Impacts of decoy elements on result set evaluations in knowledge-based recommendation

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Abstract: State-of-the-art recommender systems only partially consider psychological aspects of consumer behaviour. Taking into account those aspects helps to improve the overall understanding of related decision processes. In this paper we investigate influences triggered by so called decoy effects which are known phenomena in decision psychology and marketing. Particularly, we focus on changes in the perceived product utility and the effect on the subjectively felt confidence in a customer's own decision in a potential sales situation. To this end, we report the results of two empirical studies which analyse decoy effects in not yet investigated item/attribute constellations.

Keywords: KBRs; knowledge-based recommenders; decoy effects; confidence.

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1 Introduction

There are various approaches to online recommendation (Burke, 2002). Collaborative filtering (Herlocker et al., 2004; Konstan et al., 1997) exploits similarities between ratings of different users for the derivation of new recommendations. Content-based filtering (Mooney and Roy, 2000; Pazzani and Billsus, 1997) exploits preferences of the current user to derive new recommendations with item descriptions similar to those in the user profile. Finally, KBRs (Burke, 2000; Felfernig et al., 2006, 2007; Schmitt et al., 2001) exploit deep domain knowledge in order to calculate suitable items for the customer. The domain knowledge is stored in a recommender knowledge base in an explicit form. To communicate with the customer, KBRs offer an explicit sales dialog (Felfernig and Kiener, 2005). Such a dialog is supported by explanations (Felfernig et al., 2006; Friedrich, 2004) (reasons for questions and certain recommendations) and intelligent repair mechanisms (Felfernig et al., 2006) which serve the aim of dissolving inconsistent user requirements. After completing the dialog phase, the recommender calculates suitable items which are in turn presented to the customer (as an item list or in the form of an item comparison page).

In this paper we focus on *decoy effects* which represent a specific type of non-conscious influence on a user's buying behaviour. Basic properties of decoy effects have been analysed in numerous studies, see, e.g., Callander and Wilson (2006), Colman et al. (2007), Ouyang (2004), Paramesh (1973), Pechtl (2005a, 2005b), Quesada et al. (2005), Ratneshwar et al. (1987) and Schweizer (2005).

In recommender applications, decoy effects play a special role in the presentation of result sets to customers: given a specific set of n items, the introduction of an additional item (the decoy) to the result set can significantly change the selection distribution of the other items. In this context, decoys often do not obtain a significant market share. Which is even more important for recommender result pages than how to trigger additional decoy effects is the fact that in a realistic setting decoy effects may (and typically do) occur incidentally. As decoy effects can significantly influence both choice distribution of result items and subjective confidence in a decision task (which is also shown in this paper), it is crucial to get a deeper understanding of such phenomena in order to control for such unforeseen effects.

Existing literature regarding decoy effects is mostly related to decision tasks with two items described by two corresponding attributes. The first experiment reported in this paper generalises existing work in the terms of a higher number of items and corresponding attributes and two different item domains (digital cameras and washing machines). Thus, the reported user study can be seen as more realistic from the perspective of recommender systems. Furthermore, we report results regarding the impact of an increasing number of dominated attributes (i.e., number of attributes in which the decoy is inferior) in result items on the existence of decoy effects.

The second experiment presented in this paper investigates if decoy elements are able to increase the subjective confidence of customers in decision situations like on result pages of recommender systems. The reported results have a strong impact on the presentation of result sets and potentially (issue of future work) on the presentation of explanations and repair alternatives.

This paper is organised as follows. In Section 2 we give an overview of related work. In Section 3 we give a short overview about decoy effects. In Section 4 we present the results of two studies. The first shows the influence of the asymmetric dominance effect in a multidimensional item and attribute space on the probability of selection of specific items in a choice set. The second study investigates whether decoys impact on the subjective confidence levels of persons in choice situations. With Section 5 we conclude the paper and discuss some aspects of future work.

2 Related work

If we want to successfully deploy recommender applications in commercial environments, we must have a clear understanding of the influencing factors users are exposed to. There are many studies related to user behaviour in different types of decision making tasks – see, e.g., Martin et al. (2005) and Payne et al. (1993). Need for cognition (Martin et al., 2005) is a property that provides an indicator to which extent a user accepts cognitive efforts related to the identification of items fitting her wishes and needs. Accepted cognitive efforts are higher for high-involvement decisions such as buying a car or deciding about the penalty for a crime (Busemeyer and Johnson, 2004) than for more simple decisions such as buying a book. In addition, users have limited cognitive resources which forces them to adapt their decision behaviour depending on the complexity of the decision making task at hand (Payne et al., 1993). Both, the complexity of a decision making task and the degree of need for cognition influence the decision strategy – this phenomenon is well known as decision making under bounded rationality (Kahneman, 2003).

Decision making under bounded rationality acts as door opener for different kinds of non-conscious influences on buying decisions and therefore has to be investigated and taken into account in the context of recommender application development. This aspect is strongly related to the fact that recommender applications support users in preference construction processes (users in many cases do not have a clear view on their preferences) but not primarily implement preference elicitation processes. Therefore the design of a recommender (e.g., in terms of dialog structures, result pages, explanations, or repairs) can have a strong impact on the outcome of decision making tasks (Felfernig et al., 2007; Tan et al., 2004).

One type of phenomenon which can occur because of bounded rationality are decoy effects. There are many areas where decoy effects have already been investigated (Callander and Wilson, 2006; Colman et al., 2007; Ouyang, 2004; Paramesh, 1973; Pechtl, 2005a, 2005b; Quesada et al., 2005; Ratneshwar et al., 1987; Schweizer, 2005). A compact overview of different basic types of decoy effects can be found in Pechtl (2005b). The aspect of choice contrast is addressed in Tan et al. (2004). It is shown that item sets consisting of only the best items lead to inferior selling results as users are overwhelmed by the complexity of the comparison task. Better results can be expected if there are as well items in the choice set that are clearly dominated by the other items. In the work of Schweizer (2005) a user study is presented that shows decoy effects in the area of jurisdiction. The authors show that judicial decisions are clearly influenced by the set of potential alternatives (verdicts) given. Decoy effects in the context of political elections are discussed in Callander and Wilson (2006) where the insertion of additional (decoy) candidates can influence the success rate of the other candidates. A user study answering the question whether decoy effects can be found in marketplaces is presented in Ouyang (2004). One of the major results is that the addition of a non-leading brand into an item line, the selling of some leading brands can be increased. Most studies related to decoy effects are concentrating on only two items (+ decoy) and two item features (in most of the cases quality and price). Our work presents the results of a study which exploited extended (higher-cardinality) item sets with an increased number of additional item attributes. The reason is that on recommender result pages the number of presented items is typically not limited to three. In order to obtain a deeper understanding on how decoy effects perform in realistic settings found on recommender result pages, it is crucial to extend study settings both from the point of view of number of alternatives and number of attributes.

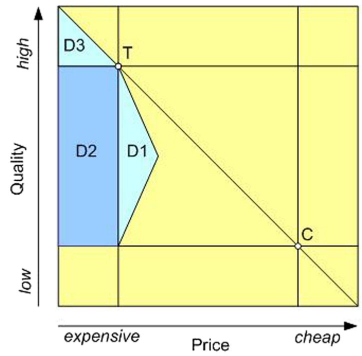
Moreover, our first study investigates empirically how an asymmetrically decoy has to be constituted in order to have the biggest influences. One major aspect of this paper is the investigation of the impact of decoy elements on the confidence levels of a user.

Persuasive Technologies. Persuasion is making people change their attitudes towards items or behaviours. Persuasive technologies are found in many different areas like marketing, education, healthcare and many others. An extensive overview of persuasion approaches in computer systems is given, for instance, in Fogg (2003). Persuasive technologies and their potentials in the context of recommender applications has not been investigated so far – the introduction of theories from cognitive and decision psychology is a new approach with great potential for further increasing the applicability of those systems in industrial environments. In Felfernig et al. (2007) two user studies are presented which examine the persuasive potential of primacy and recency effects (serial position effects) in the context of knowledge-based recommendation. The results of the study show a clear interaction between the ordering of item explanations and the corresponding item preferences. The investigation of the persuasive potential of decoy options in the context of knowledge-based recommendation processes is in the same line of research.

3 Decoy effects: overview

Decoy effects (Bateman et al., 2008; Pechtl, 2005a, 2005b; Simonson, 1989) occur in decision situations where a certain *target item T* can look much more attractive than a *competitor item C* when a *decoy item D* is added to the set of alternatives. There are different types of decoys which are defined on the basis of their relative position w.r.t. *T*. Figure 1 shows the regions and relative positions of decoys triggering the attraction- (D1), asymmetric dominance- (D2) and the compromise effect (D3) in the two dimensional case. Note that Figure 1 can only be seen as a diagrammatic explanation of decoy effects. For a mathematical model which calculates decoy effects in the multi-dimensional case in the context of recommender systems please see Felfernig et al. (2008).

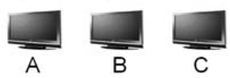
Figure 1 Decoy effects: different types of decoy items (see online version for colours)



Attraction effect. The decoy item $D1$ (see Figure 1) causes the *attraction effect* (Ratneshwar, et al., 1987; Simonson, 1989) since the attractiveness of the target option T is increased by adding $D1$ to the result set $\{T, C\}$. The basic explanation for this effect is that items which are only a little bit more expensive but have a significantly higher quality are of higher utility for the customer. Figure 2 depicts an example for the *attraction effect* in the domain of LCD TVs. There are two TVs (A and B) and A is the target item. Where customers are undecided in the two-item constellation or even tend to select B, the situation changes after adding option A' (of type $D1$). By including A', most customers concentrate on A and A' as they are directly competing. B looses attraction as it is not part of the group (different attribute values in both dimensions). In this context, the probability of selecting A increases because it is only little more expensive but offers a significantly larger screen than A'.

Figure 2 Attraction effect

LCD TV		
Products	A	B
Screen Size (cm)	110	90
Price	€ 1.500,--	€ 1.000,--

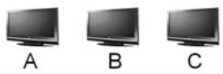


LCD TV			
Products	A (T)	B (C)	A' (D1)
Screen Size (cm)	110	90	100
Price	€ 1.500,--	€ 1.000,--	€ 1.400,--

Compromise effect (Ouyang, 2004; Simonson, 1989; Wernerfelt, 1995). The introduction of decoy item *D3* triggers the *compromise effect*: *T* becomes a good compromise between *D3* and *C*. The basic explanation of this effect is that the customer evaluates *T* as the most favourable alternative since it has a significantly lower price but is of only negligible lower quality compared to the decoy item *D3*. Furthermore, there is no attribute any more where *T* is the worst alternative. Figure 3 depicts a corresponding example. The reason why *A* looks more attractive than *B* after addition of *A′* is that *A* becomes a good compromise between *B* and *A′*. *A′* has the largest screen but is very expensive. *A* has a screen of nearly the same size and is (although not as cheap as *B*) much cheaper than *A′* which seems to make *A* the optimal choice.

Figure 3 Compromise effect

LCD TV		
Products	A	B
Screen Size (cm)	110	90
Price	€ 1.500,--	€ 1.000,--

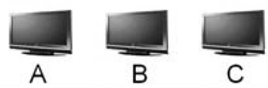


LCD TV		
Products	A (T)	B (C)	A' (D3)
Screen Size (cm)	110	90	112
Price	€ 1.500,--	€ 1.000,--	€ 1.800,--

Asymmetric dominance effect. The decoy item *D*2 in Figure 1 triggers the *asymmetric dominance effect* (Bateman et al., 2008; Colman et al., 2007; Pechtl, 2005b): *T* dominates *D*2 in all attributes (it has a better quality and a lower price) but *C* does not (it only has a lower price). The basic explanation of this effect is that customers follow a pair-wise comparison strategy and evaluate *T* as the most favourable alternative since it dominates *D*2 in all dimensions (in contrast to *C* which dominates the decoy *D2* in only one dimension). Figure 4 depicts an example for the *asymmetric dominance effect*. TV *A* (the target) shows an increased attractiveness after the addition of *A′*. The reason is that *A* is stronger than *B* in one dimension (larger screen) and *B* is stronger than *A* in the other dimension (cheaper). From this point of view there is no clear winner. However, *A* is stronger than *A′* in both dimensions (larger screen and cheaper) whereas *B* is stronger than *A′* in only one dimension (cheaper), which seems to make *A* the best choice.

Figure 4 Asymmetric dominance effect

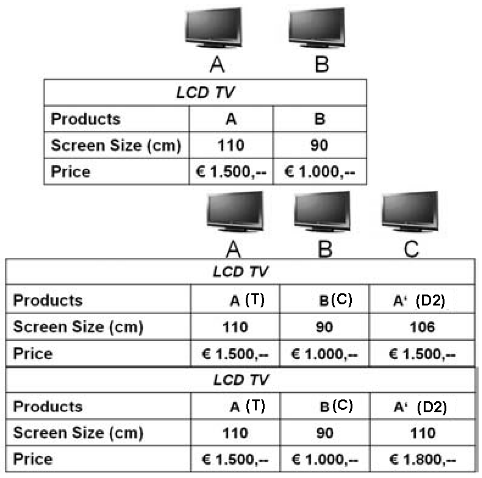
LCD TV		
Products	A	B
Screen Size (cm)	110	90
Price	€ 1.500,--	€ 1.000,--



LCD TV			
Products	A (T)	B (C)	A' (D2)
Screen Size (cm)	110	90	106
Price	€ 1.500,--	€ 1.000,--	€ 1.600,--

We can identify another two decoy effects which are special cases between *D*2, *D*1 and *D*3 (see Figure 5). *A* is always stronger than *A′* in one dimension and has the same value in the other dimension. *B* is better than *A′* in one dimension and worse in the second one. Those decoys also trigger the asymmetric dominance effect, as *A* is dominating *A′* (better in one attribute and equal in the other one) whereas B does not dominate *A′* (better in one but worse in the other attribute dimension).

Figure 5 Special cases



LCD TV		
Products	A	B
Screen Size (cm)	110	90
Price	€ 1.500,--	€ 1.000,--

LCD TV			
Products	A (T)	B (C)	A‘ (D2)
Screen Size (cm)	110	90	106
Price	€ 1.500,--	€ 1.000,--	€ 1.500,--

LCD TV			
Products	A (T)	B (C)	A‘ (D2)
Screen Size (cm)	110	90	110
Price	€ 1.500,--	€ 1.000,--	€ 1.800,--

We want to emphasize that decoy effects have higher selection shifts when people are not completely sure which option to select. If a customer is convinced that TV *B* has the optimal screen size or he or she only has € 1000 available then the positioning of decoy options has less influence. These decoy effects can be directly exploited if we want to increase the attractiveness of certain items in a recommendation result. Although these effects are quite well known in the literature of decision psychology, they have hardly been investigated in the context of recommender systems. This was the major motivation for investigating these effects in the development of knowledge-based recommender systems. Questions related to decoy effects in knowledge-based recommender systems are among the major research questions of the COHAVE project.[1]

4 User studies: reproduction of decoy effect in multi- dimensional choice settings and impact on confidence in choice

The results of the studies presented in this section are exclusively related to the asymmetric dominance effect (*D*2 in Figure 1) and the special cases of the asymmetric dominance effect (between *D*2 and *D*1/*D*3 respectively, see Figure 5). The small selection share (see for example (1)) of a dominated alternative makes the asymmetric dominance effect the most appropriate for recommendation issues as it should not be the aim to increase the selection probabilities of products showing low utilities for customers.

In our first experiment we exploited item descriptions from two different domains (digital cameras and washing machines) (see Figures 6 and 7). The items were organised in different *segments* (*basic*, *medium-class* and *high-end*), such that *high-end* items where *more expensive* but of *higher quality* compared to *basic* items. Within each segment, selection sets presented to the participants of the study were organised in three *distance groups* (*low, medium* and *high*), such that the items in the *high distance* group where more different to each other than in the *low distance* group. For example, in the *basic* segment of Figure 7 the distance (=difference) between camera *A* and camera *B* in the *low distance* group is smaller than the distance between *A* and *B* in the *high distance* group (in terms of all three attributes). The number of item attributes presented to the subjects was set to three: digital cameras were described by the attributes *price*, *resolution* and *optical zoom*; washing machines were described by the attributes *price*, *water* (consumption), *energy* (consumption). Three item alternatives {*A*, *B*, *C*} were presented to the subjects in cases where no decoy item was included in the choice set. Four selection alternatives {*A*, *B*, *C*, *D*} were presented to the subjects when a decoy item was included in the choice set, where *D* = *dAn* denotes a decoy item inferior in the *nth* attribute compared to alternative *A* (target) and *D* = *dA_all* denotes a decoy item inferior in all attributes compared to decision alternative *A*.

The subjects ($N = 469$) were randomly assigned to one of the groups depicted in Table 1. Each participant had the task to subsequently select items with the best price/performance ratio in a sequence of 18 choice sets (2 domains × 3 segments × 3 distances). Participants of the study had to provide their email address in order to participate in a lottery (1 × 200€ were drawn among those participants who completed the selection tasks within a reasonable (pre-tested) amount of time).

Figure 6 Used item set (digital cameras)

Segment	Distance	Attribute	A	B	C	dA1	dA2	dA3	dA_all	dB1	dB2	dB3	dB_all	dC1	dC2	dC3	dC_all
Basic	Low	Price (Euro)	216	165	123	246	216	216	246	189	165	165	189	143	123	123	143
		Resolution (Mpix)	6,5	5,3	4,2	6,5	5,9	6,5	5,9	5,3	4,7	5,3	4,7	4,2	3,8	4,2	3,8
		Zoom (x)	8	6	4	8	8	7	7	6	6	5	5	4	4	3	3
	Medium	Price (Euro)	246	165	105	279	246	246	279	189	165	165	189	123	105	105	123
		Resolution (Mpix)	7,3	5,3	3,8	7,3	7,3	7,3	6,5	5,3	4,7	5,3	4,7	3,8	3,4	3,8	3,4
		Zoom (x)	9	6	3	9	9	8	8	6	6	5	5	3	3	2	2
	High	Price (Euro)	279	165	89	315	279	279	315	189	165	165	189	105	89	89	105
		Resolution (Mpix)	8,1	5,3	3,4	8,1	7,3	8,1	7,3	5,3	4,7	5,3	4,7	3,4	3	3,4	3
		Zoom (x)	10	6	2	10	10	9	9	6	6	5	5	2	2	1	1
Medium-class	Low	Price (Euro)	246	189	143	279	246	246	279	216	189	189	216	165	143	143	165
		Resolution (Mpix)	7,3	5,9	4,7	7,3	6,5	7,3	6,5	5,9	5,3	5,9	5,3	4,7	4,2	4,7	4,2
		Zoom (x)	9	7	5	9	9	8	8	7	7	6	6	5	5	4	4
	Medium	Price (Euro)	279	189	123	315	279	279	315	216	189	189	216	143	123	123	143
		Resolution (Mpix)	8,1	5,9	4,2	8,1	7,3	8,1	7,3	5,9	5,3	5,9	5,3	4,2	3,8	4,2	3,8
		Zoom (x)	10	7	4	10	10	9	9	7	7	6	6	4	4	3	3
	High	Price (Euro)	315	189	105	355	315	315	355	216	189	189	216	123	105	105	123
		Resolution (Mpix)	9	5,9	3,8	9	9	9	8,1	5,9	5,3	5,9	5,3	3,8	3,4	3,8	3,4
		Zoom (x)	11	7	3	11	11	10	10	7	7	6	6	3	3	2	2
High-end	Low	Price (Euro)	279	216	165	315	279	279	315	246	216	216	246	189	165	165	189
		Resolution (Mpix)	8,1	6,5	5,3	8,1	7,3	8,1	7,3	6,5	5,9	6,5	5,9	5,3	4,7	5,3	4,7
		Zoom (x)	10	8	6	10	10	9	9	8	8	7	7	6	6	5	5
	Medium	Price (Euro)	315	216	143	355	315	315	355	246	216	216	246	165	143	143	165
		Resolution (Mpix)	9	6,5	4,7	9	8,1	9	8,1	6,5	5,9	6,5	5,9	4,7	4,2	4,7	4,2
		Zoom (x)	11	8	5	11	11	10	10	8	8	7	7	5	5	4	4
	High	Price (Euro)	355	216	123	399	355	355	399	246	216	216	246	143	123	123	143
		Resolution (Mpix)	10	6,5	4,2	10	9	10	9	6,5	5,9	6,5	5,9	4,2	3,8	4,2	3,8
		Zoom (x)	12	8	4	12	12	11	11	8	8	7	7	4	4	3	3

Figure 7 Used item set (washing machines)

Segment	Distance	Attribute	A	B	C	dA1	dA2	dA3	dA_all	dB1	dB2	dB3	dB_all	dC1	dC2	dC3	dC_all
Basic	Low	Price (Euro)	437	385	339	465	437	437	465	410	385	385	410	361	339	339	361
		Water (L)	42,2	46,5	51,4	42,2	44,3	42,2	44,3	46,5	48,9	46,5	48,9	51,4	54,1	51,4	54,1
		Energy (kW/h)	0,29	0,4	0,53	0,29	0,29	0,34	0,34	0,4	0,4	0,46	0,46	0,53	0,53	0,6	0,6
	Medium	Price (Euro)	465	385	319	496	465	465	496	410	385	385	410	339	319	319	339
		Water (L)	40,2	46,5	54,1	40,2	42,2	40,2	42,2	46,5	48,9	46,5	48,9	54,1	56,9	54,1	56,9
		Energy (kW/h)	0,24	0,4	0,6	0,24	0,24	0,29	0,29	0,4	0,4	0,46	0,46	0,6	0,6	0,67	0,67
	High	Price (Euro)	496	385	299	528	496	496	528	410	385	385	410	319	299	299	319
		Water (L)	38,4	46,5	56,9	38,4	40,2	38,4	40,2	46,5	48,9	46,5	48,9	56,9	60	56,9	60
		Energy (kW/h)	0,19	0,4	0,67	0,19	0,19	0,24	0,24	0,4	0,4	0,46	0,46	0,67	0,67	0,75	0,75
Middle-class	Low	Price (Euro)	465	410	361	496	465	465	496	437	410	410	437	385	361	361	385
		Water (L)	40,2	44,3	48,9	40,2	42,2	40,2	42,2	44,3	46,5	44,3	46,5	48,9	51,4	48,9	51,4
		Energy (kW/h)	0,24	0,34	0,46	0,24	0,24	0,29	0,29	0,34	0,34	0,4	0,4	0,46	0,46	0,53	0,53
	Medium	Price (Euro)	496	410	339	528	496	496	528	437	410	410	437	361	339	339	361
		Water (L)	38,4	44,3	51,4	38,4	40,2	38,4	40,2	44,3	46,5	44,3	46,5	51,4	54,1	51,4	54,1
		Energy (kW/h)	0,19	0,34	0,53	0,19	0,19	0,24	0,24	0,34	0,34	0,4	0,4	0,53	0,53	0,6	0,6
	High	Price (Euro)	528	410	319	562	528	528	562	437	410	410	437	339	319	319	339
		Water (L)	36,6	44,3	54,1	36,6	38,4	36,6	38,4	44,3	46,5	44,3	46,5	54,1	56,9	54,1	56,9
		Energy (kW/h)	0,14	0,34	0,6	0,14	0,14	0,19	0,19	0,34	0,34	0,4	0,4	0,6	0,6	0,67	0,67
High-End	Low	Price (Euro)	496	437	385	528	496	496	528	465	437	437	465	410	385	385	410
		Water (L)	38,4	42,2	46,5	38,4	40,2	38,4	40,2	42,2	44,3	42,2	44,3	46,5	48,9	46,5	48,9
		Energy (kW/h)	0,19	0,29	0,4	0,19	0,19	0,24	0,24	0,29	0,29	0,34	0,34	0,4	0,4	0,46	0,46
	Medium	Price (Euro)	528	437	361	562	528	528	562	465	437	437	465	385	361	361	385
		Water (L)	36,6	42,2	48,9	36,6	38,4	36,6	38,4	42,2	44,3	42,2	44,3	48,9	51,4	48,9	51,4
		Energy (kW/h)	0,14	0,29	0,46	0,14	0,14	0,19	0,19	0,29	0,29	0,34	0,34	0,46	0,46	0,53	0,53
	High	Price (Euro)	562	437	339	599	562	562	599	465	437	437	465	361	339	339	361
		Water (L)	35	42,2	51,4	35	36,6	35	36,6	42,2	44,3	42,2	44,3	51,4	54,1	51,4	54,1
		Energy (kW/h)	0,1	0,29	0,53	0,1	0,1	0,14	0,14	0,29	0,29	0,34	0,34	0,53	0,53	0,6	0,6

Table 1 Assignment of subjects to groups

GROUP	*n*	*Target*	*Decoy*
0	36	–	–
1	28	A	dA1
2	37	A	dA2
3	39	A	dA3
4	39	A	dA_all
5	35	B	dB1
6	33	B	dB2
7	32	B	dB3
8	36	B	dB_all
9	45	C	dC1
10	35	C	dC2
11	29	C	dC3
12	45	C	dC_all

In the *control group* (group# 0), subjects were not confronted with decoy alternatives, i.e., they had to select items from 18 choice sets (also denoted as *core sets*) without any decoy items included. Choice sets with three alternatives have been chosen for the control group for homogeneity reasons, i.e., participants should not be biased by changing cardinalities of item sets. Participants in the remaining groups had to select the item with the best price-performance ratio where the underlying choice sets included decoy items. For homogeneity reasons, the choice set cardinality in this case was constantly set to four, i.e., the participants had to select the best performing item from a set that included a corresponding decoy item.

In our study we introduced two major types of asymmetric dominated decoy items which should trigger the asymmetric dominance effect. First, for each target item of {*A*, *B*, *C*} three decoys were defined which were dominated in exactly one attribute and equal in the other two. This can be seen as special cases between *D*2 and *D*1/*D*3 respectively (see Figures 1 and 5). Second, one decoy was defined which was dominated in all dimensions. For example, in the *low distance* group of the *basic* segment the decoys *dA*1…3 are dominated in only one attribute by the target item *A* and *dA_all* denotes decoys dominated in all dimensions. Figures 6 and 7 provide a complete overview of the items used in our experimental setting.

Within the scope of our study, we have investigated the following hypotheses. Hypotheses *H*1 and *H*2 focus on the extension of existing studies on decoy effects to situations with more than three items and more than two attributes. Hypothesis *H*3 focuses on the question whether decoy items dominated in all attribute values have a higher impact (in terms of selection probability) than those dominated in only one attribute value.

H1: The asymmetric dominance effect can also be found in choice sets with more than three alternatives.

H2: The asymmetric dominance effect can also be found in choice sets with more than two item attributes.

H3: Decoy items dominated in all attribute values increase the selection probability of the target relatively more than those dominated in only one value.

The assessment whether the inclusion of a decoy item has a significant impact on the selection probability of the target item has been implemented as follows: The distribution of item selections in any given core set (choice set without a decoy item) can be interpreted as probability of selection (relative frequencies). We now suppose that this distribution of probabilities is affected by the introduction of a decoy item.

For each target item out of {*A*, *B*, *C*}, we dichotomised the appropriate relative frequencies. For example, if we want to test the effect of a decoy for item *A*, we calculate the probability of *A* vs. the probability of the other items in the core set. Formally this would yield $p(A_c)$, vs. the other items $p(\neg A_c)$ or $1-p(A_c)$. The distribution of choices in the decoy-set among *A*, *B*, *C and the decoy item* was dichotomised to the absolute frequency of *A* vs. the other items. With this data, we conducted a *binomial test* with the null hypothesis that the target item's number of selections in the decoy set does not differ from its probability in the core set. The resulting *p*-values indicated how likely we might observe the given data under the null hypothesis. We chose a *type-I-error* of $\alpha = 5\%$ for testing.

Hypotheses *H1* and *H2* are confirmed by the study results, i.e., the asymmetric dominance effect exists in settings with more than three alternatives and more than two item attributes. This property has been shown for two different item domains (digital cameras and washing machines). In Table 2 we see that target items have been selected significantly more often in the corresponding decoy setting compared to the selection of the item in the control group. For example, item *A* in the digital camera domain has been selected significantly more often in the decoy constellation (47.7%) than in the corresponding control group (20.7%).

Table 2 Increase of target selections by decoy inclusion

Domain		*Target* (*A*)	*Target* (*B*)	*Target* (*C*)
Digital cameras	No decoy	20.7%	61.7%	17.6%
	With decoy	47.7%	78.3%	18.8%
	p-value	$p < 0.001$	$p < 0.001$	$p < 0.230$
Washing machines	No decoy	44.1%	47.8%	8.0%
	With decoy	70.9%	53.8%	17.0%
	p-value	$p < 0.001$	$p < 0.001$	$p < 0.001$

On the basis of the binomial test the results were significant (see the *p*-values in Table 2) with the exception of *C*-items (only digital cameras) that represented the lowest-quality items in every selection set. For such item types we can observe a tendency of an increased number of selections due to the inclusion of decoy items, however, decoys can be expected to have a smaller impact.

We can confirm Hypothesis *H3* since for all groups of item sets: the increase of target item selections was significant when a corresponding decoy element with three dominated attribute values was included (see *all-attributes* in Table 3). In the case of decoy elements with one dominated attribute value the situation is similar since in about 60% of the cases the increase in target item selections was significant. In the remaining 40% we can observe a corresponding tendency; however, the effect in this case is smaller than in the case of three dominated attribute values. For example the single-dominated decoys for target (C) in the digital camera domain where to weak in order to act as real decoy for target (C) whereas the multi-dominated decoys performed well.

The share of decoy bookings is typically very low when using dominated decoys, as it should be obvious that the decoy cannot be the best alternative. There is at least one item (target) which is better in one attribute and at least equally good in all other attribute dimensions. This is in line with the empirical findings of the presented study. The percentage of decoy item selections was marginal in both domains (digital cameras: 0.94%; washing machines: 1.15%).

In order to investigate the impact of the presence of decoy elements on the user's confidence in its own decision, we conducted a small user study with 55 persons. Based on the results of the study described above, we selected one item set which showed big and stable decoy effects. The selected set is listed in Table 4.

Table 3 Increase of target selections (detail)

Digital cameras		*Target* (*A*)	*Target* (*B*)	*Target* (*C*)
Price	No decoy	20.7%	61.7%	17.6%
	With decoy	54.4%	74.9%	18.5%
	p-value	$p < 0.001$	$P < 0.001$	$p = 0.602$
Resolution	No decoy	20.7%	61.7%	17.6%
	With decoy	32.4%	73.0%	15.2%
	p-value	$p < 0.001$	$P < 0.001$	$p = 0.300$

Table 3 Increase of target selections (detail) (continued)

Digital cameras		*Target* (*A*)	*Target* (*B*)	*Target* (*C*)
Optical zoom	No decoy	20.7%	61.7%	17.6%
	With decoy	42.5%	78.8%	17.2%
	p-value	$p < 0.001$	$P < 0.001$	$p = 0.935$
All-attributes	No decoy	20.7%	61.7%	17.6%
	With decoy	62.7%	85.8%	23.0%
	p-value	$p < 0.001$	$P < 0.001$	$p = 0.006$
Washing machines				
price	No decoy	44.1%	47.8%	8.0%
	With decoy	76.2%	52.7%	19.3%
	p-value	$p < 0.001$	$P = 0.091$	$p < 0.001$
water	No decoy	44.1%	47.8%	8.0%
	With decoy	64.0%	44.8%	10.2%
	p-value	$p < 0.001$	$p = 0.296$	$p = 0.176$
energy	No decoy	44.1%	47.8%	8.0%
	With decoy	67.8%	52.8%	22.6%
	p-value	$p < 0.001$	$p = 0.099$	$p < 0.001$
all-attributes	No decoy	44.1%	47.8%	8.0%
	With decoy	76.9%	64.2%	16.5%
	p-value	$p < 0.001$	$p < 0.001$	$p < 0.001$

The following hypothesis was produced:

H4: Users feel more confident in decision taking if decoy elements are added to a choice set.

The study comprised two steps: First, the experimenters had to choose the camera with the best price-performance ratio out of three (control group) respectively four items (decoy group).

In a second step, on a 6-point-likert-scale the experimenters had to state how confident they were about having chosen the best item.

Table 4 Item set for user study 2

	DigiCam A	*DigiCam B*	*DigiCam C*	*DigiCam D* (*Decoy for A*)
Price	216	165	123	246
Resolution	6.5	5.3	4.2	5.9
Optical zoom	8	6	4	7

The mean confidence reported in the control group without decoy ($n = 27$) was 4.00 (std = 0.620) and in the decoy group ($n = 28$) 4.57 (std = 1.034). The corresponding t-test for equality of means was significant on the 0.05 level ($p < 0.017$), so that we also can confirm H4. The increased standard deviation in the decoy group (1.034 vs. 0.620) is resulting from one single subject who stated a confidence of 1, where as all other subjects reported a confidence level between 3 and 6 (in both groups). When we remove this single case from statistical analysis, the mean of the decoy group (now $n = 27$) was 4.70 (std = 0.775) and the t-test is significant on the 0.001 level ($p < 0.001$).

5 Conclusions and future work

In this paper we provided an overview of different types of decoy effects which make users susceptible for changing their choice strategies when confronted with additional item alternatives. Furthermore, we have shown decoy effects in higher cardinality settings regarding the number of included items and the number of attributes which can have a significant impact on the selection distribution of items. Moreover, a user study is presented which shows the clear impact on the confidence in a decision task. There is clear evidence that decoy elements, although irrelevant, increase the subjectively felt confidence in a choice task and thus shows great potential to alleviate the decision. Moreover this fact indicates that decoy effects show big potential for increasing the overall probability of a purchase on a sales platform which uses decoy techniques. Thus this paper contributes to the integration of different research disciplines (recommender systems, cognitive and decision psychology) with the goal of understanding human decision behaviour in online buying situations.

Further research issues. In the study reported in this paper we have shown decoy effects (asymmetric dominance effects) for item settings with $n > 2$ attributes and $n > 3$ items. The question (which is within the focus of future work) is to which extent different decoy effects (in which combinations) still occur when the number of attributes and items is further increased, e.g., at what moment do users switch, e.g., to non-compensatory evaluation strategies (Payne et al., 1993). A major aspect to be investigated in more detail is the influence of different price/quality segments and the distance between items on item selections, i.e., which combinations show a higher probability of a switch in a user's decision making strategy. A question which is strongly related to the aspect of diversity in recommendations (Bradley and Smyth, 2001): which type of diversity in item sets maximises or minimises the impact of decoy effects.

Recommender applications support explanations in the sense that items recommended are equipped with an additional argumentation as to why it fits the wishes and needs of customers (Felfernig et al., 2006). Furthermore, explanations can be given in the form of repair actions which provide an indication as to why no recommendation can be found given the current set of customer requirements. An issue of future work is to evaluate to which extent decoy settings in the presentation of repair alternatives can influence a customer's final choice. Furthermore, we have to gain deeper insights regarding cardinality and complexity properties of repairs which maximise or minimise the probability of decoy effects.

In the research area of knowledge-based recommender systems (see, e.g., Burke, 2000; Felfernig and Kiener, 2005), decoy effects have not been investigated in detail so far. Our work closes this gap by pinpointing important decision phenomena playing a major role in the context of presenting choice alternatives to users (e.g., in the form of a result list or an item comparison page). In addition to the mentioned presentation and selection of interesting items, the discussed decision phenomena could have an impact on the selection of repair alternatives within a recommendation session (Felfernig et al., 2006).

Further impacts could be expected in the selection of items and compound critiques in critiquing-based recommender applications (see, e.g., Burke et al., 1997). These systems display a set of potentially interesting items (candidates) which in the following can be critiqued by users. The cardinality of a recommendation set is typically between one and three items (which perfectly fits to the different decoy effects discussed in this paper). Compound critiques are change proposals (proposed critiques) for the current of recommended items. The number of such critiques typically proposed to users is as well around three – a setting which supports the idea of further investigations regarding the existence of decoy effects in compound critiquing environments.

An interesting open research issue is the influence of graphical item descriptions on human choice behaviour. It is already known that photos (image of the source of a message) can influence the persuasibility and trust level of an audience (Nguyen and Masthoff, 2007). Further research in the area is needed in order to answer questions such as whether there exist decoy effects in the evaluation of graphically represented solution alternatives. A loosely related but important issue is the comparability of brands and the preconditions for moving preferences from one (potentially preferred) brand to another.

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Note

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