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On the Influence of Context-Based Complexity on Information Search Patterns: An Individual Perspective

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Although context-based complexity measured as the similarity and conflict across alternatives is dependent on individual preference structures, existing studies investigating the influence of context-based complexity on information search patterns have largely ignored that context-based complexity is user- and preference-dependent. Addressing this research gap, this article elicits the individual preferences of decision makers by using the pairwise-comparison-based preference measurement (PCPM) technique and records individuals' search patterns using eye tracking. Our results show that an increased context-based complexity leads to an increase in information acquisition and the use of a more attribute-wise search pattern. Moreover, the information search pattern changes within a choice task as information is processed attribute-wise in earlier stages of the search process and alternative-wise in later ones. The fact that we do not find an interaction effect of context-based complexity and decision stages on the search patterns indicates that the influence of complexity on search patterns stays constant throughout the decision process and suggests that the more complex the choice task is, the later the switch from attribute-wise strategies to alternative-wise strategies will be.

Keywords: decision behavior, context-based complexity, eyetracking, preference measurement, decision strategies

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Context-Based Complexity and Decision Strategies

When faced with a choice task, decision makers select an alternative from a set of alternatives presented to them. An example of a choice task would be the selection of a product in an online shop or the selection of a specific applicant among a variety of applicants. When choosing among alternatives, decision makers follow a decision strategy, which is defined as a "set of operations used to transform an initial stage of knowledge into a final goal state of knowledge where the decision maker feels the decision problem is solved" (Payne, Bettman, Coupey, & Johnson, 1992, p. 108). Decision makers do not always follow the same decision strategy but rather adaptively select from a repertoire of different decision strategies (Gigerenzer, Hertwig, & Pachur, 2011; Gigerenzer & Selten, 2001; Payne, Bettman, & Johnson, 1993; Riedl, Brandstätter, & Roithmayr, 2008). Decision makers may, for instance, compare alternatives step-by-step in an attribute-wise fashion or they may first completely evaluate one alternative before continuing with the next one. To find out which decision strategies are applied by decision makers, it is therefore helpful to identify such information search patterns.

The choice of the decision strategy used is determined by (a) the decision makers' personal characteristics (e.g., cognitive ability, the decision makers' prior knowledge), (b) the social context (e.g., accountability, group membership), and (c) the characteristics of the problem such as task-based complexity and context-based complexity (Ford, Schmitt, Schechtman, Hults, & Doherty, 1989; Payne et al., 1993). Task-based complexity captures the general aspects of a choice task, such as the amount of information (e.g., number of alternatives or attributes) and the way it is presented. Context-based complexity is user-specific and assesses whether particular attribute levels and their relationship to one another make a choice task difficult for a particular decision maker (Payne et al., 1993; Swait & Adamowicz, 2001).

Prominent examples of variables that are used to measure context-based complexity are the similarity of alternatives and the conflict of alternatives. A conflict occurs when trade-offs force the decision maker to balance one attribute level against another. While there is a huge body of literature concerning the influence of task-based complexity on decision-making behavior (Bettman, Johnson, & Payne, 1991; Conlon, Dellaert, & Soest, 2001; Ford et al., 1989; Payne et al., 1992), mostly stemming from psychological research, there is only limited research about the influence of context-based complexity on the decision process (Böckenholt, Albert, Aschenbrenner, & Schmalhofer, 1991; Fasolo, Hertwig, Huber, & Ludwig, 2009; Luce, Bettman, & Payne, 1997). In contrast to the finding that each decision maker may value the same attribute levels differently (Böckenholt et al., 1991; Keller & Staelin, 1987; Russo & Dosher, 1983; Swait & Adamowicz, 2001), most studies on the influence of context-based complexity on decision processes neglect the existence of individual preference structures and assume that attribute level utilities are equal for different decision makers (notable exceptions are Russo and Dosher [1983]; Böckenholt et al. [1991]; and Luce et al. [1997]). The resulting inaccurate measurement of context-based complexity might also be a reason why most studies did not find an influence of context-based complexity on information search patterns.

This article addresses the fact that context-based complexity is user-specific and studies how the context-based complexity of a choice task affects the decision process of human decision makers. It considers a large number of participants ($N = 60$) and measures the individual context-based complexity of choice tasks using the pairwise-comparison-based preference measurement approach (PCPM; Scholz, Meißner, & Decker, 2010). The decision process of the participants is monitored using eyetracking. The combination of pairwise-comparison-based preference measurement and eyetracking allows us to study how the context-based complexity of choice tasks affects the information search patterns of individuals. Due to the user-specific measurements, we are able to show that an increased context-based complexity leads to a more attribute-wise search; a result which is contrary to existing studies. Furthermore, we use eye fixations to define decision stages and find a switch to alternative-wise search in later stages. We also find that the influence of complexity on the search pattern remains constant throughout the whole decision process.

The remainder of the article is structured as follows: the next section reviews existing measures for quantifying context-based complexity and presents a summary of the most important empirical results. Then, we derive hypotheses regarding the influence of context-based complexity on decision processes, describe the experimental setup, present the results, discuss them, and conclude with final remarks.

Different Measures of Context-Based Complexity

A choice task consists of n alternatives alt_j, $j = 1, \ldots, n$, $n \geq 2$, which are described by *attribute levels* a_{ij}, one for each of the m attributes, $attr_i$, $i = 1, \ldots, m$ (Harte & Koele, 2001; Keeney & Raiffa, 1993). Attribute levels are concrete occurrences of the attributes. As an example, imagine a set of different coffee brewers (alternatives) that are all described by the same set of attributes, such as brand, material, and price. Each coffee brewer is characterized by several attribute levels, for instance, Braun (brand), plastic (material), and €189.99 (price). *Attribute level utilities* $v(a_{ij})$ are user-specific and reflect the degree of attractiveness of the attribute levels for a particular decision maker. The total utility value $u(alt_j)$ of an alternative alt_j can be calculated as the sum of all attribute level utilities, $\sum_i v_i(a_{ij})$.

Relevant measures for context-based complexity of choice tasks are *similarity* and *conflict* among attributes (Fasolo, Hertwig, et al., 2009; Luce et al., 1997; Payne et al., 1993; Swait & Adamowicz, 2001). Similarity captures the degree to which alternatives differ from each other and is typically either operationalized by

• the variety of attribute level utilities per attribute (*attribute range*) (Bettman, Johnson, Luce, & Payne, 1993; Biggs, Bedard, Gaber, & Linsmeier, 1985; Fasolo, Hertwig, et al., 2009; Payne et al., 1993), or

• the difference of the alternatives' total utility values (*attractiveness difference*) (Böckenholt, Albert, Aschenbrenner, & Schmalhofer, 1991; Swait & Adamowicz, 2001).

Conflict arises when an alternative has both advantages and disadvantages compared to other alternatives. Formally, conflict occurs when there are at least two different attributes, $attr_l$, $attr_k$, and two different alternatives alt_p, alt_q, where alt_p is better on $attr_l$ and worse on $attr_k$ than alt_q: $v_l(a_{lp}) > v_l(a_{lq})$ and $v_k(a_{kp}) < v_k(a_{kq})$.

Previous studies that focused on the influence of context-based complexity on decision-making behavior (except Russo and Dosher [1983] and partly Böckenholt et al. [1991] and Luce et al. [1997]) did not measure individual attribute level utilities (Bettman et al., 1993; Biggs et al., 1985; Iglesias-Parro, la Fuente, & Ortega, 2002; Payne, Bettman, & Johnson, 1988). These studies coded attribute levels, for instance, as integer values from 1 (*very poor*) to 10 (*very good*); instead of naming an exact price, such as "price of coffee machine A is €189 and price of machine B is €129", they record "price of coffee machine A is very poor [value 1] and price of B is good [value 8]" (Biggs et al., 1985). This implies that decision makers are assumed to have the same attribute level utilities (i.e., a price of €189 is very poor for all decision makers), which are predetermined by the researchers. This assumption is contradictory to most of the work on decision behavior (Böckenholt et al., 1991; Keller & Staelin, 1987; Russo & Dosher, 1983; Swait & Adamowicz, 2001) and latent class and hierarchical Bayes preference measurement models that capture participant heterogeneity (differences in preferences across decision makers; Johnson & Orme, 2003).

Russo and Dosher (1983) address the problem that decision makers value attribute levels differently by conducting a standard conjoint analysis and estimating individual utility functions with a multiple linear regression. However, they only do this for the first part of their study because of "the time-consuming measurement of individual utility" (Böckenholt et al., 1991, p. 685) and only for six participants. In addition, two of the six participants were removed from the study because their attribute level utilities were nonequal (one of the three attributes had no influence on the user's decision behavior). Two more papers partly address the problem. Böckenholt et al. (1991) use a simplified approach in the second experiment of their paper. They let participants rank-order the attribute levels individually such that they were able to construct alternatives with attribute levels that are perceived to be superior or inferior to other alternatives. Yet, such an ordinal scale does not address the problem of heterogeneous attribute level utilities adequately because it neither considers the distances of attribute levels nor the fact that some attributes might be more important than others. Luce et al. (1997) measure how important attributes are for the participants but do not determine the attribute level utilities.

Similarity

Attribute range (AR) has been operationalized by the average variance of attribute level utilities per attribute. The depth of search describes the amount of information searched by a decision maker; the breadth of search describes the number of different attribute levels considered during the search. Biggs et al. (1985) and Böckenholt et al. (1991) found that low AR (high similarity) leads to an increase of both breadth and depth of search. The same result was found for gambling tasks where the range of the outcome probabilities was manipulated (Bettman et al., 1993; Payne et al., 1988). The effects were even stronger in the cases of high conflict; that is, when the alternatives differ substantially regarding advantages and disadvantages (Bettman et al., 1993). The same studies showed that the lower the AR is, the more consistent the search was: participants spent an evenly distributed amount of time on both attributes and alternatives (Bettman et al., 1993; Payne et al., 1988) and they spent more time making a choice (Bettman et al., 1993; Iglesias-Parro et al., 2002; Payne et al., 1988). Furthermore, participants considered a constant amount of attribute levels per attribute in the cases of low AR and an inconsistent amount in the cases of high AR (Biggs et al., 1985). In a simulation study, Fasolo, Hertwig, et al. (2009) used a measure that is related to AR in terms of the number and distribution of attribute levels. They found that the more the attribute levels differed and the more evenly and dense the distribution of the attribute levels was, the more time was needed to make a decision.

Information search patterns describe whether decision makers acquire the different pieces of information either by alternatives or by attributes. In an alternative-wise search, decision makers examine all the attribute levels of a single alternative before they continue with the next alternative. In an attribute-wise search, decision makers compare several alternatives on a single attribute before they continue with a further attribute. Concerning information search patterns, results are contradictory. Payne et al. (1988) and Bettman et al. (1993) found an increase in alternative-wise search in cases of low AR and an increase in attribute-wise search in cases of higher AR. In contrast, Iglesias-Parro et al. (2002) and Russo and Dosher (1983) did not find any influence of AR.

In summary, most studies suggest that a low AR, indicating high context-based complexity, leads to increased cognitive effort. Results on information search patterns are less clear. While two papers did not find any influence, two others found a more alternative-wise search in cases of high context-based complexity.

Attractiveness difference (AD) has been operationalized by the variance over the total utility values of the alternatives (Böckenholt et al., 1991). Swait and Adamowicz (2001) introduced an entropy measure that additionally takes into account the number of alternatives: the more alternatives and the closer their utility values are, the higher the entropy and thus the choice difficulty is. Böckenholt et al. (1991) also investigated the overall attractiveness of alternatives which reflects whether decision alternatives are very attractive (high utility) or rather unattractive (low utility) to the participants. In Böckenholt et al. (1991), the AD was manipulated by creating choice tasks whose first two attributes had an overall difference of either one level at most, or one level at least (large difference). They found an increased breadth of search both for cases of low AD and low overall attractiveness. Swait and Adamowicz (2001) used a structural modeling approach to measure the influence of entropy on the participants' estimated utility functions (assuming that a utility-maximizing decision strategy is applied). The authors compared the estimated attribute importance in choice tasks (low vs. high entropy) and found that for high entropy, participants tend to focus on only a few attributes and search more inconsistently.

Russo and Dosher (1983) examined whether AD has an influence on information search patterns but could not find any evidence for this.

In line with the results on AR, most studies suggest that the more similar the alternatives within the choice task are with respect to the AD, the more complex the choice task is and the more effort decision makers spend on the decision process. Significant influences of AD on information search patterns have not been found up to now.

Conflict

Typically, conflict has been measured by computing the mean pairwise correlation coefficient of attribute vectors (Fasolo, Carmeci, and Misuraca, 2009; Luce et al., 1997), where the attribute vector of $attr_l$ is defined as: $attr_l = (v_l(a_{l1}), v_l(a_{l2}), \ldots, v_l(a_{ln}))$. When attribute vectors are correlated positively, one alternative tends to be better than the other alternatives on most attributes. Thus, the higher the correlation between attribute vectors is, the lower the conflict is and the less complex the choice task is.

The correlation of attribute vectors influences the depth and consistency of search. Bettman et al. (1993) and Luce et al. (1997) observed an increased depth of search and Bettman et al. (1993) found more consistent search with negative correlations. Iglesias-Parro et al. (2002) found that decision makers spend more time on the decision when correlations were negative.

Luce et al. (1997) and Iglesias-Parro et al. (2002) examined the information search patterns of participants but did not find an effect of conflict on information search patterns. However, in a further analysis, Luce et al. (1997) observed that participants started with an attribute-wise search and later switched to an alternative-wise search. Different findings were presented by Bettman et al. (1993) and Fasolo, Misuaraca, and McClelland (2003) who observed alternative-wise information acquisition in the context of negative correlations.

In summary, the results suggest that the bigger the conflict is, the more complex the choice task is and the more effort decision makers spend. The influence of conflict on the information search pattern is still unclear. Researchers either found no consistent influence or they found a more alternative-wise search, when the task was more complex.

Synthesis

The earlier review of previous findings suggests that decision makers acquire more information, spend more time on the choice task, and search more consistently when both similarity and conflict among alternatives are high (Bettman et al., 1993; Biggs et al., 1985; Böckenholt et al., 1991; Payne et al., 1988). The effect on the information search pattern, whether the search is more alternative-wise or attribute-wise, is unclear because little evidence was found (Bettman et al., 1993; Biggs et al., 1985; Iglesias-Parro et al., 2002; Luce et al., 1997; Payne et al., 1988). Table 1 summarizes the reviewed studies. It also shows which process tracing method was used to record the decision process. The mouse-tracking technique (most often called Mouselab) is the predominant method used in these studies.[1]

In all the studies mentioned, the attribute level utilities were not measured on an individual level. This is crucial because participants may value attribute levels differently (Böckenholt et al., 1991). We therefore argue that, unless the attribute level utilities are accurately measured, the context-based complexity cannot be precisely determined.

Only Russo and Dosher (1983) considered individual attribute level utilities when investigating the influence of context-based complexity on decision processes. They observed that the search pattern was independent from the context-based complexity. However, the meaning of this observation is very limited as only four subjects were examined and there was a large variation in the time the four individuals followed either a more attribute-wise or a more alternative-wise processing. In addition, these four subjects had similar preference structures since two other individuals who weighted the attributes differently were excluded from the study.

Against the background of this research deficit, the aim of the present study is to more solidly investigate the influence of context-based complexity on information search patterns by measuring preference structures on the individual level. We argue that the missing and partly contradictory results concerning search patterns found in previous studies might have been caused by the inaccurate measurement of context-based complexity.

[1] A Mouselab software keeps track of information acquisition, response time, and choices by recording mouse movements in a product-comparison matrix on a computer screen (Bettman, Johnson, & Payne, 1990). All attribute levels are hidden behind boxes. Only by clicking or moving the cursor on each box can the participant retrieve the attribute level information.

Table 1
Summary of Literature Review

Study	Methods	Measures	Result
Bettman et al. (1993)	ML	AR, CO	Increase of the decision time & depth of search & consistency & more alternative-wise search with increase of the CO and decrease of the AR
Biggs et al. (1985)	ID, VP	AR	Increase of the depth of search & consistency with decrease of the AR
Böckenholt et al. (1991)	ML	AR, AD	Increase of the breadth of search with decrease of the AD and the AR
Fasolo et al. (2003)	ML	CO	More alternative-wise search with increase of the CO
Fasolo, Hertwig, et al. (2009)	SIM	AR	Increase of the decision time with decrease of the AR
Iglesias-Parro et al. (2002)	ML	AR, CO	Increase of the decision time with increase of the CO and decrease of the AR, no influence on search pattern
Luce et al. (1997)	ML	CO	Increase of the decision time & depth of search with increase of the CO, no influence on search pattern, only more attribute-wise in case of CO on most important attribute
Payne et al. (1988)	AR	ML	Increase of the decision time & depth of search & consistency & more alternative-wise search with decrease of the AR
Russo & Dosher (1983)	ET, VP	AR, AD	No influence found on search pattern
Swait & Adamowicz (2001)	SMO	AD	Decrease of the consistency with increase of the AD (decrease of the entropy)

Note. AR = attribute range; AD = attractiveness difference; CO = conflict; ML = Mouselab; VP = verbal protocols; ID = information display board; ET = eye tracking; SIM = simulation study; SMO = structural modeling.

Theory and Hypotheses

How does context-based complexity influence decision processes? Most studies were not able to find any influence on the search pattern (Iglesias-Parro et al., 2002; Luce et al., 1997; Russo & Dosher, 1983), and some found a more alternative-wise search with increasing context-based complexity (Bettman et al., 1993; Fasolo et al., 2003; Payne et al., 1988). However, many studies find that decision makers search for more information when context-based complexity is high (Biggs et al., 1985; Böckenholt et al., 1991; Iglesias-Parro et al., 2002; Luce et al., 1997) and that they need more time for the decision (Bettman et al., 1993; Iglesias-Parro et al., 2002; Payne et al., 1988).

We predict that high complexity implies not only that decision makers search for more information and need more time, but also that they acquire information using a more attribute-wise information acquisition process. In agreement with Russo and Dosher (1983) and Tversky (1969), we argue that excluding alternatives is less demanding if alternatives are compared attribute-wise rather than alternative-wise. That is because it is cognitively easier to find out whether one specific alternative performs low on an attribute (e.g., exclusion of an alternative because of a very high price compared with other alternatives) than excluding an alternative based on low performance on several attributes.

As a consequence, we expect decision makers to process information more attribute-wise the more complex the choice task is because they reduce complexity by excluding alternatives using a more attribute-wise search.

> *Hypothesis 1:* The higher the context-based complexity is, the more decision makers will be prone to searching attribute-wise.
>
> *Hypothesis 2:* The higher the context-based complexity is, the more information decision makers will search for.
>
> *Hypothesis 3:* The higher the context-based complexity is, the more time decision makers will need in order to make the decision.

To better understand the influence of context-based complexity, the analysis can be extended with respect to decision stages as proposed by

Russo and Leclerc (1994). In the earlier stages (the screening phase) decision makers try to reduce choice task complexity by excluding alternatives. In later stages (the in-depth comparison phase), they put more effort into comparing the remaining alternatives (Olshavsky, 1979; Payne, 1976; Payne et al., 1988; Reisen, Hoffrage, & Mast, 2008; Svenson, 1979). While in earlier stages, decision makers may use simplifying decision strategies and focus only on a few attributes, in the later stages they may consider the choice task in more detail, thereby using more effortful strategies (Bettman & Park, 1980; Gilbride & Allenby, 2004, 2006; Luce et al., 1997; Payne, 1976; Reisen et al., 2008).

The most prominent decision strategies that exclude alternatives are the elimination-by-aspects (EBA), lexicographic, and conjunctive strategies. The deterministic variant of the EBA strategy starts by eliminating alternatives that do not meet the aspiration level of the most important attribute. The elimination process then proceeds with the second most important attribute and stops when there is only one alternative left (Tversky, 1972). The lexicographic strategy (LEX) chooses the alternative which is best in terms of the most important attribute. In the case of a tied decision, LEX proceeds with the second most important attribute, and so forth The conjunctive strategy (CON) excludes each alternative that violates an aspiration level at least once (Coombs & Kao, 1955). Thus, CON compares the alternatives alternative-wise.

Studies examining the use of decision strategies in various stages of a decision process present mixed results. Some researchers have hypothesized that decision makers use EBA or CON in earlier stages, but empirical evidence for favoring one or the other strategy is mixed (Gilbride & Allenby, 2006; Payne, 1976). Bettman and Park (1980) provide evidence that decision makers usually start with a more attribute-wise rather than a more alternative-wise search. Based on the previous findings we assume that information acquisition changes from a more attribute-wise to a more alternative-wise search at a later decision stage. The fact that decision makers switch from a more attribute-wise search to a more alternative-wise search would indicate a shift in strategies. Following other studies (Gilbride & Allenby, 2006; Luce et al., 1997), we hypothesize that decision makers first exclude alternatives to reduce complexity and then compare the remaining alternatives in detail using an alternative-wise process. This gives rise to our next two hypotheses.

> *Hypothesis 4:* Decision makers first search attribute-wise and then they switch to alternative-wise search.

> *Hypothesis 5:* Decision makers exclude alternatives from further consideration during a choice task. As a consequence, they consider fewer alternatives, the later they are in the decision process.

The question remains whether a decision maker changes his or her decision strategy during the task based on the context-based complexity of the task. Russo and Leclerc (1994) argue that there are three different stages: orientation, evaluation and verification. During the orientation stage, decision makers gain an overview of the product set and might start excluding alternatives, while in the evaluation stage they compare different products in more detail, exclude products and make their final choice. Finally, in the verification stage, they try to validate their choice.

If decision makers' reactions to context-based complexity were different in different stages of the decision process, we would expect that in cases of high context-based complexity, decision makers compare alternatives attribute-wise particularly during the orientation and evaluation stage. The underlying reason is that a decision maker might perceive the complexity to be particularly high in earlier stages of the decision process and might perceive a decrease in complexity the longer she has been involved in the same choice task. More specifically, in the orientation stage, processing new information requires a great amount of cognitive activity. Following this, the decision maker can reduce complexity by excluding alternatives during the evaluation phase. Once the exclusion of inferior alternatives is completed and the decision maker has finally chosen an alternative, one could argue that decision makers would generally execute a comparable alternative-wise search pattern - independently from the overall context-based complexity of the choice task. This alternative-wise processing would indicate that people evaluate the alternatives holistically in the final stage of the decision process, independently from the context-based complexity. This holistic evaluation might include a verification process that reconsiders the information of the chosen alternative.

Therefore, we tested whether context-based complexity influences decision makers differently in different stages and formulated the following interaction hypotheses concerning the effect of complexity and stages on the search pattern:

> *Hypothesis 6:* There is an interaction effect of decision stage and complexity on search pattern. The influence of complexity on the search pattern is stronger at the beginning than at the end of the decision process.

Method

Operationalization

For analyzing the main dependent variable in our study, the search pattern, there have been two approaches presented in literature. First, the search index (*SI*; Payne, 1976) measures whether the search pattern in a choice task is more alternative-wise or more attribute-wise by putting the number r_{alt} of alternative-wise transitions in relation to the number r_{attr} of attribute-wise transitions. It varies from -1 to $+1$, with -1 indicating a completely attribute-wise search (only attribute-wise transitions) and $+1$ indicating a completely alternative-wise search

$$SI = \frac{r_{alt} - r_{attr}}{r_{alt} + r_{attr}}. \tag{1}$$

The *SI* has been criticized by Böckenholt and Hynan (1994), who showed that it is biased toward alternative-wise search if the number of attributes exceeds the number of alternatives (and vice versa). To overcome this bias, they proposed a strategy measure (*SM*), which is defined as

$$SM = \frac{\sqrt{N}\left(\left(n \cdot \frac{m}{N}\right)(r_{alt} - r_{attr}) - (m - n)\right)}{\sqrt{n^2(m-1) + m^2(n-1)}}, \tag{2}$$

where n denotes the number of alternatives, m the number of attributes, and N the number of transitions. Because *SM* is *not* constrained to lie between -1 and $+1$, its interpretation is more difficult. In general, $SM < 0$ indicates a more attribute-wise search, while $SM > 0$ indicates a more alternative-wise search. Thus, a higher *SM* value indicates a more alternative-wise search. Because *SM* can be calculated separately for each stage of a decision process, this measure can be used to indicate a possible shift from a more attribute-wise search in the beginning to a more alternative-wise search at the end of the decision process. Because the number of attributes exceeds the number of alternatives in our study, the *SM* measure is more appropriate than the *SI* measure. The *SM* index has been used in a multitude of studies until recently (see, e.g., Horstmann, Ahlgrimm, & Glöckner [2009]; Pachur, Hertwig, Gigerenzer, & Brandstätter [2013]) and is "the preferred index at the moment" (Schulte-Mecklenbeck, Kühberger, & Ranyard, 2011, p. 736) for quantifying information search behavior.

Hypothesis 1 states that if context-based complexity increases, decision makers acquire information more attribute-wise (the *SM* decreases). We operationalize the complexity of choice tasks using similarity (attribute range and attractiveness difference) and conflict, which are both user-specific and depend on the attribute level utilities of each participant.

Attribute level utilities can be measured using compositional approaches that are based on the direct self-report of participants' preferences concerning all attribute levels of an alternative. Rating scales are typically used to evaluate the desirability of attribute levels. However, compositional approaches, especially self-explicated approaches, have problems eliciting meaningful utilities as they do not capture well the trade-offs between attributes (von Nitzsch & Weber, 1993). Thus, in this study we use an improved compositional approach called PCPM (Scholz et al., 2010), which addresses these deficits and allows for a better handling of inconsistencies in preference judgments. We applied PCPM at the end of the experiment. Participants had to answer pairwise comparison questions and the utilities were then calculated as described in Scholz et al. (2010).

We measure the *attribute range* of a choice task *ct* with the mean sample standard deviation (*SD*) of all attribute level utilities over all attribute vectors as

$$AR(ct) = \frac{1}{m}\sum_{i=1}^{m}\sqrt{\frac{1}{n-1}\sum_{j=1}^{n}(v(a_{ij}) - \bar{v}_i)^2}, \tag{3}$$

where $\bar{v}_i$ is the average of all attribute level utilities of attribute i.

For *attractiveness difference*, we use two measures. AD_{sd} is the sample *SD* of the total utility values of alternatives in a choice task *ct* (Böckenholt et al., 1991)

$$AD_{sd}(ct) = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}(u(alt_j) - \bar{u})^2}, \quad (4)$$

where $\bar{u}$ is the average total utility value of all alternatives in a choice task. Second, AD_{en}, measures the entropy of a choice task (Swait & Adamowicz, 2001) as

$$AD_{en}(ct) = -\sum_{j=1}^{n}\pi(alt_j)\log\pi(alt_j), \quad (5)$$

where $\pi(alt_j)$ is the probability that alternative *j* is chosen. The choice probability $\pi(alt_j) = \frac{u(alt_j)}{\sum_{alt_l \in ct} u(alt_l)}$ of an alternative *j* is the ratio of the total utility value $u(alt_j)$ of that alternative and the total utility values of all alternatives included in a choice task.

We measure conflict (*CO*) in a choice task by the *correlation of attribute vectors* (Luce et al., 1997) as

$$CO(ct) = \frac{m(m-1)}{2}\sum_{\forall i,l;i\neq l;attr_i,attr_l \in AV} CORR(attr_i, attr_l), \quad (6)$$

where AV is the set of the *m* attribute vectors, $attr_l = (a_{11}, a_{12}, \ldots, a_{1n}), \ldots, attr_m = (a_{m1}, a_{m2}, \ldots, a_{mn})$ and CORR stands for the Pearson correlation.

Hypothesis 2 states that if context-based complexity increases (higher similarity, higher conflict), decision makers will search for more information while Hypothesis 3 states an increased decision time. We use two measures to quantify the amount of information acquired: the total number of eye fixations (depth of search) and the number of different attribute levels that were fixated at least once (breadth of search). Decision time is measured in milliseconds.

Hypothesis 4 states that decision makers switch from an attribute-wise search to an alternative-wise search. To distinguish between earlier and later stages of the decision process, the stream of eye fixations within a choice task can be separated into different stages. Although we do not know when a specific participant switches from one stage to the next, we can assume that in all cases attribute-wise processing is more prevalent in earlier stages than in later ones.

We use two different methods to determine the stages: *fixed-length* (Luce et al., 1997) and *refixation* (Russo & Leclerc, 1994).[2] In the fixed-length approach, we take the total number of eye fixations for each participant and split them into a constant number of stages of equal size. Because changing the number of stages to two, three, four, or five yields similar results and most researchers assume three stages (Gidlöf et al., 2013; Russo & Leclerc, 1994), we only report results for three stages. In the refixation stage, we subdivide the decision process into three stages as suggested by Russo and Leclerc (1994). They assumed that the first stage starts with the first product fixation, the second with the first refixation on a product, and the third with the announcement of the choice decision. We slightly adapted this approach by considering fixations on attribute levels rather than fixations on products and we also had to take into account that participants did not verbally express their choice decision. Thus, in our refixation approach, the first stage starts with the first fixation on an attribute level, the second starts with the first refixation on an attribute level, and the third stage starts with the last refixation on any attribute level. The last refixation terminates the evaluation process because the participant does not return to any of the previously observed attribute levels of the choice task. Furthermore, in order to obtain a sufficient number of observations to calculate *SM*, we follow the advice by Böckenholt and Hynan (1994) and exclude all decision processes where the stages contain less than five eye fixations for both the fixed-length (9% of the choice tasks) as well as for the refixation approach (55%).[3]

Hypothesis 5 states that decision makers exclude alternatives during a choice task. As a consequence, they should consider fewer alternatives in the last stages of the choice tasks than

[2] Recently, Gidlöf, Walling, Dewhurst, and Holmqvist (2013) proposed an alternative to the definition by Russo and Leclerc (1994), but their definition of stages is conceptualized for when mobile eyetracking systems are used in an in-store environment.

[3] The results are similar when including all fixations in the analysis, for details see Appendix.

in the early stages. To test this hypothesis, we compare the number of alternatives with at least one eye fixation for the different stages of the decision process.

Finally, Hypothesis 6 states that decision makers are more influenced by complexity in the earlier stages of the decision process than in the later ones. We test this hypothesis by examining whether the difference in *SM* measured at earlier and later stages depends on the context-based complexity.

Participants

A total of 110 participants took part in an experiment (70 women, 40 men). Of these Participants 50 were excluded from the analysis because of calibration problems or incomplete fixation data. This leaves a total of 60 for further analysis. The participants were asked to choose a single-cup coffee brewer from a set of alternatives. Eighty-five percent of the participants consumed 1–3 cups of coffee per day, and 15% consumed even more, indicating that participants had a high product experience with the product category.

Design and Procedure

In a prestudy with 20 participants, we used the direct dual questioning method (Myers & Alpert, 1968) to determine the six most relevant attributes. We found the attributes shown in Table 2 to be the most important ones.

We created choice tasks using the complete enumeration technique as implemented in the Sawtooth Software (2013). This way we could also estimate utility values by using choice-based conjoint (CBC) analysis. Because we found very similar results with CBC and PCPM, we only present results of the compositional PCPM approach in the following section. Each choice task consisted of three alternatives and six attributes (plus a no-choice alternative). All in all, each participant responded to 18 choice tasks (Figure 1). The first part consisted of four warm-up tasks. The second part, the core of the experiment, confronted participants with 14 choice tasks (two blocks of six randomly generated choice tasks and another two holdout choice tasks), which were used in our analysis. In the third part, preference measurement with PCPM was carried out. Participants had to compare the six attributes in 12 pairwise comparisons (according to a two-cyclic design) and attribute levels in another 25 pairwise comparisons (Scholz et al., 2010).

Eye Tracking

To record participants' eye movements we used the SMI EyeLink II System, which features two monitors—one for the participant and one for the experimenter. Participants wore a light helmet with two fixed minicameras that recorded their eye movements. Four infrared sensors (installed on the participant's monitor) were used to adjust to changes in the seating positions of the participants.

The screen (see Figure 2 for an example) was divided according to a grid structure, consisting of 35 cells with different pieces of information, such as the instruction (cell 1), the names of alternatives (cells 2–5), the attributes (cells 6–11), the attribute level cells (12–29), the no-choice option (cell 30) and the buttons to choose one alternative or to proceed to the next screen (cells 31–35). The eye-tracking system monitors the participants' eye movements and records all eye fixations. A participant fixates one cell if he focuses his eyes for at least 50 ms on this cell. The participants' eye fixations were uniquely assigned to one of the 35 cells. The

Table 2
Attributes and Attribute Levels of the Choice Tasks

Attribute	Level 1	Level 2	Level 3	Level 4
Price	€ 99.99	€ 129.99	€ 159.99	€ 189.99
Brand	Braun	Krups	Philips	Severin
Material	Stainless steel	Plastic	Brushed aluminium	
Design	Design A	Design B	Design C	Design D
System	Pad	Capsule		
Price per cup	€ 0.12	€ 0.22	€ 0.32	

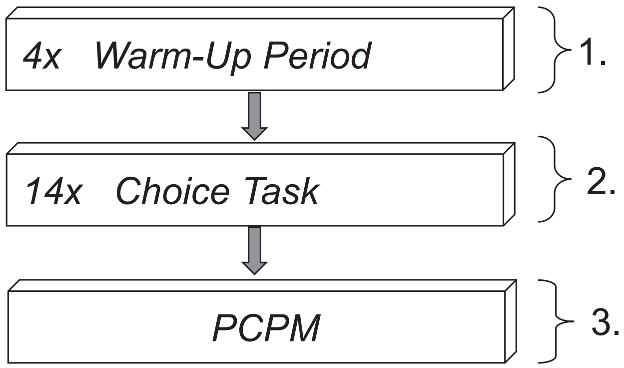

Figure 1. Experimental procedure.

cells 12 to 29 of each choice task displayed the attribute levels and were used for the analysis of participants' eye tracking patterns (excluding the warm-up tasks). Fixations in one of the other cells were not considered, because they had no influence on the SM. Thus, if we observed a transition on the cells 12–6–8–14, the two fixations on the cells 6 and 8 would not be included in the analysis and we would count only the 12–14 transition as an alternative-wise transition.

Results

Of the 18 cells representing attribute levels (Figure 2), participants fixated on average on 13.94 (SD = 3.01) cells at least once. The average number of fixations in a choice task decreased from 55.28 (SD = 29.56) in the first to 32.74 (17.19) in the last choice task. Results indicate that participants became acquainted with the choice tasks since the mean decision time decreased from 18.82 s (SD = 14.93) in the first choice task to 11.15 s (SD = 5.93) in the last one. Analogously, there was a decrease in the relative number of fixations outside the matrix (i.e., cells below 12 and above 29 in Figure 2), the more tasks had been completed ($r = -.292$, $p < .01$). Apparently, participants learned about the decision environment (cells 12–29) and avoided unnecessary fixations outside of the choice matrix (Orquin, Bagger, & Mueller Loose, 2013). Furthermore, we found that participants' attention to the price attributes (price per cup and price for the machine) increased toward the end of the choice tasks, whereas the attention to the brand attribute decreased (for details, see Meißner & Decker, 2010; Meißner, Decker, & Scholz, 2011).

Hypothesis 1 states that if context-based complexity increases, decision makers will search more by attributes. Context-based complexity is high if (a) the attribute range is low (low AR), (b) the attractiveness difference is low (low AD_{sd} and high AD_{en}) and (c) conflict is high (low CO). Because a negative value of the SM index indicates searching by attributes, Hypothesis 1 postulates a positive relationship for AR, AD_{sd}, and CO and the SM index, and a negative relationship for AD_{en}.

To take into account the heterogeneity of participants, we test Hypothesis 1 with random-effect estimators (GLS regression).[4] Hypothesis 1 is supported for all four complexity measures because all regression coefficients are significant in the predicted direction (see Table 3 for results). Our results confirm that decision makers search more attribute-wise when context-based complexity increases, but more alternative-wise when complexity decreases.

Hypothesis 2 states that if context-based complexity increases, decision makers will search for more information, and Hypothesis 3 states that they will also need more time to complete the choice task. Hypotheses 2 and 3 thus predict a negative regression coefficient of the context-based complexity for depth of

[4] Hausman tests indicate that the random-effects specification is appropriate. Therefore we did not use fixed-effect regressions. Furthermore, our results are robust to correcting the standard errors for heteroskedasticity (Greene, 2000).

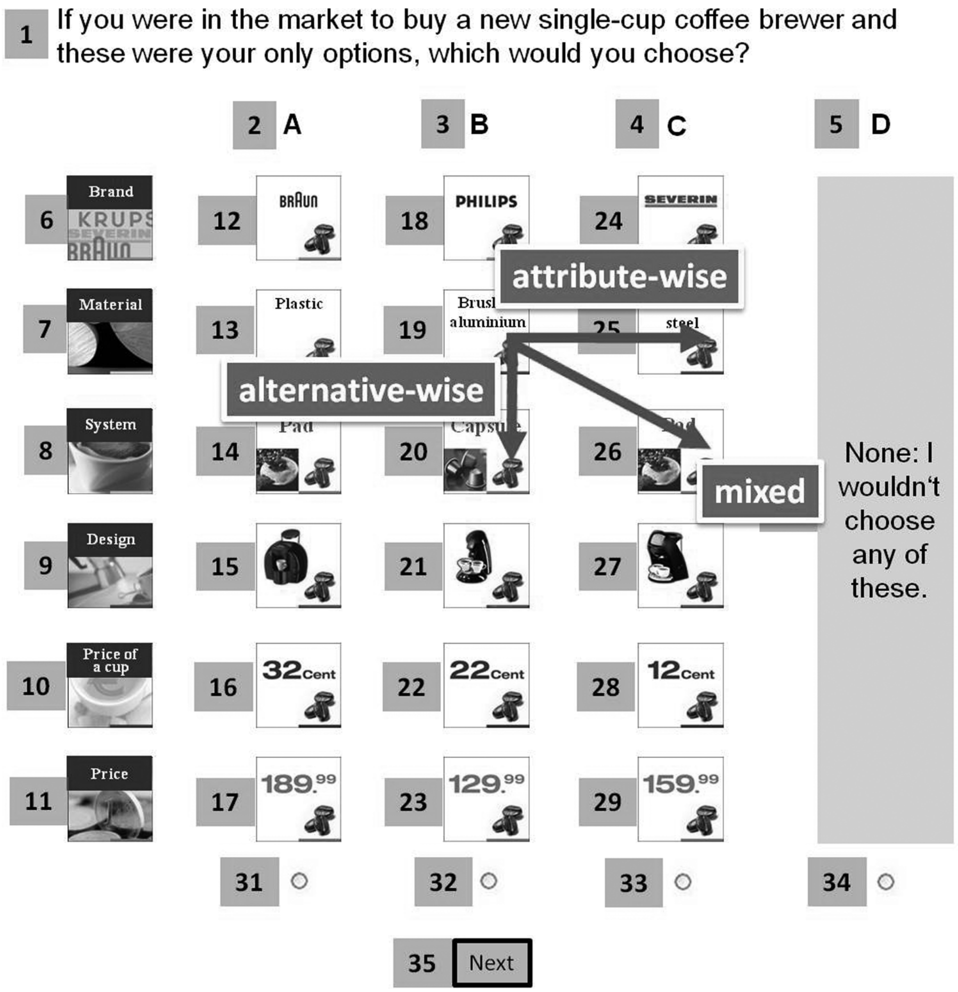

Figure 2. Example of a choice task. The labeling of the cells (1–35) was not visible for the decision maker. Only cells 12 to 29 were used to calculate search patterns.

search, breadth of search and decision time, respectively. For AD_{en}, we expect a positive coefficient for these factors. Using a random-effect regression, we found significant coefficients in the predicted directions for all measures except *AR* (Table 4).

Hypothesis 4 states that decision makers switch from an attribute-wise search to an alternative-wise search in a choice task. To test this hypothesis, for each participant and for each choice task we divided the number of fixations into three stages using the two methods described above (fixed-length and refixation) and calculated the average *SM* index for each participant and each stage. If Hypothesis 4 were correct, the mean *SM* index would be negative in the first stage(s) of the decision process but positive in the last stage(s). Our results with a *t*-test confirm this result. Indeed, in the first stage both for fixed-length and refixation, the mean *SM* per participant is negative, and in the last stage, the mean *SM* is positive (all $p < .01$). Furthermore, with a repeated-measure analysis of variance (ANOVA), we see that the *SM* changes during the decision process both for the fixed-length, $F(2, 118) = 77.308$, $p < .01$, and the refixation, $F(2, 116) = 40.277$, $p < .01$, analysis (Table 5). The results are

Table 3
Results for Hypothesis 1: Estimated Regression Coefficients for the Influence of Complexity on the Strategy Measure (SM) Index

	SM		
Complexity	β	*SE*	*p*
AR	.85	.27	<.01
AD_{sd}	.13	.05	<.05
AD_{en}	−.90	.25	<.01
CO	.97	.30	<.01

Note. AR = attribute range; AD_{sd} = attractiveness difference (SD); AD_{en} = attractiveness difference (entropy); CO = conflict.

similar when including observations with less than five fixations per stage in the analysis and can be found in the Appendix in Table A1.

Hypothesis 5 states that decision makers exclude alternatives during a choice task. As a consequence, they are expected to consider fewer alternatives in the later stages of the decision process. To test Hypothesis 5, we calculated the number of alternatives that were fixated at least once for each participant for each stage. If Hypothesis 5 were correct, this number would decline. Table 6 shows that our results support the hypothesis. Indeed, the mean number of alternatives that were fixated by each participant is smaller in the last stage of the task than in the first one $p < .01$ using a post hoc analysis with Bonferroni correction). It is interesting that with the refixation method, the number of alternatives considered in the second stage is larger than in the first and third stage. One reason might be that the second stage has considerably more fixations (*mean(M)* = 22.38, *SD* = 16.62) than Stage 1 (*M* = 6.41, *SD* = 2.66) and Stage 3 (*M* = 6.04, *SD* = 2.12).

Table 5
Strategy Measure (SM) for the Three Stages

M (*SD*)				
Stage 1	Stage 2	Stage 3	*F*	*p*
Fixed-length				
−.61 (1.09)	−.11 (.87)	.56 (.77)	77.308	<.01
Refixation				
−.44 (.96)	−.04 (1.50)	.45 (.68)	40.277	<.01

Supposedly, participants refixate attribute levels early.

With Hypothesis 6, we answer the question whether a decision maker's switch to a different decision strategy during a choice task depends on context-based complexity. To do this, we test whether there is an interaction effect that would result in a larger influence of context-based complexity at the beginning of the search process than at the end. In particular, we investigate whether the increase from attribute-wise to alternative-wise processing is higher in choice tasks of high complexity than in choice tasks of low complexity. Thus, we subtract the *SM* from earlier stages from the *SM* of later stages (indeed, we calculate the *SM* differences for Stage 3 vs. Stage 2, Stage 2 vs. Stage 1, and Stage 3 vs. Stage 1) and regress complexity on these new variables, using a random-effects estimator. Hypothesis 6 predicts a negative regression coefficient for the complexity measures (for AD_{en}, we expect a positive coefficient). The results do not support the hypothesis (Table 7) and indicate that the influence of complexity stays constant throughout the decision process (an analysis for the refixation approach when including observations with less than five fixations per stage in the analysis can be found in the Appendix in Table A2).

Table 4
Results for Hypotheses 2 and 3: Estimated Regression Coefficients for the Influence of Complexity on the Breadth and Depth of Search as Well as the Decision Time Needed for Each Choice Task in Milliseconds

	Breadth of search			Depth of search			Decision time		
Complexity	β	*SE*	*p*	β	*SE*	*p*	β	*SE*	*p*
AR	−.69	.38	.07	−2.70	2.07	.19	79.83	959.70	.93
AD_{sd}	−.33	.07	<.01	−1.69	.39	<.01	−533.59	173.22	<.01
AD_{en}	1.21	.34	<.01	4.94	1.84	<.01	1,619.66	817.10	<.05
CO	−2.50	.41	<.01	−1.31	2.18	<.01	−3,665.20	966.38	<.01

Note. AR = attribute range; AD_{sd} = attractiveness difference (SD); AD_{en} = attractiveness difference (entropy); CO = conflict.

Table 6
Number of Alternatives With at Least One Fixation for the Three Stages

M (SD)				
Stage 1	Stage 2	Stage 3	F	p
Fixed-length				
2.88 (.13)	2.75 (.20)	2.64 (.21)	42.135	<.01
Refixation				
2.43 (.24)	2.74 (.28)	2.21 (.24)	78.411	<.01

Discussion and Conclusions

In our literature review, we found contradicting results concerning the influence of context-based complexity on information search patterns (Bettman et al., 1993; Biggs et al., 1985; Iglesias-Parro et al., 2002; Luce et al., 1997; Payne et al., 1988). We argued that this might be because most previous studies had not measured context-based complexity on the individual level. The majority of research works have either neglected the existence of individual preference structures or used very restrictive assumptions concerning the attribute level utilities. It thus appears that unless the attribute level utilities are measured accurately, the context-based measurement cannot be precisely determined.

The current study used PCPM to measure attribute level utilities for each individual decision maker. Based on individual preferences, context-based complexity was quantified via four different measures, namely (a) the variation *AR* of attribute level utilities, (b) the *SD* AD_{sd} of the total utility values of the alternatives, (c) the entropy AD_{en} of the choice task, and (d) the average correlation *CO* of attribute vectors.

Eye tracking was used to monitor how decision makers search for information. To characterize the search pattern, we used the well-established *SM* index, which describes the search pattern as being either more attribute-wise or more alternative-wise. Furthermore, we measured the depth and breadth of search as well as the time participants needed for each choice task.

We conjectured that the search pattern changes within choice tasks. This behavior indicates a switch between decision strategies. At the beginning, decision makers tend to acquire information by using an attribute-wise process, whereas as time goes by, they search for information using an alternative-wise process. When we divided the entire decision process of each choice task into three stages, the *SM* index rose from −.61 to −0.11 to .56, which strongly supports this hypothesis. This result is robust for different methods of determining stages and also for allowing a different number of stages (2, 3, 4, and 5 stages) For the fixed-length definition of stages, we observed a monotonic decrease of considered alternatives. When the refixation approach was used, results were less clear since the second stage is much longer than

Table 7
Hypothesis 6: Estimated Regression Coefficients for the Influence of Complexity on the Increase of Strategy Measure (SM) Over Stages to Test the Interaction Effect

	SM:3–1			SM:2–1			SM:3–2		
Complexity	β	SE	p	β	SE	p	β	SE	p
Fixed-length									
AR	.12	.32	.71	.11	.27	.70	.02	.28	.94
AD_{sd}	.00	.08	.98	−.04	.07	.56	.04	.08	.60
AD_{en}	−.01	.34	.97	−.02	.31	.96	.00	.32	1.00
CO	.19	.44	.68	−.19	.40	.64	.37	.42	.37
Refixation									
AR	.25	.38	.52	.19	.44	.67	.03	.47	.95
AD_{sd}	.10	.10	.31	.18	.10	.09	−.07	.11	.51
AD_{en}	−.16	.43	.71	.12	.45	.80	−.23	.50	.64
CO	.20	.55	.72	.32	.56	.57	−.17	.64	.79

Note. AR = attribute range; AD_{sd} = attractiveness difference (SD); AD_{en} = attractiveness difference (entropy); CO = conflict.

the other two stages. Indeed, it covers the entire evaluation process, which is the main part of the decision process. Therefore, the exclusion of alternatives presumably happens during this evaluation process. As a consequence, when using the refixation definition of stages, a finer division of the evaluation stage would be necessary to be able to observe when people exactly start excluding alternatives.

Besides the change in the information acquisition process within choice tasks, we proposed an influence of context-based complexity on the used search pattern. We showed two interesting relationships: First, with increasing context-based complexity, the search pattern is more attribute-wise. Second, with increasing complexity, decision makers increase the depth and breadth of search as well as the time they spend on the choice task. This finding is valid for three of the four measures of context-based complexity.

In sum, we suggest that decision makers start by using decision strategies with a more attribute-wise information search to compare alternatives, such as LEX or EBA. They use these strategies to determine which alternative(s) they can exclude from further consideration. They then focus on the remaining alternatives and compare them by using more alternative-wise patterns. Furthermore, according to our findings (a) with increasing complexity, decision makers search information more attribute-wise (Hypothesis 3); (b) decision makers switch from attribute-wise to alternative-wise search (Hypothesis 1); (c) there is no interaction effect for complexity and stages (Hypothesis 6), we can conclude that decision makers switch later from attribute-wise to alternative-wise processing, the higher the context-based complexity is.

Because the task-based complexity, that is, the number of attributes and alternatives that are relevant to the decision situation, was held constant in the current study, the effects found in our study can presumably be attributed to the context-based complexity. One limitation of this work is that we did not control for other variables that might moderate this effect, for example the individual's tendency to maximize her utility, the individual's cognitive capacity or fatigue that could emerge during the 14 choice tasks.

A second limitation is that the saliency of the images shown in the choice task might have influenced the attention process of participants. Participants might have fixated more often on attributes with interesting icons (design or brand). While the saliency of icons does not affect the context-based complexity, it might have influenced the search pattern. In the Appendix, we added several analyses that test for saliency-effects. Our results indicate that saliency did not have a substantial effect in our study. If saliency had been important, we should have observed a high concordance of the fixation patterns within as well as between respondents. The most robust common pattern that we found is that respondents process information top-down which corresponds to the natural reading behavior of our respondents in Germany. Nevertheless, in line with Orquin and Mueller Loose (2013), we suggest that future research should investigate the saliency-effects in more detail.

Our findings contribute to forecasting how individuals will react to changes in context-based complexity. If, for example, marketing practitioners introduce new consumer goods into a market, they can predict how this will change the context-based complexity in this market and, consequently, the decision processes of potential consumers (Swait & Adamowicz, 2001). Moreover, marketing practitioners should be aware of the fact that in today's competitive markets the similarity of products has largely increased. According to our results, this leads to more direct comparisons between the firm's and the competitors' products resulting from an attribute-wise search pattern. One way of avoiding direct comparisons would be to emphasize unique product features to decrease the perceived similarity of products.

Furthermore, our findings have direct practical implications for marketing researchers using conjoint-analytic preference measurement techniques. Recently developed approaches, like the Adaptive Choice-based Conjoint (ACBC; Sawtooth Software, 2014) approach are based on an adaptive algorithm that constructs choice tasks from respondents' previous answers. A characteristic of this algorithm is that respondents have to decide between previously favored alternatives in later choice tasks. This so-called "tournament selection" will result in choice tasks with a higher context-based complexity at the end of the survey. Marketing researchers using the aforementioned technique should be aware that at the end of an ACBC survey information may be processed differently and therefore the outcome of the respective utility estimation might be affected.

Our results also contribute to the body of research which combines results from preference measurement approaches and process tracing approaches. While the relative importance of an attribute is difficult to determine in a process-tracing model, preference measurement approaches can provide this information. It has been emphasized by Louviere, Pihlenss, and Carson (2011) that more research is needed to test the effects of different levels of complexity in discrete choices. This article contributes to this research question because it shows how individuals change their information acquisition behavior. Consequently, the next step is to take context-based complexity into account when designing choice tasks for preference measurement purposes (Danthurebandara, Yu, & Vandebroek, 2011).

As Ball (1997) pointed out: "The search sequence or transitions that a decision maker uses when searching a matrix of decision information can provide important clues to the strategy guiding the processing of decision information" (p. 195). Therefore, in future analyses, the relationship between the information acquisition process and concrete decision strategies such as weighted-additive, EBA, or LEX strategies should be analyzed. Because our work supports previous findings that the information acquisition process consists of several stages, researchers should consider explaining choices with possible sequences of decision strategies used. Gilbride and Allenby (2006) recently proposed such a method.

The advantage of measuring information acquisition with eye tracking is the great level of detail it provides. However, one might criticize the artificiality of the experimental setting, which might decrease the experiment's external validity. The results presented in this article should therefore be replicated outside of the laboratory, maybe by using mobile eye tracking techniques in more common decision contexts, like supermarkets.

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Appendix

Analysis of Refixation Approach With All Fixations

Table A1
Strategy Measure (SM) for the Three Stages When Including Observations With Less Than Five Fixations per Stage in the Analysis

M (*SD*)				
Stage 1	Stage 2	Stage 3	*F*	*p*
−.48 (.78)	.01 (1.50)	.37 (.54)	65.649	<.01

In our main analysis, we followed the advice of Böckenholt and Hynan (1994) and excluded all decision processes where a stage contained less than five fixations. This led to the exclusion of 55% of the observations for the refixation approach because many respondents had less than five fixations in the orientation (28.8% of observations with less than five fixations) and/or the verification stage (29.1% with less than five fixations). To validate the robustness of this finding, we tested the two hypotheses that might be affected by this exclusion and found similar results. Regarding Hypothesis 4, a *t*-test shows that the mean *SM* per participant remains negative in the first stage and positive in the last stage (all $p < .01$; Table A1). Thus, the inclusion of observations with less than five fixations per stage does not change the result.

Regarding Hypothesis 6, again we cannot support the interaction hypothesis. In fact, we obtain only a single significant regression coefficient for the influence of the attribute range on the switch of patterns in the first versus the second stage (SM:2-1, $p = .01$ for *AR*; Table A2). In this case, the coefficient is positive, which means that the lower the complexity is, the more extreme the switch is from a more attribute-wise search pattern to a more alternative-wise search pattern. Overall this result actually strengthens our final conclusion that the more complex the choice task is, the later the switch from attribute-wise strategies to alternative-wise strategies.

Analysis of Saliency Effects

In this section, we test whether potential differences with respect to the saliency of the attributes had an influence on the order in which attributes were used in the decision processes. We structure the analysis with the following three leading questions: (1) When we use the respondent as the unit of analysis, is the attention to attributes directed in a similar way across choice tasks? (2) When we use the choice task as the unit of analysis, is the attention to attributes directed in a similar way across respondents? (3) Is attention to attributes correlated to a fixed (top-down) attribute order?

Table A2
Hypothesis 6: Estimated Regression Coefficients for the Influence of Complexity on the Increase of Strategy Measure (SM) Across Stages When Including Observations With Less Than Five Fixations Per Stage

	SM:3–1			SM:2–1			SM:3–2		
Complexity	β	*SE*	*p*	β	*SE*	*p*	β	*SE*	*p*
AR	.35	.28	.21	.78	.32	.01	−.38	.31	.23
AD_{sd}	.02	.07	.80	.04	.07	.57	−.01	.07	.91
AD_{en}	−.33	.31	.29	−.44	.33	.18	.07	.33	.83
CO	.30	.40	.75	.11	.41	.79	.25	.41	.54

Note. AR = attribute range; AD_{sd} = attractiveness difference (SD); AD_{en} = attractiveness difference (entropy); CO = conflict.

(*Appendix continues*)

Table A3
Example of Attribute Order Vector

Attribute	Rank
1	1
2	5
3	4
4	6
5	3
6	2

So as to analyze the order in which attributes are considered, we compute a vector of attribute ranks for each choice task and each respondent. The attribute whose attribute level was fixated first gets the rank 1, the next attribute level that is fixated but belongs to another attribute gets rank 2, and so on. As an example, assume that the order of the respective fixations on attribute levels of a respondent is: 12, 24, 17, 22, 26, 18, 19, 22, 15, . . . (see Figure 2 for the numbering of attribute levels). We will then get the attribute order vector as displayed in Table A3.

To quantify the similarity (or concordance) between attribute order vectors we compute Kendall's W (coefficient of concordance) which varies between 0 (*low concordance*) and 1 (*high concordance*; Holmqvist et al., 2011). Figure A1 shows the Kendall's W for all choice tasks per respondent. We see that the distribution of attention to attributes largely differs with respect to the Kendall's W across choice tasks. Some of the respondents seem to direct their attention to choice tasks in rather the same way, but most of the respondents differ in the way they direct their attention throughout choice tasks (with Kendall's W to be closer to 0 than to 1). This result shows that salience had no dominant effect on the order of acquiring attribute information across all choice tasks per respondent. If that had been the case across all choice tasks, we would expect Kendall's W to be close to 1 for most of the respondents.

Figure A2 shows that Kendall's W is close to zero in most choice tasks when we compare the search pattern of respondents. Because saliency should influence information processing of respondents in a similar way; that is, most of the respondents should have started with processing the more salient information, this result suggests that saliency has, at best, a marginal influence on the order of acquiring attribute information. However, Figure A2 also shows that respondents direct their attention in a more similar manner in earlier choice tasks than in later choice tasks. We therefore extended the analysis to find out in which order respondents most often considered the attributes.

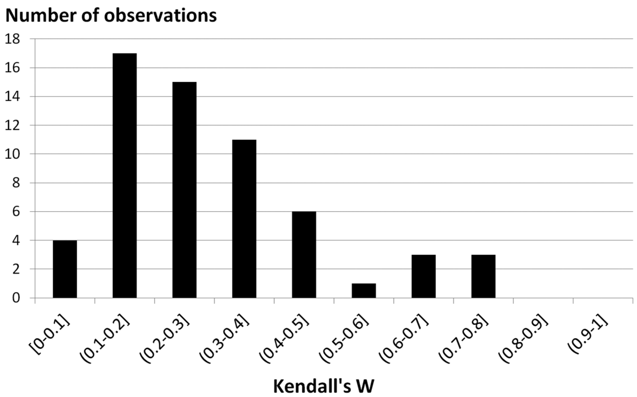

Figure A1. Coefficient of concordance per respondents over all choice tasks.

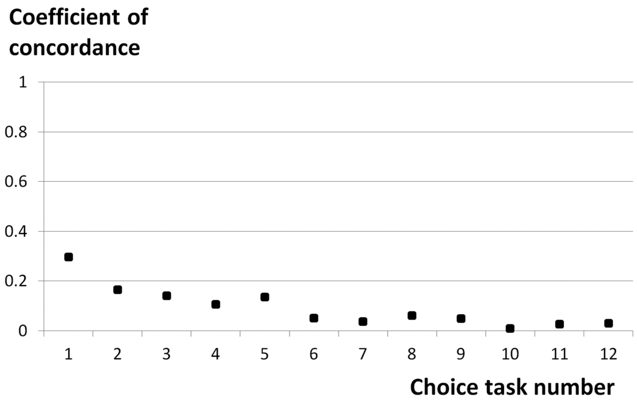

Figure A2. Coefficient of concordance per choice task over all respondents.

We computed the Spearman correlation coefficient for the observed attribute order with all possible permutations of attribute vectors, i.e., all combinations of the vector (1, 2, 3, 4, 5, 6). Coming from a West European country, all our respondents were accustomed to read top-down, so we expected that the attribute vector for top-down processing (1, 2, 3, 4, 5, 6) would have the highest correlation with the observed attribute order. Indeed, the correlation with the top-down order is stronger than with all other orders. Figure A3 shows the correlation with the top-down order. We find that respondents on average direct their attention more top-down at the beginning of the survey, and change the way in which they process information during the survey.

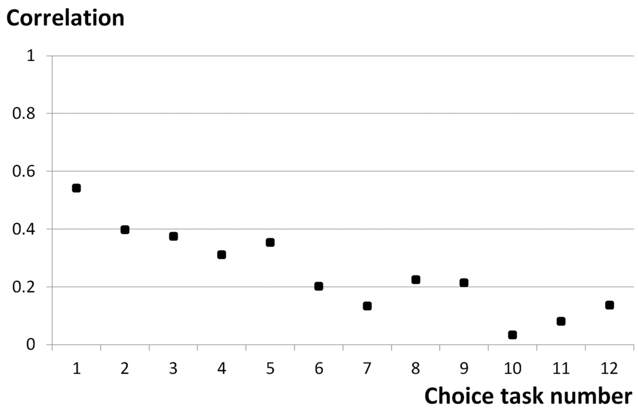

Figure A3. Correlation between the top-down attribute order and the observed attribute orders over all respondents for the first choice task.

(*Appendix continues*)

In conclusion, the results indicate that saliency had no substantial effect in our study. Otherwise, we would have observed a high concordance of the fixation patterns within respondents as well as a much higher concordance between respondents. Furthermore, a top-down process seems to best explain a common pattern for the first choice tasks. As Figure 2 demonstrates, a top-down order in our example is very unlikely to resemble the saliency of icons because we think that more salient icons are more prominent in the middle of the choice tasks (the icons of the system and the design attribute).

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