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Do online shops support customers' decision strategies by interactive information management tools? Results of an empirical analysis

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ABSTRACT

Online shops provide a multitude of products with different attributes to their customers. This enormous information supply often leads to information overload, which may negatively affect customer satisfaction and conversion rates. Therefore, interactive decision aids, particularly interactive information management tools, can help customers to control the information supply by filtering, sorting, or comparing product attributes. Moreover, interactive information management tools support different decision strategies that customers apply in online shopping decision processes. For example, a customer applying the elimination-by-aspects strategy eliminates products that do not meet the cutoff value for the most important attribute. Customers repeat this elimination process for the second most important attribute, the third most important attribute and so on, and processing continues until a single product remains. An online shop with filtering tools supports application of this strategy.

This study describes a set of well-known decision strategies, and examines whether online shops provide interactive information management tools that support the application of these decision strategies. We examined the 100 largest online shops in North America in order to analyze their provided interactive information management tools. Results show that the online shops support decision strategies which are frequently used by customers (e.g., elimination-by-aspects strategy). In general, the supported decision strategies are qualitative and noncompensatory in nature. That is, customers applying such strategies compare values in their decision process, but do not involve summing, subtracting, and/or multiplying attribute values, and customers do also not make trade-offs among attribute values. Hence, compensating for a bad value on one attribute with a good value on another attribute is uncommon. We discuss implications of our results for online shop companies and developers of online shop systems.

1. Introduction

Since online shops provide easier access to product information than traditional distribution channels (e.g., retail stores), the potential information supply increases. This fact entails the risk that customers can no longer process information purposefully for their purchase decision. In fact, information overload is a well-known phenomenon in online environments in general, and particularly in online shops, lowering customer satisfaction and negatively affecting conversion rates (Chen et al., 2009). How much information customers need for a purchase decision depends on objective factors (e.g., the nature of the product) and on subjective factors (e.g., a customer's individual information need). The objective information need can be anticipated and hence satisfied easily by online shops, because relevant attributes within a product category and the product attribute values are known. However, a customer's subjective information need in a specific purchase situation can hardly be predicted, because information on the customer's decision strategy preference and the situational context (e.g., time pressure) is not directly available. Due to these circumstances online shops integrate interactive decision aids (IDA), and particularly interactive information management tools (IIMT), into their platforms.

IDA are decision support systems in online shops that enable customers to control the high density of product information (Wang and Benbasat, 2009). IIMT, such as tools for filtering or sorting, allow customers to control the information supply (Gupta et al., 2009). Importantly, IIMT support different decision strategies that customers apply in online shopping decision processes. For example, a customer applying the elimination-by-aspects strategy

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eliminates products that do not meet the cutoff value for the most important attribute. Customers repeat this elimination process for the second most important attribute, the third most important attribute and so on, and processing continues until a single product remains. Filtering tools in an online shop support application of the elimination-by-aspects strategy (Pfeiffer et al., 2009).

Today, IDA are widely used in practice, but poorly investigated, a fact that holds particularly true for IIMT. Researchers already made calls for more IIMT investigations (e.g., Pfeiffer, 2010). One study analyzed the top 100 online shops (based on Google Page Rank) and found that these web stores mainly offered filters, but hardly any other IIMT (described in detail in Section 2.3) (Pfeiffer, 2010). Recent technological progress in the e-commerce domain (e.g., more and more platforms offer more and more features (Gevorgyan, 2016)), market developments (e.g., increased tendency to outsource the e-commerce platform development to specialized firms such as Magento (Internet Retailer, 2015)), and changes in online shopping behavior (e.g., consumers increasingly want to speed up their shopping processes, e.g., Shanthi and Kannaiah, 2015) call for an update of Pfeiffer's (2010) study. Furthermore, researchers developed several IIMT prototypes with different features in laboratories since 2010 (e.g., Pfeiffer et al., 2010, 2014a). Yet, the tools' use in practice is hardly known. Based on anecdotal evidence, however, there is reason to assume that most online shops still only provide a very limited number of IIMT, predominantly filtering and sorting tools. Other IIMT, such as tools for complex product comparison processes (Pfeiffer et al., 2010, 2014a), are hardly used in practice.

Each IIMT only supports some decision strategies, but not all available strategies (in some cases one IIMT exactly supports one decision strategy, see Section 2.3.3 for details). It follows that investigating the IIMT provided in the top 100 online shops does not only reveal the status of IIMT provision in practice, but also reveals which strategies are actually supported in online shops. Against this background, this paper surveys the decision aids available to customers who visit leading websites and examines which decision strategies customers could apply in online shops by using IIMT.

The paper is structured as follows: Section 2 presents the state-of-the-art about decision strategies and IIMT. Specifically, we conducted a comprehensive literature review to illustrate the current state of IIMT research, and we did so with a focus on empirical studies (see Appendix A for details). Section 3 describes our research methodology. In essence, we analyzed all IIMT which are provided in the top 100 online shops in North America. This analysis makes possible a conclusion on decision strategy application possibility in online shops. Section 4 describes the study results. Section 5 discusses the results and their implications for online shop companies and developers of online shop systems, and also outlines study limitations.

2. Literature review

2.1. Foundations of human decision making

Research in behavioral decision making (e.g., Schulte-Mecklenbeck et al., 2011; Wright, 2013), consumer psychology (e.g., Bettman et al., 1998; Norton et al., 2017), and behavioral economics (e.g., Cartwright, 2014; Kahneman, 2003) acknowledges that human resources such as knowledge, computational power, and time are limited. Hence, people (e.g., online shoppers) cannot process all available information and do not make perfectly rational decisions (Simon, 1959, 1990).

A seminal decision-making theory is referred to as the adaptive decision-making model (Payne et al., 1993). This theory describes decision makers as actors who adjust their information processing and decision effort as a function of the complexity and amount of information and the context within which decisions are made (Bettman et al., 1991). Hence, decision problem characteristics (e.g., number of available options), decision-maker characteristics (e.g., experience), and social context variables (e.g., time pressure) strongly influence decision strategy selection.

People in general, and online shoppers in particular, have a repertoire of decision strategies, which they assess (not necessarily in a conscious and deliberate fashion, e.g., Ariely, 2010) on their advantages and disadvantages in light of their individual goals and constraints. According to the adaptive decision-making model, decision makers apply the strategy anticipated as "best" in a specific decision situation with regard to a maximum of accuracy and a minimum of effort. It follows that decision makers trade off accuracy and effort evaluations (Payne et al., 1992, 1993). Importantly, in addition to these two main goals (accuracy and effort), evidence indicates that people tend to minimize negative emotions (Bettman et al., 2012). Also, and this is of particular importance for the present study, availability of decision aids (e.g., IIMT) influences decision strategy selection.

2.2. Decision strategies

When buying a product online, a customer deals with a decision problem. Out of a large number of products, customers select the alternative which meets the needs. If the effort for information acquisition is high, actual use of information for decision-making is low (Lohse and Johnson, 1996). Because information is only one or a few clicks away and a customer does not have to physically move from store to store, it is usually effortless to obtain information in online shops. Therefore, customers frequently process more information in online environments than in traditional retail environments to make a purchase decision (Sicilia and Ruiz, 2010).

However, considering that online shops generally provide sheer endless product information and that customers have a tendency to process more information in online than in offline environments, it is not surprising that information overload is a frequently encountered issue in online stores (Chen et al., 2009).

To arrive at a final decision, people follow a more or less systematic process and use decision strategies (Johnson and Payne, 1985). A decision strategy is defined as "a sequence of operations used to transform an initial stage of knowledge into a final goal state of knowledge in which the decision maker feels that the decision problem is solved" (Payne et al., 1992, 109). Decision strategies include the sub-processes of information acquisition, evaluation, and choice (Payne et al., 1993). In online purchase situations, decision strategies help customers to evaluate the existing products and their attributes to make a final decision.

Payne (1976) divided human decision processes into two basic phases: First, an initial phase (the screening phase), in which a high number of possible alternatives is reduced to a manageable number of alternatives. Second, an additional phase (the in-depth comparison phase), in which the remaining alternatives are compared in more detail. Customers pass through these two stages, because it is typically not possible to intensively evaluate all available alternatives (Häubl and Trifts, 2000). Thus, it is unlikely that customers make a purchase decision without a screening phase. As a consequence, IDA are important for two major reasons: first, to reduce complexity in the screening phase, and second, to compare alternatives in the in-depth comparison phase (Häubl and Trifts, 2000). Eye-tracking research confirms that human decision-making processes consist of both a screening and an in-depth comparison phase (e.g., Pfeiffer et al., 2014b).

Table 1
Multi-option, multi-attribute decision matrix.

	$Option_1$	$Option_2$	$Option_n$
$Attribute_1$	Attribute $value_{11}$	Attribute $value_{12}$	Attribute $value_{1n}$
$Attribute_2$	Attribute $value_{21}$	Attribute $value_{22}$	Attribute $value_{2n}$
$Attribute_m$	Attribute $value_{m1}$	Attribute $value_{m2}$	Attribute $value_{mn}$

Formally, decision makers have to choose between n options (for example products) opt_j, j = 1,. . .,n, which can be described by attribute values a_{ij} of m attributes att_i, i = 1,. . .m (Harte and Koele, 2001; Keeney and Raiffa, 1993). Consequently, online shop customers face a multi-option, multi-attribute decision. The attribute values represent specific features of options, in online shops for example specific product characteristics. Customers usually prefer to select the best option. Table 1 represents the structure of a decision matrix. Importantly, most online shops also present their products in matrix format, with the options in the columns and the attributes in the rows. (Note: In tables, rows are often used for entities, while columns are used for attributes. However, product comparison matrices in online shops typically use the opposite structure because the number of product attributes is typically higher than the number of products. It follows that the display of product comparison matrices in online shops is easier if the options are arranged in columns and the attributes in rows.)

2.2.1. Decision strategies in literature

Based on Riedl et al. (2008, pp. 797–798), the Table 2 lists and defines 13 important decision strategies that online shoppers may use to select a product.

2.2.2. Characteristics of decision strategies

Decision strategies have specific characteristics. Nine characteristics can be used to classify decision strategies (Riedl et al., 2008). Table 3 classifies 13 decision strategies (described in Table 2) based on these nine characteristics (see Riedl et al., 2008, 796–798).

First, some decision strategies process all attribute values, whereas others do not. It follows that strategies can be distinguished by the amount of information processed. Second, information processing is either option-wise or attribute-wise. In option-wise processing, the attribute values of a single option are considered before information about the next option is processed. In attribute-wise processing, the values of several options on a single attribute are processed before information about a further attribute is processed. Third, strategies can be distinguished by the degree to which the amount of processing is consistent or selective across attributes (i.e., whether the same amount of information is examined for each attribute or whether it varies). Fourth, strategies can also be distinguished by the degree to which the amount of processing is consistent or selective across options. Fifth, decision strategies differ with regard to the elimination of options prior to the final choice. Sixth, some decision strategies use attribute weights, while others do not. Seventh, some decision strategies use cutoff (aspiration) levels, whereas others do not. Eighth, decision strategies can be distinguished by whether they allow for compensating for a bad value on one attribute with a good value on another attribute (if allowed, strategies are called compensatory, whereas noncompensatory strategies do not require trade-offs among attributes). Ninth, decision strategies differ with respect to the degree of quantitative and qualitative reasoning used. Strategies that involve summing, subtracting, and/or multiplying values, as well as counting, are considered to be quantitative. Strategies that simply compare values are defined as qualitative.

2.3. Interactive information management tools

IIMT are "tools which enable buyers to sort through and/or compare available product alternatives. For example, these tools

Table 2
Decision strategies (Source: Riedl et al., 2008, 797–798).

#	Decision Strategy	Description
1	Additive Difference Strategy	. . .compares two options at a time, attribute by attribute. Then the difference across the attributes are summed to provide a single overall difference score across all attributes for that pair of options. The winner is then compared with the next option, and so on. The chosen option has won all comparisons.
2	Disjunctive Strategy	. . .first sets cutoff points on the attributes and then looks for the first option that is at least as good as the cutoff value on any attribute.
3	Dominance Strategy	. . .chooses the option that is at least as good as every other option on all attributes and better on at least one attribute.
4	Elimination-by-Aspects Strategy	. . .eliminates options that do not meet the cutoff value for the most important attribute. This elimination process is repeated for the second most important attribute. Processing continues until a single option remains.
5	Equal Weights Strategy	. . .chooses the option with the highest overall utility score that is defined as the sum of an option's attribute utilities. In contrast to the multiattribute utility model (see Number 10 below), the equal weights strategy simplifies decision making by ignoring attribute weights.
6	Lexicographic Strategy	. . .selects the option with the best value on the most important attribute. If there is not one but two or more options with a best value, the lexicographic strategy selects the option with the best value on the second most important attribute, and so on.
7	Least Important Minimum Heuristic	. . .first determines the worst value of each option and then chooses the option with the least important worst value.
8	Least Variance Heuristic	. . .chooses the option with the lowest variance across the attribute values. The least variance heuristic makes sense only for decision situations in which no dominant option exists.
9	Majority Strategy	. . .chooses the option with the highest number of dominant attribute values.
10	Multiattribute Utility Model	. . .chooses the option with the highest weighted overall utility score that is defined as the sum of the weighted attribute utilities. The multiattribute utility model is usually viewed as the normative rule.
11	Majority of Confirming Dimensions Strategy	. . .involves processing pairs of options (like additive difference strategy). The values for each of the two options are compared on each attribute. The option with the majority of winning attribute values is retained and is then compared with the next option. The process of pairwise comparison stops if all options have been evaluated and the final winning option has been identified.
12	Recognition Heuristic	. . .chooses the option with the best value on the attribute name recognition. The recognition heuristic can be considered as a special case of the lexicographic strategy, because it selects the option with the best value on the most important attribute—namely, name recognition. If there is not one but two or more options with a best value, the recognition heuristic selects the option with the best value on the second most important attribute, and so on.
13	Satisficing Heuristic	. . .considers options sequentially, in the order in which they occur in the choice set. The value of each attribute for a particular option is considered to see whether it meets a predetermined cutoff (aspiration) level for that attribute. If any attribute fails to meet the level, the option is rejected, and the next option is considered. The first option that satisfies the aspiration level for each attribute is chosen.

Table 3
Characteristics of decision strategies (Source: Riedl et al., 2008, 796).

	Characteristic	Additive Difference Strategy	Disjunctive Strategy	Dominance Strategy	Elimination-by-Aspects Strategy	Equal Weights Strategy	Lexicographic Strategy	Least Important Minimum Heuristic	Least Variance Heuristic	Majority Strategy	Multiattribute Utility Model	Majority of Confirming Dimensions Strategy	Recognition Heuristic	Satisficing Heuristic
1	Utility values ignored? Yes (Y) vs. No (N)	N	Y	N	Y	N	Y	N	N	N	N	N	Y	Y
2	Option-based (O) vs. Attribute-based (A) search	A	O	A	A	O	A	O	O	A	O	A	A	O
3	Consistent (C) vs. Selective (S) across attributes	C	S	C	S	C	S	C	C	C	C	C	S	S
4	Consistent (C) vs. Selective (S) across options	S	S	C	S	C	S	C	C	C	C	S	S	S
5	Elimination of options prior to final choice? Yes (Y) vs. No (N)	Y	Y	N	Y	N	Y	N	N	N	N	Y	Y	Y
6	Attribute weights used? Yes (Y) vs. No (N)	N	N	N	Y	N	Y	Y	N	N	Y	N	Y	N
7	Cutoff (Aspiration) levels used? Yes (Y) vs. No (N)	N	Y	N	Y	N	N	N	N	N	N	N	N	Y
8	Compensatory (C) vs. Noncompensatory (N)	C	N	N	N	C	N	N	N	C	C	C	N	N
9	Quantitative (QN) vs. Qualitative (QL) reasoning	QN	QL	QL	QL	QN	QL	QL	QN	QN	QN	QN	QL	QL

allow buyers to limit and sort choices on levels of various attributes and/or engage in side-by-side product comparisons in dynamically created tables" (Gupta et al., 2009, 163). Later, academics extended this definition and added that IIMT are also tools that allow users to interact with the matrix in the in-depth comparison phase (Pfeiffer, 2010). Examples are the removal of products from the matrix or change of the order of options on a screen. Accordingly, IIMT may be used in the screening phase and in the in-depth comparison phase.

We conducted a literature review to illustrate the current state of IIMT research. Appendix A shows a comprehensive overview of empirical studies in the field of IIMT.

2.3.1. IIMT in the screening phase

A set of identified IIMT served as a basis for our empirical study. Specifically, we identified FILTER, SORT and COMPARE as the most important IIMT in the screening phase (Pfeiffer et al., 2009). Fig. 1 shows examples of $\text{FILTER}_{\text{attr}}$, SORT_{opt}, and COMPARE (examples taken from www.cdw.com).

2.3.1.1. FILTER. By filtering, customers can set thresholds for attribute values to reduce the number of products in the consideration set, referred to as $\text{FILTER}_{\text{attr}}$. For example, a maximum or minimum price can be set. Another example is the reduction of the consideration set to particular brands. Filters can be distinguished depending on the underlying level of measurement (Pfeiffer, 2010). In this work, a distinction is made for nominal (e.g., brands), ordinal (e.g., product reviews), and metrical (e.g., prices) values.

2.3.1.2. SORT. By sorting, customers can determine the order of the products based on certain attributes. Alternatives can be ranked by SORT_{opt} using the values of individual attributes to show, for example, the cheapest products first.

2.3.1.3. COMPARE. This IIMT supports transition from the screening phase to the in-depth comparison phase. This can be done, for example, by activating the checkbox "Add to Compare" shown in Fig. 1. The selected products, then, can be compared in detail in a product comparison matrix.

2.3.2. IIMT in the in-depth comparison phase

Researchers describe IIMT that online shoppers could use in the in-depth comparison phase (i.e., IIMT to interact with product comparison matrices). The tools FILTER, MARK, PAIRWISE COMPARISON, REMOVE, SCORE, SORT and SUM (Pfeiffer et al., 2009) support customers in this phase. Fig. 2 summarizes the IIMT of the in-depth comparison phase. In some cases, it was not possible to find examples in practice. It follows that these tools are only described as prototypes in the academic literature (see Pfeiffer et al., 2009), but are not yet used in real-life online shops.

2.3.2.1. FILTER. In addition to $\text{FILTER}_{\text{attr}}$ (see screening phase), in the in-depth comparison phase it is possible for customers to filter by markings ($\text{FILTER}_{\text{markings}}$).

2.3.2.2. MARK. By marking individual cells of the product comparison matrix, options with undesirable attribute values can be highlighted by $\text{FILTER}_{\text{markings}}$.

2.3.2.3. PAIRWISE COMPARISON. This IIMT allows to compare two options at a glance. Therefore, all the attributes of the options are listed and shown in a product comparison matrix.

2.3.2.4. REMOVE. This tool either removes options ($\text{REMOVE}_{\text{opt}}$) or attributes ($\text{REMOVE}_{\text{attr}}$) from the product comparison matrix.

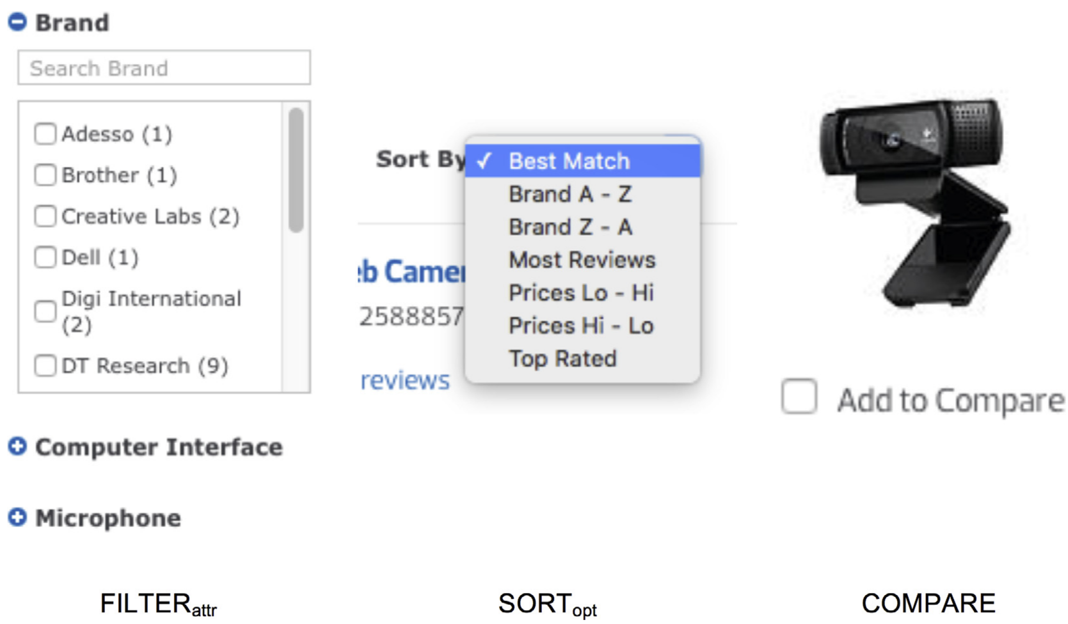

Fig. 1. Examples for IIMT in the screening phase. Source: www.cdw.com

Customers can remove options to exclude them from the consideration set. To limit the available information to relevant information (that should be shown on one screen), customers can also hide attributes.

2.3.2.5. SCORE. This tool allows to evaluate options (SCORE$_{opt}$), attributes (SCORE$_{attr}$), and individual attribute values of cells of the product comparison matrix (SCORE$_{cell}$). This allows customers to weight attributes differently.

2.3.2.6. SORT. In addition to SORT$_{opt}$ (see screening phase), the order of attributes can be changed by SORT$_{attr}$.

2.3.2.7. SUM. The tool SUM$_{simple}$ sums all values which have been given to each attribute by using SCORE$_{cell}$ and hence provides an overall value for each option. SUM$_{weighted}$ additionally considers attribute weights (by SCORE$_{attr}$).

2.3.3. Support of decision strategies by IIMT

IIMT support different decision strategies that customers apply in online shopping environments. Pfeiffer et al. (2009) formally analyzed which IIMT are necessary to apply a specific decision strategy. Table 4 shows the link between IIMT and application of specific decision strategies. While some strategies only require availability of one IIMT (e.g., elimination-by-aspects strategy only requires filtering tools), other strategies imply availability of several IIMT (for details, see Table 4).

3. Methodology

Based on our literature review, we conducted a statistical analysis to examine which decision strategies (see Table 2) customers could apply in online shops by using the corresponding IIMT (see Table 4). To this end, we examined the 100 largest online shops in North America in order to analyze their provided IIMT. The United States had the worldwide highest e-commerce sales in 2015, followed by China, Japan, the United Kingdom, and Germany (Digital Market Outlook, 2016). Sales was chosen as a ranking criterion, because companies with higher sales have the financial background to design and integrate IIMT into their online shops (based on our dataset we calculated corresponding correlations; for details see Appendix B). Our data source was an annual study of Internet Retailer (2015). This study lists the 500 top-selling e-commerce retailers based on sales numbers. Some of the top 100 online shops had no common online shop (Netflix Inc., Symantec Corp., Google Play, Hulu LLC, Ancestry.com Inc., Adobe Systems Inc., The Kroger Co., Microsoft Corp.) or we could not reach them at the time of the study (Costco Wholesale Corp.). We replaced these shops by the following shops in the ranking (starting with 101 etc.).

We evaluated the presence of IIMT in these 100 online shops (only desktop versions were analyzed because they offer more features than mobile versions). The evaluation took place from March 25 until April 2, 2016. In addition to the presence of the IIMT, we also evaluated design elements. Our analyses started at the category pages of the online shops. Therefore, we deliberately chose product categories with a higher probability of IIMT in use. Research indicates that IIMT are implemented in the following product groups with decreasing frequency: electrical products, computers, home/garden, office supplies, sporting, entertainment, and food/fashion (Pfeiffer, 2010). We took this order into account when selecting the product category.

4. Results

Fig. 3 shows the number of online shops in which the respective IIMT was implemented, both in the screening- and in the in-depth comparison phase. Next, the IIMT are analyzed in detail.

4.1 Implementation of IIMT in the screening phase

In the screening phase, all IIMT were found in the investigated online shops: FILTER, SORT and COMPARE. Appendix C shows in detail which specific online shop had implemented which IIMT in the screening phase.

4.1.1. FILTER

A tool to filter was implemented in 93 online shops. Hence, FILTER was the most common IIMT in the screening phase.

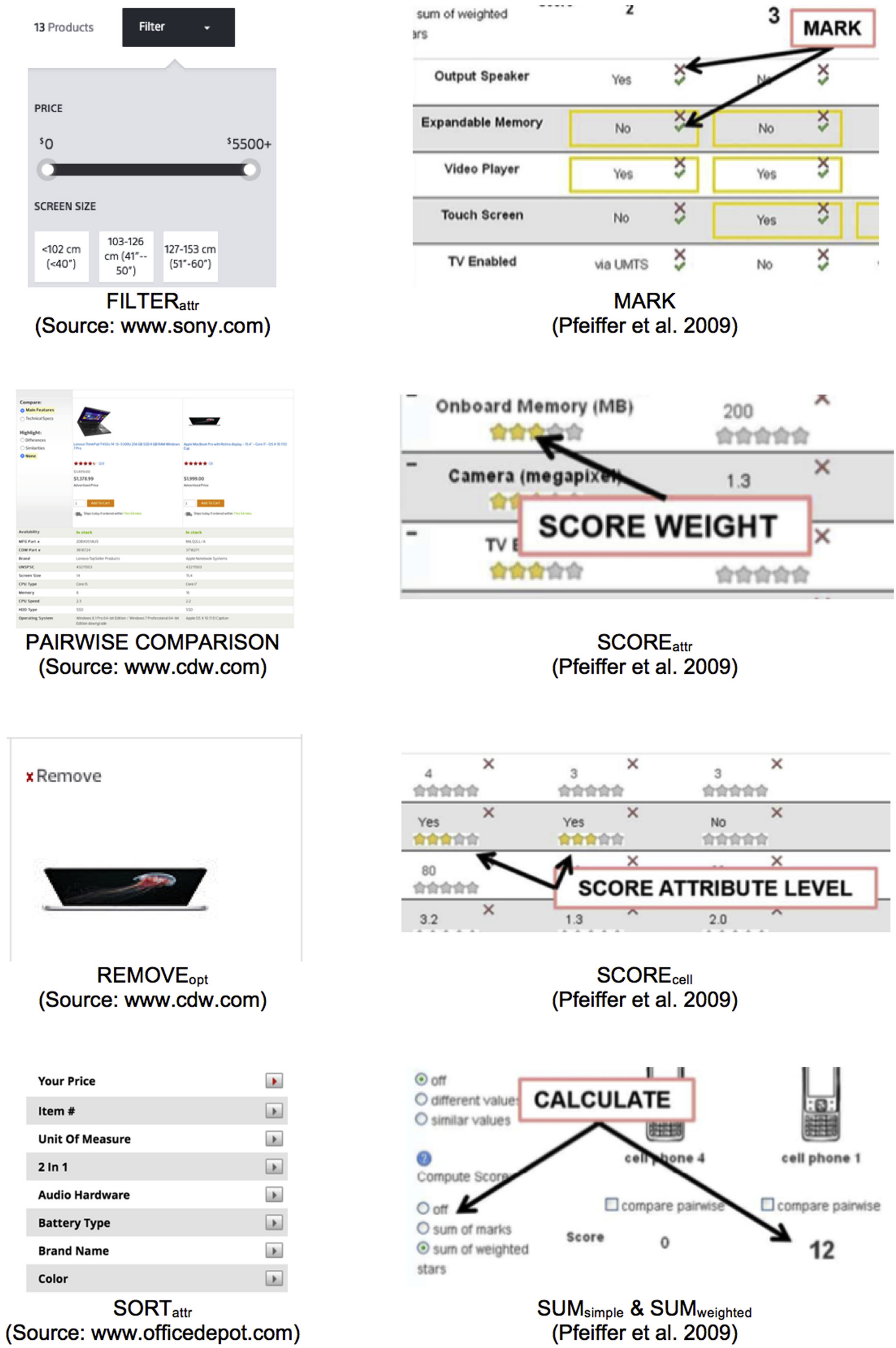

Fig. 2. Examples for IIMT in the in-depth comparison phase.

Table 4
Support of decision strategies by IIMT (based on Pfeiffer et al., 2009).

	Additive Difference Strategy	Disjunctive Strategy	Dominance Strategy	Elimination-by-Aspects Strategy	Equal Weights Strategy	Lexicographic Strategy	Least Important Minimum Heuristic	Least Variance Heuristic	Majority Strategy	Multiattribute Utility Model	Majority of Confirming Dimensions Strategy	Recognition Heuristic	Satisficing Heuristic
$FILTER_{attr}$		×		×									×
$FILTER_{markings}$													
MARK													
PAIRWISE											COMPARISON	×	
$REMOVE_{opt}$	×		×			×					×	×	
$REMOVE_{attr}$													
$SCORE_{opt}$							×	×					
$SCORE_{attr}$										×			
$SCORE_{cell}$	×				×			×	×	×	×		
$SORT_{opt}$						×						×	
$SORT_{attr}$													
SUM_{simple}	×				×				×		×		
$SUM_{weighted}$										×			

A special case of FILTER is the search by keywords. In 10% of the online shops with FILTER, this function was available.

One way for users to control FILTER is the presence of CLEAR FILTER. By CLEAR FILTER users can reset all set filters. In the investigated online shops either all filters, specific filters or individual attribute characteristics could be reset. Overall, 90% of the online shops with FILTER offered CLEAR FILTER.

The number of available attributes for filtering shows significant industry differences. The analyzed products of the industry "Computers/Electronics" showed the highest number of attributes to filter. In contrast, in the online shops of the industry "Apparel/Accessories" and "Food/Drug" only few attributes were filterable. This demonstrates that online shops with information-intensive products have a higher number of attributes to filter. On average, the online shops with FILTER provided 8.9 attributes for filtering. Fig. 4 shows the industry comparison in descending order.

To rank a filtered product set, SORT can be implemented in online shops.

4.1.2. SORT

90 of the 100 online shops offered a function to sort the options according to specific attributes. On average, the online shops provided 4.3 different criteria for sorting. We did not observe differences by industry.

4.1.3. COMPARE

This IIMT supports the transition from the screening- to the in-depth comparison phase. In 29 of the 100 online shops it was possible to transfer products to a product comparison matrix. Researchers argued that this IIMT is important for products with many attributes (e.g., for products in information-intensive industries) (e.g., Pfeiffer, 2010). Our empirical findings support this argument because in the industries "Hardware/Home Improvements" and "Computer/Electronics" most online shops provided this IIMT. However, in the online shops of the industries "Apparel/Accessori es", "Mass Merchant" and "Food/Drug" this IIMT was hardly available. Fig. 5 shows the share of online shops with COMPARE by industries.

4.2. Implementation of IIMT in the in-depth comparison phase

For the 29 online shops which offered COMPARE in the screening phase, we analyzed the IIMT in the in-depth comparison phase in a second step. In the in-depth comparison phase fewer IIMT were offered than in the screening phase. In addition to PAIRWISE COMPARISON, we only found REMOVE at a notable extent (i.e., in 27 out of 29 online shops, 93%). Fig. 3 shows the number of online shops in which the respective IIMT were found. Appendix D shows in detail which specific online shop had implemented which IIMT in the in-depth comparison phase.

4.2.1. PAIRWISE COMPARISON

In all 29 online shops which offered COMPARE it was possible to compare products in a pairwise fashion. However, we observed differences in the matrix design. In 28 of the 29 online shops, the matrix was arranged with options as columns and attributes as rows. In contrast, the online shop of Cabela's Inc. arranged the matrix with options as rows and attributes as columns. The second presentation format appears to be less suitable, because only a few attributes can be seen on the screen in this format.

4.2.2. FILTER

We could not observe a high prevalence of FILTER in the in-depth comparison phase. To filter products directly in the product comparison matrix was only possible in the online shop of Sony Electronics Inc.

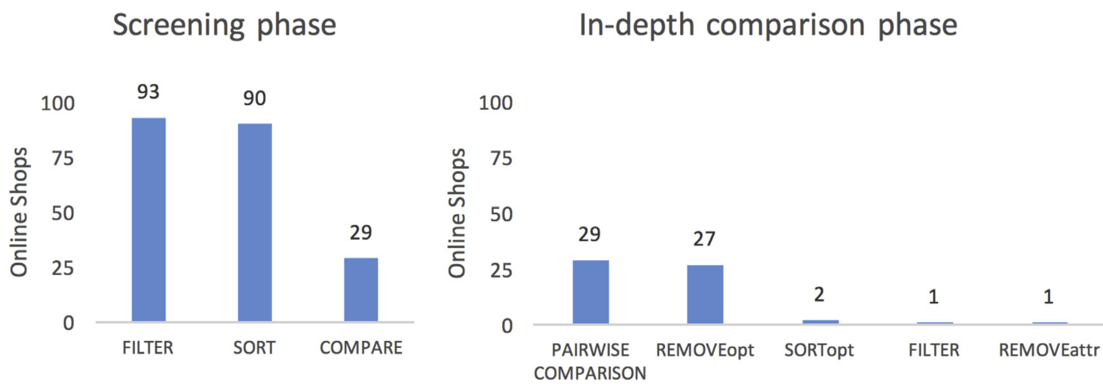

Fig. 3. Number of online shops in which the respective IIMT was found in the screening phase (left) and in the in-depth comparison phase (right).

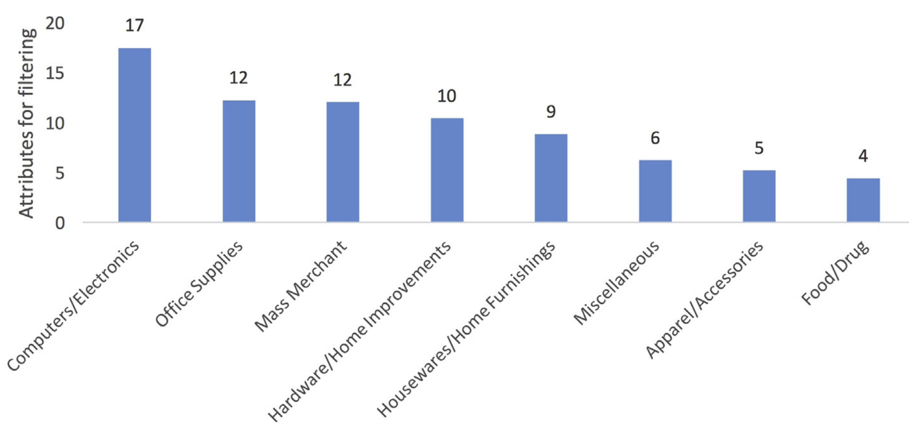

Fig. 4. Average number of possible attributes for filtering by industries.

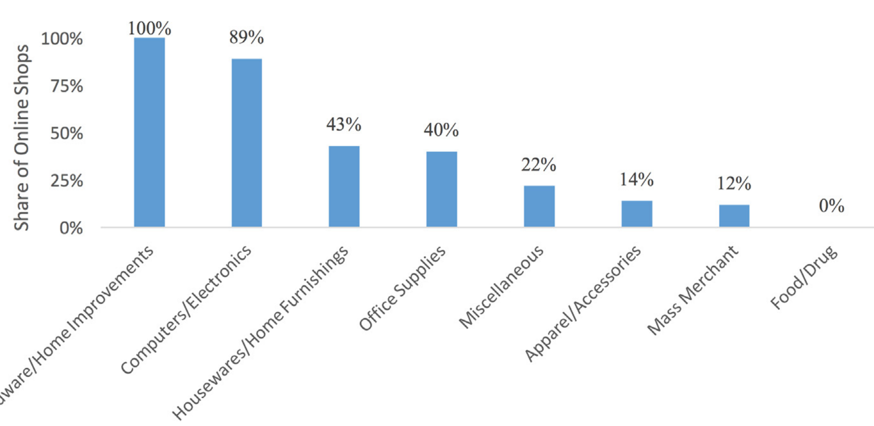

Fig. 5. Share of online shops with COMPARE by industries.

4.2.3. REMOVE

In 27 of the 29 online shops with COMPARE, it was possible to remove options from the matrix by $REMOVE_{opt}$.

In the online shops of Dell Inc. and Musician's Friend Inc. $REMOVE_{attr}$ was found. In addition, in both online shops it was possible to hide attributes in cases in which the products had the same attribute values.

4.2.4. SORT

We could not observe a high prevalence of SORT comparable to the screening phase in the in-depth comparison phase. In only two of the 29 online shops products in product comparison matrices could be sorted by $SORT_{opt}$ (Sony Electronics Inc. and Office Depot. Inc.). As shown in Fig. 6, next to each attribute a button was integrated which ranked the options by the attribute values. A ranking by "Brand Name" resulted in an alphabetical order (A to Z). A ranking by "Your Price" resulted in a metrical order (lowest price to highest price). We could not identify $SORT_{attr}$ in any online shop.

4.2.5. MARK, SCORE, SUM

We could not observe these IIMT in any online shop.

4.3. Comparison of the Pfeiffer (2010) results with the present study results

Table 5 summarizes the comparison. The IIMT are grouped into the screening phase and the in-depth comparison phase. For tools in the screening phase, we only observe a significant change

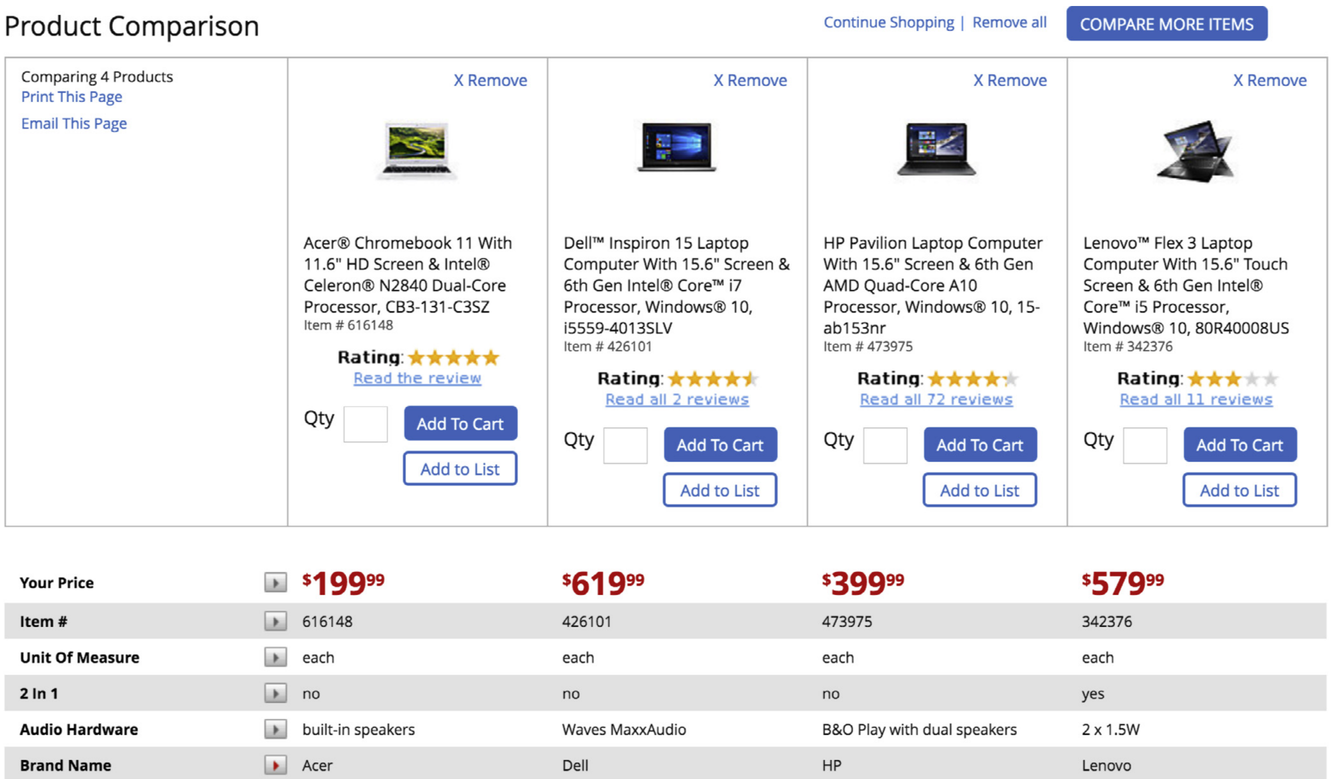

Fig. 6. $SORT_{opt}$ in a product comparison matrix. Source: www.officedepot.com

regarding SORT (a rise from 70 to 90 online shops). However, with respect to FILTER and COMPARE the changes are marginal. Note that the Pfeiffer (2010) study did not analyze the number of attributes to filter and the number of criteria for sorting. Hence, we cannot make a comparison. For tools in the in-depth comparison phase, we do not observe significant changes either.

4.4. Supported decision strategies

In the evaluated online shops, IIMT support six of the 13 decision strategies: the disjunctive strategy, the dominance strategy, the elimination-by-aspects strategy, the lexicographic strategy, the recognition heuristic, and the satisficing heuristic. It follows that application of the additive difference strategy, the equal weights strategy, the least important minimum heuristic, the least variance heuristic, the majority strategy, the multiattribute utility model, and the majority of confirming dimensions strategy is not supported in any of the evaluated online shops. Moreover, we found that the disjunctive strategy, the elimination-by-aspects strategy, and the satisficing heuristic are supported in more than 90% of the online shops, while the dominance strategy, the lexicographic strategy, and the recognition heuristic are supported in approximately a quarter of the shops. Fig. 7 summarizes the results. Appendix E gives a detailed overview of the support of decision strategies in the analyzed online shops.

The disjunctive strategy, the elimination-by-aspects strategy, and the satisficing heuristic only need $FILTER_{attr}$. This IIMT was implemented in 93 of the 100 online shops. In all 93 cases the IIMT was implemented on the category pages in the screening phase (in addition, in the online shop of Sony Electronics Inc. the IIMT was also implemented in the in-depth comparison phase). The dominance strategy, the lexicographic strategy, and the recognition heuristic are only supported if a tool exists to remove products ($REMOVE_{opt}$ from the consideration set). This IIMT is associated with use in the in-depth comparison phase (Pfeiffer et al., 2009). We only observed $REMOVE_{opt}$ in this phase. Consequently, the dominance strategy, the lexicographic strategy, and the recognition heuristic can only be applied in online shops in which COMPARE can transfer products to product comparison matrices (i.e., if the transition from the screening phase to the in-depth comparison phase is supported by COMPARE). The dominance strategy can be applied in 27 of the 100 online shops, namely in the online shops where $REMOVE_{opt}$ was available in the in-depth comparison phase. The lexicographic strategy and the recognition heuristic can be applied in 26 of the 100 online shops. These decision strategies were supported in online shops that have implemented both $SORT_{opt}$ and $REMOVE_{opt}$.

5. Discussion, limitations, and concluding comment

5.1. Discussion

In this section, we first discuss the findings and their major implications for both online shop companies and developers of online shop systems, followed by a more specific discussion of the study results with respect to IIMT and decision strategies.

With respect to *online shop companies*, the present article has the following major implications:

- They must recognize the necessity to actively get engaged in the planning and implementation of IIMT. If implemented properly and in a parsimonious way, such tools may increase user satisfaction, improving conversion rates and sales. A/B-testing can identify the tools' positive and negative effects before a large scale rollout.
- Our study suggests that they should primarily focus on FILTER, SORT, and $REMOVE_{opt}$ because these tools predominantly support frequently used decision strategies (for details, see the Results section).

Table 5
Comparison of the Pfeiffer (2010) results with the results of the present study.

Phase	IIMT	Pfeiffer (2010)	Present Study
		– period of evaluation: January 2009 – Examination: top 100 online shops (based on Google Page Rank)	– Period of evaluation: March 25 until April 2, 2016 – Examination: top 100 online shops (based on sales)
Screening-Phase	FILTER	– Availability: 100/100 – Most attributes were filterable; regardless of the level of measurement (nominal, ordinal, metrical)	– Availability: 93/100 – Most attributes were filterable; regardless of the level of measurement (nominal, ordinal, metrical) – Average number of attributes to filter: 8.9 – Online shops with information-intensive products have a higher number of attributes to filter
	SORT	– Availability: 70/100 – Only a few attributes were sortable; mostly price and customer ratings – Sorting of nominal values (like color) was not possible	– Availability: 90/100 – Only a few attributes were sortable; mostly price and customer ratings – Sorting of nominal values (like color) was not possible – Average number of criteria for sorting: 4.3
	COMPARE	– Availability: 27/100 – Mostly reachable by clicking “compare” checkboxes	– Availability: 29/100 – Mostly reachable by clicking “compare” checkboxes
In-depth comparison Phase	PAIRWISE COMPARISON	– Product comparison matrices especially available for products with many attributes	– Product comparison matrices especially available for products with many attributes – Options as columns/attributes as rows: 28/29 – Options as rows/attributes as columns: 1/29
	REMOVE_{opt}	– Availability: 21/27	– Availability: 27/29
	SORT_{opt}	– Availability: 2/27	– Availability: 2/29
	FILTER	– Availability: not specified	– Availability: 1/29
	REMOVE_{attr}	– Availability: 2/27	– Availability: 2/29

- However, the mere existence of these tools is a necessary, but not sufficient precondition for success. For instance, a key point in the design of FILTER is to avoid that null products remain in the consideration set. However, in 17 online shops we found that application of FILTER may result in null products, a fact that constitutes potential for improvement. In this case, an online shop should at least recommend related products. In bricks-and-mortar stores, a trained shoe salesman, for example, would recommend a similar shoe, if a specific shoe is no longer available in the desired size. This logic is not yet implemented well in online shops (it could not be found in any of the 100 online shops). Hence, this finding constitutes a basis for improvement in the future.
- Generally, the design of tools is critical, as poor designs have the potential to worsen a current situation (e.g., a FILTER where null products remain in the consideration set). That is, while decision aids are implemented to reduce information overload, provision of too many tools and/or tools with a low degree of perceived ease of use may counteract their objective and even further increase users' cognitive load.

With respect to *developers of online shop systems* (e.g., Magento or Shopify), we see the following major implications:

- Because many online shop companies do not develop their systems themselves, but customize existing systems (60% of the analyzed online shops use online shop systems, Internet Retailer, 2015), developers' design decisions strongly affect support of users' decision strategies. It is both time-consuming and expensive for online shop companies to integrate self-constructed decision aids into existing e-commerce platforms.
- From the perspective of developers, better consideration of IIMT in their platforms may constitute a competitive advantage because a larger variety of software features may be perceived as a benefit by online shop companies.

Furthermore, our study revealed that in the analyzed online shops qualitative and noncompensatory decision strategies in which not all attributes are considered for the decision are supported through IIMT (except the dominance strategy). The supported decision strategies are consistent with the actually applied strategies in practice (e.g., Riedl and Brandstätter, 2007). By using FILTER_{attr}, the disjunctive strategy, the elimination-by-aspects strategy, and the satisficing heuristic can be applied. A product comparison matrix in the in-depth comparison phase in which products can be removed by REMOVE_{opt} further allows application of the dominance strategy, the lexicographic strategy,

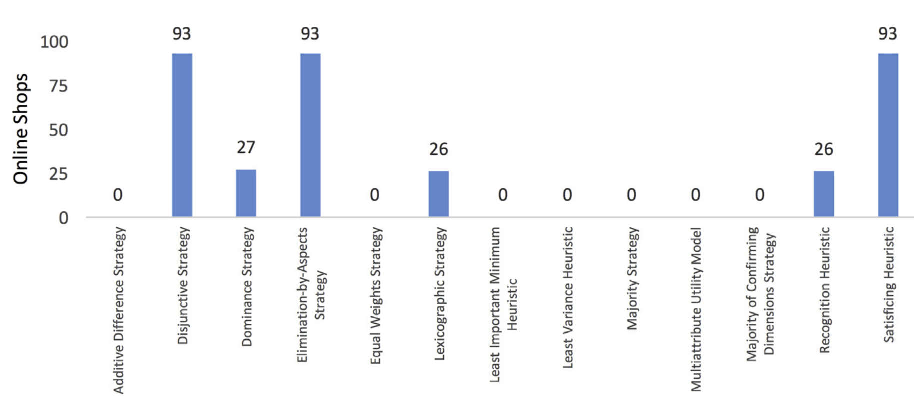

Fig. 7. Number of online shops with support of a specific decision strategy.

and the recognition heuristic. Additionally, the lexicographic strategy and the recognition heuristic require $SORT_{opt}$.

The high prevalence of FILTER and SORT is assessed positively because these IIMT support many decision strategies typically preferred by decision makers. However, our empirical study revealed that the number of available attributes for filtering depends on the specific product. In the "Computer/Electronics" industry, 17 attributes, on average, were available for filtering. In contrast, only four were available in the "Food/Drug" industry. With respect to the number of attributes for sorting, our study revealed a relatively small number. There were only 4.3 attributes, on average, for sorting available, and even these attributes were mostly general attributes such as "Top Seller", "New Arrivals", or "Price" and not product-specific attributes. Because many product attributes could not be sorted, this prevented application of some decision strategies. For example, $SORT_{opt}$ supports the lexicographic strategy and the recognition heuristic. Importantly, support is only given if it is possible to sort by the most important attribute. Hence, to support decision strategies, it is of paramount importance to provide all existing attributes in FILTER and SORT. Both online shop companies and developers of online shop systems should consider that in their future engineering efforts.

In information-intensive industries ("Hardware/Home Improvements" and "Computers/Electronics") it was possible to compare products in a matrix. In online shops of the industries " Apparel/Accessories", "Mass Merchant" and "Food/Drug", however, this was only possible in a few cases. In general, in the in-depth comparison phase far fewer IIMT were offered than in the screening phase. Only PAIRWISE COMPARISON and $REMOVE_{opt}$ were available in a larger number of shops. $SORT_{opt}$ could only be found in two shops, and both FILTER and $REMOVE_{attr}$ in one shop only. In particular, the low prevalence of SORT and FILTER in the in-depth comparison phase is problematic, as these IIMT would also support decision strategies in this phase. We could not observe IIMT which support quantitative decision strategies (SCORE, SUM) in any online shop. However, since customers hardly use quantitative decision strategies in practice (rather, they are normative decision strategies described in the scientific literature, e.g., Riedl et al., 2008), this non-availability is not a serious issue. This assessment holds particularly true because most shops in our sample are active in the business-to-consumer-domain, and not in the business-to-business domain (an example in this category is www.supplyworks.com). Unlike in the business domain, consumers typically do not have to justify their decisions like in management environments. Hence, application of normative decision strategies such as the multi-attribute utility model is not essential. An individual who uses the multi-attribute utility model chooses the option with the highest weighted overall utility score that is defined as the sum of the weighted attribute utilities (Anderson, 1974; Keeney and Raiffa, 1993; von Winterfeldt and Fischer, 1975). However, our reasoning also suggests that if business-to-business e-commerce platforms were to play a more prominent role in the future, then tools such as SCORE and SUM would become more important in practice.

From a practice perspective, it is also important to emphasize that only a few IIMT are needed to support many decision strategies. $FILTER_{attr}$ supports the application of the disjunctive strategy, the elimination-by-aspects strategy, and the satisficing heuristic. Moreover, a product comparison matrix in the in-depth comparison phase (made possible by COMPARE), where products can be removed by $REMOVE_{opt}$, supports application of the dominance strategy, the lexicographic strategy, and the recognition heuristic. For the lexicographic strategy and the recognition heuristic, in addition $SORT_{opt}$ is required. Thus, developers and online shops should primarily provide the tools $FILTER_{attr}$, $SORT_{opt}$, COMPARE, and $REMOVE_{opt}$. When online shops implement these tools in both the screening- and the in-depth comparison phase, many frequently applied decision strategies are supported.

5.2. Limitations

While we consider our study to provide value to practitioners (e.g., online shop managers and engineers) and researchers who are interested in online decision-making, there are limitations which have to be considered.

First, we reviewed 13 decision strategies, although the literature discusses some more strategies. However, because those strategies only slightly differ from those described in this paper, we do not consider this limitation to be severe. As an example, the satisficing-plus strategy is equivalent to the satisficing heuristic but only a few attributes are considered by the decision maker (Pfeiffer et al., 2014a).

Second, customers do not necessarily use one single decision strategy in their purchase decision process. Rather, it is possible that they use multiple strategies or mix them. The current analysis does not take this fact into account. Despite this limitation, our results outline whether the top 100 online shops in North America support "pure" decision strategies or not.

Third, in this study we analyzed desktop websites. Future research should also examine mobile websites or mobile apps to find out whether the current results can be replicated in the mobile context. However, we stress that we have deliberately chosen the desktop versions as the mobile versions currently offer much fewer IIMT. It is likely that this fact will not change quickly in the future because application of IIMT on small screens is a difficult task (at least based on current IIMT designs); this fact holds particularly true for IIMT in the in-depth comparison phase. To provide first evidence for this conjecture, we analyzed the 29 online shops which offer COMPARE in the desktop version; analysis was based on a Samsung Galaxy S6 device. We found that in 16 out of 29 cases COMPARE was *not* available in the mobile version. However, considering the increasing trend towards mobile device use, we anticipate that IIMT provision and use in mobile environments could become an important avenue for future research.

Fourth, while the present study argues for the use of IIMT in online shopping environments, we emphasize that such use must be executed in a parsimonious way. Offering too many decision aids may cause cognitive overload in users as they have to figure out which decision tool(s) to use. Thus, offering too many tools would counteract the tools' main objective, namely to reduce users' information overload. In fact, Wang and Benbasat (2009, pp. 93–94) found evidence for this argument, they write: "Decision tools [...] that mainly support non-compensatory decision strategies do not necessarily improve the efficiency and effectiveness of decision-making [...] Specifically, when both of them were available, the combined effect in reducing decision time and effort and in improving decision satisfaction was not necessarily better compared with the situation when only one was available." Against this background, online shops should deliberately decide which tools the users are likely to need in order to make better and less cognitively effortful decisions.

5.3. Concluding comment

IIMT and their impact on purchase decisions have a great importance for online shops. The implementation of IIMT supporting decision strategies which are frequently used by customers represents a chance for online shops to increase sales. Thus, a better understanding of human decision strategies by online shop managers and developers is pivotal for online shop success. It is hoped that the present study contributes to an underdeveloped research field and instigates further research and applications in practice.

Appendix A.

Overview of empirical papers in the field of interactive information management tools (IIMT).

Authors and years	Title	Journal/ Conference/Book	Purpose	Research method	Independent variable	Dependent variable	Data collection	Research subject	Results
Todd and Benbasat (1991)	An Experimental Investigation of the Impact of Computer Based Decision Aids on Decision Making Strategies	Information Systems Research (ISR)	What impact has the presence and the level of support of computer-aided decision support to the kind of information processing and the applied decision strategy?	Laboratory experiment	A) Presence of decision aids; B) Amount of alternatives (5 & 10)	A) Kind of information processing (option- or attribute-wise); B) Applied decision strategy	A) Thinking Aloud Protocol; B) Logfile	28 Subjects (15f/13 m)	A) Presence of decision aid has an impact on the type of information search; B) Subjects with decision aids searched attribute-wise; C) Subjects without decision aids searched option-wise; D) Increasing complexity (higher number of alternatives) reinforced this; E) Decision makers fit decision strategy to the existing decision aids
				Laboratory experiment	A) Presence of decision aids; B) Amount of alternatives (10 & 20)	A) Kind of information processing (option- or attribute-wise); B) Applied decision strategy	A) Thinking Aloud Protocol; B) Logfile	28 Subjects (14f/14 m)	
				Laboratory experiment	Level of support of decision aids	Applied decision strategy	A) Thinking Aloud Protocol; B) Logfile	28 Subjects (11f/17 m)	
Todd and Benbasat (1992)	The Use of Information in Decision Making: An Experimental Investigation of the Impact of Computer-Based Decision Aids	MIS Quarterly	What is the influence of decision aids on the information processing effort?	Laboratory experiment	A) Decision aids; B) Amount of alternatives (5 & 10)	Effort for information processing	A) Thinking Aloud Protocol; B) Logfile	28 Subjects (15f/13 m)	Subjects with the support of decision aids do not use more information than subjects without support.
				Laboratory experiment	A) Decision aids; B) Amount of alternatives (10 & 20)	Effort for information processing	A) Thinking Aloud Protocol; B) Logfile	28 Subjects (14f/14 m)	
Todd and Benbasat (1994)	The Influence of Decision Aids on Choice Strategies Under Conditions of High Cognitive Load	Organizational Behavior and Human Decision Processes	What is the impact of decision aids to applied decision strategies considering the effort for the use of the aids?	Laboratory experiment	Level of support of decision aids	Applied decision strategy	A) Thinking Aloud Protocol; B) Logfile	32 Subjects (17f/15 m)	Applied decision strategy depends on the effort for the use of the supporting decision aid.
Häubl and Trifts (2000)	Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids	Marketing Science	What effects have IDA on decisions of customers of online shops.	Laboratory experiment	Presence of IDA	A) Searching for product information; B) Size and quality of the consideration sets; C) Decision quality	Questionnaire	249 Subjects	The presence of recommendation agents and product comparison matrices led to: A) less effort for searching product information; B) smaller consideration set; C) higher quality of the consideration set; D) better rated purchase decision
Al-Qaed and Sutcliffe (2006)	Adaptive Decision Support System (ADSS) for B2C E- Commerce	International conference on Electronic commerce (ICEC)	Have different scenarios (situations) influence on the preferred decision aid?	Laboratory experiment	Scenarios	Preferred decision aid	Interview	20 Subjects (9f/11 m)	A) In different situations different decision aids are preferred; B) Different decision aids are important; C) Subjects preferred the decision aids recommended by an avatar.
Gupta et al. (2009)	How Task-Facilitative Interactive Tools Foster Buyers' Trust in Online Retailers: A Process View of Trust Development in the Electronic Marketplace	Journal of Retailing	Investigation of the effect of IIMT on perceived support by the user and perceived trust in the online shop.	Laboratory experiment	IDA	A) Perceived support; B) Perceived trust in the online shop	Questionnaire	246 Subjects (143f/103 m)	A) IIMT increase the perceived support of customers in online shops by the reseller; B) IIMT increase the trust of customers in the online shop
				Laboratory experiment	IDA	A) Perceived support; B) Perceived trust in the online shop	A) Questionnaire; B) Thinking Aloud Protocol	223 Subjects	Confirmation of the results from the first study

Appendix A. (*continued*)

Authors and years	Title	Journal/ Conference/Book	Purpose	Research method	Independent variable	Dependent variable	Data collection	Research subject	Results
Wan et al. (2009)	The Paradoxical Nature of Electronic Decision Aids on Comparison-Shopping: The Experiments and Analysis	Journal of theoretical and applied electronic commerce research	At what number of products and attributes in product comparison matrices an information overload can be measured?	Laboratory experiment	Decision task	A) Decision quality; B) Time period of decision; C) Trust in the decision; D) Satisfaction with the decision	A) Logfile; B) Questionnaire	224 Subjects	Without any IIMT a number of 20 products with 10 attributes resulted in a measurable information overload.
			What is the impact of IIMT on information overload?	Laboratory experiment	IDA	A) Decision quality; B) Time period of decision; C) Trust in the decision; D) Satisfaction with the decision	Questionnaire	240 Subjects	The presence of multiple IDA led to: A) higher cognitive effort of the users; B) lower user satisfaction compared to the presence of only one IDA.
Castagnos and Pu (2010)	Consumer Decision Patterns Through Eye Gaze Analysis	Proceedings of the 2010 workshop on Eye gaze in intelligent human machine interaction (EGIHMI)	Is there a different for whom something is purchased in an online shop (for yourself or for someone else) relating to which elements are considered in an online shop.	Laboratory experiment	Person for whom a product is purchased.	Considering online shop elements	A) Eye-Tracking; B) Questionnaire	18 Subjects (9f/9m)	A) By shopping for another person, product recommendations are less important; B) But after viewing product recommendations most products are added to the shopping cart.
Pfeiffer (2010)	Interaktive Entscheidungshilfen	Vertriebsinformationssysteme (Buch)	Which presence have IDA in online shops?	Evaluation of platforms				100 (OS)	A) High presence of IIMT in the screening phase (filtering and sorting); B) less IIMT in the in-depth comparison phase; C) no presence of recommendation agents
			Which IDA prefer customers?	Laboratory experiment	IDA	User ratings	Questionnaire	32 Subjects (15f/17 m)	User prefer IIMT compared with recommendation agents. IIMT have: A) Higher perceived usability; B) Higher perceived usefulness; C) Higher trust among users
Pfeiffer et al. (2010)	A Theory-Based Approach for a Modular System of Interactive Decision Aids	Proceedings of the Americas Conference on Information Systems (AMCIS)	Theory-based design of IDA: The aim was to design an IIMT prototype (according to requirements identified in the literature). This will be evaluated by experts in terms of usability.	Usability Study (Prototyping)			Questionnaire	5 Experts	A confusing design, a possible strain on the user and an insufficient description of the functionalities have been criticized.
			The first experiment was followed by a re-evaluating by non-experts after the prototype was revised.	Usability Study (Prototyping)			A) Thinking Aloud Protocol; B) Questionnaire	7 Subjects (4f/3m)	A) Logical errors, programming errors, design flaws and missing features have been criticized.; B) There was a further revision of the prototype.
Reisen and Hoffrage (2010)	The Interactive Choice Aid: A New Approach to Supporting Online Consumer Decision Making	AIS Transactions on Human-Computer Interaction	Theory-based design of IDA: The aim was designing an IIMT prototype based on research results in the field of decision strategies. The effect of this design to user ratings should finally be verified.	Laboratory experiment (Prototyping)	IDA	A) Comprehensibility; B) Usability; C) Ease to remove products; D) Ease to compare products; E) Satisfaction with the decision	A = Question naire; B) Interview	24 Subjects (10f/14 m)	The developed prototype with high functionality resulted in significantly lower usability and to a significantly higher ease of comparing products.
Tan et al. (2010)	Assessing Screening and Evaluation Decision Support Systems: A Resource-Matching Approach	Information Systems Research (ISR)	What influence do different IDA and a different number of attributes of products have on decisions?	Laboratory experiment	A) Level of support of decision aids; B) Number of attributes	A) Time period of decision; B) Decision Quality; C) Perceived decision quality; D) Perceived quality of the decision aid	Questionnaire	156 Subjects (80f/76 m)	The quality of decisions is increased by IDA because complex decisions would need too high cognitive performance without support.

(*continued on next page*)

Appendix A. (*continued*)

Authors and years	Title	Journal/ Conference/Book	Purpose	Research method	Independent variable	Dependent variable	Data collection	Research subject	Results
Gokhan and Veryzer (2012)	The Effects of Electronic Decision Aids on Consumers' Cue Utilization in Product Evaluations	Journal of Marketing Development and Competitiveness	What effect does the use of IDA have on the use of product information and the evaluation of products	Laboratory experiment	A) IDA; B) Number of extrinsic (brand, price,..) and intrinsic (product-specific attributes like resolution of a TV) attributes	A) Product ratings; B) Perceived quality	Questionnaire	507 Subjects	A) Use of IDA influences the buying decision.; B) IIMT allow a better comparison of products and their characteristics.; C) This leads to a higher rated perceived quality of decision.
Pfeiffer et al. (2012)	Inferring decision strategies from clickstreams in decision support systems: a new process-tracing approach using state machines	Zeitschrift für Betriebswirtschaft	Is it possible to conclude from clickstream data to predefined decision strategy?	Laboratory experiment	Predefined decision strategies	Decision strategy determined by an algorithm	Click-stream	17 Subjects	From clickstream data it is possible to accurately conclude to decision strategies
			Is it possible to conclude from clickstream data to real decision strategy?	Laboratory study			Click-stream	38 Subjects	A) Decision strategy could be assigned again.; B) Customers not only use just one strategy. They mix strategies during the decision process.
Kailer et al. (2014)	Supporting customers' decision making with Rated Tags	International conference on Electronic commerce (ICEC)	What influence have product reviews by customers on the purchase decision?	Laboratory experiment	Product ratings	A) Decision quality; B) Required effort for the decision	Questionnaire	36 Subjects	Reviews can lead to a higher decision quality and to lower cognitive efforts for the consumer.
Pfeiffer et al. (2014a)	Minimally Restrictive Decision Support Systems	Proceedings of the International Conference on Information Systems (ICIS)	Design of an IIMT prototype, which supports a broad variety of decision strategies. Will this prototype be preferred by users?	Laboratory experiment (Prototyping)	IDA	User ratings	Questionnaire	73 Subjects	A) Proposal for the design of IIMT, which supports a large number of strategies; B) Users use different strategies in different situations and mix them.; C) The prototype led to lower cognitive effort, higher perceived ease of use and higher intention for reuse it.
Wei Shi and Zhang (2014)	Usage Experience with Decision Aids and Evolution of Online Purchase Behavior	Marketing Science	How does use of IDA change over a longer period?	Case study			Click-stream	1 Online Shop	A) Use of IDA changes in the course of the customer relationship; B) The possibility to sort by price can reduce customer loyalty; C) Shopping lists or retrieving previous order lists can improve the customer relationship
Heimbach et al. (2015)	On the Design of Sales Support Systems for Online Apparel Stores	Wirtschaftsinformatik Proceedings	How IDA are used for the purchase of products that are purchased because they give a sense of uniqueness (clothes, luxury items)?	Laboratory study			A) Video protocol; Questionnaire	34 Subjects (34f/0m)	A) Subjects with high involvement searched with higher intense; B) Most used IDA: sorting and filtering functions, internal search; C) Recommendation systems are used less.

Appendix B.

Correlation of online shop web sales and number of IIMT.

A Pearson correlation coefficient was computed to assess the relationship between the web sales of the analyzed online shops (all web sales are listed in Appendix C in $) and the number of IIMT (see Appendices C and D). Based on an analysis of all 100 analyzed online shops, there was no significant correlation between the two variables ($r = -0.031$, $p = .759$).

Descriptive statistics

	Mean	Std. deviation	N
Web sales (rank 1–100)	2.421.145.445	8.225.351.269	100
IIMT (rank 1–100)	2.4400	1.17482	100

Correlations

		Web sales	IIMT
Web sales (rank 1–100)	Pearson Correlation	1	-0.031
	Sig. (2-tailed)		0.759
	N	100	100
IIMT (rank 1–100)	Pearson Correlation	-0.031	1
	Sig. (2-tailed)	0.759	
	N	100	100

Importantly, the total web sales of the four online shops with the highest web sales (i.e., rank 1–4: Amazon.com Inc., Apple Inc., Walmart.com, Staples Inc.) are higher (51% of the total web sales of all 100 analyzed online shops) than the total web sales of all remaining online shops (i.e., rank 5–100). To account for this abnormal distribution of data, the top four online shops were excluded from a second calculation. Based on data from the online shops 5–100, there was a significant positive correlation between the two variables ($r = 0.327$, $p = .001$).

Descriptive statistics

	Mean	Std. deviation	N
Web sales (rank 5–100)	1.235.891.088	1.132.343.357	96
IIMT (rank 5–100)	2.4688	1.18724	96

Correlations

		Web sales (rank 5–100)	IIMT (rank 5–100)
Web sales (rank 5–100)	Pearson Correlation	1	0.327*
	Sig. (2-tailed)		0.001
	N	96	96
IIMT (rank 5–100)	Pearson Correlation	0.327*	1
	Sig. (2-tailed)	0.001	
	N	96	96

*Correlation is significant at the 0.01 level (2-tailed).

Fig. A1 shows the frequency distribution of the number of integrated IIMT across all 100 online shops. Almost 2/3 of the online shops have two IIMT and approximately 1/5 have four IIMT.

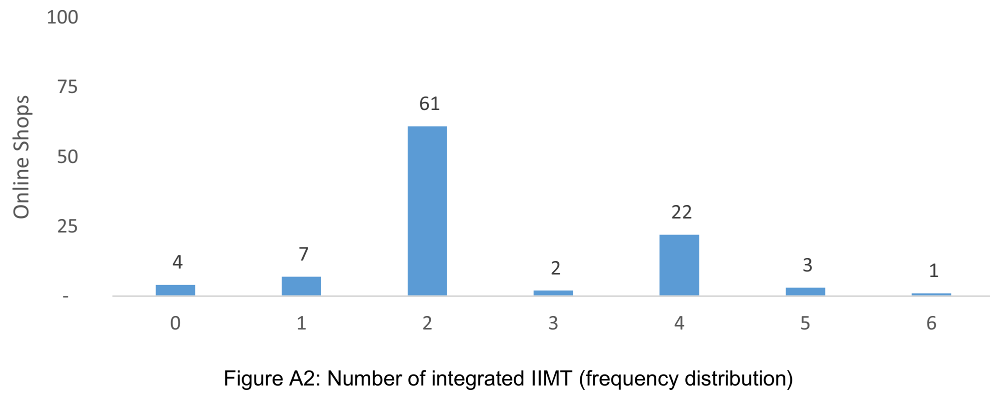

Fig. A1. Number of integrated IIMT (frequency distribution).

Appendix C.

IIMT in the screening phase of the analyzed online shops.

Rank	Company	2014 web sales	Category	FILTER	SORT	COMPARE
1	Amazon.com Inc.	$79.480.000.000	Mass Merchant	X	X	
2	Apple Inc.	$20.621.000.000	Books/Music/Video			X
3	Walmart.com	$12.136.000.000	Mass Merchant	X	X	
4	Staples Inc.	$11.232.000.000	Office Supplies	X	X	
5	Sears Holdings Corp.	$5.700.000.000	Mass Merchant	X	X	X
7	Macy's Inc.	$5.400.000.000	Mass Merchant	X	X	
8	Office Depot Inc.	$4.300.000.000	Office Supplies	X	X	X
9	CDW Corp.	$3.800.000.000	Computers/Electronics	X	X	X
10	The Home Depot Inc.	$3.762.000.000	Hardware/Home Improvements	X	X	X
12	Dell Inc.	$3.650.000.000	Computers/Electronics	X	X	X
13	W.W. Grainger Inc.	$3.600.000.000	Office Supplies	X	X	X
14	Best Buy Co. Inc.	$3.540.000.000	Computers/Electronics	X	X	X
15	QVC Inc.	$3.533.000.000	Mass Merchant	X	X	X
16	Target Corp.	$2.990.000.000	Mass Merchant	X	X	
17	Newegg Inc.	$2.830.000.000	Computers/Electronics	X	X	X
18	Gap Inc.	$2.500.000.000	Apparel/Accessories	X		
19	Nordstrom Inc.	$2.500.000.000	Apparel/Accessories	X	X	
20	Williams—Sonoma Inc.	$2.371.000.000	Housewares/Home Furnishings			
21	Sony Electronics Inc.	$2.200.000.000	Computers/Electronics	X	X	X
22	Kohl's Corp.	$2.168.000.000	Mass Merchant	X	X	
24	Etsy Inc.	$1.930.000.000	Mass Merchant	X	X	
25	HSN Inc.	$1.722.400.000	Mass Merchant	X	X	
26	Liberty Ventures Group	$1.698.000.000	Mass Merchant	X	X	
28	L Brands Inc.	$1.628.000.000	Apparel/Accessories	X	X	
29	Amway	$1.605.000.000	Health/Beauty	X	X	
30	Groupon Goods	$1.564.149.000	Mass Merchant	X	X	
31	Overstock.com Inc.	$1.497.000.000	Mass Merchant	X	X	
32	Systemax Inc.	$1.400.000.000	Computers/Electronics	X	X	X
33	Wayfair LLC	$1.300.000.000	Housewares/Home Furnishings	X	X	
34	L.L. Bean Inc.	$1.284.107.000	Apparel/Accessories	X	X	X
35	Vistaprint (Cimpress)	$1.270.200.000	Office Supplies	X		
36	Lowe's Cos. Inc.	$1.265.000.000	Hardware/Home Improvements	X	X	X
37	J.C. Penney Co. Inc.	$1.220.000.000	Mass Merchant	X	X	
38	Lands' End	$1.201.000.000	Mass Merchant	X	X	
39	zulily Inc.	$1.200.079.000	Apparel/Accessories	X		
40	Toys 'R' Us Inc.	$1.200.000.000	Toys/Hobbies	X	X	
41	MSCIndustrial Supply	$1.198.200.000	Hardware/Home Improvements	X	X	X
42	HP Home & Home Office Store	$1.160.000.000	Computers/Electronics	X	X	X
43	Neiman Marcus	$1.148.500.000	Apparel/Accessories	X	X	
44	Walgreen Co.	$1.125.000.000	Food/Drug	X	X	
45	Fanatics Inc.	$1.100.000.000	Apparel/Accessories	X	X	

Appendix C. (*continued*)

Rank	Company	2014 web sales	Category	FILTER	SORT	COMPARE
46	APMEX Inc.	$1.053.406.368	Specialty/Non-Apparel	X	X	
47	BarnesandNoble.com	$1.040.000.000	Books/Music/Video	X	X	
48	Lenovo Group Ltd.	$1.000.000.000	Computers/Electronics	X	X	
49	Urban Outfitters Inc.	$953.880.000	Apparel/Accessories	X	X	
50	Shutterfly Inc.	$921.600.000	Specialty	X	X	
51	Rakuten.com	$910.000.000	Mass Merchant	X	X	
52	J. Crew Group Inc.	$900.000.000	Apparel/Accessories	X		
53	PC Connection Inc.	$882.500.000	Computers/Electronics	X	X	X
54	Foot Locker Inc.	$859.940.000	Apparel/Accessories	X	X	
55	Abercrombie & Fitch Co.	$847.000.000	Apparel/Accessories	X	X	
56	1–800-Flowers.com Inc.	$815.000.000	Flowers/Gifts	X	X	
58	GameStop Corp.	$792.000.000	Toys/Hobbies	X	X	
59	Ralph Lauren Media	$780.000.000	Apparel/Accessories	X	X	
60	Bluestem Brands Inc.	$775.000.000	Apparel/Accessories	X	X	X
61	Nike Inc.	$767.000.000	Apparel/Accessories	X	X	
62	Restoration Hardware	$766.173.000	Housewares/Home Furnishings			
63	Cabela's Inc.	$750.000.000	Sporting Goods	X	X	X
64	Market America	$724.292.907	Mass Merchant	X	X	
65	Avon Products Inc.	$705.000.000	Health/Beauty	X	X	
66	NoMoreRack.com Inc.	$700.000.000	Mass Merchant		X	
67	Musician's Friend Inc.	$680.000.000	Catalog/Call Center	X	X	X
68	Gilt Groupe	$670.000.000	Apparel/Accessories	X	X	
69	Peapod LLC	$649.350.000	Food/Drug	X	X	
70	Dick's Sporting Goods	$626.888.000	Sporting Goods	X	X	
72	REI	$608.000.000	Sporting Goods	X	X	X
73	Estee Lauder	$603.750.000	Health/Beauty		X	
74	Advance Auto Parts Inc.	$600.500.000	Automotive Parts/Accessories	X	X	
75	American Eagle	$600.000.000	Apparel/Accessories	X	X	
76	Build.com Inc.	$525.000.000	Hardware/Home Improvements	X	X	X
78	Follett Higher Education	$517.000.000	Books/Music/Video	X	X	
79	Deluxe Corp.	$510.000.000	Office Supplies	X	X	
80	Bed Bath & Beyond Inc.	$507.500.000	Housewares/Home Furnishings	X	X	X
81	Crate and Barrel	$507.000.000	Housewares/Home Furnishings	X	X	X
82	Coach Inc.	$500.000.000	Apparel/Accessories	X	X	
83	FreshDirect LLC	$499.500.000	Food/Drug	X	X	
84	RueLaLa.com	$480.000.000	Apparel/Accessories	X	X	
85	Blue Nile Inc.	$473.516.000	Jewelry	X	X	
86	Disney Store USA LLC	$460.000.000	Specialty	X	X	
87	Ascena Retail Group	$450.000.000	Apparel/Accessories	X	X	
88	Chico's FAS Inc.	$449.500.000	Apparel/Accessories	X	X	
89	Weight Watchers	$437.400.000	Food/Drug	X	X	
90	Interline Brands Inc.	$436.524.179	Hardware/Home Improvements	X	X	X
91	1–800 Contacts Inc.	$434.248.000	Health/Beauty			
94	Ann Inc.	$405.000.000	Apparel/Accessories	X	X	
95	Hayneedle Inc.	$404.000.000	Housewares/Home Furnishings	X	X	X
96	Scholastic Inc.	$402.907.000	Books/Music/Video	X	X	
97	Hudson's Bay Co.	$400.200.000	Apparel/Accessories	X	X	
98	JustFab Inc.	$400.000.000	Apparel/Accessories			
99	Oriental Trading Co.	$395.900.000	Specialty	X	X	
100	Keurig Green Mountain Inc.	$395.000.000	Food/Drug	X	X	
101	The Net-a-Porter Group LLC	$368.340.000	Apparel/Accessories	X	X	
102	Express Inc.	$354.200.000	Apparel/Accessories	X	X	
103	Eddie Bauer LLC	$350.750.000	Apparel/Accessories	X	X	
104	VF Corp.	$350.000.000	Apparel/Accessories	X	X	X
105	Shoebuy.com Inc.	$346.500.000	Apparel/Accessories	X	X	
106	One Kings Lane	$345.000.000	Housewares/Home Furnishings	X	X	
107	AutoZone Inc.	$343.144.000	Automotive Parts/Accessories	X		X
108	LuluLemon Athletica Inc.	$330.000.000	Apparel/Accessories	X	X	X
110	Bass Pro	$325.500.000	Sporting Goods	X	X	

Appendix D.

IIMT in the in-depth comparison phase of the analyzed online shops.

Rank	Company	Category	FILTER		MARK	PAIRWISE COMPARISON	REMOVE		SCORE			SORT		SUM	
			attr	markings			opt	attr	opt	attr	cell	opt	attr	simple	weighted
2	Apple Inc.	Books/Music/Video				X									
5	Sears Holdings Corp.	Mass Merchant				X	X								
8	Office Depot Inc.	Office Supplies				X	X					X			
9	CDW Corp.	Computers/Electronics				X	X								
10	The Home Depot Inc.	Hardware/Home Improvements				X	X								
12	Dell Inc.	Computers/Electronics				X	X	X							
13	W.W. Grainger Inc.	Office Supplies				X	X								
14	Best Buy Co. Inc.	Computers/Electronics				X	X								
15	QVC Inc.	Mass Merchant				X	X								
17	Newegg Inc.	Computers/Electronics				X	X								
21	Sony Electronics Inc.	Computers/Electronics	X			X	X					X			
32	Systemax Inc.	Computers/Electronics				X	X								
34	L.L. Bean Inc.	Apparel/Accessories				X	X								
36	Lowe's Cos. Inc.	Hardware/Home Improvements				X	X								
41	MSCIndustrial Supply	Hardware/Home Improvements				X	X								
42	HP Home & Home Office Store	Computers/Electronics				X	X								
53	PC Connection Inc.	Computers/Electronics				X	X								
60	Bluestem Brands Inc.	Apparel/Accessories				X									
63	Cabela's Inc.	Sporting Goods				X	X								
67	Musician's Friend Inc.	Catalog/Call Center				X	X	X							
72	REI	Sporting Goods				X	X								
76	Build.com Inc.	Hardware/Home Improvements				X	X								
80	Bed Bath & Beyond Inc.	Housewares/Home Furnishings				X	X								
81	Crate and Barrel	Housewares/Home Furnishings				X	X								
90	Interline Brands Inc.	Hardware/Home Improvements				X	X								
95	Hayneedle Inc.	Housewares/Home Furnishings				X	X								
104	VF Corp.	Apparel/Accessories				X	X								
107	AutoZone Inc.	Automotive Parts/ Accessories				X	X								
108	LuluLemon Athletica Inc.	Apparel/Accessories				X	X								

Appendix E.

Support of decision strategies in online shops.

Rank	Company	Additive Difference Strategy	Disjunctive Strategy	Dominance Strategy	Elimination-by-Aspects Strategy	Equal Weights Strategy	Lexicographic Strategy	Least Important Minimum Heuristic	Least Variance Heuristic	Majority Strategy	Multiattribute Utility Model	Majority of Confirming Dimensions Strategy	Recognition Heuristic	Satisficing Heuristic
1	Amazon.com Inc.		X		X									X
2	Apple Inc.													
3	Walmart.com		X		X									X
4	Staples Inc.		X		X									X
5	Sears Holdings Corp.		X	X	X		X						X	X
7	Macy's Inc.		X		X									X
8	Office Depot Inc.		X	X	X		X						X	X
9	CDW Corp.		X	X	X		X						X	X
10	The Home Depot Inc.		X	X	X		X						X	X
12	Dell Inc.		X	X	X		X						X	X
13	W.W. Grainger Inc.		X	X	X		X						X	X
14	Best Buy Co. Inc.		X	X	X		X						X	X
15	QVC Inc.		X	X	X		X						X	X
16	Target Corp.		X		X									X
17	Newegg Inc.		X	X	X		X						X	X
18	Gap Inc.		X		X									X
19	Nordstrom Inc.		X		X									X
20	Williams—Sonoma Inc.													
21	Sony Electronics Inc.		X	X	X		X						X	X
22	Kohl's Corp.		X		X									X
24	Etsy Inc.		X		X									X
25	HSN Inc.		X		X									X
26	Liberty Ventures Group		X		X									X
28	L Brands Inc.		X		X									X
29	Amway		X		X									X
30	Groupon Goods		X		X									X
31	Overstock.com Inc.		X		X									X
32	Systemax Inc.		X	X	X		X						X	X
33	Wayfair LLC		X		X									X
34	L.L. Bean Inc.		X	X	X		X						X	X
35	Vistaprint (Cimpress)		X		X									X
36	Lowe's Cos. Inc.		X	X	X		X						X	X
37	J.C. Penney Co. Inc.		X		X									X
38	Lands' End		X		X									X
39	zulily Inc.		X		X									X
40	Toys 'R' Us Inc.		X		X									X
41	MSC Industrial Supply		X	X	X		X						X	X
42	HP Home & Home Office Store		X	X	X		X						X	X
43	Neiman Marcus		X		X									X
44	Walgreen Co.		X		X									X
45	Fanatics Inc.		X		X									X
46	APMEX Inc.		X		X									X
47	BarnesandNoble.com		X		X									X
48	Lenovo Group Ltd.		X		X									X
49	Urban Outfitters Inc.		X		X									X
50	Shutterfly Inc.		X		X									X
51	Rakuten.com		X		X									X
52	J. Crew Group Inc.		X		X									X
53	PC Connection Inc.		X	X	X		X						X	X
54	Foot Locker Inc.		X		X									X
55	Abercrombie & Fitch Co.		X		X									X
56	1–800-Flowers.com Inc.		X		X									X
58	GameStop Corp.		X		X									X

(*continued on next page*)

Appendix E. (*continued*)

Rank	Company	Additive Difference Strategy	Disjunctive Strategy	Dominance Strategy	Elimination-by-Aspects Strategy	Equal Weights Strategy	Lexicographic Strategy	Least Important Minimum Heuristic	Least Variance Heuristic	Majority Strategy	Multiattribute Utility Model	Majority of Confirming Dimensions Strategy	Recognition Heuristic	Satisficing Heuristic
59	Ralph Lauren Media		X		X									X
60	Bluestem Brands Inc.		X		X									X
61	Nike Inc.		X		X									X
62	Restoration Hardware													
63	Cabela's Inc.		X	X	X		X						X	X
64	Market America		X		X									X
65	Avon Products Inc.		X		X									X
66	NoMoreRack.com Inc.													
67	Musician's Friend Inc.		X	X	X		X						X	X
68	Gilt Groupe		X		X									X
69	Peapod LLC		X		X									X
70	Dick's Sporting Goods		X		X									X
72	REI		X	X	X		X						X	X
73	Estee Lauder													
74	Advance Auto Parts Inc.		X		X									X
75	American Eagle		X		X									X
76	Build.com Inc.		X	X	X		X						X	X
78	Follett Higher Education		X		X									X
79	Deluxe Corp.		X		X									X
80	Bed Bath & Beyond Inc.		X	X	X		X						X	X
81	Crate and Barrel		X	X	X		X						X	X
82	Coach Inc.		X		X									X
83	FreshDirect LLC		X		X									X
84	RueLaLa.com		X		X									X
85	Blue Nile Inc.		X		X									X
86	Disney Store USA LLC		X		X									X
87	Ascena Retail Group		X		X									X
88	Chico's FAS Inc.		X		X									X
89	Weight Watchers		X		X									X
90	Interline Brands Inc.		X	X	X		X						X	X
91	1–800 Contacts Inc.													
94	Ann Inc.		X		X									X
95	Hayneedle Inc.		X	X	X		X						X	X
96	Scholastic Inc.		X		X									X
97	Hudson's Bay Co.		X		X									X
98	JustFab Inc.													
99	Oriental Trading Co.		X		X									X
100	Keurig Green Mountain Inc.		X		X									X
101	The Net-a-Porter Group LLC		X		X									X
102	Express Inc.		X		X									X
103	Eddie Bauer LLC		X		X									X
104	VF Corp.		X	X	X		X						X	X
105	Shoebuy.com Inc.		X		X									X
106	One Kings Lane		X		X									X
107	AutoZone Inc.		X	X	X									X
108	LuluLemon Athletica Inc.		X	X	X		X						X	X
110	Bass Pro		X		X									X

References

Al-Qaed, F., Sutcliffe, A., 2006. Adaptive Decision Support System (ADSS) for B2C E-Commerce. ICEC '06 Proceedings of the 8th international conference on Electronic commerce, pp. 492–503.

Anderson, N.H., 1974. Algebraic models of perception. In: Carterette, E.C., Friedman, M.P. (Eds.), Handbook of Perception, vol. 2. Academic Press, New York.

Ariely, D., 2010. Predictably Irrational, The Hidden Forces That Shape Our Decisions. Harper, London. Revised and Updated Edition.

Bettman, J.R., Johnson, E.J., Payne, J.W., 1991. Consumer decision making. In: Robertson, T.S., Kassarjian, H.H. (Eds.), Handbooks of Consumer Theory and Research. Prentice-Hall, Englewood Cliffs, New York, pp. 50–84.

Bettman, J.R., Luce, M.F., Payne, J.W., 1998. Constructive consumer choice processes. J. Consum. Res. 25 (3), 187–217.

Bettman, J.R., Luce, M.F., Payne, J.W., 2012. Consumer decision making: a choice goal approach. In: Haugtvedt, C.P., Herr, P.M., Kardes, F.R. (Eds.), Handbook of Consumer Psychology. Taylor and Francis, New York, pp. 589–610.

Cartwright, E., 2014. Behavioral Economics (Routledge Advanced Texts in Economics and Finance). Routledge, New York.

Castagnos, S., Pu, P., 2010. Consumer Decision Patterns Through Eye Gaze Analysis. EGIHMI '10 Proceedings of the 2010 workshop on Eye gaze in intelligent human machine interaction, pp. 78–85.

Chen, Y., Shang, R., Kao, C., 2009. The effects of information overload on consumers' subjective state towards buying decision in the internet shopping environment. Electron. Commer. Res. Appl., 48–58

Digital Market Outlook. 2016. *statista*. Retrieved April 15, 2016, from statista: http://de.statista.com/statistik/daten/studie/485047/umfrage/umsaetze-im-e-commerce-nach-laendern-weltweit/.

Gevorgyan, M. 2016. *engadget*. Retrieved May 25, 2017, from engadget: https://www.engadget.com/2016/11/03/ecommerce-platform-market-share-looking-at-the-companies-that-d/.

Gokhan, K., Veryzer, R., 2012. The effects of electronic decision aids on consumers' Cue utilization in product evaluations. J. Mark. Dev. Competitiveness, 74–80.

Gupta, P., Yadav, M., Varadarajan, R., 2009. How task-facilitative interactive tools foster buyers' trust in online retailers. A process view of trust development in the electronic marketplace. J. Retail., 159–176

Harte, J., Koele, P., 2001. Modelling and describing human judgement processes: the multiattribute evaluation case. Thinking Reasoning, 29–49.

Häubl, G., Trifts, V., 2000. Consumer decision making in online shopping environments: the effects of interactive decision aids. Mark. Sci., 4–21

Heimbach, I., Kraus, C., Hinz, O., 2015. On the design of sales support systems for online apparel stores. Wirtschaftsinformatik Proc. 2015, 1618–1633.

Internet Retailer, 2015. Top 500 Guide of the 500 largest E-Commerce Sites in North America.

Johnson, E., Payne, J., 1985. Effort and accuracy in choice. Manage. Sci., 395–414

Kahneman, D., 2003. Maps of bounded rationality: psychology for behavioral economics. Am. Econ. Rev. 93 (5), 1449–1475.

Kailer, D., Mandl, P., Schill, A., 2014. Supporting customers' decision making with rated tags. Int. Conf. Electron. Commerce (ICEC), 33–40.

Keeney, R., Raiffa, H., 1993. Decisions with Multiple Objectives: Preferences and Value Tradeoffs. Cambridge University Press, Cambridge.

Lohse, G., Johnson, E., 1996. A Comparison of Two Process Tracing Methods for Choice Tasks. In: Proceedings of the 29th Annual Hawaii International Conference on System Sciences – 1996, pp. 86–97.

Norton, M.I., Rucker, D.D., Lamberton, C., 2017. The Cambridge Handbook of Consumer Psychology (Cambridge Handbooks in Psychology). Cambridge University Press, Cambridge.

Payne, J., 1976. Task complexity and contingent processing in decision making: an information search and protocol analysis. Organ. Behav. Hum. Perform., 366–387

Payne, J.W., Bettman, J.R., Coupey, E.J., Johnson, E.J., 1992. A constructive process view of decision making: multiple strategies in judgment and choice. Acta Psychol., 107–141

Payne, J.W., Bettman, J.R., Johnson, E.J., 1993. The Adaptive Decision Maker. Cambridge University Press, New York.

Pfeiffer, J., 2010. Interaktive Entscheidungshilfen. In: Becker, J., Knackstedt, R., Winkelmann, A. (Eds.), Vertriebsinformationssysteme. Springer, Berlin, pp. 105–123.

Pfeiffer, J., Riedl, R., Rothlauf, F., 2009. On the relationship between interactive decision aids and decision strategies: a theoretical analysis. Wirtschaftsinformatik Proc., 160–170

Pfeiffer, J., Vogel, F., Stumpf, S., Kiltz, C., 2010. A theory-based approach for a modular system of interactive decision aids. AMCIS 2010 Proceedings (35), pp. 1–9.

Pfeiffer, J., Probst, M., Steitz, W., Rothlauf, F., 2012. Inferring decision strategies from clickstreams in decision support systems: a new process-tracing approach using state machines. Zeitschrift für Betriebswirtschaft (ZfB), 25–46.

Pfeiffer, J., Benbasat, I., Rothlauf, F., 2014a. Minimally restrictive decision support systems. Int. Conf. Inf. Syst., 1713–1727

Pfeiffer, J., Meißner, M., Brandstätter, E., Riedl, R., Decker, R., Rothlauf, F., 2014b. On the influence of context-based complexity on information search patterns: an individual perspective. J. Neurosci. Psychol. Econ., 103–124

Reisen, N., Hoffrage, U., 2010. The interactive choice aid: a new approach to supporting online consumer decision making. AIS Trans. Hum.-Cumput. Interact., 112–126

Riedl, R., Brandstätter, E., 2007. Die Strategie der Entscheidung: Alte Probleme und neue Lösungen. NeuroPsychoEconomics, 59–75.

Riedl, R., Brandstätter, E., Roithmayr, F., 2008. Identifying decision strategies: a process- and outcome-based classification method. Behav. Res. Methods, 795–807.

Schulte-Mecklenbeck, M., Kuehberger, A., Ranyard, R., 2011. A Handbook of Process Tracing Methods for Decision Research (Society for Judgment and Decision Making). Psychology Press, New York.

Shanthi, R., Kannaiah, D., 2015. Consumers' Perception on Online Shopping. J. Mark. Consum. Res., 14–20

Sicilia, M., Ruiz, S., 2010. The effects of the amount of information on cognitive responses in online purchasing tasks. Electron. Commer. Res. Appl., 183–191.

Simon, H.A., 1959. Theories of decision-making in economics and behavioral science. Am. Econ. Rev. 49, 253–283.

Simon, H.A., 1990. Invariants of human behavior. Annu. Rev. Psychol. 41 (1), 1–20.

Tan, C., Teo, H., Benbasat, I., 2010. Assessing screening and evaluation decision support systems: a resource-matching approach. Inform. Syst. Res., 305–326

Todd, P., Benbasat, I., 1991. An experimental investigation of the impact of computer based decision aids on decision making strategies. Inform. Syst. Res., 87–115

Todd, P., Benbasat, I., 1992. The use of information in decision making: an experimental investigation of the impact of computer-based decision aids. MIS Q., 373–393

Todd, P., Benbasat, I., 1994. The influence of decision aids on choice strategies under conditions of high cognitive load. Organ. Behav. Hum. Decis. Process., 537–547

von Winterfeldt, D., Fischer, G.W., 1975. Multiattribute utility theory: models and assessment procedures. In: Wendt, D., Viek, C.A.J. (Eds.), Utility, Probability, and Human Decision Making. Riedel, Dordrecht, pp. 47–86.

Wan, Y., Menon, S., Ramaprasad, A., 2009. The paradoxical nature of electronic decision aids on comparison-shopping: the experiments and analysis. J. Theor. Appl. Electron. Commerce Res., 80–96

Wang, W., Benbasat, I., 2009. Interactive decision aids for consumer decision making in E-commerce: the influence of perceived strategy restrictiveness. MIS Q., 293–320

Wei Shi, S., Zhang, J., 2014. Usage experience with decision aids and evolution of online purchase behavior. Mark. Sci., 871–882

Wright, G., 2013. Behavioral Decision Making. Springer, New York.