Consumer Preferences for Product Information and Price Comparison Apps

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Abstract. Product information and price comparison apps on smartphones play an increasing role in consumers' purchase decision process. Consumers are able to choose from a variety of product information search applications (apps) which mainly differ with respect to the information that is provided to consumers during their search process. The goal of this study is to analyze preferences regarding different information types that such apps provide. We conduct an adaptive choice-based conjoint analysis combined with a between subject experiment for a sample of 330 consumers. We identify differences between high- and low-involvement products. Individual differences are explained using psychometric latent constructs. Our results reveal heterogeneous preferences which also depend on the product category. Consumer attitudes like quality vs. price consciousness and green consumer values influence the valuation of certain information types.

Keywords: Consumer preferences, adaptive choice-based conjoint analysis, mobile commerce, smartphone applications

1   Introduction

The diffusion of smartphones increasingly improves consumers' means to search and access information online using the mobile internet. For instance, in the domain of product information and price comparison consumers are able to choose among many different smartphone applications (apps) for product information search. Such apps are widely used [1, 2]. We consider product information search apps as smartphone applications that provide information on physical products using the mobile internet. Most of these apps provide barcode scanning, location-based services and different types of product information. Today's product information search apps provide a magnitude of different features that go well beyond basic price comparison [2].

There is some research on app success in general. For instance, Lee and Raghu [3] conduct a survival analysis on 300 apps in Apple's App Store and Yang investigates the acceptance of mobile applications among young Americans [4]. However, to the best of our knowledge, there is no literature on consumer preferences regarding app features that is category specific. In particular, so far there is little known about product information search apps and consumers. The goal of this study is to analyze consumer

preferences regarding different features of product information search apps with a clear focus on different types of product information that an app might provide. We conduct an adaptive choice-based conjoint analysis combined with a between subject experiment for an online sample of 330 consumers. Here we identify differences between the searches for high- versus low-involvement products. Because consumers' preferences are estimated on an individual level, differences can be explained using psychometric latent constructs in a regression analysis.

Towards this goal we work with three research questions that are related to research gaps that we identify: (1) Which types of product information do consumers prefer in their search process using smartphone apps? (2) How does the distribution of the relative attribute importance differ between information searches for high- versus low-involvement products? and (3) Can information search behavior be explained by a certain set of psychometric constructs? The results are relevant for marketers and smartphone app developers alike. Developers will be able to include consumer preferences in their requirements when designing new apps. Marketers might benefit from our insights in their targeting activities. For instance, retailers could use our findings to provide app suppliers with specific product information for inclusion in their app.

We aim to contribute to the literature in different ways. First, we measure consumers' preferences regarding product information search apps and identify "must-have" and "nice-to-have" features. Here, we focus on features that are related to different types of product information. Second, we provide evidence that these preferences and thus app usage behavior depends on the product category. Third, we explain consumer specific differences based on various consumer attitudes.

The remainder of this paper is organized in the following way: We first review related literature to identify research gaps. Then, we outline our data and method. Next, we present the results of our empirical study with the two subsections adaptive choice-based conjoint analysis and regression analysis. Finally, we discuss implications for practitioners as well as for researchers.

2   Related Literature

In consumer search the identification of sellers and the determination of prices are important, as Stigler [5] points out in his seminal paper. However, the search for information (which is required e.g., for price comparisons) is costly and therefore market inefficiencies may be partly explained by search or transaction costs [5]. The internet facilitates information search and it is widely acknowledged that the internet has a major impact on consumer search behavior [6]. Search on the internet even substitutes search in other channels [7]. The diffusion of smartphones adds a new dimension with the mobile internet. While early stage mobile internet search was mainly browser-based [8], today search is usually driven by apps. Mobile devices (smartphones and tablet computers) are used as both research and purchase devices [9]. Since they are portable and provide location-independent access to the internet they reduce consumers' overall search costs [10].

Smartphones support product information search [1]. While there is some research on optimal product information search [e.g., 14, 15] the term product information is manifold and depends on the context. There are various attributes of products that may be relevant in the decision-making process of consumers. An obvious attribute is price. However, Dickson and Sawyer [11] find that not all consumers engage in price comparisons. Nevertheless, price is an important component of offerings. Product quality, which is reflected by different product characteristics, is also a very important attribute [12]. Furthermore, there are consumers that look also on other aspects, for instance information on environment-friendly production processes [13]. Companies' approach to corporate social responsibility is considered by certain consumers [16]. Furthermore, information on sustainability is relevant for some consumers. Winkler von Mohrenfels and Klapper [17] find that relevant mobile product information may increase brand perception and at least for some product categories (e.g., organic foods) it may increase consumers' willingness-to-pay. Finally, consumers might look for reports of other consumers on their user experience. Such information is easily conveyed via the internet in form of consumer reviews or electronic word-of-mouth [18].

As consumers are subjected to a vast quantity of information their judgment eventually could be blurred. This phenomenon is called information overload. It assumes that consumers exhibit "finite limits to the amount of information they can assimilate and process" [19] and that if these limits are exceeded consumers become confused and make poorer decisions. While it is known what technology (i.e. product information search apps) is able to provide and which different types of product information may be relevant in consumer decision making, it remains open which features of such apps (i.e. which product information) are preferred by their users. This leads us to our first research question: (1) Which types of product information do consumers prefer in their search process using smartphone apps?

Based on previous research the importance of different types of product information seems to vary depending on the situation. There is empirical evidence that information choice behavior of consumers differs by product category [1]. This is consistent with earlier reports that in general consumer behavior varies by product category [20]. During information search, price information is more intensely requested by consumers looking for durables compared to consumables [1]. User reviews are more relevant for consumables. User reviews are also more retrieved in product search concerning utilitarian goods, while the price seems to be more important for hedonic goods. Looking at search goods, information on product characteristics is slightly more demanded as opposed to experience or credence goods [1]. In general, product information needs are correlated with the involvement of consumers [21]. Hence, our second research question is: (2) How does the distribution of the relative attribute importance differ between information searches for high- versus low-involvement products?

Previous literature suggests that consumer preferences are heterogeneous. Based on existing literature a set of consumer attitudes can be identified that potentially plays a role in product information search. The attitude of quality consciousness [22] is an indicator of how thoroughly consumers inform themselves about a product before a

purchase. Depending on green consumer values consumers might differently assess information on the sustainability of products or their production processes [23]. Furthermore, price consciousness is an indicator of the effort that consumers take to strike a good deal [24]. With our third research question (3) Can information search behavior be explained by a certain set of psychometric constructs? We will analyze various influencing factors on consumer preferences in this context.

In this study we analyze consumer preferences regarding different features of product information search apps with a clear focus on different types of product information. While there is research on app features like mobile technologies, media integration and social network capabilities (e.g., [2]), or research on category independent app characteristics like price of the app or number of apps by the same developer [3], to the best of our knowledge so far there is no previous research that focuses on features that are related to different types of product information in product information search apps.

3   Data and Method

3.1   Study Design

To answer our three research questions we design a modular study consisting of an online discrete choice experiment with a between subjects design. Regarding the first two research questions we apply a form of conjoint analysis. In this conjoint analysis, we represent a situation in which participants are asked to make choices about product information search apps. We conduct an adaptive choice-based conjoint (ACBC) analysis to estimate consumer preferences.

We gather data through an online survey. For the purpose of a comparative analysis to answer the second research question, we design an online questionnaire with two versions. The two versions differ in regards to the focal product – a high-involvement (HI) product (a laptop computer) and a low-involvement (LI) product (an energy drink). Participants are randomly assigned to one of the questionnaire versions. 330 completed questionnaires could be used for the analysis (156 in the HI- and 174 in the LI-group). The sample consists mainly of students and all the relevant socio-demographic characteristics are approximately equally distributed to ensure for a proper comparison between the two experimental groups (high- and low-involvement product).

In addition to the ACBC analysis, we gather socio-demographic and psychographic data by measuring various latent constructs. These constructs are used to explain the results of the ACBC analysis which relate to the third research question. Here, we apply multiple linear regressions with four relative attribute importance values as dependent variables. The relative attribute importance is estimated through the ACBC using Hierarchical Bayes (HB) on an individual level. As independent variables we employ the constructs mentioned above as they cover individual characteristics regarding consumers' search and purchasing processes. All constructs are measured using a 7-point Likert-type scale. Except for opinion seeking, which contains a reverse-coded item, all constructs are coded in a way that higher scores represent higher levels of the construct.

Consumers' importance of quality and their subsequent effort of gathering information about products before making final purchase decisions are measured by the Quality Consciousness scale [22]. The scale Opinion Leaders and Opinion Seekers [25] is limited to the opinion seeking items in our study because we are only interested in whether consumers are potentially influenced by the attitude of others. In order to measure the degree to which the characteristic trait of considering the environmental impact of one's purchase and consumption behavior influences one's information search, the Green Consumer Values scale [23] is included in the survey. The psychometric measurement of consumers' search effort is based on the search costs scale of Srinivasan and Ratchford [26]. We also include the construct Price Consciousness [24] that evaluates the consumers' willingness to spend an extra effort in order to find low prices for a specified product category.

3.2 Adaptive Choice-Based Conjoint Analysis

Choice of Method and Design. Conjoint analysis (CA) can be characterized as a method for determining consumer preferences for products or services which consist of various distinct attributes [27]. In this paper we apply the adaptive choice-based conjoint (ACBC) analysis which achieves to combine the benefits of adaptive and choice-based conjoint procedures [28]. While classical CA or adaptive conjoint analysis (ACA) ask the respondent to either rank the product concepts or rate them on a scale, choice-based conjoint (CBC) analysis realistically imitates the decision process [29]. ACBC analysis makes use of the benefits of ACA as respondents are able to indicate whether a certain attribute level is completely unacceptable and therefore should be excluded from later questions. In addition, it is possible to indicate "must-have" or "unacceptable" attribute levels which leads to a definite in- or exclusion in the rest of the questionnaire.

To identify suitable products for the two settings (high- and low-involvement product), we transfer generic characteristics of high- and low-involvement purchase decisions – i.e. careful versus superficial information processing, systematic information search versus rather casual information reception, high correlation with personality and lifestyle versus a low correlation, decision for the subjective best product versus decision for an acceptable product and a high influence of reference groups versus a low influence – to particular product categories. Especially computer laptops for the high- and energy drinks for the low-involvement category fulfill the above-mentioned requirements. In course of a pretest we reviewed the selected product categories by applying the Involvement with the Product Category scale by Coulter et al. [30]. The obtained test results suggest a proper choice of product categories. On average energy drinks were rated 2.17 on the involvement scale whereas laptops scored an average rating of 4.5.

Adaptive choice-based conjoint analysis consists of three sections: The build your own (BYO) configuration section, the screening section and the tournament section. In the first section respondents are asked to design their ideal product concept by selecting their preferred attribute levels. As the following concepts will consist of attribute levels

that are relatively concentrated around the respondent's preferred levels, the BYO section is used to reduce the error levels during the rest of the survey.

In the second section of the interview, the screening section, the respondent runs through seven screening tasks, each consisting of four product concepts. Accordingly, each attribute level is depicted at least five times. In the screening section the respondents should indicate the product concepts they would potentially use. The section is intended to realize non-compensatory rules. Therefore, it contains so-called "unacceptable" and "must-have" questions. While the respondents answer the questions in the screening task the software identifies attribute levels, which are systematically being avoided or favored. Correspondingly, after the third screening task the respondent is asked whether one of these recognized attribute levels is completely "unacceptable" or a "must-have". According to the respondents' choices all further product concepts shown will satisfy these specifications.

The tournament section is the last and most important part of the survey. Here, the respondent is asked to make a final decision on a set of product concepts that strictly conform to any cut-off ("unacceptable" / "must-have") rules and that are close to their specified product in the BYO section. Correspondingly, participants can now focus on requirements of secondary importance [28].

All the choice tasks are designed with the software package Sawtooth Software SSI Web, except for the two hold-out tasks that were created manually. These tasks serve as a quality indicator [31] and are constant over all questionnaire versions. According to Johnson and Orme [31] these tasks were created using level overlap. They contain the same concepts in a different order. In contrary to the other choice tasks, hold-out tasks are not utilized for the estimation of the relative importance of the attributes [31].

Choice of Attributes and Levels. In this study, we ask participants to evaluate alternative hypothetical product information search apps based on their attributes. These attributes are the different information features provided by the apps. In order to identify the relevant attributes, a two-stage research process was selected. First, we conduct a market analysis on product information search apps to receive a list of information features that are actually being used in different apps. Second, we execute a literature review to validate the importance and influence of these information features from a theoretical perspective. In course of the market analysis we study six product information search apps, namely Barcoo, Check24, Codecheck, Guenstiger.de, Idealo and Redlaser. The consolidation of the results of the initial market analysis and the literature review yields a total of six attributes, which were chosen for the study at hand. All attributes and their levels are shown in table 1.

The first attribute – price – refers to the fact whether the app provides information on the price of the searched product or not. This attribute relates to the fundamental search literature (e.g., [5]). The second attribute is user reviews and the third is neutral product tests. Both exhibit the same levels as price. Riegner [32] highlights the influence of consumer reviews on purchase decisions in a statistically more descriptive manner, for instance stating that the power of reviews is particularly efficient for pricey electronic products like computers. The fourth attribute is product characteristics. It entails detailed information on product characteristics (e.g., quality information or ingredients

for food). This attribute is divided into three levels. First, product characteristics could be "not available". Second, it could be available in a raw form or third, it could be available in a condensed or illustrative form. In the latter case the information is presented in a way that helps the consumer to evaluate the information at hand. A typical example for condensed product characteristics is a signal similar to a traffic light. For instance, based on the amount of sugar in a comestible the signal shows red (high amount), amber (average amount) or green (low amount). Since such signals provide an orientation to consumers we assume that they are of higher value in the consumers' decision process compared to raw product characteristics, especially in times of information overload. The fifth attribute is purchase possibility. We differentiate the following three levels: (1) "no information" on the purchase possibility, (2) "only the name of the retailer" or (3) "exact distance to the retailer" (including the name of that store). It could be shown that consumers might change purchase intentions when they receive information on better offers in the vicinity [33]. The last attribute is information on sustainability. Haws et al. [23] for example conceptualize and demonstrate the influence of an environmentally friendly mind-set on consumer preferences.

4   Empirical Results

4.1   Reliability and Validity

Before presenting and discussing the results of the study, an analysis of the goodness of the available data is required. We assess the reliability of the latent constructs by calculating Cronbach's Alpha separately for the high-involvement (HI) group and for the low-involvement (LI) group: Quality Consciousness ($\alpha_{LI} = 0.77$; $\alpha_{HI} = 0.79$), Opinion Seeking ($\alpha_{LI} = 0.95$; $\alpha_{HI} = 0.97$), Price Consciousness ($\alpha_{LI} = 0.86$; $\alpha_{HI} = 0.67$), Green Consumer Values ($\alpha_{LI} = 0.94$; $\alpha_{HI} = 0.92$) and Cost of Search ($\alpha_{LI} = 0.83$; $\alpha_{HI} = 0.88$). The analysis of Cronbach's Alpha reveals that all latent constructs exhibit a high reliability [34].

Next the reliability, predictive validity and internal validity of the ACBC analysis have to be evaluated. Participant's choices are potentially influenced by several factors, e.g. negligence and lack of interest. To control for potential biases, two identical hold-out tasks were integrated in the survey. The result of the test-retest statistic shows that 88.4 % of all participants in the HI questionnaire and 82.2 % respectively in LI questionnaire chose the same products in both hold-out tasks. Compared to other studies this test-retest validity is high [35].

To assess the predictive validity of the CBC analysis, we also make use of the hold-out tasks. The predictive validity refers to the ability to predict participants' choices by using the estimated utility parameters [36]. The corresponding validity measure is the hit-rate. The observed choices were compared to the estimated choices. Here, the hit rate is 76.4 % for the LI and 82.7 % for the HI study. Compared to a random hit rate of 33 % (there are three possible choices) such a hit-rate is considered to be high [37].

The hit-rate which depicts the number of correctly estimated choices can also be used to test the internal validity. Here, we predict subjects' responses to the choice tasks used for estimation. The subsequent hit-rates of 83.4 % for the LI and 85.5 % for the HI study show that a large degree of participants' choices is predicted correctly. The internal validity can thus be considered as high [38]. For the purpose of calculating the predictive and internal validity the none-choice option was not included because in the tournament section of the ACBC the none-alternative was not selectable.

4.2   Estimation and Results

In table 1 we depict the estimated part-worth utilities for the attribute levels in the different groups. Those parameters are normalized (zero-centered) HB estimates. These results indicate face validity. Attribute levels with a higher information content provide higher part-worth utilities. One exception is the attribute purchase possibility in case of HI products. A possible explanation for this finding is consumers' tendency to avoid information overload. As the point of time of searching for information on HI products and the point of time of buying those products might not be identical. Due to the fact that normalized part-worth utilities sum up to zero for each and every attribute, negative part-worth utilities simply denote less desired levels. All signs and therefore the direction of the impact of these utility parameter estimates on the overall utility are plausible.

In contrast to the part-worth utilities of the single attribute levels, a direct interpretation of the superordinate attributes cannot be accomplished [39]. Therefore the measurement of the relative attribute importance is used. The relative attribute importance measures the relevancy of one attribute utility compared to the sum of all attribute utility ranges. To calculate the relative attribute importance, the part-worth utility ranges of each attribute are used. Their part-worth utility ranges are the difference between the highest and the lowest part-worth utility parameter of each attribute. The relative attribute importance of the attribute price is calculated by the utility range of the price divided by the sum of all attribute utility ranges. The same applies to the relative importance of all other attributes. The relative importance for each attribute is depicted in figure 1.

In order to test whether the information search behavior differs significantly for LI and HI products we first compare the variances of each attribute importance. Then we apply a two sample t-test with either equal or unequal variances. While there is no significant deviation of the mean values of the relative attribute importance for the information type price and information on sustainability, all other mean relative attribute importance values differ significantly. Non-parametric Wilcoxon-Mann-Whitney-tests provide congruent results. Thus, these results indeed indicate search behavior to be significantly different for the two product categories.

In both studies price information (34.5 % LI; 33.2 % HI) is of the highest importance for respondents. Likewise product characteristics (24.7 % LI; 27.1 % HI) can be identified to be the second most important feature. The rest of the priority order of the attributes differs in the two groups. In context of information search for LI products participants indicate purchase possibility to be third in the ranking of priority with

15.2 %. This attribute only receives the fifth place in the HI group. This difference might originate from the larger share of the travel costs in the overall price of the product to be purchased.[1] Hence, information on the exact location of a retailer becomes more important the less expensive a product is (ratio of travel costs and price is higher). This interpretation is supported by Kahneman and Tversky's prospect theory. In their behavioral theory they show that consumers perceive decision outcomes as gains and losses, which are defined relative to a certain reference point [40]. As the amount of travel costs increases the overall price (product price plus travel costs) increases, too. In prospect theory travel costs represent losses. In this context a fixed amount of loss x is relatively high for cheaper products.

Table 1. Part-worth utilities (=PWU; HI = High-involvement; LI = Low-involvement product)

Attribute	Levels	PWU HI	PWU LI
Price	Available	99.50	102.90
	Not available	-99.50	-102.90
User reviews	Available	36.06	26.93
	Not available	-36.06	-26.93
Neutral product tests	Available	39.53	28.07
	Not available	-39.53	-28.07
Product characteristics	Condensed information	50.88	49.38
	Raw information	43.22	34.11
	No information	-94.10	-83.50
Purchase possibility	Exact distance to the retailer	9.41	29.14
	Only the name of the retailer	15.43	14.13
	No information	-24.84	-43.27
Information on sustainability	Available	17.61	16.79
	Not available	-17.61	-16.79

A relatively high priority in context of information search is obtained by the attributes user reviews (HI: 12.2 %; LI 9.5 %) and neutral product tests (HI: 13.2 %; LI: 9.5 %). It is quite interesting that the values for the relative importance for these two attributes are that close to each other. This could imply that customers regard user reviews as substitutes for neutral product test reports and vice versa.

In both studies the field of the relative attribute importance is tailed by information on sustainability. Although 59.2 % in the LI study and 69.2 % in the HI study choose to integrate that information feature in the BYO section, the attribute comes up with a relative importance of only 6.2 % in the HI and 6.7 % in the LI group respectively. Correspondingly, consumers value other attributes higher when it comes to a trade-off situation. This finding is confirmed by the results of the screening section. Only 3.6 % of the respondents of the LI and 3.1 % of the respondents of the HI group classify the fact of missing information on sustainability as being unacceptable. Accordingly, for merely 1.6 % (LI group) and 0.7 % (HI group) information on sustainability must be available. Here, it becomes obvious that information on sustainability is rather a "nice-

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[1] Please note that here overall price reflects product price plus transaction costs.

to-have" feature. We also identify hygiene factors, e.g., price and product characteristics. Over 96 % of the respondents in both groups choose these two features to be a part of their ideal product information search app. Additionally, the screening section reveals the absence of one of these features to be unacceptable for the majority of the participants.
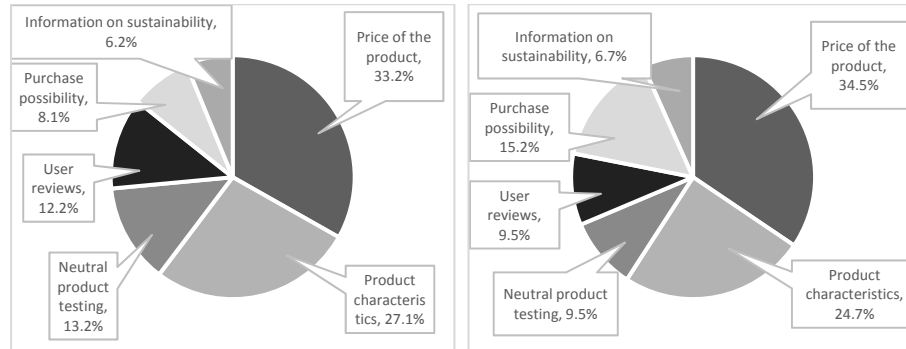

Figure 1. Relative attribute importance (left: HI product; right: LI product)

Subsequently, we analyze the four most important relative attribute importance of the ACBC analysis as a function of the psychometric constructs that we have measured. The relative attribute importance (RAI) provides insights on consumers' attitude towards the different information features while the psychometric constructs measure individual traits concerning consumers' search and purchasing processes. We use multiple linear regressions to explain the relative attribute importance by several psychometric constructs. We estimate the following linear model:

$$
\begin{aligned}
RAI_{ij} = \ &\beta_{0j} + \beta_{1j} \times quality\ consciousness_i + \beta_{2j} \times \\
&opinion\ seeking_i + \beta_{3j} \times price\ consciousness_i + \beta_{4j} \times \\
&green\ consumer\ values_i + \beta_{5j} \times cost\ of\ search + \beta_{6j} \times \\
&product\ type + \beta_{7j} \times smartphone\ owner_i + \beta_{8j} \times \\
&experience\ with\ product\ information\ search\ app_i + \varepsilon_{ij}
\end{aligned}
\tag{1}
$$

where the dependent variable represents the relative attribute importance of the attributes price, product characteristics, user reviews and neutral product tests. The betas are the estimators of the independent variables of participant *i*. Index *j* reflects the attribute (price, product characteristics, etc.).

First, we test for violations of the assumptions of the linear regression model. To test if our model has a proper functional form, we use the Ramsey test. The results indicate that our models are specified properly. The Breusch-Pagan/Cook-Weisberg test indicates that heteroskedasticity is a problem, however. We therefore use models with robust standard errors [41]. A test for the normality of residuals indicates that the residuals of our models are normally distributed. It is assumed that the residuals are

identically and independently distributed. Finally, multicollinearity is not a problem since the maximum variance inflation factor (VIF) is 2.01.

Table 2. Linear regression results

Independent Variable	RAI price	RAI product characteristics	RAI user reviews	RAI neutral product tests
Quality Consciousness	-0.015**	0.016***	0.0001	0.005
	(0.006)	(0.005)	(0.004)	(0.003)
Opinion Seeking	-0.003	-0.003	0.003	0.002
	(0.005)	(0.004)	(0.003)	(0.002)
Price Consciousness	0.018***	-0.006	-0.002	-0.003
	(0.005)	(0.004)	(0.002)	(0.002)
Green Consumer Values	-0.013**	0.010**	-0.009***	-0.003
	(0.005)	(0.004)	(0.003)	(0.002)
Cost of Search	0.004	-0.004	0.003	-0.003
	(0.004)	(0.003)	(0.002)	(0.002)
Product Type	-0.021	0.028	0.023**	0.031***
[0 = LI; 1 = HI]	(0.018)	(0.016)	(0.010)	(0.008)
Smartphone Owner	-0.027	-0.002	0.016	0.024***
[0 = no; 1 = yes]	(0.019)	(0.016)	(0.011)	(0.009)
Experience	-0.0004	-0.008	0.002	-0.007
[0 = no; 1 = yes]	(0.014)	(0.012)	(0.008)	(0.006)
Intercept	0.440***	0.166***	0.106***	0.066***
	(0.042)	(0.038)	(0.024)	(0.021)
R²	0.098	0.081	0.095	0.142
F-test	4.48***	3.89***	4.82***	8.19***
Observations	330	330	330	330

Robust standard errors in parentheses; *** p<0.01, **p<0.05, * p<0.1

The F-tests depict the overall significance of the particular regression models. All models are highly significant (see table 2). The dummy product type shows that the category of the inspected product (HI vs. LI) plays a significant role for user reviews (+0.023, p<0.05) and neutral product tests (+0.031, p<0.01). The special importance of user reviews and neutral product tests in case of HI products can be explained by two facts. First, consumers are interested in reducing their perceived risk by gathering as much information as possible and second, they strive for aligning their purchase decisions with the interest of their reference groups. Both information features user reviews and neutral product tests, help to satisfy this need. When looking at price as an information feature of product information search apps quality consciousness (-0.015, p<0.05), price consciousness (+0.018, p<0.01) and green consumer values (-0.013, p<0.05) are significant. Whereas price consciousness has a positive impact on the relative importance of the attribute price, the constructs quality consciousness and green consumer values exhibit a negative influence. This means that people who are willing

to spend an additional effort in order to find low prices for a certain product are more inclined to use the price information during their search process. This seems to be plausible as the primary concern and objective of price conscious consumers is to detect and realize relatively low prices in the process of their buying decisions. Contrary to that, opposite signs of quality consciousness (+0.016, $p<0.01$) and green consumer values (+0.01, $p<0.05$) can be observed in the model for the product characteristics. People that consider the environmental impact of their purchase and consumption behavior are less motivated to use the information feature price. Price is not their primary decision criterion. In fact, highly environmentally conscious people even seem to omit the information feature price to not be distracted from their main intention: to make purchase decisions with integrity. This finding also proposes that the price of a product does not primarily effect their purchase decision. Consequently, they exhibit a higher willingness-to-pay if the product satisfies their needs for sustainability. The same relation is observed for quality-conscious consumers. Furthermore, ecologically-thinking consumers refrain from implying user reviews in their search process (-0.009, $p<0.05$). Ecologically thinking consumers might be less influenced by the opinions of others. Whereas, prior experience with product information search apps is not significant in all models, smartphone ownership has a significant positive influence on neutral product tests (+0.024, $p<0.01$). Despite the wide diffusion of smartphones, the smartphone owner group might still include the more solvent consumers. Neutral product test reports are typically not available for free in contrast to user reviews in form of user-generated content.

5   Conclusion

In this paper we analyze consumers' preferences regarding features of product information search apps with a clear focus on different types of information using an adaptive choice-based conjoint analysis. Price information and product characteristics are the most important features across both product categories. The preferences for other features depend on the product category of the focal product. When searching information on high-involvement products neutral-product test information is important. For low-involvement products consumers value information on purchase possibilities more.

As we estimate consumers' preferences on an individual level, we are able to explain differences using psychometric constructs in a linear regression. Consumer attitudes like quality consciousness, price consciousness and green consumer values influence the valuation of app features. For instance, for quality conscious consumers or consumers with high green consumer values price information is less important. Ecologically-thinking consumers prefer quality information and information on sustainability over user-generated content, such as user-reviews.

Our findings provide various implications for practitioners. With product information search apps consumers are not only increasingly better able to conduct mobile price comparisons they are also better informed about product characteristics. Marketers might provide specific types of product information depending on the product category

and depending on consumers' characteristics. App users could be targeted with dedicated mobile advertising [42]. They are not only more likely to find a better alternative offer but they are also more likely to react to the advertising [43]. Furthermore, app developers might include these findings on consumer preferences in their requirements when designing new product information search apps or refining existing ones. As this preference information translates well into real app success in major app stores, those findings are highly relevant for developers as well.

As most research, this study also comes with some limitations: For example, we collect our data using a survey. Therefore our analysis is based on stated preferences which are not consequential for consumers and therefore could lead to a hypothetical bias. However, stated preferences can be used to predict consumer behavior to a significant extent [44]. In addition, the attributes of our ACBC analysis are not exhaustive. The multitude of real apps (across different categories) encompasses many more available features (e.g., barcode scanning vs. manual search). Finally, our survey is based on one country. These limitations provide some avenues for future research. It would be interesting to know if the results are different for other product types (e.g., food vs. electronics). Furthermore, aspects such as customer experience or consumer interaction inside a store when using a product information and price comparison app could be analyzed in further research.

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