *Search interfaces*; *Recommender systems*.

KEYWORDS

Human factors, User experience, User Modeling

ACM Reference Format:
Timm Kleemann, Magdalena Wagner, Benedikt Loepp, and Jürgen Ziegler. 2021. Modeling User Interaction at the Convergence of Filtering Mechanisms, Recommender Algorithms and Advisory Components. In *Mensch und Computer 2021 (MuC '21), September 5–8, 2021, Ingolstadt, Germany*. ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/3473856.3473859

MuC '21, September 5–8, 2021, Ingolstadt, Germany

1 INTRODUCTION

Identifying content that meets the user's preferences has become increasingly difficult due to the steadily growing number of items available in online shops, on music and video streaming platforms, or on flight and hotel booking pages. To address the resulting information overload [24, 35], a variety of methods has been proposed to support the user's decision making. First, conventional *filtering mechanisms* allow users to specify precisely for what they are looking. While the level of granularity is high when specifying requirements in this way, this however requires profound knowledge of product domain and search goal. Moreover, users have to invest a significant amount of interaction effort to arrive at meaningful results [18]. Second, as a consequence of these drawbacks, many system providers started to employ *recommender algorithms*. These algorithms work in the background to identify items that match the preferences expressed by the user, for example, based on similarities to other users or items [55]. Due to the high level of automation, this makes the search process cognitively less demanding and limits interaction effort. Yet, this goes hand in hand with a lower degree of flexibility and user control, since the only option to affect the results usually is providing ratings for single items—if this is possible at all [25, 39]. Third, somewhere in between the aforementioned approaches, dialog-based *advisory components* have emerged, especially on e-commerce platforms. They support users during the decision-making process in a conversational manner by asking questions on the goal they pursue in relation to the products. With each question, the results are then refined and constrained to products that match the requirements indicated by the given answers [16, 29]. Since questions are often phrased on an application-oriented rather than a technical level, profound domain knowledge is not necessary to interact with such a dialog.

In some way or the other, all these methods alleviate the information overload problem. However, they not only have individual limitations, as already pointed out, but are also not equally useful for each user in every situation. For instance, small domain knowledge makes it difficult to come up with search terms and to define appropriate filter criteria [26]. Other users may feel too much dominated by recommendations because they can only accept the output of the algorithms, but have no means to articulate their actual preferences due to the insufficient possibilities to intervene in the underlying process. The fact that this process is largely automated is another problem for users who want to understand why they are confronted with certain results, and may consequently reduce their trust in the systems [58]. Intelligent product advisors offer users with little domain knowledge an easy way to find suitable products, but as soon as their expertise increases, the questions asked may be below the level of detail they are looking for.

Fortunately, on many e-commerce platforms, users can choose flexibly from the whole range of decision aids. Therefore, they can rely on the method that feels most appropriate depending on their current situation. However, users are neither supported in this choice, nor can they easily switch to a different method once they follow a specific strategy to achieve their goal, since the individual components are usually implemented in an isolated manner, i.e. without close connections between. To facilitate decision making and increase user experience, it would thus be helpful to present users proactively the right method, i.e. automatically determine which method offers the highest value at the present time, and support them in continuing with this method without losing the current progress. In light of this goal, we implemented a fictitious online shop that allowed users to choose from all aforementioned decision aids at their own discretion. Then, we conducted a user study with $n = 72$ participants who had to use this shop and perform different search tasks. This allowed us to model search behavior, including the usage of the different methods, in relation to personal characteristics, demographic information, and situational factors. In the following, we provide a brief overview of the literature on the constructs we used in this context. Afterwards, we describe the experiment in detail and present the model of user interaction we derived as a basis for making predictions about the usefulness of the respective methods for the current user. We conclude the paper with a discussion of the potential of this model for a more user-oriented selection of the right mechanisms in light of the likely convergence of these decision aids in future systems.

2 LITERATURE OVERVIEW

Online purchasing behavior differs from traditional shopping [10]. The established model of the buying decision process [12] has already been adapted to the behavior of users in online environments [11]. While in internal search, known products are taken into consideration, users look for other alternatives in external search, for example, based on the advice of other persons. Decision aids, as we address them in this paper, are other typical examples that contribute to the latter, making users aware of other solutions to their problem and enabling them both to make comparisons of suggested products and to understand why these products fit their needs. With respect to the selection of the most suitable decision aid, the following steps described by the model seem particularly relevant: search, evaluation, and purchase. In these steps, the buying decision process varies highly between users, depending on a variety of factors. During the process, individual characteristics, but also situational and economic aspects affect the user's decision making. In addition, it depends on the user's beliefs, knowledge, and intentions whether a product is finally bought [11, 12]. In this paper, we lay our attention on exactly these factors to further investigate their impact on the user's search behavior, and consequently, on his or her choice of decision aids. The model shown in Fig. 1 provides an overview of these factors in accordance with the model of the buying decision process from [11], classifying them into: personal characteristics, demographic information, and situational aspects.

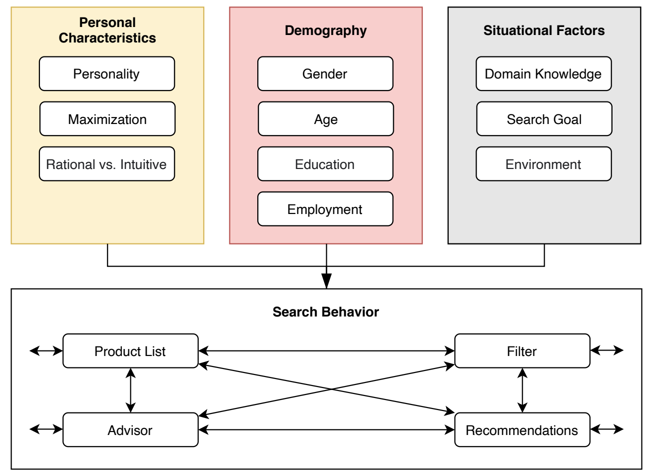

Figure 1: The three categories of factors that affect the user's search behavior in online shops, and thus, their choice of decision aids during the buying decision process.

Overall, many efforts have already been made to personalize user interfaces of information retrieval or recommender systems in order to improve user experience [23, 30, 59, 65]. However, these personalization efforts are often restricted to a specific component in the user interface, e.g. a filtering *or* a recommendation component, instead of presenting users also with entirely different tools as a means to continue their search. Examples include approaches to reorder the facets in filtering interfaces [32] or to extract relevant filters from user queries [60]. Also, a common purpose of recommender research is increasing transparency of the systems [34] or enabling users to control the underlying algorithms [39]. For this, various approaches have been proposed that also take aspects such as personality factors or situational aspects into account [23, 50, 59, 65]. Next, however, we provide a broader overview of works in which these factors, at least to some extent, have been investigated in terms of their influence on the user's search behavior.

2.1 Personal characteristics

Personality. Personality is one of the important determinants for decision making, and thus, the user's search behavior. Also for online shoppers, it has been shown that their buying behavior is influenced by personality [6, 7, 20]. In psychology, a common approach is to classify personality based on the five-factor model, which includes openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism [43]. For example, a high degree in openness to new experiences typically goes hand in hand with larger creativity and curiosity. Conversely, a low level is often correlated with conservative behavior and reluctance to adventure. In line with that, it has been shown, for instance, that users with low openness values prefer less serendipity in recommendation lists [46]. Also, all these characteristics have an influence on the acceptance of recommendations [17].

Maximization. Another important personal characteristic that affects the search process is the maximization behavior, which describes the effort users are willing to invest in relation to the suitability of the results [21]: Maximizers attempt to achieve the best possible result in exchange for a longer duration of the search [27]. In contrast, satisficers are content with results that meet at least some of their search criteria. As a consequence, maximizers often look for additional information and browse more intensively through the space of available items, considering alternatives and moving back and forth a lot [8, 51]. Furthermore, they apply a larger number of search criteria [27], but make fewer use of more automated decision aids [62].

Rational & intuitive. Another distinction is often made between rational and intuitive decision making. Search patterns of intuitive users are driven automatically and emotionally by the result. Occurring quickly and preconscious, this process is inscrutable and incomprehensible to the user [47]. In contrast, rational users tend to follow analytical search patterns, acting in an intentional and process-oriented manner [48]. These users are typically aware of the underlying cause-, effect-, and rule-based process, and also capable of controlling it. In online shopping, for instance, rationality has been identified as the predominant style when making purchase decisions, and should therefore be taken into account for an effective personalization of the environment [28].

2.2 Demography

Demographics of users likewise affect their search behavior [36]. For instance, gender has been shown to influence how consumer attitudes are formed by the product presentation in online environments: Men are more likely to consider the level of interactivity and perceived risk of a particular online shop [14], whereas woman are persuaded by the vividness of the representation and the level of detail of the provided information. In general, the attitude towards a product presentation influences men more strongly than women in their purchase intention [36]. In addition, gender also influences the relationship between the perceived quality of an online shop and the perceived value of a product, which is more prevalent for men than for women in case of task-oriented purchases [13]. Age is another moderator for this relationship: For experience products, a positive relation is more important for younger than for older customers, an effect that is less or not at all present for task-oriented purchases [13]. With respect to recommender systems, gender and age have been shown, for example, to affect the perception of the results. Both male and elderly people are more likely to engage with recommendations than younger persons or female users [3]. Other factors such as the education level or the employment situation also play a non-negligible role for users in determining the quality of recommendations [53] or when browsing online platforms [56].

2.3 Situational factors

Domain knowledge. The knowledge about certain products and their features likewise has a significant influence on the buying decision process [27]. Users with high domain knowledge who already have a precise notion of the products they are looking for usually start directly with the evaluation of the products with respect to their goal. Often, they already have possible solutions in mind, are experienced with evaluation criteria, and can reliably assess the provided information. This reduces the amount of time they need for searching and evaluating the products [9]. In recommender systems, these users are also able to approximate the value of recommendations more precisely [38]. In contrast, users with little domain knowledge have limited capabilities to adequately evaluate the provided information [41]. As a consequence, they need to consider more alternatives, which leads to additional evaluation cycles, and, overall, a longer evaluation process [27]. In addition, domain knowledge influences the perceived accuracy of decisions [52], the acceptance and interaction with online shops, and the desired extent of control over the systems [17]. Accordingly, it has already been suggested to offer users of interactive recommender systems feedback mechanisms depending on their level of expertise [30], for instance, more sophisticated mechanisms for expert users, but simpler variants for novices [4].

Search goal. The search situation of users is, of course, also an important factor with respect to the question which decision aid is more appropriate for the user in the current situation. Usually, possible goals are classified into factual or exploratory [42]. Due to mostly precise parameters, factual search is rather straightforward and users require only few steps to reach their goal [2]. In contrast, exploratory search focuses on knowledge acquisition, where the goal is vague and open-ended. Accordingly, in this case, there are multiple ways to meet the user's information needs. Neither is there an obvious path that leads directly to the desired result, nor is it clear when exactly the search should end, which makes exploratory search much more complex [2, 64]. Between users, different behavior patterns have been shown. For example, some users fixate longer during factual searches and are more concentrated [40], which is, however, mediated by personality [1]. Also, the query length is often considerably longer than in exploratory searches, where users have only a vague idea of their goal and therefore use fewer keywords. Another indication of this uncertainty is that users scroll more in exploratory searches to evaluate a larger number of alternatives, which ultimately also requires more time in total to reach the search goal [2].

Environment. Finally, the online environment itself, including structure and design of the user interface as well as possible interaction, is an important factor that needs to be considered when modeling user behavior for systems in which multiple decision aids are available: A design that supports users in their search can reduce the effort they need to invest. It has been shown, that both the information itself and the technologies used in online shops influence consumer's purchase intention [22, 49]. Additionally, users are more likely to remember the provided product information if the online environment matches their search behavior [19]. The amount of information provided at the user interface has been shown to affect the user's ability to approximate the value of recommendations [38]. For some users, the availability of interactive features contributes more to the satisfaction with a recommender system than for others [31]. The perceived quality of the environment has also been shown to have a direct effect on the buying decision process [61], depending on attractiveness, user-friendliness, and, of course, product availability [37]. For example, high subjective attractiveness and the implementation of a straightforward navigation positively affect the purchase decision in online shops [63]. In addition, personalization can be a major factor for the acceptance of an online environment [33].

3 MODELING USER INTERACTION

With the goal of identifying characteristics that affect the search behavior of users in online shops, we lay our focus on three widely used decision aids: Manual filtering, automated recommendations, and a conversational advisor. Naturally, a product list with browsing functionalities complements these mechanisms. We assume that the availability of these options constitutes an appropriate point of departure for both novices and experts. Conventional search, on the other hand, is different from the above mechanisms, and thus, not within our scope, as it poses additional requirements such as a specific syntax for fine-tuning the results, and is prone to errors due to the difficulty of formulating information needs on the same level of complexity.

Our underlying assumption, however, is that not all components are equally helpful for all users at the different stages of their search. If the tool that currently would be the most appropriate one is not available to a certain user, this can have a negative effect on both the search and the decision-making process. Therefore, the model we propose includes factors that have been shown in the literature review in the previous section to affect user behavior: Personal characteristics, demographic information, and situational aspects, including domain knowledge, current search goal, and respective environment. The search behavior that is represented by this model summarizes the three steps *search*, *evaluation*, and *purchase* of a typical online buying decision process [11]. By analyzing this behavior, we assume that it will be possible to determine the most suitable components for each user given his or her current situation, thereby providing initial guidance for a more user-oriented selection of decision aids when implementing online shops.

3.1 Method

To study the influence of the different factors on the usage of the decision aids included in our model, we conducted a user experiment. For the online study, which ran for a month, participants were acquired through social media. Among the participants were students of the University Duisburg-Essen, who were rewarded with study credit for participation. Participants were able to complete the study using their own desktop computer or laptop, but other devices were not allowed.

3.1.1 Prototype & tasks. In line with our goal, we wanted to ask participants to interact with a fictitious online shop. For this purpose, we set up the system that is shown in Fig. 2, in which all the components mentioned above were available: Participants had access to a number of filters, a list of product recommendations, a conversational advisor, and a product list. We randomized the positions of these components to prevent that the arrangement affects participants' behavior (in the result section below, we refer to these different arrangements as the "environment"). However, as the familiar design of an online shop had to be retained, we only changed the position of the product list from the left to the right side of the screen. In addition, product details were provided on a separate page, which could be reached by clicking on a product. Recommendations were displayed in accordance with the respective search goal (see below). Furthermore, it was possible to request recommendations for similar products on the product detail page. For the purpose of the study, we also implemented a shopping cart.

Also in line with our goal, we laid our focus on search products [57], where many different factors have to be considered, and finding the right component for the right user is therefore of particular importance. As a running example, we chose the domain of laptops. Here, a variety of (often not obvious) features is usually available, even for single models from a specific brand. We used a dataset from *NBB.com*, a German notebook retailer[1], consisting of 1303 items and corresponding information on 20 product features, along with prices and ratings on a 5-star scale.

To vary the search goal, one of the situational factors in our model, under the circumstances of the study, we confronted participants with different tasks. In all tasks they had to accomplish in the online shop, participants had to find a laptop for a friend. However, task descriptions were either more factual or more explorative, but always without using explicit criteria. By this means, we wanted to avoid that participants simply translate the given requirements into filter criteria. As a result, we randomly assigned participants to the following four tasks in a between-subject design:

- F Factual: "*Your friend only wants to use the laptop from home to play video games. To do this, she/he wants a display that is as large as possible. She/he does not care about the price.*"
- SF Strongly factual: "*Your friend only needs the laptop to create documents. She/he commutes for half an hour every day and wants to be able to use the laptop in the meantime. She/he is willing to spend about 200€ for it.*"
- E Explorative: "*Your friend does not know much about laptops and trusts you to find a suitable laptop. She/he is willing to spend up to 2000€ .*"
- SE Strongly explorative: "*Your friend does not know much about laptops and trusts you to pick out a suitable laptop for him. She/he does not care about the price.*"

Participants were allowed to finish the respective task once they found a suitable item, i.e. there was no time limit.

3.1.2 Questionnaire & interaction data. Once participants finished the interaction with the online shop, they were confronted with a questionnaire. If not indicated otherwise, all questionnaire items had to be answered on positive 1–5 Likert response scales. Concretely, we assessed personality based on the well-known five-factor model [44] using the *BFI-10* questionnaire [54]. To assess the behavior when making decisions, we used the *Maximization Scale* [45] (positive 1–7 Likert scale) and the *Decision Style Scale* [15]. Furthermore, we assessed domain knowledge of participants with self-constructed items and collected demographic data.

In addition, we measured user experience of our system by means of the *System Usability Scale* (SUS) [5], and asked participants to comment on the individual components and their functionality. Answers to these open-ended questions were optional.

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

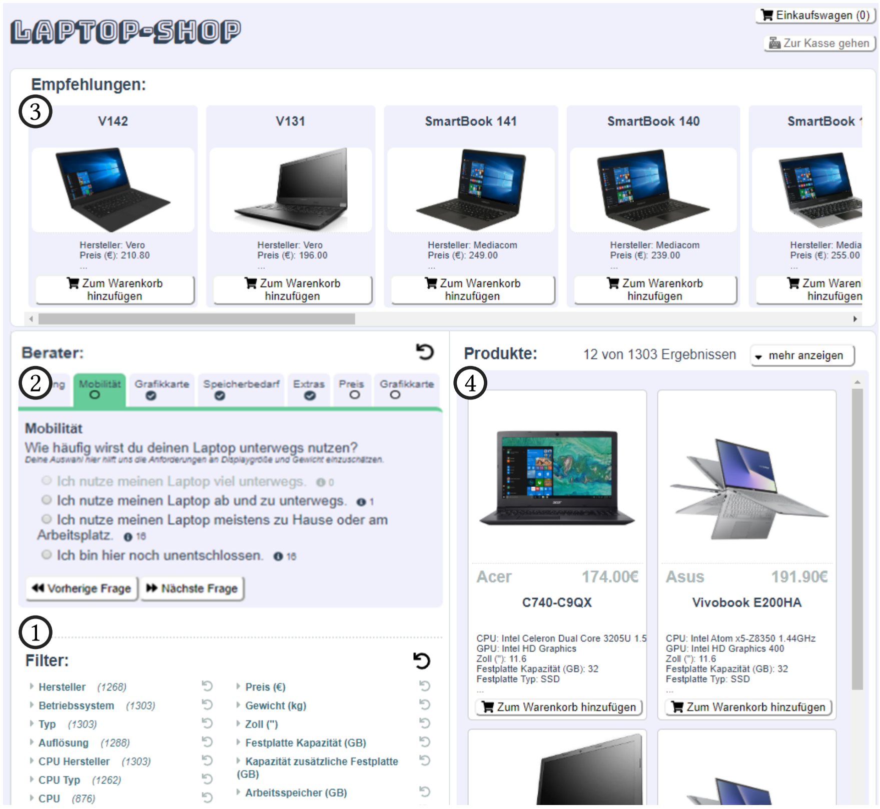

Figure 2: Fictitious online shop: Users have the possibility to use filters (1) or to answer the questions of the advisor (2). Initially, all filters are collapsed, but can be opened up individually. In addition, product recommendations are displayed (3). When applying filters or answering questions of the advisor, the product list is immediately updated, showing products that match the specified requirements (4). Clicking on a products lead to the corresponding product detail page.

Originally, we had planned to use eye tracking as we thought this would be the best possibility to draw conclusions regarding the actual usefulness of the different components given the respective situation. However, due to the COVID-19 pandemic, we were not able to invite participants in our lab due to hygiene restrictions. As a loose approximation of the original design, we integrated our online shop with mouse tracking, which also provided us additional information on the usage of the decision aids. We logged mouse movements and other actions such as adjusting the filters and answering the questions of the advisor.

3.1.3 Participants. From the 152 recruited participants, 26 dropped out before interacting with the system. Overall, 90 participants both answered the mandatory questionnaire items and completed the given task. To ensure that only participants were included in our analysis who seriously interacted with the prototype system, we only considered those who had at least 5 interactions with the four components of the system, which left us with $n = 72$.

Personal characteristics. On average, participants' scores in the dimensions related to personal characteristics were relatively high. With respect to personality, extraversion showed a mean of 3.2 (SD = 0.4), agreeableness of 3.2 (SD = 0.7), conscientiousness of 3.6 (SD = 0.6), neuroticism of 3.0 (SD = 0.6), and openness of 3.1 ($SD = 0.4$). With respect to decision making, we observed a higher degree of maximization ($M = 4.2$, $SD = 1.0$) and rationality ($M = 3.9$, $SD = 0.7$), whereas participants seemed to be less intuitive ($M = 3.1$, $SD = 0.8$). As expected, we found a significant negative correlation between rationality and intuition ($r = -0.56$, $p < .001$).

Demography. 50 of the 72 participants were female. Their age ranged from 17 to 50 ($M = 23.7$, $SD = 2.5$). The majority of 76 % were students, 18 % were employed. All participants finished secondary school, 89 % had a higher education entrance qualification, 28 % a university degree.

Situational factors. Participants' domain knowledge was rather average ($M = 3.1$, $SD = 0.7$). Their satisfaction with our prototype system was generally high, as indicated by an average SUS score of 87.6. For the four different environments, we obtained $SUS_{Env1} = 87.1$, $SUS_{Env2} = 85.3$, $SUS_{Env3} = 85.4$, and $SUS_{Env4} = 92.0$, and thus, always "good" usability. As described above, all 72 participants completed the given task, i.e. interacted with our online shop. The search goals, represented by the different tasks, were equally distributed among participants, with $n_F = 19$, $n_{SF} = 17$, $n_E = 16$, and $n_{SE} = 20$.

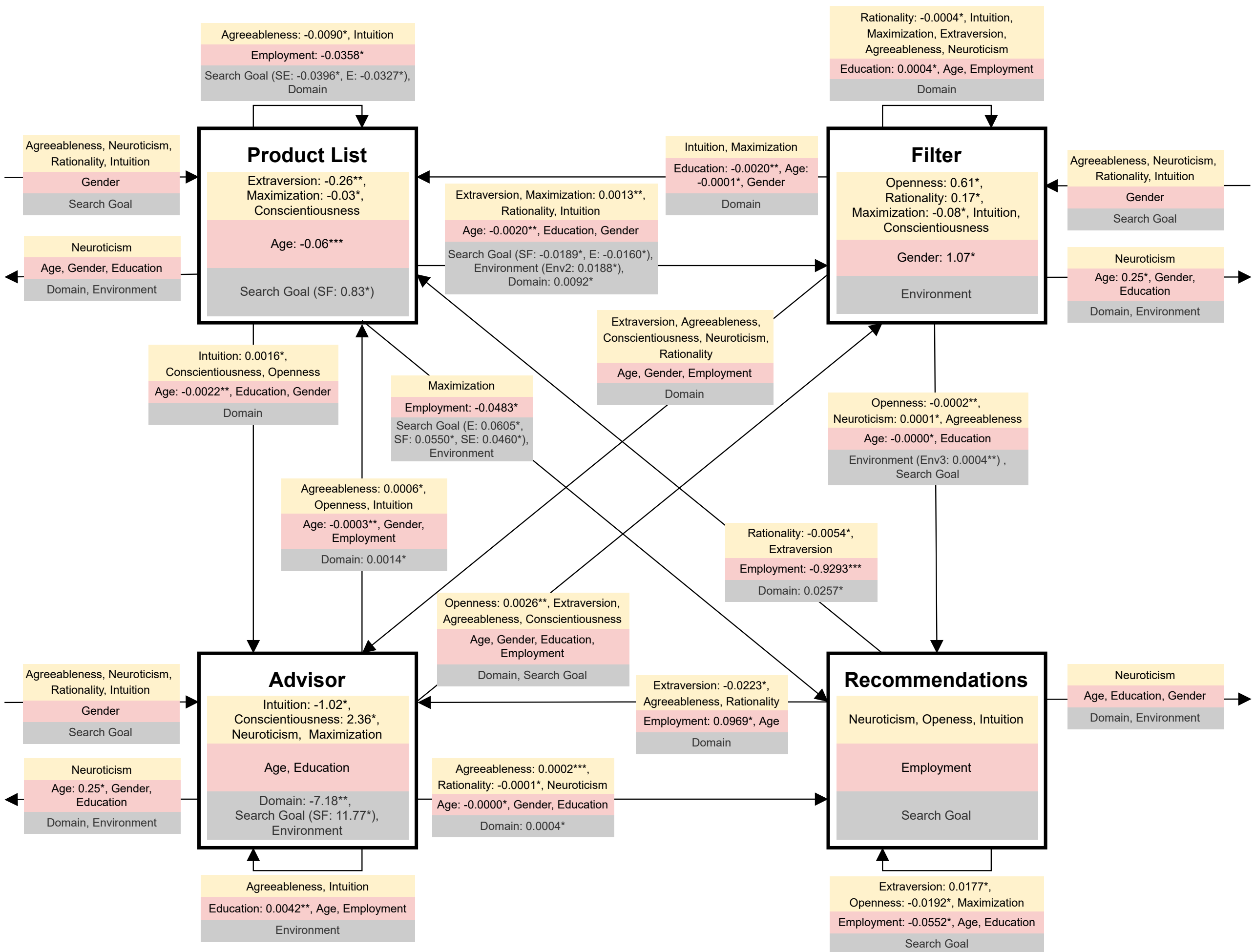

Figure 3: The model shows the typical components of an online shop, as implemented for our experiment. Edges represent transitions between these components, as well as the component with which the interaction started (incoming) and ended (outgoing). Results of significant regressions ($^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$), including significant (with B value) and non-significant (without B value) predictors, are shown for each of the three categories of factors: personal characteristics (yellow), demography (red), situational factors (gray). In each box, significant values are sorted in descending order by effect size.

3.2 Results

Next, we present the results we obtained through the interaction analysis. We start with general results regarding the duration of the interaction with the online shop and the number of interactions performed by participants (Section 3.2.1). Then, we elaborate on the components participants used to start and end the interaction, as well as on their overall usage frequency (Section 3.2.2). Finally, we describe in detail which factors had an influence on the transitions between the components, i.e. were responsible for participants' decision to continue using a certain method, or to proceed with another one (Section 3.2.3, 3.2.4, 3.2.5, and 3.2.6).

To estimate the influence of the different factors, we calculated multinomial and multiple (robust if preconditions were violated) logistic regressions based on an analysis of the log data from our online shop, i.e. frequencies with which participants interacted with (clicked on) the different components. Unless stated otherwise, preconditions for these calculations were met. We used an α-level of .05 for all statistical tests.

3.2.1 Duration & number of interactions. The duration of the interaction varied from 28 seconds to 39 minutes ($M = 230.31$, $SD = 302.07$). However, a large majority of participants (70.8 %) spent between 1 and 6 minutes in our shop, while only 13.9 % required more than 6 minutes, and 15.3 % were faster. On the duration, conscientiousness ($t(68) = 2.43$, $p = .018$; $d = 0.35$), domain knowledge ($t(68) = -2.41$, $p = .019$; $d = -0.34$), and the strongly factual search goal ($t(68) = 2.97$, $p = .004$; $d = 0.42$), had a significant influence, as shown by the significant multiple regression, $F(10, 57) = 2.26$, $p = .027$, $R^2 = .313$. In addition, all factors related to decision style and demography turned out to be non-significant predictors.

The total number of interactions performed by participants within the online shop was influenced by personal characteristics, as indicated by a robust multiple regression $F(4, 66) = 6.45$, $p < .001$, $R^2 = .261$. We found a significant influence of intuition ($t(71) = -2.58$, $p < .012$; $d = -0.37$) and maximization ($t(71) = -3.07$, $p < .003$; $d = -0.44$). Moreover, there were effects of one of the personality factors (openness) and of gender.

3.2.2 *Interaction behavior.*

Next, we present the results of the regressions we used to predict which of the provided components (product list, advisor, filter, recommendations) participants used to start or end their interaction, and which factors influenced the overall usage frequency of these components.

Start components. First, to predict the start component, illustrated in Fig. 3 by the incoming edges of the four components, which are represented as boxes with thick borders, we calculated a multinomial logistic regression, $LR\text{-}\chi^2(16) = 42.56$, $p < .001$, $Pseudo\text{-}R^2 = .317$. The choice of the component participants started the interaction with was mainly affected by personal characteristics, but also by gender and search goal, as shown in the boxes (without borders) that are depicted at the incoming edges. The recommendations component was never chosen first.

End components. Second, the components participants ended their interaction with, and the results of the corresponding regression, $LR\text{-}\chi^2(24) = 52.39$, $p < .001$, $Pseudo\text{-}R^2 = .324$, are illustrated in Fig. 3 by the outgoing edges of the four components (boxes with thick borders). Participants left the online shop and continued with the questionnaire from different components, depending on gender, education, environment, and domain knowledge, as shown in the boxes (without borders) that are depicted at these edges. Moreover, we observed a significant effect of age on participants' decision to leave the online shop from the advisor ($z(70) = 2.26$, $p = .024$) or the filter component ($z(70) = 2.20$, $p = .028$).

Overall usage frequency of components. Within the four component boxes in Fig. 3 (boxes with thick borders), the results of multiple regressions are shown. This includes factors that had an influence on the overall usage frequency for each of these components. Detailed results of the associated t-tests can be found in Tab. 1, though for the sake of compactness only significant predictors of the regressions are reported.

For the *product list*, a robust and significant multiple regression, $F(7, 61) = 6.45$, $p < .001$, $R^2 = .392$, indicated that age, extraversion, and maximization influenced significantly the usage frequency. Moreover, as also shown in the first section of Tab. 1, the strongly factual search goal had a significant influence. Conscientiousness was another, but non-significant predictor of this regression.

Similarly, the multiple regression for the frequency with which participants used the *advisor* was significant, $F(13, 54) = 2.44$, $p = .011$, $R^2 = .219$. As shown in the second section of Tab. 1, the situational factors domain knowledge and the strongly factual search goal were significant predictors, as well as the personality factors intuition and conscientiousness. Additionally, maximization, neuroticism, age, education, and the environment had a certain effect. Not being significant, these effects are only visible in Fig. 3.

The usage of the *filter* component was predicted by all three decision styles (i.e. rationality, intuition, maximization), openness and conscientiousness, as well as the environment, $F(9, 60) = 3.88$, $p < .001$, $R^2 = .273$. As shown in the third section of Tab. 1, the effects of rationality, maximization and openness were significant predictors. Moreover, gender had a significant effect.

Table 1: Overall usage frequencies of the four components: Detailed t-test results for significant predictors of the corresponding multiple regressions.

Components	Significant predictors	t	p	d
Product list ($df = 69$)	Age	-4.87	<.001	-0.65
	Search goal SF	3.30	.002	0.44
	Extraversion	-3.09	.003	-0.41
	Maximization	-2.27	.027	-0.30
Advisor ($df = 68$)	Domain knowledge	-3.42	.001	-0.52
	Search goal SF	2.91	.005	0.44
	Intuition	-2.67	.010	-0.41
	Conscientiousness	2.06	.044	0.31
Filter ($df = 70$)	Openness	2.57	.013	0.37
	Gender	2.33	.023	0.34
	Rationality	2.23	.030	0.32
	Maximization	-2.02	.048	-0.29
Recommendations ($df = 70$)	*No significant predictors*			

Finally, the usage of *recommendations* was predicted by intuition, neuroticism, and openness, along with employment status and search goal, as shown by a robust multiple regression $F(7, 62) = 2.18$, $p = .048$, $R^2 = .220$. As shown at the bottom of Tab. 1, we could not identify any significant predictors.

3.2.3 *Transitions from the product list.*

To identify which factors determined whether participants continued using the product list or made a transition to another component, we performed multiple regressions. The transitions are represented in Fig. 3 by the edges between the product list box and the other three component boxes, i.e. with thick borders. Within each box depicted at these edges, i.e. without a border, the factors that had an influence on the respective transition are shown. In addition to Fig. 3, where also non-significant factors are listed, Tab. 2 shows the detailed t-test results for the significant predictors of the multiple regressions.

Product list → Product list: Consecutive use of the product list occurs when participants close the product detail page and subsequently interact with the product list again. We were able to predict the likelihood that participants keep interacting with the product list by means of a significant regression, $F(7, 61) = 3.01$, $p = .009$, $R^2 = .172$. As depicted in the first section of Tab. 2, significant predictors were agreeableness, employment as well as the search goal in the explorative and the strongly explorative variant. Intuition and domain knowledge had a non-significant influence.

Product list → Advisor: When participants went from the product list back to the advisor, $F(7, 61) = 4.81$, $p < .001$, $R^2 = .282$, this was predicted by age and intuition (Tab. 2). In addition to these significant predictors, conscientiousness, openness, education, and gender affected participants' behavior.

Product list → Filter: Similarly, we were able to predict the switch back to the filter component, $F(14, 54) = 3.88$, $p < .001$, $R^2 = .373$. This transition was influenced by age, maximization as well as the

Table 2: Transitions from the product list: Detailed t-test results for significant predictors of the corresponding multiple regressions.

Transitions		Significant predictors	t	p	d
Product list	→ Product list (df=69)	Employment	-2.50	.015	-0.39
		Search goal E	-2.47	.016	-0.38
		Agreeableness	-2.23	.030	-0.35
		Search goal SE	-2.14	.037	-0.33
	→ Advisor (df=69)	Age	-3.66	.001	-0.53
		Intuition	2.07	.043	0.30
	→ Filter (df=69)	Age	3.69	.001	0.50
		Maximization	2.95	.005	0.40
		Search goal SF	-2.64	.011	-0.36
		$\text{Environment}_{Env2}$	2.57	.013	0.35
		Search goal SE	-2.31	.025	-0.31
		Domain knowledge	2.29	.026	0.31
	→ Recommendations (df=70)	Search goal SE	2.58	.012	0.41
		Employment	2.39	.020	0.38
		Search goal SF	2.39	.020	0.38
		Search goal E	2.05	.045	0.32

situational factors domain knowledge and search goal (strongly factual and explorative). Moreover, when participants were confronted with the second environment (Env2), i.e. the variant of the online shop in which filter and advisor (aligned below each other) were shown at the left-hand side, this also had an influence (Tab. 2). The other personal characteristics, rationality, intuition and extraversion, along with the factors education and gender, were non-significant predictors of the regression.

Product list → Recommendations: Switching from product list to recommendations was likewise modeled by a significant regression, $F(8, 61) = 2.22$, $p = .038$, $R^2 = .124$. Here, employment as well as strongly factual, explorative and strongly explorative search goal were significant predictors (Tab. 2). Again, maximization and the environment had a non-significant influence.

3.2.4 Transitions from the advisory component. Next, we lay our attention on factors that determined which component participants used after they interacted with the advisory component. These transitions are represented in Fig. 3 by the edges between the advisor box and the other component boxes. Again, the results of the multiple regressions are depicted within the boxes (without a border) that are depicted at the edges, but also in Tab. 3.

Advisor → Product list: As shown in the first section of Tab. 3, a significant regression indicated that age, agreeableness, and domain knowledge had an influence on the likelihood of going to the product list after using the advisory component, $F(7, 61) = 4.41$, $p < .001$, $R^2 = .260$. Moreover, intuition, employment, openness, and gender had a non-significant influence.

Advisor → Advisor: The regression for staying in the advisory component was also significant, $F(8, 59) = 2.30$, $p = .032$, $R^2 = .134$. The only factor that had a significant influence was participants' education (Tab. 3). Intuition, agreeableness, age, employment, and the environment had a non-significant influence.

Advisor → Filter: We also found a significant robust regression for this transition, $F(12, 56) = 2.86$, $p = .004$, $R^2 = .398$, but the only

Table 3: Transitions from the advisory component: Detailed t-test results for significant predictors of the corresponding multiple regressions.

Transitions		Significant predictors	t	p	d
Advisor	→ Product list (df=69)	Age	-3.20	.002	-0.47
		Agreeableness	2.26	.028	0.33
		Domain knowledge	2.10	.040	0.31
	→ Advisor (df=68)	Education	2.86	.006	0.46
	→ Filter (df=69)	Openness	2.83	.006	0.37
	→ Recommendations (df=69)	Agreeableness	3.78	<.001	0.52
		Domain knowledge	2.68	.010	0.37
		Rationality	-2.39	.020	-0.33
		Age	-2.32	.024	-0.32

significant predictor was openness (Tab. 3). Extraversion, conscientiousness and agreeableness, domain knowledge, all demographic factors and search goals were non-significant predictors.

Advisor → Recommendations: Again, there was a significant regression, $F(7, 61) = 5.98$, $p < .001$, $R^2 = .339$. Important factors, presented at the bottom of Tab. 3, were agreeableness, rationality, and age. Furthermore, neuroticism, education, and gender had a non-significant effect.

3.2.5 Transitions from the filter component. Third, we describe the factors that had an influence on the transitions from the filter component. Again, these factors are depicted in Fig. 3. Detailed results for the significant predictors of the multiple regressions are reported in Tab. 4.

Table 4: Transitions from the filter component: Detailed t-test results for significant predictors of the corresponding multiple regressions.

Transitions		Significant predictors	t	p	d
Filter	→ Product list (df=70)	Education	-2.95	.004	-0.43
		Age	-2.40	.019	-0.35
	→ Advisor (df=68)	*No significant predictors*			
	→ Filter (df=69)	Rationality	-2.33	.023	-0.34
		Education	-2.11	.039	-0.31
	→ Recommendations (df=69)	Openness	-3.27	.002	-0.50
		$\text{Environment}_{Env3}$	2.76	.008	0.43
		Age	-2.41	.019	-0.37
		Neuroticism	2.10	.040	0.32

Filter → Product list: Regarding the transition of participants from the filter component to the product list, we obtained another significant regression, $F(6, 63) = 5.12$, $p < .001$, $R^2 = .264$. Age and education were significant predictors (Tab. 4). In addition, intuition, maximization, domain knowledge, and gender showed an effect on the likelihood of using the product list after the filter component.

Filter → Advisor: Although we obtained a significant robust multiple regression also for this transition $F(9, 58) = 2.34$, $p = .025$, $R^2 = .372$, we did not find significant predictors (see second section of Tab. 4). Rationality and all personality factors except openness at least had a non-significant influence. The same was true for domain knowledge, age, gender, and employment status.

Filter → Filter: As shown in Tab. 4, continuing to use the filter component was significantly affected by rationality and education, as indicated by a robust regression, $F(10, 58) = 2.13$, $p = .037$, $R^2 = .279$. Again, several other factors had an influence as well, both personal characteristics (maximization, extraversion, agreeableness, and neuroticism) and situational factors (domain knowledge). Furthermore, some demographic factors had an influence on this transition (age and employment).

Filter → Recommendations: Whether participants went from the filter to the recommendations component was significantly affected by openness and neuroticism, $F(11, 57) = 2.35$, $p = .018$, $R^2 = .179$. Furthermore, age and whether participants used the third environment, i.e. the variant of the online shop in which advisor and filter component (aligned below each other) were shown at the right-hand side, were significant predictors (Tab. 4). Besides, agreeableness, education, and the search goal had an influence on the likelihood of a transition between these two components.

3.2.6 Transitions from the recommendations component. Finally, we present the results from the interaction analysis regarding the recommendations component, and describe based on multiple regressions the factors that were responsible for participants' decision to continue using this component or to switch to a different one. The transitions are illustrated in Fig. 3 by the outgoing edges of the recommendations component. Detailed results of the significant predictors are provided in Tab. 5.

Table 5: Transitions from the recommendations component: Detailed t-test results for significant predictors of the corresponding multiple regressions.

	Transitions	Significant predictors	*t*	*p*	*d*
Recommendations	→ Product list ($df = 70$)	Employment	-4.16	<.001	-0.62
		Domain knowledge	2.01	.049	0.30
		Rationality	-2.01	.048	-0.30
	→ Advisor ($df = 69$)	Extraversion	-2.11	.039	-0.27
		Employment	2.05	.044	0.26
	→ Filter	*No significant predictors (no significant regression)*			
	→ Recommendations ($df = 69$)	Extraversion	2.44	.018	0.36
		Openness	-2.36	.022	-0.34
		Employment	-2.24	.029	-0.33

Recommendations → Product list: The transition of participants from recommendations to the product list was modeled by a significant regression, $F(4, 65) = 6.11$, $p < .001$, $R^2 = .229$. Here, as depicted in the first section of Tab. 5, employment and domain knowledge as well as rationality were significant predictors, extraversion a non-significant factor.

Recommendations → Advisor: By means of another robust multiple regression, we modeled the likelihood that participants used the advisor after the recommendations component, $F(6, 62) = 5.83$, $p < .001$, $R^2 = .433$. Predictors for this transition were extraversion and employment (Tab. 5). Rationality, agreeableness, domain knowledge, and age were identified as influencing factors.

Recommendations → Filters: We did not find a significant regression with respect to the transition from recommendations to the filter component, i.e. none of the factors had any effect. Therefore, there is also no edge from the recommendations component to the filter component in Fig. 3.

Recommendations → Recommendations: Consecutive use of the recommendations occurs when participants, after clicking on a product in the list of recommended items, click on another recommendation displayed within the product detail page. In addition, this transition occurs when participants close the product detail page and subsequently interact with the recommendations component again. Either way, when participants used the recommendations component, the likelihood to remain in this component was modeled by another significant robust regression, $F(9, 59) = 2.10$, $p = .044$, $R^2 = .270$, including the significant predictors employment, openness, and extraversion (Tab. 5). Other influencing factors were maximization, age, education, and the search goal.

4 IMPLICATIONS

Next, we discuss the results of our experiment against the background of the literature review provided in Section 2, drawing first conclusions for a more user-oriented selection of decision aids in future systems. For this, we step again through the three categories of factors described by the model initially shown in Fig. 1, and explain how the individual factors influenced participants' search behavior, in our study represented through duration and number of interactions, usage frequency of components, and transitions between. In addition, we refer to four exemplary users, participants of our experiment for whom we also provide heat maps of their recorded mouse movement (Fig. 4). Note that while we would have liked to show aggregations for groups of participants, this was not possible due to the randomization of the interface described in Section 3.1 together with the sample size.

4.1 Personal characteristics

First, it is worth noting that we were able to identify personal characteristics which actually had an influence on the search behavior of participants. For these factors, and in the remainder of this section, we use median split to discuss the results, for which we reported mean values in Section 3.1.3, in a dichotomized fashion, i.e. splitting into participants groups with low or high factor values.

According to current research, a low level of conscientiousness leads to faster completion of search tasks. Accordingly, we observed that participants with a high level of conscientiousness searched longer than participants with a low level. Although we observed a significant effect of the style of decision making on duration of the interaction, we were unable to confirm earlier findings: Contrary to [27], maximizers spent on average less time for the tasks than satisficers. A possible explanation is that participants fulfilled the characteristics of maximizers, but that these characteristics did not come to light when they tried to accomplish the fictitious tasks given in the experiment. We assume that this would be different in real search situations, in which users behave in accordance with their own personal goal.

Maximizers are also known to browse more intensively than satisficers during an information search. We captured browsing

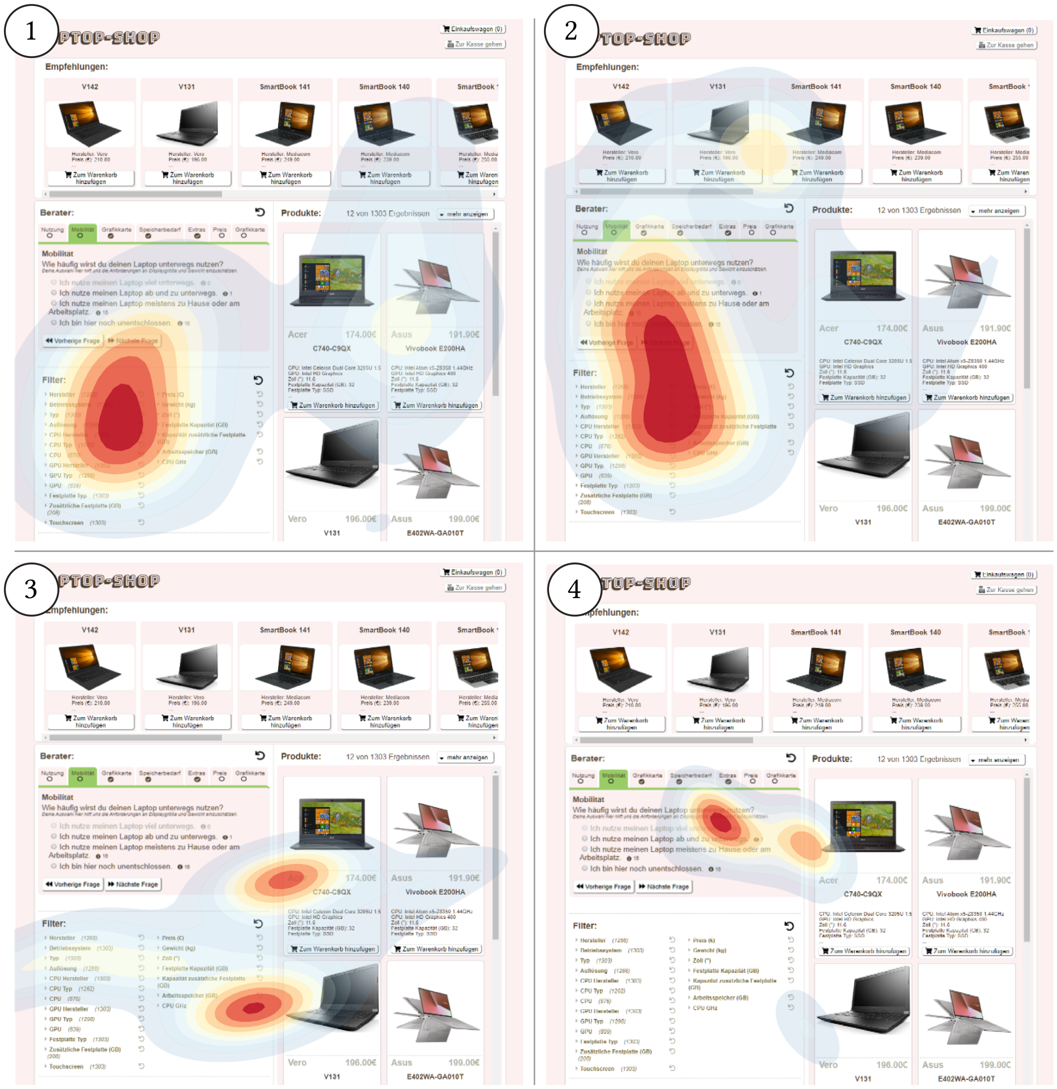

Figure 4: Heat maps of the mouse movements of four exemplary participants: Differences in the usage of the four different components can be identified (product list, filter, advisor, recommendations). For the sake of comparison, we only show heat maps where the arrangement of components (i.e. the environment) was the same (and equal to the screenshot in Fig. 2).

by the frequency of interactions with our online shop. Here, we actually found an influence of maximization: In fact, participants with a tendency to maximization performed a larger number of interactions with the system.

We also observed an influence of personal characteristics on the usage frequency of the different components and the transitions between. Here, especially rationality and personality showed an effect on the choice of individual decision aids. The analysis of the mouse behavior reflected this accordingly. One of the examples is participant 1, who apparently relied mostly on the filter component (Fig. 4, 1). This participant had particularly high values for rationality (5.0) and conscientiousness (4.5). Also, the values for intuition (3.2) and openness (3.5) were higher than the average, which seems to be in line with the frequent usage of the filter component.

Participant 2, in contrast, mainly concentrated on the filter and advisor (see Fig. 4, 2). This aligns with the predictions by our model: The participant had high values for rationality (4.0) and openness (4.0), which indicates a frequent usage of the filter component. Additionally, this participant had low values in intuition (2.2) and neuroticism (2.0), both predictors for a frequent usage of the advisory component. In line with the predictions of the model, the participant stated that "*[...] the filters are very valuable in combination with the questions about product use [in the advisor].*"

4.2 Demography

To a certain extent, demographics also affected participants' search behavior and their choice of certain components. For example, we found significant effects of age and education. Overall, however, the influence was less substantial. A possible explanation is that demographic information such as age and education in principle have an effect, but not a strong one in the scenarios induced by our task descriptions, and, in particular, with the specific domain. Aspects such as personality or domain knowledge, in contrast, seem more decisive. Nevertheless, we want to remark that participant 1, a male person, constitutes a good example that is actually in accordance with our model predictions: He used the filter component most often, as shown in Fig. 4 (1), and stated accordingly that he liked to "*[...] select multiple answers with the filter, which unfortunately was not possible with the advisor, [so that he] would personally rather use the filter, even though the advisor is a good idea.*"

4.3 Situational factors

Again in line with current research, domain knowledge had a negative influence on the duration of the search tasks performed in our online shop, i.e. participants with higher domain knowledge were faster. In addition to domain knowledge, the search goal had an influence: A strongly factual search made it more difficult to fulfill all requirements, which accordingly took more time.

We did not observe any significant effects of the environment on the duration of the interaction. Previous studies showed that a personalized online environment can reduce search duration [19]. However, our system not yet provided personalization, so that we had no a priori expectations regarding this variable. More importantly, the different environments were primarily used to avoid that a specific component arrangement causes a particular benefit. The absence of considerable effects was thus in line with our assumptions. Nevertheless, the fact that exactly those two environments where SUS scores were lower (Env2 and Env3) appeared as significant predictors in our model calls for further research.

A reason why the recommendations component was never used at the beginning of the search process might be that participant did not perceive the recommended items as suitable products for the given task, even though we selected them specifically with the respective search goal in mind. Another possibility was mentioned explicitly by one participant, who noted that he or she perceived the recommendations as "*[...] advertisements, and therefore did not consider them at all.*" This as well as the fact that participants focused on components they were familiar with may also have caused this behavior. On the other hand, the recommendations component and the product list were used generally less often than the advisor and the filter component. For this, a reason could also be that the interaction that was possible with these components had limited degrees of freedom, whereas there were much more options to interact with the advisor and the filter component. Consequently, we acknowledge it as a limitation of our research that we mainly took into consideration frequencies based on click data. We had different plans originally, in particular, to observe participants' preferences for components at certain points in time during the search process via eye tracking. Unfortunately, this was not possible due to the COVID-19 restrictions. Nevertheless, we assume that the current analysis serves as an appropriate approximation that can already provide valuable insights regarding the usefulness of different decision aids.

Circling back to domain knowledge and search goal, it is also worth mentioning that we found large effects of these factors on the usage of the components provided in the online shop. Domain knowledge had a negative influence on the usage of the advisor. Thus, higher domain knowledge indicates a reduced likelihood of using this component. Participant 3 is an example (Fig. 4, 3): He or she primarily relied on the filter component and product details. Whereas the heat maps for the product detail page are not shown here for the sake of compactness, the mouse movement was clearly focused on the product list that directly led to this page. Occasionally, this participant made also use of the advisor. He or she had small domain knowledge (1.9), which was along with age (21 years) and lower educational level (no college degree) in line with the predictions of our model. Overall, he or she used multiple decision aids, and even stated to be willing to use the recommendations more often if they would better match his or her expectations. Regarding their current quality, he or she answered to the open-ended question: "*I think the recommendations are fine, although in my case none of them appealed to me.*"

Moreover, the predictions by our model suggest that the advisor is particularly useful for participants with higher domain knowledge. Also, the search goal was shown to affect participants' behavior in this regard: For example, the strongly factual search goal was a significant predictor of advisor usage. We assume that the more factual description of the search goal was so restrictive that participants wanted to be absolutely sure to find a suitable product. Apparently, they felt able to do so with the advisor because of the task-oriented questions and answers of the conversational dialog. This made it probably much easier to formulate their information needs than translating the goal into concrete filter criteria, while the recommendations, on the other hand, were not specific enough. The mouse behavior of participant 4, a person with slightly higher domain knowledge (3.4) who had to accomplish the strong factual task, was in line with these findings, showing that he or she mainly focused on the advisor and product the list (Fig. 4, 4). The increased engagement with the product list in combination with the advisor could be another consequence of the strong factual search goal. With such a goal, it seems natural that participants frequently needed to evaluate whether suitable products were already contained in the product list—and continued narrowing down the product list by answering more questions in the advisor dialog if this was not the case.

5 CONCLUSIONS AND FUTURE WORK

In this paper, based on an analysis of the factors that typically influence the buying decision process, we proposed a model for the user interaction during the search process in online shopping environments. With the help of the fictitious online shop that we used in our user experiment, we were able to show that personal characteristics, demography, and situational aspects, actually have an effect on the user's search behavior. Although by far not all factors included in our model had a significant effect, this enabled us to make predictions regarding the decision aid that appears most useful for the respective user in his or her current situation. While we expect that our findings can be generalized to other domains thanks to our choice of typical search products as a running example, further investigation is clearly necessary with other product groups, including experience products.

This seems particularly important given that the decisions aids that are usually available, i.e. filtering mechanisms, recommender algorithms, and advisory components, mostly coexist in online shops with almost no connection in between. As a consequence, users can choose from a broad range of methods, but are neither supported in this choice, nor is it possible to switch between the components while keeping the progress with respect to the fulfillment of their goal. However, for a convergence of the underlying methods, our model can serve as an initial basis, allowing to support users by proactively presenting them the right decision aids at the right time. Further research is yet required to derive practical implications for system designers. Still, the findings emphasize the overall value of user interface adaptation for online shops, for example, to personality and style of decision making, to search goal and to domain knowledge. Therefore, we aim at using our model and this knowledge about users in future work to actually personalize such interfaces accordingly.

For this, we also intend to evaluate our model more thoroughly. In particular, not only the frequency of the used components should be included in the model (the fact that a user does not click on an element does not indicate that this element is irrelevant), but also more subjective indications of the usefulness of individual components. We suspect that an eye-tracking study would lead to a better approximation of the user's preferences for the components at a certain point in time, and therefore plan to complement our present research accordingly in future work. In this context, we will also consider temporal dynamics in our model, as usefulness of components is likely changing in the course of the interaction with an online shop more than we are able to capture currently by means of the transitions between components.

REFERENCES

[1] Hosam Al-Samarraie, Atef Eldenfria, and Husameddin Dawoud. 2017. The Impact of Personality Traits on Users' Information-Seeking Behavior. *Information Processing & Management* 53, 1 (2017), 237–247. https://doi.org/10.1016/j.ipm.2016.08.004

[2] Kumaripaba Athukorala, Dorota Głowacka, Giulio Jacucci, Antti Oulasvirta, and Jilles Vreeken. 2016. Is Exploratory Search Different? A Comparison of Information Search Behavior for Exploratory and Lookup Tasks. *J. Assoc. Inf. Sci. Technol.* 67, 11 (Nov. 2016), 2635–2651. https://doi.org/10.1002/asi.23617

[3] Joeran Beel, Stefan Langer, Andreas Nürnberger, and Marcel Genzmehr. 2013. The Impact of Demographics (Age and Gender) and Other User-Characteristics on Evaluating Recommender Systems. In *Research and Advanced Technology for Digital Libraries*, David Hutchison, Takeo Kanade, Josef Kittler, Jon M. Kleinberg, Friedemann Mattern, John C. Mitchell, Moni Naor, Oscar Nierstrasz, C. Pandu Rangan, Bernhard Steffen, Madhu Sudan, Demetri Terzopoulos, Doug Tygar, Moshe Y. Vardi, Gerhard Weikum, Trond Aalberg, Christos Papatheodorou, Milena Dobreva, Giannis Tsakonas, and Charles J. Farrugia (Eds.). Lecture Notes in Computer Science, Vol. 8092. Springer Berlin Heidelberg, Berlin, Heidelberg, 396–400. https://doi.org/10.1007/978-3-642-40501-3_45

[4] A. Bodaghi and E. Homayounvala. 2018. Personalization of Interactive Recommender Systems for Expert Users. In *2018 4th International Conference on Web Research (ICWR)*. 58–62. https://doi.org/10.1109/ICWR.2018.8387238

[5] John Brooke. 1996. SUS: A "Quick and Dirty" Usability Scale. *Usability Evaluation in Industry* 189 (1996).

[6] Gloria Chan, Christy Cheung, Timothy Kwong, Moez Limayem, and Lei Zhu. 2003. Online Consumer Behavior: A Review and Agenda for Future Research. *BLED 2003 Proceedings* (2003), 43.

[7] H. Chen. 2011. Personality's Influence on the Relationship between Online Word-of-mouth and Consumers' Trust in Shopping Website. *J. Softw.* 6 (2011), 265–272.

[8] Tilottama G. Chowdhury, S. Ratneshwar, and Praggyan Mohanty. 2009. The Time-Harried Shopper: Exploring the Differences Between Maximizers and Satisficers. *Marketing Letters* 20, 2 (June 2009), 155–167. https://doi.org/10.1007/s11002-008-9063-0

[9] Elizabeth Cowley and Andrew A. Mitchell. 2003. The Moderating Effect of Product Knowledge on the Learning and Organization of Product Information. *Journal of Consumer Research* 30, 3 (2003), 443–454. https://doi.org/10.1086/378620

[10] Silvana Dakduk, Enrique ter Horst, Zuleyma Santalla, German Molina, and José Malavé. 2017. Customer Behavior in Electronic Commerce: A Bayesian Approach. *Journal of Theoretical and Applied Electronic Commerce Research* 12, 2 (2017), 1–20. https://doi.org/10.4067/S0718-18762017000200002

[11] William K. Darley, Charles Blankson, and Denise J. Luethge. 2010. Toward an Integrated Framework for Online Consumer Behavior and Decision Making Process: A review. *Psychology & Marketing* 27, 2 (2010), 94–116. https://doi.org/10.1002/mar.20322

[12] James F Engel, David T Kollat, Roger D Blackwell, D Kollat, R Blackwell, and J Engel. 1968. A Model of Consumer Motivation and Behavior. *Research in Consumer Behavior, Holt, Rinehart and Winston, Inc., New York, NY* (1968), 3–20.

[13] Jiaming Fang, Benjamin George, Chao Wen, and V.R. Prybutok. 2016. Consumer Heterogeneity, Perceived Value, and Repurchase Decision-Making in Online Shopping: The Role of Gender, Age, and Shopping Motives. *Journal of Electronic Commerce Research* 17 (05 2016).

[14] Sandra M Forsythe and Bo Shi. 2003. Consumer Patronage and Risk Perceptions in Internet Shopping. *Journal of Business Research* 56, 11 (2003), 867–875. https://doi.org/10.1016/S0148-2963(01)00273-9 Strategy in e-marketing.

[15] Katherine Hamilton, Shin-I Shih, and Susan Mohammed. 2016. The Development and Validation of the Rational and Intuitive Decision Styles Scale. *Journal of personality assessment* 98, 5 (2016), 523–535.

[16] Gerald Häubl and Kyle B. Murray. 2005. Double Agents: Assessing the Role of Electronic Product Recommendation Systems. *Sloan Management Review* 47, 3 (2005), 8–12. https://doi.org/10.2139/ssrn.964191

[17] Chen He, Denis Parra, and Katrien Verbert. 2016. Interactive Recommender Systems: A Survey of the State of the Art and Future Research Challenges and Opportunities. *Expert Systems with Applications* 56 (2016), 9–27. https://doi.org/10.1016/j.eswa.2016.02.013

[18] Marti A. Hearst. 2009. *Search User Interfaces* (1st ed.). Cambridge University Press, USA.

[19] Weiyin Hong, James Y.L. Thong, and Kar Yan Tam. 2004. The Effects of Information Format and Shopping Task on Consumers' Online Shopping Behavior: A Cognitive Fit Perspective. *Journal of Management Information Systems* 21, 3 (2004), 149–184. https://doi.org/10.1080/07421222.2004.11045812

[20] Adrian Horzyk, Stanislav Magierski, and Grzegorz Miklaszewski. 2009. An Intelligent Internet Shop-Assistant Recognizing a Customer Personality for Improving Man-Machine Interactions. *Recent Advances in Intelligent Information System* (2009), 13–26.

[21] Sheena S. Iyengar, Rachael E. Wells, and Barry Schwartz. 2006. Doing Better but Feeling Worse: Looking for the "Best" Job Undermines Satisfaction. *Psychological Science* 17, 2 (2006), 143–150. https://doi.org/10.1111/j.1467-9280.2006.01677.x

[22] Zhenhui (Jack) Jiang and Izak Benbasat. 2007. The Effects of Presentation Formats and Task Complexity on Online Consumers' Product Understanding. *MIS Quarterly* 31, 3 (2007), 475–500.

[23] Yucheng Jin, Nava Tintarev, Nyi Nyi Htun, and Katrien Verbert. 2020. Effects of Personal Characteristics in Control-Oriented User Interfaces for Music Recommender Systems. *User Modeling and User-Adapted Interaction* 30, 2 (April 2020), 199–249. https://doi.org/10.1007/s11257-019-09247-2

[24] Quentin Jones, Gilad Ravid, and Sheizaf Rafaeli. 2004. Information Overload and the Message Dynamics of Online Interaction Spaces: A Theoretical Model and Empirical Exploration. *Information Systems Research* 15, 2 (2004), 194–210. https://doi.org/10.1287/isre.1040.0023

[25] Michael Jugovac and Dietmar Jannach. 2017. Interacting with Recommenders – Overview and Research Directions. *ACM Transactions on Interactive Intelligent Systems* 7, 3 (2017), 10:1–10:46.

[26] Arnold A. Kamis and Edward A. Stohr. 2006. Parametric Search Engines: What Makes Them Effective When Shopping Online for Differentiated Products? *Information & Management* 43, 7 (2006), 904–918. https://doi.org/10.1016/j.im.2006.08.006

[27] Sahar Karimi, K. Nadia Papamichail, and Christopher P. Holland. 2015. The Effect of Prior Knowledge and Decision-Making Style on the Online Purchase Decision-Making Process: A Typology of Consumer Shopping Behaviour. *Decision Support Systems* 77 (2015), 137–147. https://doi.org/10.1016/j.dss.2015.06.004

[28] Alireza Kazeminia, Marjan Kaedi, and Beenazir Ganji. 2019. Personality-Based Personalization of Online Store Features Using Genetic Programming: Analysis and Experiment. *Journal of Theoretical and Applied Electronic Commerce Research* 14 (01 2019). https://doi.org/10.4067/S0718-18762019000100103

[29] Timm Kleemann and Jürgen Ziegler. 2019. Integration of Dialog-Based Product Advisors into Filter Systems. In *Proceedings of Mensch Und Computer 2019* (Hamburg, Germany) *(MuC'19)*. Association for Computing Machinery, New York, NY, USA, 67–77. https://doi.org/10.1145/3340764.3340786

[30] Bart P. Knijnenburg, Niels J.M. Reijmer, and Martijn C. Willemsen. 2011. Each to His Own: How Different Users Call for Different Interaction Methods in Recommender Systems. In *Proceedings of the Fifth ACM Conference on Recommender Systems* (Chicago, Illinois, USA) *(RecSys '11)*. Association for Computing Machinery, New York, NY, USA, 141–148. https://doi.org/10.1145/2043932.2043960

[31] Bart P. Knijnenburg, Martijn C. Willemsen, Zeno Gantner, Hakan Soncu, and Chris Newell. 2012. Explaining the User Experience of Recommender Systems. *User Modeling and User-Adapted Interaction* 22, 4 (Oct. 2012), 441–504. https://doi.org/10.1007/s11257-011-9118-4

[32] Jonathan Koren, Yi Zhang, and Xue Liu. 2008. Personalized Interactive Faceted Search. In *Proceedings of the 17th International Conference on World Wide Web* (Beijing, China) *(WWW '08)*. Association for Computing Machinery, New York, NY, USA, 477–486. https://doi.org/10.1145/1367497.1367562

[33] Vinodh Krishnaraju, Saji K. Mathew, and Vijayan Sugumaran. 2016. Web Personalization for User Acceptance of Technology: An Empirical Investigation of E-Government Services. *Information Systems Frontiers* 18, 3 (June 2016), 579–595. https://doi.org/10.1007/s10796-015-9550-9

[34] Johannes Kunkel, Benedikt Loepp, and Jürgen Ziegler. 2017. A 3D Item Space Visualization for Presenting and Manipulating User Preferences in Collaborative Filtering. In *IUI '17: Proceedings of the 22nd International Conference on Intelligent User Interfaces*. ACM, New York, NY, USA, 3–15.

[35] Chia-Ying Li. 2017. Why do Online Consumers Experience Information Overload? An Extension of Communication Theory. *Journal of Information Science* 43, 6 (2017), 835–851. https://doi.org/10.1177/0165551516670096

[36] Xiaolin Lin, Mauricio Featherman, Stoney L. Brooks, and Nick Hajli. 2019. Exploring Gender Differences in Online Consumer Purchase Decision Making: An Online Product Presentation Perspective. *Information Systems Frontiers* 21, 5 (2019), 1187–1201. https://doi.org/10.1007/s10796-018-9831-1

[37] Yong Liu, Hongxiu Li, and Feng Hu. 2013. Website Attributes in Urging Online Impulse Purchase: An Empirical Investigation on Consumer Perceptions. *Decision Support Systems* 55, 3 (2013), 829–837. https://doi.org/10.1016/j.dss.2013.04.001

[38] Benedikt Loepp, Tim Donkers, Timm Kleemann, and Jürgen Ziegler. 2018. Impact of Item Consumption on Assessment of Recommendations in User Studies. In *RecSys '18: Proceedings of the 12th ACM Conference on Recommender Systems*. ACM, New York, NY, USA, 49–53.

[39] Benedikt Loepp, Tim Donkers, Timm Kleemann, and Jürgen Ziegler. 2019. Interactive Recommending with Tag-Enhanced Matrix Factorization (TagMF). *International Journal of Human-Computer Studies* 121 (2019), 21–41.

[40] Jing Luan, Zhong Yao, FuTao Zhao, and Hao Liu. 2016. Search Product and Experience Product Online Reviews: An Eye-Tracking Study on Consumers' Review Search Behavior. *Computers in Human Behavior* 65 (2016), 420–430. https://doi.org/10.1016/j.chb.2016.08.037

[41] Naresh K. Malhotra. 1983. On 'Individual Differences in Search Behavior for a Nondurable'. *Journal of Consumer Research* 10, 1 (1983), 125–131.

[42] Gary Marchionini. 2006. Exploratory Search: From Finding to Understanding. *Commun. ACM* 49, 4 (April 2006), 41–46. https://doi.org/10.1145/1121949.1121979

[43] Robert McCrae and Paul Costa. 1987. Validation of the Five Factor Model of Personality Across Instruments and Observers. *Journal of Personality and Social Psychology* 52 (02 1987), 81–90. https://doi.org/10.1037/0022-3514.52.1.81

[44] Robert R. McCrae and Oliver P. John. 1992. An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality* 60, 2 (1992), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

[45] Gergana Y Nenkov, Maureen Morrin, Barry Schwartz, Andrew Ward, and John Hulland. 2008. A Short Form of the Maximization Scale: Factor Structure, Reliability and Validity Studies. *Judgment and Decision making* 3, 5 (2008), 371–388.

[46] Tien T. Nguyen, F. Maxwell Harper, Loren Terveen, and Joseph A. Konstan. 2018. User Personality and User Satisfaction with Recommender Systems. *Information Systems Frontiers* 20, 6 (Dec. 2018), 1173–1189. https://doi.org/10.1007/s10796-017-9782-y

[47] Thomas P. Novak and Donna L. Hoffman. 2009. The Fit of Thinking Style and Situation: New Measures of Situation-Specific Experiential and Rational Cognition. *Journal of Consumer Research* 36, 1 (2009), 56–72. https://doi.org/10.1086/596026

[48] Thomas P. Novak, Donna L. Hoffman, and Adam Duhachek. 2003. The Influence of Goal-Directed and Experiential Activities on Online Flow Experiences. *Journal of Consumer Psychology* 13, 1 (2003), 3–16. https://doi.org/10.1207/153276603768344744

[49] Jihye Park, Sharron J. Lennon, and Leslie Stoel. 2005. On-line Product Presentation: Effects on Mood, Perceived Risk, and Purchase Intention. *Psychology & Marketing* 22, 9 (2005), 695–719. https://doi.org/10.1002/mar.20080

[50] Rex Eugene Perera. 2000. Optimizing Human-Computer Interaction for the Electronic Commerce Environment. *J. Electron. Commerce Res.* 1, 1 (2000), 23–44.

[51] Evan Polman. 2010. Why are Maximizers Less Happy Than Satisficers? Because They Maximize Positive and Negative Outcomes. *Journal of Behavioral Decision Making* 23, 2 (2010), 179–190. https://doi.org/10.1002/bdm.647

[52] Girish Punj. 2012. Consumer Decision Making on the Web: A Theoretical Analysis and Research Guidelines. *Psychology & Marketing* 29, 10 (2012), 791–803. https://doi.org/10.1002/mar.20564

[53] Dimitrios Rafailidis and Alexandros Nanopoulos. 2016. Modeling Users Preference Dynamics and Side Information in Recommender Systems. *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 46, 6 (2016), 782–792. https://doi.org/10.1109/TSMC.2015.2460691

[54] Beatrice Rammstedt and Oliver P John. 2007. Measuring Personality in One Minute or Less: A 10-item short version of the Big Five Inventory in English and German. *Journal of research in Personality* 41, 1 (2007), 203–212.

[55] Francesco Ricci, Lior Rokach, and Bracha Shapira (Eds.). 2015. *Recommender Systems Handbook*. Springer US, Berlin, Germany.

[56] Courtney Anne Schmidt and Richard David Evans. 28.06.2018. Evaluating Socioeconomic Influences on Pinterest Consumer Behavior. In *2018 IEEE Technology and Engineering Management Conference (TEMSCON)*. IEEE, 1–6. https://doi.org/10.1109/TEMSCON.2018.8488427

[57] Sylvain Senecal and Jacques Nantel. 2004. The Influence of Online Product Recommendations on Consumers' Online Choices. *Journal of Retailing* 80, 2 (2004), 159–169. https://doi.org/10.1016/j.jretai.2004.04.001

[58] Rashmi Sinha and Kirsten Swearingen. 2002. The Role of Transparency in Recommender Systems. In *CHI '02 Extended Abstracts on Human Factors in Computing Systems* (Minneapolis, Minnesota, USA) *(CHI EA '02)*. Association for Computing Machinery, New York, NY, USA, 830–831. https://doi.org/10.1145/506443.506619

[59] Dereck Toker, Cristina Conati, Giuseppe Carenini, and Mona Haraty. 2012. Towards Adaptive Information Visualization: On the Influence of User Characteristics. In *User Modeling, Adaptation, and Personalization*, Judith Masthoff, Bamshad Mobasher, Michel C. Desmarais, and Roger Nkambou (Eds.). Springer Berlin Heidelberg, Berlin, Heidelberg, 274–285.

[60] Daniel Tunkelang. 2006. Dynamic Category Sets: An Approach for Faceted Search. In *ACM SIGIR*, Vol. 6. Citeseer.

[61] Ceyda Aysuna Turkyilmaz, Sakir Erdem, and Aypar Uslu. 2015. The Effects of Personality Traits and Website Quality on Online Impulse Buying. *Procedia - Social and Behavioral Sciences* 175 (2015), 98–105. https://doi.org/10.1016/j.sbspro.2015.01.1179 Proceedings of the 3rd International Conference on Strategic Innovative Marketing (IC-SIM 2014).

[62] Preeti Virdi, Arti D. Kalro, and Dinesh Sharma. 2020. Online Decision Aids: The Role of Decision-Making Styles and Decision-Making Stages. *International Journal of Retail & Distribution Management* 48, 6 (Jan. 2020), 555–574. https://doi.org/10.1108/IJRDM-02-2019-0068 Publisher: Emerald Publishing Limited.

[63] John Wells, Veena Parboteeah, and Joseph Valacich. 2011. Online Impulse Buying: Understanding the Interplay between Consumer Impulsiveness and Website Quality. *Journal of the Association for Information Systems* 12, 1 (2011), 32–56. https://doi.org/10.17705/1jais.00254

[64] Ryen W. White and Resa A. Roth. 2009. Exploratory Search: Beyond the Query-Response Paradigm. *Synthesis Lectures on Information Concepts, Retrieval, and Services* 1, 1 (2009), 1–98. https://doi.org/10.2200/S00174ED1V01Y200901ICR003

[65] Xiangmin Zhang and Mark Chignell. 2001. Assessment of the Effects of User Characteristics on Mental Models of Information Retrieval Systems. *Journal of the American Society for Information Science and Technology* 52, 6 (2001), 445–459. https://doi.org/10.1002/1532-2890(2001)9999:9999<::AID-ASI1092>3.0.CO;2-3