Think Twice Before You Buy!
How Recommendations Affect Three-Stage Purchase Decision Processes

Completed Research Paper

Verena Dorner
University of Passau,
Innstraße 43,
94032 Passau, Germany
verena.dorner@uni-passau.de

Olga Ivanova
University of Passau,
Innstraße 43,
94032 Passau, Germany
olga.ivanova@uni-passau.de

Michael Scholz
University of Passau,
Innstraße 43,
94032 Passau, Germany
michael.scholz@uni-passau.de

Abstract

Consumer decision-making is usually modeled as a two-stage process of initial screening and subsequent in-depth consideration of attractive alternatives. Recent evidence indicates, however, that consideration is not necessarily the direct precursor of choice: consumers may narrow their consideration sets further to the choice set. We examine how choices in a three-stage purchase decision process evolve by observing consumer behavior in an online shopping experiment. Specifically, we examine the effects of system- and user-generated recommendations (SGR and UGR) moderated by gender. Our contribution to information systems research is threefold. First, we suggest a new experimental design for observing the stages in purchasing processes. Second, we show that effects of SGR and UGR indeed vary between stages. UGR reduce consideration set size and increase females' choice probability while SGR reduce males' transition probabilities. Third, our results suggest that omitting choice set formation can lead to incorrect estimates of choice probabilities.

Keywords: Consumer Decision Making, Decision Aids, Laboratory Experiment

Introduction

Consumer decision-making is usually modeled as a two-stage process of initial screening and subsequent in-depth evaluation of attractive alternatives (e.g. Andrews and Srinivasan 1995; Gilbride and Allenby 2004). The outcome of the screening stage is the *consideration set*; the outcome of the evaluation stage is the consumer's *final choice*. The process of consideration set formation and its effects on choice have been attracting increasing attention from information systems researchers recently (e.g. Gu et al. 2011; Parra and Ruiz 2009; Pathak et al. 2010). Results from other research areas have fueled hopes of improving predictions of consumer behavior: numerous studies have shown that i) decision-makers fairly often use multi-stage models to simplify complex choices (e.g. Nedungadi 1990; Wu and Rangaswamy 2003) and that ii) choice predictions are much more accurate when the underlying model includes the consideration set (e.g. Andrews and Srinivasan 1995; Chiang et al. 1999; Hauser 1978).

However, evidence from recent research in marketing (e.g. hotel choices of online consumers) and other areas (e.g. university choices of undergraduates) indicates that the consideration stage is not necessarily the direct precursor of final choice (Dawes and Brown 2005; Häubl and Trifts 2000; Jang et al. 2012). Instead, decision-makers may take the additional step of reducing the consideration set to the *choice set*, which is made up of only the few alternatives decision-makers consider immediately prior to choice (Häubl and Trifts 2000; Shocker et al. 1991).

Distinguishing between consideration set and choice set is important to understand and support decision-making better because decision-makers typically choose to process different information for creating the two sets and even process the information differently (Shocker et al. 1991; Jang et al. 2012; Moe 2006). These changes indicate that decision-makers use different risk relievers to mitigate the risk of choice at different stages (Roselius 1971). Hence, different decision aids will produce different effects at different stages of the decision process (Jang et al. 2012; Wu and Rangaswamy 2003); but so far, only a few of these effects have been studied (Dellaert and Häubl 2012; Häubl and Trifts 2000; Jang et al. 2012). Investigating multi-stage decision models is particularly interesting for research and practice in information systems and e-commerce because the results of this research bear directly on design and deployment of consumer decision aids. At present, consumers are usually offered the same decision aids regardless of the decision process stage they are at. But if consumers' information needs vary with decision stages, this "one-aid-fits-all" solution is likely to be less than optimal for supporting consumer information search and processing. Tailoring decision support to fit the cognitive processes at the different stages could improve consumer decision accuracy and reduce the effort required to select and choose a product. Our study contributes to clarifying the question of how and when consumers use standard e-commerce decision aids.

Introducing the distinction between sets into decision models is also important from an economic point of view. Omitting the choice set may lead to model misspecification and thus to incorrect parameter estimates (Shocker et al. 1991; Williams and Ortuzar 1982). Two-stage models without choice sets imply that choice probabilities are greater than zero for all considered alternatives (e.g. Andrews and Srinivasan 1995; Gilbride and Allenby 2004). But if consumers follow a three-stage process and choose from their choice sets only, choice probabilities will be greater than zero only for those alternatives in the consideration set which are transferred into the choice set. In this case, correctly predicting the choice probabilities of alternatives requires predicting their transition probabilities first.

Investigating multi-stage models of choice is challenging from a methodological point of view. Consideration and choice sets are formed dynamically during the decision process and are not persistent (Nedungadi 1990; Shocker et al. 1991), which makes both survey-based research and latent set modeling difficult. The concept of "sets" might not always be "meaningful to respondents" (Nedungadi 1990), which would invalidate self-reported data. Inferring the consideration set from observed purchase data produces large errors in the estimates (Roberts and Lattin 1997). In line with Moe (2006), we therefore suggest observing the decision process directly. We propose a new experimental design for identifying consideration set and choice set based on clickstream data in a realistic online shopping setting.

This paper examines the question how choices in three-stage decision processes evolve by observing consumer behavior in an online shopping experiment. Specifically, we investigate how different decision aids affect the formation of consideration sets, choice sets, and final choice decisions. We focus on the

effects and interaction effects of two decision aids that are commonly available on retailing websites: system-generated recommendations (SGR) and user-generated recommendations (UGR). Because female and male consumers have repeatedly been shown to differ in their perceptions of the risks of online shopping (Riedl et al. 2010; Garbarino and Strahilevitz 2004); in their purchase intentions (Bae and Lee 2011; Mitchell and Walsh 2004); and in their reactions towards SGR and UGR (Bae and Lee 2011; Awad and Ragowsky 2008), we paid particular attention to gender differences in adopting SGR and UGR.

The results from our experimental study indicate that consumers indeed follow a three-stage process. Omitting the choice set from analysis can lead to a skewed view of consumer decision-making, where apparently only one type of recommendation (UGR) has an effect on consumers' final choices. In fact, as the results for the three-stage model show clearly, consumers use both SGR and UGR, but at different stages of the decision process. During the screening stage, consumers used summary UGR, e.g. number of user recommendations, to form their consideration sets. During the selection stage, consumers used detailed UGR to make their final choice. Female consumers transferred more products to the choice set when SGR were present and had higher choice probabilities when UGR were present. For male consumers, the effects of SGR and UGR were reversed: they were less inclined to transfer products to the choice set with SGR and had lower choice probabilities with UGR. Our results also indicate that the transition probability, i.e. the ratio of products in the consideration set transferred to the choice set, is the single most important predictor for choice, thus providing additional support for our three-stage model.

This paper contributes to research on consumer choice modeling in three ways. First, we use a new experimental design for observing consumer decision-making to test the three-stage model in an online shopping experiment. Second, using a three-stage model reveals differential effects of decision aids on consumer choice that remain hidden in a two-stage model – supporting our supposition that tailoring decision support to accommodate different decision process stages is preferential to the current one-aid-fits-all solutions. Third, our results support the supposition that omitting the stage of choice set formation can lead to incorrect estimates of choice probabilities for (considered) products.

The Effects of Recommendations on the Outcomes of Multi-Stage Purchase Decision Processes

In both offline (e.g. Hauser and Wernerfelt 1990) and online (e.g. Moe 2006) environments, consumers split the purchase decision process into several stages to reduce information gathering and processing costs. Initially, consumers perform superficial product screening, which is cognitively less expensive than full comparisons, to eliminate unattractive products. Then they employ more expensive compensatory decision strategies to evaluate the (relative) attractiveness of the remaining products (Gilbride and Allenby 2004; Hauser and Wernerfelt 1990). The result of the first stage is thus the *consideration set*; the set of all attractive products (Hauser and Wernerfelt 1990; Shocker et al. 1991).

We posit that the first stage does not necessarily lead directly to the *final choice* (e.g. Andrews and Srinivasan 1995; Gilbride and Allenby 2004) but rather to the formation of the *choice set*; the set of all products attractive enough to be considered immediately before purchase (Häubl and Trifts 2000; Shocker et al. 1991; Wu and Rangaswamy 2003). It is among the products in the choice set that a consumer will finally choose the product with the highest utility (Andrews and Srinivasan 1995; Jang et al. 2012) if the utility exceeds the consumer's utility threshold (Roberts and Lattin 1991) and if the perceived purchasing risk is acceptable (Roselius 1971).

Figure 1 illustrates how the three-stage model which we examine in this paper extends the generally used two-stage model. The remainder of this section summarizes the results of prior research on multi-stage consumer decision processes and on the effects of system- and user-generated recommendations on purchase decisions.

Figure 1. Purchase Decision Process
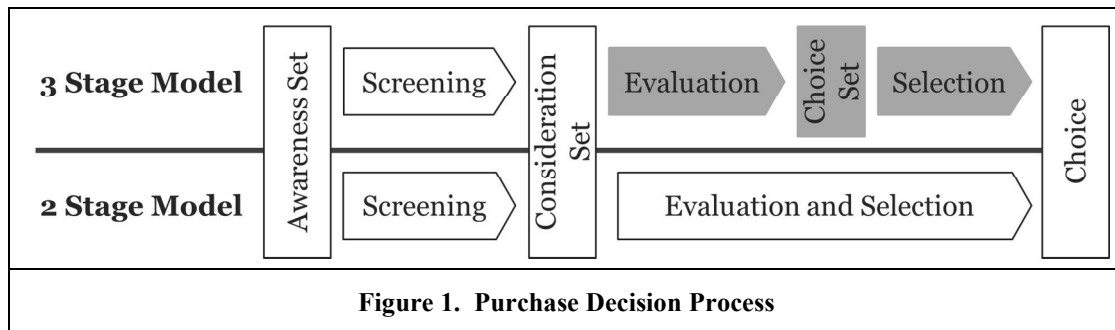
System-generated and User-generated Recommendations

Consumers strive for a balance between decision *effort* and *accuracy* (Payne 1982; Payne et al. 1992). This precludes their using all available information for decision-making, e.g. making attribute-level comparisons between all available products (Hauser and Wernerfelt 1990). The most important information, and the most likely to be incorporated in the decision process, are those which reduce product quality uncertainty and the risk associated with the purchase (Akdeniz et al. 2013; Dimoka et al. 2012). A (purchase) decision is perceived as risky if its consequences are uncertain and some are more desirable than others (Roselius 1971). Perceived risk is determined subjectively by each consumer as the expected loss associated with a purchase (Stone and Winter 1987) – higher levels of perceived risk decrease consumers' purchase intention (Cunningham et al. 2005). To reduce the perceived risk of a purchase to an acceptable[1] level, consumers use information from external sources as risk relievers (Greatorex and Mitchell 1993; Roselius 1971; Urbany et al. 1989).

In online shopping environments, online consumers usually have direct access to two kinds of external information sources, or cues, to help them find and choose the individually best (i.e. utility-maximizing) product: system-generated recommendations (e.g. Xiao and Benbasat 2007) and user-generated recommendations (e.g. Jang et al. 2012). System-generated recommendations (SGR) are usually provided based on either content-based mechanisms – recommending products similar to the ones a consumer purchased before – or collaborative filtering mechanisms – recommending products which other consumers with similar preferences bought before (Xiao and Benbasat 2007). User-generated recommendations (UGR) are usually provided in the shape of consumer reviews (e.g. Benlian et al. 2012; Pathak et al. 2010).

SGR and UGR suggest a solution for the problem of balancing decision effort and accuracy: instead of carrying out detailed comparisons and information search, consumers can make use of summarized or second-hand information about products they might consider buying (Benlian et al. 2012; Kumar and Benbasat 2006; Smith et al. 2005). In other words, SGR promise to increase decision accuracy at a lower or at least no higher level of effort than consumers would expend without decision aids (e.g. Pfeiffer and Scholz 2013; Todd and Benbasat 2000); textual UGR involve higher processing effort but also promise increased accuracy (Benlian et al. 2012; Xia and Bechwati 2008). SGR and UGR act as risk relievers by reducing the uncertainty of purchase consequences (Benlian et al. 2012; Häubl and Trifts 2000; Roselius 1971) and therefore affect consideration and choice set formation.

SGR can expand consumers' awareness sets by pointing out new, attractive products (Fleder and Hosanagar 2009) and help consumers build their consideration and choice sets faster and more accurately (Häubl and Trifts 2000). When SGR are presented *in descending order* (of product utilities), the average expected utility of the next product in the recommendations list is higher, but the marginal expected utility (of inspecting the next product) decreases with the number of previously inspected products (Dellaert and Häubl 2012). The screening phase is shorter and the consideration set contains fewer products with more homogeneous utilities (Parra and Ruiz 2009). Consumer focus shifts from screening to evaluating the products in the consideration set (Dellaert and Häubl 2012; Lenton and Francesconi 2010). The indirect effect of SGR on purchase decisions is generally found to be positive: purchase intentions (Benlian et al. 2012) and sales increase (Gorgoglione et al. 2011; Pathak et al. 2010),

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[1] "Acceptable" perceived risk in this case means "low enough to make the purchase attractive".

and choice quality improves (Häubl and Trifts 2000; Xiao and Benbasat 2007). But SGR are often provided *without information about the order in which they are presented* (Schafer et al. 2001). Research by Dellaert and Häubl (2012) indicates that *unordered SGR* may indeed have little or no effect on consumer decision-making: it is hard for consumers to determine the diagnosticity of unordered SGR and to decide whether to incorporate them in their decision process. Consumers need to expend additional effort evaluating unordered SGR in order to determine whether they will improve decision accuracy. Lower transparency in SGR generation (and, implicitly, order) accordingly leads to lower consumer adoption intention towards SGR (Wang and Benbasat 2007). Different findings on the effects of SGR on purchase decisions (Benlian et al. 2012; Lajos et al. 2009; Sismeiro and Bucklin 2004) could thus be due to different types of SGR and different models of consumer decision processes having been investigated; if no distinctions are made, direct and indirect effects of SGR on the final purchase decision cannot be discerned.

Consumers use UGR to reduce uncertainty about product quality (Dimoka et al. 2012; Mudambi and Schuff 2010) and to ascertain the level of expected (individual) product utility (Li et al. 2011). Compared to SGR, consumers generally consider UGR to be more credible (Benlian et al. 2012) and trustworthy (Bae and Lee 2011). For consideration set formation, consumers are more likely to rely on *summary UGR* (Jang et al. 2012), like mean product rating or number of recommendations for consideration set formation, because they are more easily accessible than *textual UGR*. Note that the different types of UGR – summary UGR and textual UGR – affect effort and accuracy of decision-making differently. Summary UGR more closely correspond to ordered SGR in that they enable fast processing, i.e. discerning attractive and unattractive products quickly. Textual UGR provide detailed information and are thus cognitively much more expensive to process but promise greater increases in decision accuracy. Reading about other consumers' usage experiences helps form a clearer opinion on product quality and also about the level of agreement between the reader's and writer's preferences and opinions. In contrast to SGR, textual UGR provide reasons and elaborations for product quality claims (Awad and Ragowsky 2008). The indirect effect of UGR on purchase decisions is generally found to be positive: choice quality (Jang et al. 2012) and purchase intention (Ivanova et al. 2013; Shu et al. 2011) increase, and search and evaluation costs decrease (Mudambi and Schuff 2010). However, most studies either concentrated on textual UGR only or did not distinguish between summary and textual UGR; neither did they take into account varying information needs depending on the stages of the purchase process (with the notable exception of Jang et al. 2012). As a result, there is very little evidence to show how UGR affect consumers at the different stages of the purchasing process - specifically whether consumers use textual UGR for evaluation or selection.

There is equally little research on the effect of both SGR and UGR being present. Some evidence indicates that the interaction effect of SGR and UGR may be smaller than their accumulated main effects. Kumar and Benbasat (2006), for instance, reported a 24% increase in perceived social presence if UGR were available compared to when they were not. SGR improved perceived social presence by 16%, but the availability of both types of recommendations improved consumers' perceived social presence to only 31%. Their combined effects on the outcomes of different stages of the purchasing process, however, are unclear.

To summarize, prior research found similar effects of SGR and UGR on purchase intention and choice quality, especially in those cases where both types of recommendations reduce decision effort and increase accuracy. How they affect the intermediate stages of consideration set formation and choice set formation is less clear. An important moderating factor for the effects of SGR and UGR during the decision process appears to be gender: SGR and UGR can have quite different effects on male and female consumers, due to gender differences in valuations of effort and accuracy (Mitchell and Walsh 2004) and information processing (Meyers-Levy and Maheswaran 1991); perceptions of the risks of online shopping (Garbarino and Strahilevitz 2004); trust (Bae and Lee 2011; Riedl et al. 2010); and social behavior (e.g. Laroche et al. 2000; Seock and Bailey 2008).

The Moderating Effect of Gender and Individual Decision Process Variables

Male consumers typically value effort reduction more than female consumers: males are predisposed to use informational cues for fast processing whenever possible, rather than more effortful detailed processing (Darley and Smith 1995; Meyers-Levy and Maheswaran 1991). They also typically have a more

positive attitude to online shopping due to its high efficiency and convenience (e.g. Seock and Bailey 2008; Van Slyke 2012). As a consequence, reliance on SGR is higher among male consumers: SGR offer highly diagnostic cues (e.g. product order) for schema-based processing and reduce the time required for product screening (Häubl and Trifts 2000). Females, on the other hand, place greater emphasis on avoiding the consequences of a wrong decision (Croson and Gneezy 2004) – they value decision accuracy more highly (Mitchell and Walsh 2004) and are more inclined towards detailed information search and processing (Meyers-Levy and Maheswaran 1991). They use SGR and UGR more extensively than male consumers (Doong and Wang 2011), but their tendency to engage in detailed processing reduces the impact of SGR's informational cues. Instead, female consumers rather rely on textual UGR which are rich in details. This tendency is reinforced by female consumers' higher propensity to trust information conveyed by word-of-mouth (Awad and Ragowsky 2008) and their appreciation of high levels of social presence of a website (Chai et al. 2011); high social presence in turn increases trust in the recommendations posted on the website (Chai et al. 2011). As a consequence, UGR can affect female consumers' perceptions of purchasing risk and purchase intentions more strongly than those of male consumers (Bae and Lee 2011; Garbarino and Strahilevitz 2004).

Some of the most important individual consumer characteristics that influence specific purchase decisions are product experience and product type-specific preferences (e.g. Hoch 2002; Pan and Lehman 1993). Although mainly individual, these characteristics have been shown to be gender-specific under certain circumstances. Depending on product type, perceived product experience often varies with gender: apart from gender-specific products, male consumers tend to have greater perceived experience with, for instance, beer (Wu and Wyer 2010) or with technical and electronic products like smartphones (Karjaluoto et al. 2005) and computers (Sebastianelli et al. 2008), but lower experience with beauty products (Wu and Wyer 2010). Greater product experience reduces the effort of processing product-related information because informational cues can be used for fast processing (Beatty and Smith 1987; Anderson et al. 1979) and increases decision accuracy because the consumer is better able to determine whether product attributes match his or her preferences (Mason and Bequette 1998). Especially in terms of processing UGR, experienced consumers will be able to determine more easily how closely their preferences match those of the UGR creator and thus judge the relevance of UGR faster and more accurately. Experienced consumers typically have better formed preferences (Hoeffler and Ariely 1999) and are thus better prepared for determining SGR and UGR diagnosticity and to use them effectively in their decision processes.

Although quite a lot of research has been carried out regarding gender differences in online shopping, few studies examine female and male reactions to SGR[2] and UGR at different stages of the purchasing process. We propose to close this gap by investigating the effects and interaction effects of both recommendation types on the outcomes of all three stages – consideration set formation, choice set formation and choice – and their effect on male and female consumers.

Research Model

Figure 2 summarizes our research model and hypotheses which we explain in detail in the following subsections.

Consideration Set

SGR and UGR can reduce search and evaluation effort during screening (Häubl and Trifts 2000; Todd and Benbasat 2000). When SGR can be processed as cues for products' expected relative utilities, consumers will stop screening sooner (Häubl and Trifts 2000). SGR are only diagnostic, however, if consumers receive additional information about the order in which SGR are displayed, e.g. in descending order of their utilities (Dellaert and Häubl 2012). Otherwise, consumers have no means of judging a recommended product's relative attractiveness, and SGR will not influence their consideration set formation.

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[2] Our research specifically addresses unordered SGR. Although they are commonly used in practice (e.g. Amazon.com), they are evaluated far less frequently in experimental settings than ordered SGR.

Figure 2. Research Model and Hypotheses
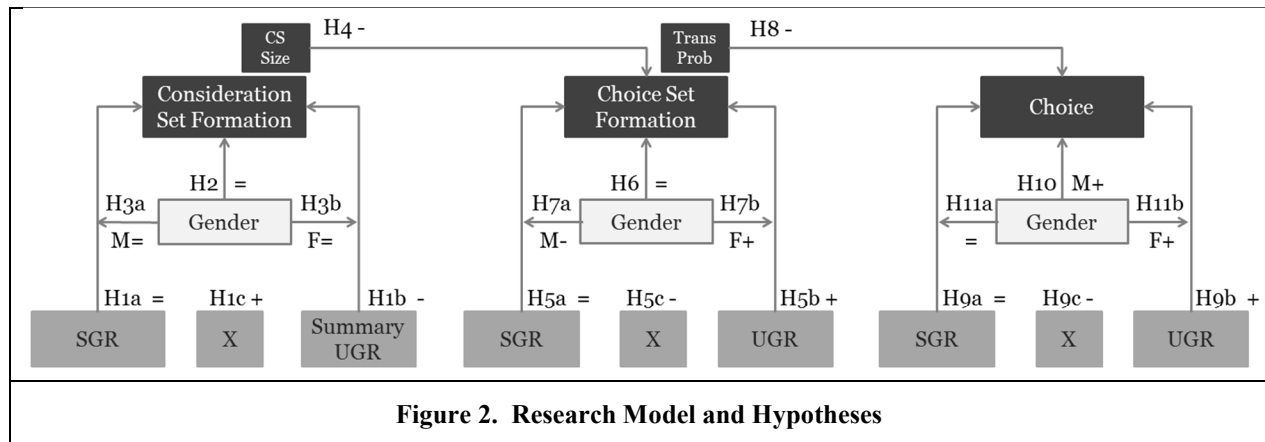
UGR against purchasing a product are particularly valuable for identifying and discarding unattractive products quickly. Consumers use summary statistics of UGR rather than textual UGR for consideration set formation because the former are less effortful to process (Jang et al. 2012). In contrast to SGR, order is of little importance: summary UGR provide information about the relative attractiveness of products, e.g. average "star ratings", and it is easy for the consumer to infer product order.

> *H1a: Consumers' consideration sets sizes do not diminish when (unordered) SGR are present.*

> *H1b: Consumers' consideration sets diminish when summary UGR are present.*

If both unordered SGR and UGR are present, we would expect to find a reduction in accumulation, which in our case means a smaller decrease in consideration set size. Having used summary UGR to quickly identify attractive products, consumers may feel unsure, when additionally presented with unordered SGR, about the latter products' utility and decide to include some of them in their consideration set to reduce the risk of discarding attractive products so early in the purchasing process.

> *H1c: Presenting unordered SGR along with summary UGR reduces their (accumulated) effect on consideration set size.*

Because cognitive processing capacity is limited, including more than around 7 products (Miller 1956) to the consideration set will make detailed product evaluation in the next stage extremely effortful or even cognitively impossible. However, minimizing second-stage effort by including very few products in the consideration set would require that consumers limit their choices severely at the first stage even though at this point product uncertainty is very high. We therefore suggest that the difference between male and female consumers in consideration set formation lies less in the absolute sizes of their consideration sets (Häubl and Trifts 2000; Parra and Ruiz 2009) than in the effort they expend to form it. Female consumers tend to screen more products (e.g. Seock and Bailey 2008) because they are more risk-averse and place greater emphasis on decision accuracy (Mitchell and Walsh 2004).

> *H2: Consideration set size does not vary with gender.*

Instead, these differences in information processing incur differences between the genders in their reliance on decision aids and thus have an indirect effect on consideration set size. Male consumers are generally thought to be more likely to rely on SGR because they particularly value efficiency in shopping (Seock and Bailey 2008; Van Slyke 2012). However, the cues offered by unordered SGR are of low diagnosticity and promise little gain in efficiency (Dellaert and Häubl 2012): we would not expect either male or female consumers to rely on them.

Female consumers are generally thought to be more likely to rely on UGR because they find them more credible (Awad and Ragowsky 2008) and value the increase in social presence through UGR more highly (Chai et al. 2011; Kumar and Benbasat 2006). Importantly, however, previous studies did not distinguish between summary and textual UGR. Summary UGR serve much the same purpose as ordered SGR, namely as informational cues for discerning attractive and unattractive products. We therefore posit that male and female consumers will not differ in their use of summary UGR during consideration set

formation: both will use them for reducing decision effort during consideration set formation.

> H3a: *The effect of SGR on consideration set formation is not moderated by gender.*

> H3b: *The effect of UGR on consideration set formation is not moderated by gender.*

Choice Set

During the evaluation stage, consumers have a closer look at the products in the consideration set to determine their utilities and to decide which ones to consider seriously for purchase; in other words, to decide which products to transfer to their choice set. We suggest that choice set size does not grow proportionately to consideration set size but that the transition probabilities (of a product being transferred to the choice set) diminish with larger consideration sets. For one, larger consideration sets indicate greater heterogeneity in the considered products' utilities (Häubl and Trifts 2000). Prior research shows that when decision-makers are presented with (relatively speaking) bad alternatives alongside good alternatives, their decision confidence increases (Aljukhadar et al. 2012). In our case, consumers will be more confident in discarding (relatively) low-utility products from the consideration set, and will keep only a small number in the choice set. By contrast, consumer will be more inclined to keep a greater proportion of products (i.e. have a higher transition probability) from small consideration sets (with more homogeneous utilities).

> H4: *Transition probability diminishes with larger consideration sets.*

Ordered SGR affect choice set formation uniformly across gender due to a decrease in effort and an increase in accuracy (Dellaert and Häubl 2012; Häubl and Trifts 2000).We suggest that unordered SGR have opposite effects on consumers of different gender (see H7a). Therefore, we would not expect to see a uniform main effect.

Textual UGR provide consumers with additional information on the products in the consideration set, which makes the evaluation task more complex (e.g. Hauser and Wernerfelt 1990). Having used summary UGR for discarding low-utility products, the consideration set will consist of products with relatively homogeneous utilities. Evaluating and comparing these products' relative attractiveness will require greater effort, even when textual UGR are used for support: reading and processing such detailed information is cognitively demanding. Prior research found that UGR increase choice probability, but did not take into account the stage of choice set formation (e.g. Shiu et al. 2011). We suggest that UGR could indeed increase transition probability because consumers will be able to process only part of the available information with reasonable effort. Thus they will be aware of the possibility of not having processed a vital piece of information (correctly), which will increase the perceived risk of discarding an attractive product too soon.

> H5a: *Transition probability is not (uniformly) affected by unordered SGR.*

> H5b: *Transition probability increases in the presence of UGR.*

During product evaluation, consumers gain a better understanding of the considered products' relative attractiveness. As a result, they are better able to judge the actual informational value of SGR. If they deem SGR to be highly diagnostic, consumers will feel more confident in their decision to seriously consider a doubly recommended product for purchase and decide to forego the effort of transferring additional products to the choice set. If SGR are deemed to be of low diagnostic value, consumers will feel more confident in discarding these products from their consideration sets. In both cases, the accumulated effect on transition probability is reduced.

> H5c: *Presenting both SGR and UGR reduces their (accumulated) effect on transition probability.*

The question of how many products to transfer to the choice set depends on the size and, implicitly, quality of the consideration set (Häubl and Trifts 2000) in terms of product utilities. Gender does not affect transition probability directly.

> H6: *Transition probability does not vary with gender.*

Indirectly, however, gender can affect transition probabilities due to gender-specific reactions to SGR. When only SGR are present, male consumers will be more inclined to using them in order to save effort;

either by using them as cues to confirm their product opinions in case of high diagnosticity or by using them as cues to facilitate discarding products in case of low diagnosticity (H5c). Female consumers without access to UGR, however, are likely to react in the opposite way: their uncertainty may even increase if SGR are of low diagnosticity, and they may defer discarding a product to diminish the risk of reducing decision accuracy.

Textual UGR simultaneously increase effort and accuracy of choice set formation (see H5b) but do not provide easily accessible cues for fast decisions on product inclusion into or exclusion from the choice set. In such situations, male consumers tend to process information similarly to female consumers (Meyers-Levy and Mahareswaran 1990). While the direction of the effect is thus identical, it will be stronger for female consumers. They place more emphasis than males on avoiding the consequences of a wrong decision (Croson and Gneezy 2004), in this case a reduction in decision accuracy by having discarded an attractive product too soon.

> *H7a: In the presence of SGR, transition probability decreases for males only.*

> *H7b: In the presence of UGR, transition probability increases more strongly for females than for males.*

Choice

The uncertainty associated with a purchase increases with the number of products that appear to be a close match to a consumer's preferences, which in turn increases choice deferral (Walsh and Mitchell 2005). At the same time, consumers value being able to choose from a large array of attractive products (e.g. Iyengar, Wells and Schwartz 2006); small numbers of attractive products can lead to weaker preferences and decreased choice satisfaction (Chernev 2003). In both cases, transition probability will be high because consumers will have been more inclined to transfer products from the consideration set to the choice set – either to reduce the risk of prematurely discarding an attractive product, or to reduce the risk of being left with only one option.

> *H8: Choice probability diminishes with higher transition probabilities.*

We suggest that SGR only have an indirect effect on choice probability through transition probability. Contrary to their potential value during choice set formation, unordered SGR will not affect the final choice because they cannot provide information relevant to the final decision, i.e. product order or a rationale why one product might be a better fit to consumer preferences than another product.

UGR, on the other hand, provide information from which product (utility) order and preference fit can be inferred, although this can be a cognitively difficult task (Benlian et al. 2012), thus reducing pre-purchase uncertainty and the likelihood of choice deferral (Dimoka et al. 2012).

> *H9a: Choice probability is not affected by SGR.*

> *H9b: Consumers are more likely to purchase a product from their choice set if UGR are present.*

Similar to the interaction effect of SGR and UGR on consideration set size and choice set size, we expect to see a reduced accumulation of the effects of SGR and UGR on choice probabilities.

> *H9c: Presenting both SGR and UGR reduces their (accumulated) effect on choice probability.*

Male consumers are generally more inclined to make an actual purchase online because they are motivated by the perceived gains of their purchase decision rather than its perceived risks (Awad and Ragowsky 2008; Seock and Bailey 2008). Female consumers, on the other hand, place greater emphasis on avoiding the consequences of a wrong decision.

> *H10: Male consumers are more likely to make a purchase than female consumers.*

Since SGR are of little informational value for the final choice, we would not expect either male or female consumers to be affected by them. UGR, on the other hand, enable consumers to infer product order and can thus be used in the final decision. Female consumers' choice probability is likely to increase when UGR are present because they judge recommendations by word-of-mouth to be more trustworthy (Bae and Lee 2011; Garbarino and Strahilevitz 2004). UGR doubly affect female consumers: for one, UGR suggest higher website trustworthiness because other consumers have successfully shopped there (Awad

and Ragowsky 2008), and for another, UGR reduce product quality uncertainty (Hu et al. 2008).

> *H11a: Gender does not moderate the effect of SGR on choice probability.*

> *H11b: Gender moderates the effect of UGR on choice probability. Female consumers are more likely than male consumers to make a purchase when UGR are present.*

To summarize, we suggest that SGR and UGR affect effort and accuracy to varying degrees at the different stages of the purchase decision process, i.e. whether to include products in the consideration set; whether to transfer them to the choice set; and, ultimately, whether to buy them. Because male and female consumers differ in their information processing strategies, their valuations of effort and accuracy, and risk aversion and trust, their reactions to SGR and UGR are likely to differ at several stages.

Empirical Investigation

Experimental Design

Measuring the choice set is subject to similar operational issues as measuring the consideration set: self-reporting is liable to produce biased data (Moe 2006); inferring consideration sets from purchasing data to produce large estimation errors (Roberts and Lattin 1997). We therefore decided to collect observational clickstream data (Moe 2006) in an online experiment. In line with prior definitions of consideration set ("products evaluated in detail"; Häubl and Trifts 2000; Hauser and Wernerfelt 1990), we operationalized it as all products on which participants clicked to obtain more detailed information. The choice set (defined as "products considered immediately prior to purchase"; Shocker et al. 1991) was operationalized as all products which participants did not drop from the consideration set after detailed evaluation but retained up to the moment when they made their final choice. We were thus able to capture the dynamics of consumer choice; to determine whether consumers actually used two distinct sets and a three-stage decision process; and to examine how SGR and UGR affect decisions at each stage.

We used a 2x2 between-subject design to test our hypotheses, generating four different versions of the Amazon website in real time to isolate the effects of SGR and UGR in a maximally realistic environment. We chose Amazon in order to eliminate the effect which different levels of trust towards a website may have on consumer behavior (Dimoka et al. 2012; Komiak and Benbasat 2004; Riedl et al. 2010). Amazon is very popular and has a good reputation for customer service (Barnes and Vidgen 2005); we could be reasonably certain that our participants would be familiar with Amazon and consider it a trustworthy vendor. Login buttons were disabled to eliminate quality differences between SGR for logged-in users and for anonymous users. All participants received SGR based on click-stream data only.

Participants were instructed to search for a new digital camera on the Amazon website. Before starting the search task, they completed an online survey about their perceptions of Amazon. After the search task, they completed a second survey on individual and demographic variables. Participants were under no time constraints for their search; they were merely instructed to quit searching as soon as they had come to a final decision whether to purchase a camera. There were no constraints as to the information search methods or decision strategies employed. The participants were only asked to open each camera they wanted to evaluate in detail in a separate browser tab. These cameras constitute the consideration set. When participants decided not to consider a camera for purchase any longer, they closed the tab. The cameras retained in open tabs at the end of the experiment constitute the choice set. We logged all clicks on the Amazon website as well as browser tab opening and closing during the entire experiment.

Pretest and Sample

We carried out one-on-one pretests with 3 students, who did not take part in the final experiment, in each experimental condition. The 12 pretest participants' opinions of and thoughts on every step in the experiment were elicited in think-aloud protocols. We also tested the manipulation checks and found that all pretest participants correctly perceived presence or absence of SGR and UGR on the Amazon website.

233 undergraduate and graduate students from the University of Passau participated in our experiment. All participants were familiar with the Amazon website and had purchased at least one product within the

last 3 month at Amazon.com. Participants were assigned randomly to one of the four experimental conditions. Table 1 presents the descriptive statistics for participants' purchasing processes by gender and assigned condition.

Table 1. Descriptive statistics of our sample								
	no UGR, no SGR		no UGR, SGR		UGR, no SGR		UGR, SGR	
	Female	Male	Female	Male	Female	Male	Female	Male
Participants	39	25	50	13	34	17	36	19
Consideration Set Size	7.846 (4.660)	6.800 (4.010)	7.600 (3.010)	6.846 (2.794)	5.941 (2.510)	6.529 (3.223)	6.472 (3.229)	6.526 (2.065)
Choice Set Size	1.744 (1.117)	1.720 (1.137)	2.200 (1.325)	1.385 (0.961)	1.912 (1.288)	1.824 (1.131)	1.667 (1.171)	1.737 (1.727)
Transition Probability to Choice Set	0.222 (0.242)	0.253 (0.235)	0.322 (0.242)	0.279 (0.303)	0.289 (0.233)	0.202 (0.163)	0.258 (0.303)	0.266 (0.220)
Choice Probability	0.256	0.720	0.320	0.462	0.500	0.588	0.444	0.579

The average set sizes and choice probabilities are similar to those reported in other studies (Dellaert and Häubl 2012; Gu et al. 2011; Häubl and Trifts 2000). Our participants considered between 1 and 26 products, but transferred only up to 8 products to their choice set. In support of our conjecture for H8, we indeed found a strong positive relationship between transition probability and choice set size ($p < 0.001$).

Manipulation Check

After concluding the search task, participants completed another online survey, this time answering questions on their final purchase decision and on their perceptions of the presence (absence) of SGR and UGR on a 7-point scale. ANOVA results (Table 2) indicate that our participants correctly perceived presence or absence of the manipulated conditions.

Table 2. ANOVA Results for Manipulation Check						
Source	Manipulation Check	Sum of Squares	df	Mean Square	F	Sig.
Actual Support for SGR	Perception of SGR	291.904	1	291.904	79.071	<0.001
	Perception of UGR	3.564	1	3.564	0.966	0.327
Actual Support for UGR	Perception of SGR	7.480	1	7.480	2.270	0.133
	Perception of UGR	570.200	1	570.200	173.159	<0.001
Actual Support for SGR x UGR	Perception of SGR	80.513	1	80.513	17.479	<0.001
	Perception of UGR	207.860	1	207.860	42.598	<0.001

We recoded the variable for experimental condition as an ordinal variable by multiplying perception strength (measured on a 7-point scale) with the binary variables indicating whether SGR and UGR were present or not. If, for instance, participants relied heavily on UGR during their search process, they would be absolutely certain of their presence; but if they did not, they might be less certain.

Gender-related Differences in Control Variables

Since we used digital cameras as our experimental product, it was likely that there would be gender-related differences in the participants' product experience and preferences. Male consumers often have

more experience and thus better-defined preferences for computers (e.g. Sebastianelli et al. 2008), which might change how they perceive and use SGR and UGR. We therefore conducted ANOVAs for both variables and indeed found the expected gender differences, i.e. higher experience and more specific preferences among male consumers. We then used the residuals as independent variables in our main regression models to determine whether differences in experience and preferences not expressed by gender influenced the participants' behavior at the different stages of the decision process. Regression results were robust; introducing the two additional variables did not change the effects of SGR and UGR on the outcome of any stage.

To exclude the possibility that the gender-specific effects we found in our regression models (Table 3) were due to experience or preference differences only, we re-ran the regressions without gender and the full experience and preference variables. We did not find corresponding effects between experience or preference and SGR and UGR; nor did we find a significant effect of experience and preference on the final result of the purchase decision process, choice probability. In sum, all our cross-checks support our notion that gender-specific differences beyond experience and preference lead to different reactions of male and female consumers towards SGR and UGR and to different purchasing behavior.

We also conducted an ANOVA to determine the gender-specific differences in trust towards SGR and UGR and included the trust residuals as independent variable in the main regression models. This did not change the effects of SGR or UGR but had a significant positive effect on choice probability for both genders (0.742, robust SE = 0.170). The ANOVA results indicated that female participants perceived UGR as more trustworthy, confirming prior findings (Awad and Ragowsky 2008). There were no differences between genders in their trust towards SGR.

Effects on Consideration Set Size, Transition Probability and Choice

We performed separate regression analyses for each of the three stages to test for effects of gender and experimental condition on the outcome of each stage (Table 3). The outcome of the screening stage, consideration set size, being a count variable without overdispersion, we performed a Poisson regression. The outcome of the evaluation stage is the transition probability, which corresponds to the ratio of trials (consideration set size) and successes (choice set size), on which we performed a logistic regression. The outcome of the selection stage, final choice, depends on both intermediate stages. We used the transition probability as an independent variable in the logistic regression on final choice and added the independent variable *choice set filled* to control for the effect of participants deciding prematurely against purchasing any product (choice set size zero) as opposed to making the decision during the third stage (choice set size at least 1).

SGR did not affect consideration set size (H1a), supporting the supposition that consumers only reduce consideration set size if they are informed that recommendations are sorted by their utilities (Dellaert and Häubl 2012): Amazon does not provide explicit information about the presentation order. Consideration sets shrank in the presence of UGR (H1b): separating attractive from unattractive products became easier, allowing consumers to stop screening sooner and focus on evaluating fewer products in detail (Dellaert and Häubl 2012). Interestingly, presenting unordered SGR and UGR simultaneously did not increase consideration set size (H1c). As expected, gender did not affect consideration set size (H2) or moderate the effects of SGR or UGR on consideration set size (H3a and H3b). This indicates that male and female consumers alike use these decision aids for reducing the effort of screening products during consideration set formation.

Transition probability diminished with larger consideration sets (H4). There were no main effects of SGR (H5a) or UGR (H5b) or indeed of gender (H6) on transition probability. When both SGR and UGR were presented, their accumulated effect on transition probability diminished (H5c). SGR also had a significant interaction effect with gender (H7a). Female participants transferred 28.9% of considered products to their choice sets when SGR were present, but only 22.2% without SGR. Male participants, on the other hand, included fewer products (20.2%) when SGR were present (25.3% without SGR). Contrary to expectations, UGR neither had a main effect on transition probability (H5b), nor was it moderated by gender (H7b). These findings indicate that consumers' reliance on decision aids varies with each stage of the decision process.

During the choice stage, participants did not rely on SGR (H9a). UGR increased choice probability (H9b)

but presenting UGR and SGR together did not affect participants' choice probability at all (H9c). Male participants' purchase probability was generally higher[3] (H10). SGR did not interact with gender (H11a), but UGR increased female participants' purchase probability and diminished male participants' purchase probability (H11b).
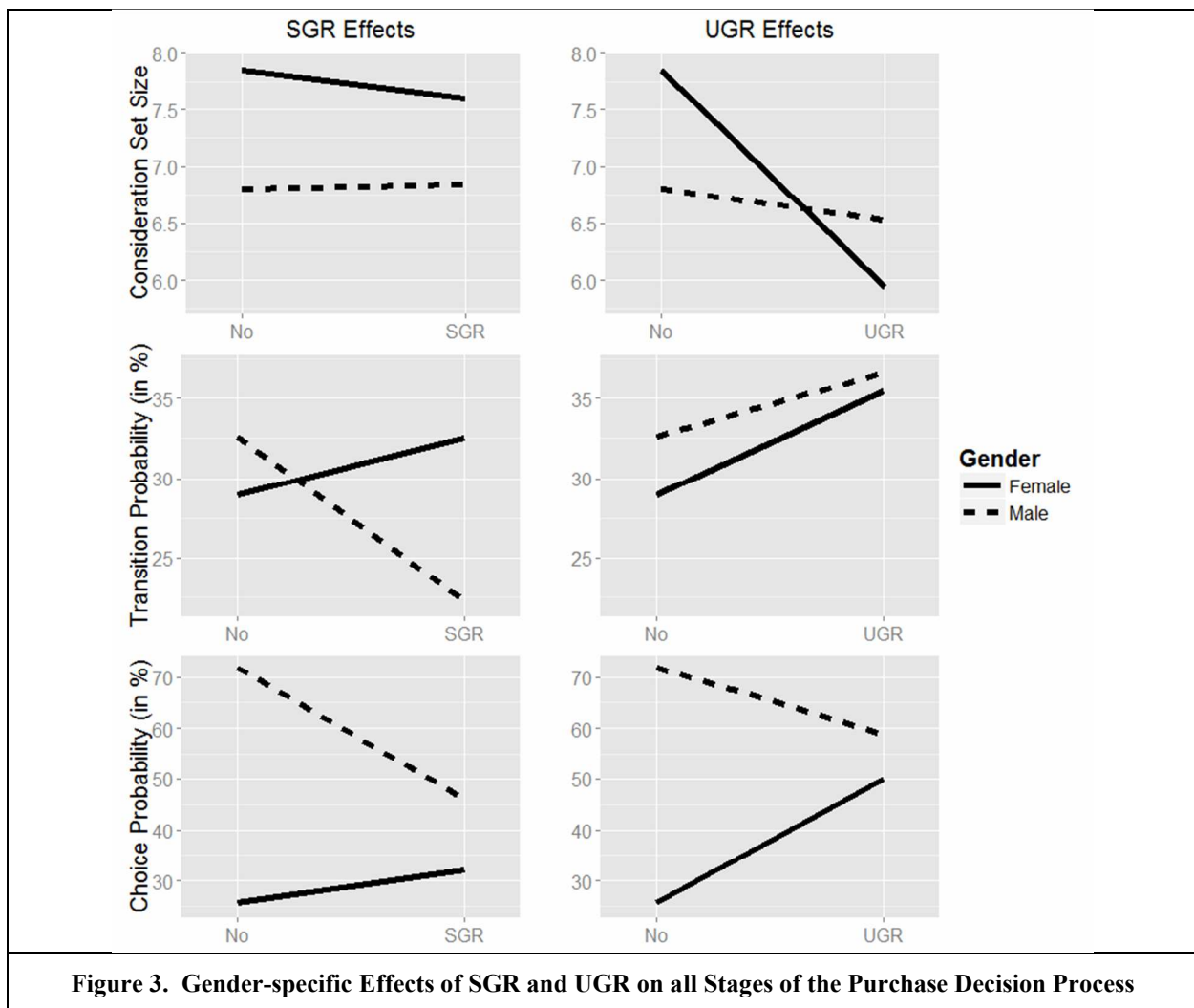
	Consideration Set Size	Hypotheses Consid. Set	Transition Probability	Hypotheses Choice Set	Choice	Hypotheses Choice
Table 3. Regression Results for 3-Stage Model [estimate (robust standard error)]						
Intercept	2.024 *** (0.088)	-	-0.640 *** (0.169)	-	-2.751 *** (0.714)	-
Consideration Set Size	-	-	**-0.096 *** (0.020)**	**H4 supp**	-	-
Transition Probability	-	-	-	-	**-2.641 *** (0.705)**	**H8 supp**
Choice Set Filled	-	-	-	-	2.580 *** (0.705)	-
SGR	**0.005 (0.017)**	**H1a supp**	**0.035 (0.020)**	**H5a supp**	**0.051 (0.083)**	**H9a supp**
UGR	**-0.039 * (0.017)**	**H1b supp**	0.021 (0.022)	H5b n.supp	**0.199 * (0.083)**	**H9b supp**
SGR x UGR	0.002 (0.003)	H1c n.supp	**-0.010 * (0.005)**	**H5c supp**	-0.010 (0.018)	H9c n.supp
Gender (Male)	**-0.135 (0.144)**	**H2 supp**	**0.051 (0.169)**	**H6 supp**	**2.261 *** (0.598)**	**H10 supp**
SGR x Gender	**0.001 (0.030)**	**H3a supp**	**-0.086 * (0.041)**	**H7a supp**	**-0.240 (0.136)**	**H11ap.supp**
UGR x Gender	**0.041 (0.029)**	**H3b supp**	-0.022 (0.039)	H7b n.supp	**-0.339 * (0.129)**	**H11b p.supp**
SGR x UGR x Gender	-0.004 (0.006)	-	0.017 (0.010)	-	0.045 (0.029)	-
Experience resid.	-0.013 (0.028)	-	-0.005 (0.042)	-	0.159 (0.163)	-
Preference resid.	0.029 (0.030)	-	0.076 (0.043)	-	-0.019 (0.151)	-
Trust resid.	-0.046 (0.035)	-	0.039 (0.041)	-	0.720 *** (0.181)	
Log-Likelihood	-599.459 (p=0.036)	-	-315.183 (p<0.001)	-	-126.519 (p<0.001)	-
Level of significance: * denotes significance at 0.05 level *** denotes significance at 0.001 level		Hypothesis tests: n. supp denotes hypothesis not supported p. supp. denotes hypothesis partially supported supp denotes hypothesis supported				

That SGR had no effect on consideration set formation presented separately (H1a) or alongside UGR (H1c), leads to the conclusion that participants across both treatments including SGR strictly reserved their judgment on SGR diagnosticity. Showing unordered SGR alongside UGR did not increase

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[3] Cross-checking (see section "Gender-related Differences in Control Variables") revealed no significant effect of experience or preference on choice probability.

participant uncertainty to the point where they would include additional products in their consideration set to avoid the risk of excluding potentially attractive products prematurely. Having evaluated the products in the second stage, consumers are better able to determine how diagnostic unordered SGR are. Male consumers use them for efficiently building their choice set whereas female consumers may become increasingly uncertain when faced with SGR of low diagnosticity (H7a). This appears to have been the case in our experimental setting: female participants' transition probabilities increase, indicating that they were less prepared to run the risk of discarding a potentially attractive product. In effect, they accepted greater effort during the purchase decision – choosing from a larger choice set – in exchange for a chance for greater decision accuracy. This interpretation is supported by the difference in product experience and preference which we found between genders. Male consumers were more certain of their preferences, thus better able to evaluate SGR, and relied more readily on them. Female participants had less experience to help them with SGR evaluation, became more uncertain and, since female consumers are generally more anxious to avoid the risk of making a wrong decision, "played it safe" by increasing the proportion of products transferred to the choice set[4].

All effects are summarized in Figure 3 with respect to the different decision aids and the participants gender.

**Figure 3. Gender-specific Effects of SGR and UGR on all Stages of the Purchase Decision Process**

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[4] Cross-checking (see section "Gender-related Differences in Control Variables") revealed no corresponding interaction effect, which supports our argument that the increase in uncertainty is also due to gender-specific factors beyond experience or preference.

Two or Three Stages

To ascertain whether a three-stage or two-stage model is better suited for modeling consumer behavior, we performed model comparison (Table 4). Both models are logistic regression models with consumers' final choice as the dependent variable. The two-stage model assumes that only consideration set size plays a role, whereas the three-stage model includes the effects of both consideration and choice set sizes on final choice. The results clearly show that the three-stage model is superior in terms of model fitness (Table 4). Modeling consumer choice as a direct transition from consideration to final choice hides the indirect influence of SGR, moderated by gender (Table 3), on final choice: SGR affect the transformation of the consideration set into the choice set.

Table 4. Comparison of Final Choice Stage in Two- and Three-Stage Models				
	Two-Stage Model		Three-Stage Model	
	Estimate	Robust Std. Err.	Estimate	Robust Std. Err.
Intercept	-1.216 *	0. 501	-2.751 ***	0.714
Consideration Set Size	-0.005	0.043	–	–
Transition Probability	–	–	-2.641 ***	0.820
Choice Set Filled	–	–	2.580 ***	0.705
SGR	0.052	0.081	0.051	0.083
UGR	0.163 *	0.080	0.199 *	0.083
SGR x UGR	-0.007	0.018	-0.010	0.018
Gender (Male)	2.140 ***	0.550	2.261 ***	0.598
SGR x Gender	-0.217	0.137	-0.240	0.136
UGR x Gender	-0.265 *	0.124	-0.339 *	0.129
SGR x UGR x Gender	0.037	0.028	0.045	0.029
Experience $_{residuals}$	0.163	0.149	0.159	0.163
Preference $_{residuals}$	0.053	0.145	-0.019	0.151
Trust $_{residuals}$	0.717 ***	0.168	0.720 ***	0.181
Log-Likelihood	-137.364 ***		-126.519 ***	
AIC	298.728		279.038	
BIC	340.141		323.901	
R²	0.238		0.336	

Omitting the transition from consideration set to choice set leads to incorrect conclusions about consumers' usage of risk relievers during the decision-making process and about choice probabilities. Notably, the two-stage-model would lead one to the (erroneous) conclusion that the consumers' purchase decisions are barely influenced by the search stage. The fact that transition probability – as the ratio of choice set size and consideration set size – is the most important predictor for the final purchase decision underlines the importance of including choice set formation in models of consumer purchase decision processes. This information is missing entirely from the two-stage model, which will thus produce systematically biased estimates of choice probability. Figure 4 summarizes our results and illustrates the effects hidden by the two-stage model.

Figure 4. Results
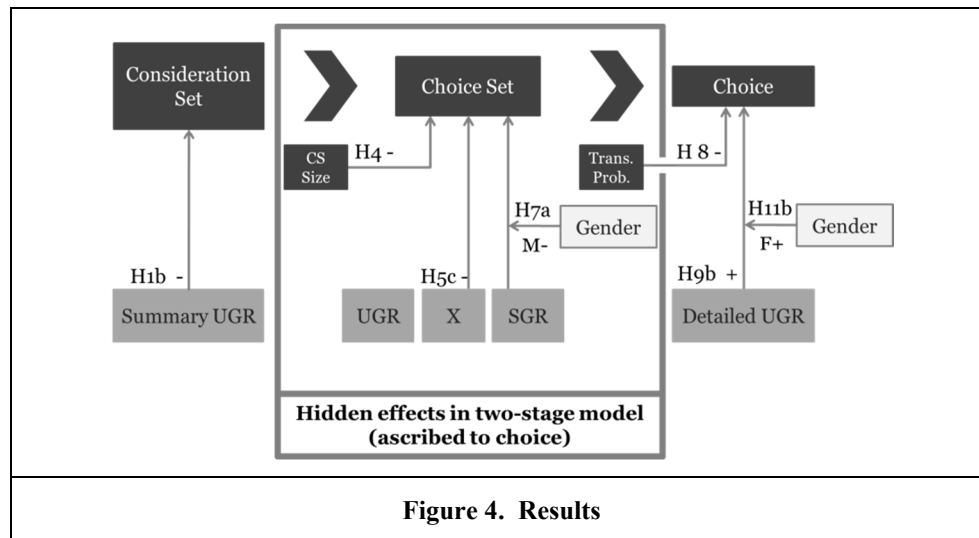
Discussion

This study contributes to research on consumer choice modeling in three ways. First, it suggests a novel way of measuring consideration sets and choice sets as observables in a realistic setting. We were thus able to monitor consumer behavior more closely and to distinguish clearly between different stages of the purchase decision process.

Second, our study provides evidence that consumers follow a three-stage rather than a two-stage decision process, supporting our supposition that tailoring decision support to accommodate different decision process stages is preferential to the current one-aid-fits-all solutions. Our results contribute to determining which decision aid is most effective at which stage, since only in the three-stage model will the differential effects of SGR and UGR on each stage of the purchase decision process become transparent. These differences are due to varying information needs at the different stages, and also to differences in valuations of decision effort and accuracy between female and male consumers.

Female consumers' choice probabilities were highest with UGR only[5]: when selling to female consumers, UGR are the best choice of decision aid. Male consumers, by contrast, had the second-to-lowest choice probabilities with UGR only. One possible explanation for this finding is found in a study by Grabe and Kawahami (2006): females tend to avoid negatively framed messages and process them less effectively than positive messages; the reverse is true for males. Male consumers tended to have clear-cut preferences and relied more readily on SGR than female consumers, but this did not translate into increased choice probabilities. One possible explanation for this finding is that due to their clearer preferences, male consumers were better able during product evaluation to determine when recommended products did not fit their preferences. Male consumers' greater emphasis on effort reduction then led them to discard the products immediately – male consumers' choice sets were most likely to be empty with only SGR available[6]. These issues certainly merit further research.

On average, i.e. without taking the influence of gender into account, three scenarios (no decision aids;

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[5] We predicted choice probabilities for all combinations of SGR and UGR as well as for all extreme values of non-gender specific experience, preference and trust for choice sets which included at least one product (CHOICESETSIZEFILLED=1). We multiplied these values with each scenario's probability of leading to empty choice sets to arrive at the final predicted choice probability.

[6] We predicted transition probabilities for all combinations of SGR and UGR as well as for all extreme values of non-gender specific experience, preference certainty and trust. Choice set sizes were then computed as predicted consideration set sizes multiplied by predicted transition probabilities for all cases. Since choice set formation is a Poisson process, we generated 10,000 Poisson distributed random numbers (predicted choice set size as lambda) and computed the ratio of numbers equaling zero.

UGR only; SGR and UGR) led to nearly identical choice probabilities. When SGR were the only decision aid available, consideration sets (of both female and male consumers) were largest[7]. These results underline the importance of making the SGR generation process or the order of SGR transparent to increase their effectiveness. Websites, like Amazon.com, that provide collaborative and content-based SGR without such additional information, could vastly improve consumer decision support by increasing SGR transparency, reducing both effort and improving decision accuracy.

Third, our results support the supposition that omitting the stage of choice set formation can lead to incorrect estimates of choice probabilities for (considered) products. Omitting choice set formation from models of consumer decision making leads to incorrect estimates of choice probabilities for (considered) products; transition probability emerged the most important predictor for choice probability in our study. Our results support our supposition that only a subset of considered products actually has purchase probabilities greater than zero: at most, females in our sample included 27.3 % of considered products in their choice sets, and males 25.0 %. Introducing a third stage into models of consumer decision-making is therefore likely to improve the accuracy of purchase (probability) predictions. This result is particularly interesting from product manufacturers' and sellers' point of view as far as market share and sales predictions are concerned. With regard to e-commerce decision support design, correctly predicting products' choice probabilities during the decision process would improve recommendation precision and accuracy, thus reducing decision effort for the consumer.

Further research is needed to reexamine the results and predictions of two-stage models of consumer behavior and its determinants, especially consumers' information needs and processing at different stages under different informational conditions. Further research into the dynamics of consideration and choice set content could expand our understanding of the kind of attributes consumers use at different stages, and shed light on whether different product types give rise to different information needs and thus require different decision aids.

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[7] We predicted consideration set sizes for all combinations of SGR and UGR as well as for all extreme values of non-gender specific experience, preference certainty and trust.

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