Antecedents of the Negative Attraction Effect: An Information-Processing Approach

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1. Introduction

In contrast to classical choice theory, the widely discussed phenomenon of an attraction effect for market entry demonstrates that changes in the composition of a choice set influence preferences substantially. The inverted scenario of market exit has so far not generated much research interest despite its significant relevance for delisting strategies and portfolio decisions. In two online experiments, the authors verify the existence of context-dependent preferences for brand removals. In particular, they validate a negative attraction effect which describes the disproportionate lower increase in a target's choice probability after the removal of an inferior brand. By building on the conceptual model of Mishra/Umesh/Stem (1993) for brand introductions, they further provide the first empirical consideration of several fundamental antecedents of the negative attraction effect. Specifically, the results of a structural model emphasize decoy share, preference strength and information relevance as major drivers of the resultant preference shifts and yield rich insights to retailers and brand managers.

In real markets, retailers’ or manufacturers’ decisions to introduce or delete brands result in varying choice sets. Following the classical model of rationality, consumer preferences and decisions are independent of the composition of a choice set. Accordingly, an unconsidered option cannot become a favored one when new items are added and the removal of an item should lead to a proportionate preference increase among the remaining options (Luce 1959).

In contrast, extensive research on consumer decision-making has provided clear evidence that context – defined as the composition of the choice set (Tversky/Simonson 1993) – matters and influences preferences substantially (Payne/Bettman/Johnson 1992; Slovic 1995; Tversky/Sattath/Slovic 1988). One well-documented and widely verified phenomenon is the attraction effect (Heath/Chatterjee 1995; Huber/Payne/Puto 1982; Kim et al. 1999; Pan/Lehmann 1993; Simonson 1989; Simonson/Tversky 1992). The attraction effect denotes an inferior product’s ability to increase the attractiveness of a similar, but superior, target alternative when the inferior product is added to the original choice set (Huber/Payne/Puto 1982; Huber/Puto 1983). Typically, researchers denominate the introduced inferior product an asymmetrically dominated decoy. It is dominated by the target but not by the competitor option and alters the choice probabilities and preferences among the two core alternatives shifting preferences to the target. Numerous studies have demonstrated that this phenomenon leads to violations of basic economic choice principles, such as regularity (Luce 1977) and the principle of independence of irrelevant alternatives which assumes that preference between alternatives do not depend on the presence or absence of additional alternatives (Tversky/Simonson 1993). There are different explanations for the favorable perception of similar but superior alternatives such as simplifying choice heuristics (Huber/Puto 1983), range frequency theory (Parducci 1974), justification of choice (Simonson 1989) and tradeoff contrast (Simonson/Tversky 1992). A study of Mishra and colleagues builds on these findings and provides an overall model to test the effect of various antecedents from the field of decision-making on the attraction effect (Mishra/Umesh/Stem 1993).
The purpose of our research is to partially replicate and extend their study by testing a conceptual model for market exit. In contrast to the introduction of new products and the practice of portfolio expansions (Mao/Krishnan 2006), the preference shifts of removed items have so far not attracted much interest (Varadarajan/DeFanti/Busch 2006). However, the deletion of inferior items represents a prevalent instrument in marketing practice. Recent studies reveal the high managerial significance of portfolio reductions by demonstrating that huge companies often realize more than 80 percent of their profits from fewer than 20 percent of their brands (Kumar 2003). Thus, firms have implemented rationalization programs to improve overall profits, e.g. Unilever (2002) reduced its portfolio from about 1600 to 400 brands by end of 2004. The elimination of brands is further a significant management issue for retailers deciding on the delisting of brands to raise private-label ranges or to strengthen negotiation power against manufacturers (Sloot/Verhoef 2008). Sivakumar/Cherian (1995) as well as Wiebach/Hildebrandt (2012) covered this problem and demonstrated that for a market exit of an asymmetrically dominated product (D), the initially superior target brand (T) loses its dominant position and will consequently be considered relatively less attractive. The relative decrease in the target’s choice probability is designated the “negative” attraction effect (NAE).

Surprisingly, little research addresses this issue. Therefore, our study is the first which provides insights regarding the potential influential factors for the NAE to better predict consumers’ choice behavior when items are eliminated from a choice set. We adapt the conceptual model of Mishra/Umesh/Stem (1993) and test the hypotheses by estimating a structural equation model with survey data at an individual level.

Our study contributes to marketing literature by discovering various antecedent variables of the NAE, i.e. the context-dependence of choice when brands are removed. An improved understanding of this phenomenon and its influencing factors will help consumer researchers to devise choice experiments more precisely, i.e. to control for important factors in the choice task and to take them into account when evaluating the magnitude of the effect. For marketers, our study delivers valuable insights on the utilization of the NAE to forecast and control customers brand choice and switching behavior when they remove items from the market. Retailers can employ the findings to predict the consequences of a delisting strategy or an out-of-stock situation, brand manufacturers can adopt the results when deciding on the reduction of their product portfolios.

In what follows, we briefly review the relevant research and describe the theoretical basis on the processes that affect the NAE. More specifically, we discuss the details with respect to the included constructs, derive hypotheses on their relations to the NAE and present a structural model framework. Next, we report on an empirical study that provides empirical support for the derived hypotheses by investigating the significant antecedents. The study concludes with a discussion of the current findings in light of related literature and implications of the present research.

2. Conceptual Framework

2.1. Overview

Research on consumer choice and preference formation has revealed different moderating variables which have a significant impact on decision making (Alba/Hutchinson 1987; Bettman 1986; Cohen/Chakravarti 1990). Accordingly, Mishra/Umesh/Stem (1993) suggest that the attraction effect is an outcome of different processes of decision making which depend on the decision task, the respondents, and the considered alternatives when new brands enter a choice set. Due to the complexity of consumers’ decision processes and the interactions of the related factors, they propose and test an overall model. We base our research on their conceptual framework but emphasize the market exit case and accordingly, the antecedents of the NAE.

2.2. Negative Attraction Effect

Refering to Sivakumar/Cherian (1995, p. 46) the attraction effect is negative “…if the target loses share due to the exit of another product”. This observed phenomenon is contrary to some standard principles applied in choice modeling and the predicted preference shifts in classical economic theory (e.g., regularity, similarity and proportionality (Luce 1959) since the relative share captured by the previously dominating target is reduced. Typically, researchers assume that the deletion of a brand leads to increased market shares of the other brands in proportion to their initial market shares (Luce 1959; 1977). This issue restates the assumption of the independence of irrelevant alternatives and reflects the currently applied Luce axiom (1959). The initial choice set for the product exit scenario consists of three options: the target T, the competitor C and the decoy D (see Figure 1). Typically, attraction effect research assumes that the alternatives differ on two attributes and the target, but not the competitor, dominates the decoy. Accordingly, recent research has defined these inferior alternatives as asymmetrically dominated decoys. They have the ability to increase the attractiveness of the target relative to the competitor. It has been found that consumers select the target with higher probability merely due to the presence of the dominated decoy (Huber/Puto 1983; Huber/Payne/Puto 1982). If the inferior decoy is removed from the choice set, the target loses its dominant position and reduces its attractiveness. Hence, the probability of choosing the previously dominating alternative T will not rise or only rise disproportionately (Sivakumar/Cherian 1995; Wiebach/Hildebrandt 2012): \[
P(T\cap [T\cap C]) \leq \frac{P(T\cap [T\cap C,D])}{P(C\cap [T\cap C])}
\]
The following analysis will reveal the factors which influence the strength of the described phenomenon by developing and estimating a structural model.

2.3. The Structural Model

Drawing on the work of Mishra/Umesh/Stem (1993), we develop our conceptual model by taking into consideration the proposed antecedents of the NAE as well as interrelationships between the other constructs. According to the well known Lisrel approach (Jöreskog 1969; Jöreskog/Sörbom 1982; 1984; 1996; 2006; Hildebrandt/Temme 2006), the following matrix equations describe the formal specification of the proposed model:

\[ \eta = B \eta + \Gamma \xi + \zeta, \quad y = \Lambda \eta + \epsilon, \quad x = \Lambda \xi + \delta. \]

The first equation represents the structural equation model, i.e. the relationship between \( m \) latent endogenous variables \( \eta \) and the \( n \) latent exogenous constructs \( \xi \). \( \zeta \) is the vector of random residuals. The second equation specifies the measurement model of the latent endogenous variables, and the third equation the measurement model of the latent exogenous variables. \( \Lambda_{\eta} \) and \( \Lambda_{\xi} \) are factor loading matrices and \( \epsilon \) and \( \delta \) denote vectors of the respective measurement errors. \( x = (x_1, \ldots, x_{11}) \) symbolize the indicators of the exogenous constructs and \( y = (y_1, \ldots, y_{11}) \) those of the endogenous constructs. \( \gamma \) indicate the path coefficients between exogenous and endogenous constructs and \( \beta \) the relationships between the endogenous constructs.

In the suggested structural model representing the determinants of the NAE (see Figure 2) exogenous constructs consist of expertise (EXP, \( \xi_1 \)), perceived decoy similarity (SIM, \( \xi_2 \)), perceived decoy popularity (POP, \( \xi_3 \)) and preference strength (PRE, \( \xi_4 \)). The endogenous constructs comprise task involvement (INV, \( \eta_1 \)), information relevance (INF, \( \eta_2 \)), decoy share (DS, \( \eta_3 \)), and NAE (NAE, \( \eta_4 \)). Direct paths leading to the NAE construct describe the hypotheses which we will be discussed in detail in the subsequent section.
2.4 The Antecedent Variables and Hypotheses

Expertise. Alba/Hutchinson (1987, p. 411) defined expertise as “... the ability to perform product-related tasks successfully”. Expertise facilitates the assimilation of contextual information in interpreting brands (Meyers-Levy/Sternthal 1993; Yi 1993). People with higher expertise levels easier take decisions than inexperienced individuals with minor knowledge about the product category. They include their experiences when selecting an alternative from a presented choice set (Metha/Hoegg/Chakravarti 2011). Consequently, these people exhibit a clear preference structure and the influence of a removed decoy should be marginal giving rise to a reduced NAE. More formally, we hypothesize that respondents with a higher level of product class expertise exhibit a lower NAE (H1).

Perceived decoy similarity. In their empirical study, Huber/Payne/Puto (1982) showed that decoys which are very similar to the target alternative lead to a greater attraction effect than dissimilar decoys. Similar decoys clarify best the dominance structure in the choice set. Accordingly, individuals easier perceive the target as being superior and therefore choose it with higher probability. As consequence of the removal of the decoy from the choice set, we expect the NAE to be stronger. Thus, we predict that the NAE will rise if perceived decoy-target similarity increases (H2).

Perceived decoy popularity. Individuals who perceive the decoy as being more popular on the one hand, will select it with higher probability and, on the other hand, will consider the target brand as more attractive (Huber/Payne/Puto 1982) as it is obviously dominating the decoy. If subjects believe that even the inferior decoy is a popular alternative, the attractiveness of the target option increases. After a removal of the popular decoy, the selection of the target represents a gain on the obviously more important dimension (e.g., dimension 1 in Fig. 1). As subjects usually use heuristics to simplify choice decisions (Bettman 1979) and decision between dominated alternatives are easier than between non-dominating ones (Huber/Payne/Puto 1982; Shugan 1980), they show the tendency to select the target with higher probability from the reduced choice set {T, C}. Hence, we predict a smaller NAE for increased decoy popularity (H3). In addition, we suppose the perceived decoy popularity to have an effect on the observed decoy share. Subjects tend to shift their preferences to the decoy and allocate more preference points to the decoy option when considering it as being more notable. Thus, we predict that decoy popularity will have a positive influence on the decoy’s share.

Preference strength. Mishra/Umesh/Stem (1993) define preference strength as a measure of conviction and trust in a specific brand. High preference strength indicates that decision-makers have a clear and stable preference structure and distinctively favor one option in the choice set. These decision-makers feel confident about their decision and consequently, variations in the choice set do not strongly affect them. Conversely, low levels of preference strength signify an individual’s indifference with regard to the selectable options. These consumers do not have well-established preferences and are unsure of their decision-making. In accordance to this, they are more likely to be affected by varying choice sets and to demonstrate the NAE. Thus, we expect that respondents with higher preference strength demonstrate a lower NAE (H4). We also assume preference strength to have an impact on another construct covered in the conceptual model – the share capture from the decoy. If preference strength is high (typically for the target brand), the decoy share consequently should be small in the complete choice set.

Task involvement. Individuals’ involvement in a decision task causes the consistency of preferences and decision-making (Johnson/Payne 1985). Highly-involved consumers typically spend a lot of effort to solve a particular problem and to make a good decision (Muehlilg/Lacznik/Andrews 1993). In doing so, they are less likely to exhibit context effects. If, on the other hand, individuals are not involved in a choice task, they may be faced with a difficult decision problem. Typically, these individuals use choice heuristics to facilitate decision-making (e.g., Highhouse 1996; Simonson 1989) and can be easier biased as they treat given information more uncritically (Nowlis/Shiv 2005) which should yield a larger NAE. Accordingly, we hypothesize that for respondents who are more involved with the choice task the NAE diminishes (H5). There is empirical evidence that personal characteristics and past experiences with a product influence respondents’ involvement with a choice task (Rothschild 1979). Therefore, we suppose that expertise has an impact on task involvement. We expect a positive effect as individuals with a higher knowledge about a product class tend to include these capabilities in a decision task.

Perceived information relevance. Following Ratneshwar/Shocker/Stewart (1987), relevance is specified as the meaningfulness of a stimulus description in choice sets. Researchers in adaptive decision theory have claimed that the perceived information relevance influences consumers’ decision-making process (Bettman 1979; Dick/Chakravarthi/Biehal 1990; Meyvis/Janiszewski 2002). If given information is perceived as being meaningless, individuals tend to decide referring to simplifying choice heuristics, for instance, by reverting to dominance structures in the presented choice set. By contrast, a higher description’s relevance facilitates their decision making process and the consequential preference structure is more stable resulting in a diminished NAE. We expect that the NAE decreases with a higher level of perceived information relevance (H6). In addition, we suppose an influence of task involvement on perceived information relevance since individuals who are not involved in the decision task will probably not consider any information as being useful or will even not make any effort in evaluating the meaningfulness of the presented information. Otherwise, if individuals enjoy the choice task, they will deem the information as more
helpful and relevant. Accordingly, we expect task involvement to exhibit a positive impact on the perceived information relevance.

Decoy share. By definition, the share captured by the decoy is typically smaller than the one of the target or the competitor brand (Simonson 1989) since it represents a dominated and inferior choice alternative. Small choice probabilities of the decoy in the complete choice set \{T,C,D\} will result in only small shifts in choice probabilities in the reduced choice set \{T,C\}. A higher share captured by the decoy involves a rather high preference for the attribute on which decoy and target excel the competitor. Thus, the removal of the decoy will shift preferences to the – with regard to the obviously more important dimension similar – target brand. Accordingly, we expect that the NAE is less noticeable if the share captured by the decoy increases (H7).

3. Method

3.1. Data Collection and Sample Selection

To estimate the conceptual model and test the research hypotheses we used data from an online survey in two different product categories. We assume that the tested categories pizza and smartphones represent products which students frequently use and which cover a wide range of involvement levels. While pizza is a repeat purchased product with a rather low-involvement level, smartphones represent high-involvement products (Antil 1984).

We distributed two standarized questionnaires to undergraduate students of a large German university via a university wide mailing list. The final sample incorporated 594 respondents for frozen pizza and 763 respondents for smartphones. Of the pizza (smartphone) sample, 63.0 percent (64.5 percent) were female, the mean age was 25 (25) and the average household size was 2.3 (2.2).

3.2. Design

We employed an original vs. an elaborated stimulus description to vary the product stimulus information used by respondents to distinguish between objects (Ratneshwar/Shocker/Stewart 1987). While the original choice set information consisted of a brief situational description and a concise presentation of the available alternatives and their respective attribute levels (e.g., pizza A at a price p and quality level q), the elaborated description included a detailed explanation of the choice situation and the available alternatives (e.g., by reporting details about the quality ranking). [2]

In contrast to our reference study of Mishra/Umesh/Stem (1993), which covered three levels of decoy popularity, we applied a two-level manipulation: In the control group, we did not communicate anything about the popularity of the decoy, whereas in the other setting, we informed respondents that the market share of the decoy amounted to 40 percent. The results of Mishra and colleagues revealed that a third distinction (5 percent market share of the decoy) was not required since the respondents did not perceive the popularity of the decoy as being different from the control scenario (Mishra/Umesh/Stem 1993, p. 338).

The experiment followed a 2 (product category: pizza vs. smartphone) × 2 (stimulus description: original vs. elaborated) × 2 (decoy popularity: control vs. 40 percent) mixed design. We randomly assigned the respondents to one of the two distributed questionnaires which cover the different experimental conditions (see Tab. 1). The between-subject characteristic of the experiment arises from the randomized group assignment to one of the two questionnaires and consequently, different experimental conditions. Thereby, we reduced the survey length to diminish respondents’ drop-out rate. In addition, each condition included a pretest-posttest within-subjects design. We asked participants to do the choice tasks on a within-subject basis to account for individual preference shifts and to measure the NAE at an individual level which is essential for using a structural equation modeling approach.

3.3. Stimuli

Keeping with previous research, we presented the alternatives which differed on two attributes in an alternative-by-attribute matrix format. We pretested attributes and attribute levels to assure an equal weighting of both attributes. Accordingly, we selected price and quality rating for pizza, and memory in gigabyte (GB) and camera in megapixel (MP) for smartphones (see Tab. 2). In the pizza setting, B represented a frequency increasing relatively inferior decoy which C asymmetrically dominated. In the smartphone setting, C characterized a range-increas-
ing decoy which B asymmetrically dominated. Alternative A demonstrated the competitor in both categories.

### 3.4 Procedure

The experiment included two major steps. In the first step, we required participants to make a choice from a complete choice set. In the second part, participants performed a choice task from a reduced choice set. Initially, we informed respondents that there were no correct or wrong responses when answering the questionnaire and that only their individual evaluation was of interest. We further addressed respondents’ familiarity and buying habits with regard to the product category including questions about product class usage, spending and experiences with regard to the product category.

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<table>
<thead>
<tr>
<th>Construct (EXPI)</th>
<th>Items</th>
<th>Measure</th>
<th>α</th>
<th>β</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expertise (EXP)</td>
<td>EXP_1 x1</td>
<td>How much do you think to know about the product category frozen pizza/smartphones? When buying a frozen pizza/smartphone, how do you rate yourself?</td>
<td>1-a bit, 7-a lot</td>
<td>0.918</td>
<td>0.734</td>
</tr>
<tr>
<td>EXP_2 x2</td>
<td>inexperienced vs. experienced</td>
<td>1-inexperienced, 7-experienced</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>EXP_3 x3</td>
<td>uniformed vs. informed</td>
<td>1-uniformed, 7-informed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXP_4 x4</td>
<td>beginner vs. expert</td>
<td>1-beginner, 7-expert</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decoy Similarity (SIM)</td>
<td>SIM_1 x3</td>
<td>How similar do you perceive the following product pairs? (C and B, A and B)1/(B and C, A and C)2</td>
<td>1-very dissimilar, 7-very similar</td>
<td></td>
<td></td>
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<tr>
<td>SIM_2</td>
<td>SIM_1,BC-SIM_1,AB, SIM_1,AC-SIM_1,BC</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Decoy Popularity (POP)</td>
<td>POP_1 x3</td>
<td>How do you assess the following statements about the popularity of product B/C? with the help of the given information?</td>
<td>1-strongly agree, 7-strongly disagree</td>
<td></td>
<td></td>
</tr>
<tr>
<td>POP_2 x3</td>
<td>Product B/C is an industry leader.</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>POP_3 x3</td>
<td>Product B/C is widely accepted.</td>
<td></td>
<td></td>
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<tr>
<td>POP_4 x4</td>
<td>Many people like product B/C.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Preference (PRE)</td>
<td>PRE_1 x10</td>
<td>Share of the most preferred brand (X) in the complete choice set.</td>
<td>P(X</td>
<td>{A,B,C})</td>
<td></td>
</tr>
<tr>
<td>PRE_2 x11</td>
<td>1 – share of the least preferred brand (Y) in the complete choice set.</td>
<td>1 – P(Y</td>
<td>{A,B,C})</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task Involvement (INV)</td>
<td>INV_1 y1</td>
<td>How inspiring were the given tasks?</td>
<td>1-a bit, 7-very</td>
<td></td>
<td></td>
</tr>
<tr>
<td>INV_2 y2</td>
<td>How enjoyable were the given tasks?</td>
<td></td>
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<td></td>
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<tr>
<td>INV_3 y3</td>
<td>How interesting were the given tasks?</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>INV_4 y4</td>
<td>How exciting were the given tasks?</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Information Relevance (INF)</td>
<td>INF_1 y5</td>
<td>Please answer the following questions according to the purchase decision you previously made.</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>INF_2 y6</td>
<td>How relevant was the given information?</td>
<td></td>
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<tr>
<td>INF_3 y7</td>
<td>How meaningful was the given information?</td>
<td></td>
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<tr>
<td>INF_4 y8</td>
<td>How useful was the given information?</td>
<td></td>
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<tr>
<td>INF_5 y9</td>
<td>How helpful was the given information?</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Decoy Share (DS)</td>
<td>DS_1 y10</td>
<td>Share of the decoy in the complete choice set.</td>
<td>P1(B</td>
<td>{A,B,C})P1(C</td>
<td>{A,B,C})</td>
</tr>
<tr>
<td>NAE (NAEi)</td>
<td>NAE_1 y11</td>
<td>Deviation from the target share expected under the Luce Model.</td>
<td>NAEi=EI[P1(</td>
<td>{A,C})]P1(C</td>
<td>{A,C})</td>
</tr>
</tbody>
</table>

### 3.5 Measures

A review of previous research on information-processing and decision-making has validated a number of pre-existing scales (Betman 1979; Chaiken/Trope 1999, Wright 1974) as well as the applied operationalization of constructs by Mishra/Umesh/Stem (1993) provided the basis for our selection of measures. Since existing research has originally developed the measures for the product entry case, we adapted some of them to incorporate choice set specific characteristics for the inverted
Negative attraction effect. To account for the occurrence of a NAE, we compare the share of the target brand (T) expected by classical choice theory and the proportionality framework in the Luce model $E_L[P(T|\{T,C\})]$ to the observed share in the reduced choice set $P(T|\{T,C\})$. Therefore, we use the ratio data which we collected by the constant sum task [5] to compute the NAE at an individual level:

$$\text{NAE}_i = E_L[P(T|\{T,C\})] - P(T|\{T,C\}).$$

If $E_L[P(T|\{T,C\})] > P(T|\{T,C\})$, we observe a NAE ($\text{NAE}_i > 0$). If $E_L[P(T|\{T,C\})] = P(T|\{T,C\})$, we do not find a NAE ($\text{NAE}_i = 0$) and if $E_L[P(T|\{T,C\})] < P(T|\{T,C\})$, we observe a positive attraction effect ($\text{NAE}_i < 0$). Positive means here that, in contrast to the hypothesized effect, the removal of the decoy strengthens the target brand $i$.

Decoy similarity. To measure the exogenous construct perceived decoy similarity, we asked respondents to indicate how similar they perceive the product pairs target and decoy as well as competitor and decoy on a 7-point Likert scale (1 = very dissimilar, 7 = very similar). In reference to Mishra/Umesh/Stem (1993), we employ the subtractive model of comparative judgment of Lynch (1985) as relative measure of similarity. Accordingly, we quantify similarity ($\text{SIM}$) as the difference between the perceived target-decoy similarity ($\text{SIM}_{TD}$) and the perceived competitor-decoy similarity ($\text{SIM}_{CD}$): $\text{SIM}_i = \text{SIM}_{TD} - \text{SIM}_{CD}$. $\text{SIM}$ provides a relative measure of similarity. We expect the NAE to emerge if participants perceive the decoy as being similar to the target but not to the competitor. Thereby, individuals can easily notice the dominance structure in the market resulting in the predicted preference shift. Conversely, the similarity measure $\text{SIM}$ would be zero if they perceive the decoy as being equally similar to the target and the competitor. Consequently, no NAE should arise. A direct measure of similarity (e.g., $\text{SIM}_{TD}$) would not consider both perceived distances and accordingly, would not include this essential aspect.

Preference strength. The independent construct preference strength (PRE) indicates the robustness and stability of a respondent’s decision structure. High preference strength involves a high preference for a particular brand. On the contrary, if a respondent is indifferent to the available alternatives and allocates approximately similar preference ratings to the available brands, preference strength would be low. While Mishra/Umesh/Stem (1993) measure preference strength as a composite of centrality of preference and relative preference on the basis of the initial two-item core set, we utilize two different items gauging relative preference on the basis of the initial three-item choice set[7] According to Urban/ Hauser/Roberts (1990), relative preference signifies the strength of preference for one brand relative to the others. In our research, the first item measuring relative preference arises from the individual preference ranking distributed to the most preferred alternative in the complete choice set ($e.g., P(T|\{T,C,D\})$) if $T$ has the highest choice probability for respondent $i$. It symbolizes a respondent’s conviction in a particular brand and varies from 0.00 – 1.00. We define the second item measure preference strength 1.00 minus the preference ranking of the least preferred option in the complete choice set and varies from 0.67 – 1.00. High values indicate a stable decision structure, while for low values there would be no clear-cut choice (each of the three options has approximately the same probability of choice).

4. Results

4.1. Validation and Reliability

Constant sum scale. To estimate the structural equation model, we use the preference points distributed by the participants on the constant sum scale task to gauge the NAE. We tested whether this preference rating reflected accurately the choice of the most preferred brand. Comparing the choices deduced from the constant sum scale task and the nominal choice task, we can conclude that for pizza 97.0 percent and for smartphones 97.8 percent of the participants showed identical choices. In addition, the high correlation coefficients between the two measures support the convergent outcomes of both responses ($r_{\text{pizza}} = 0.943, p = 0.000; r_{\text{smartphone}} = 0.954, p = 0.000$) indicating a high convergent validity of the constant sum scale.

Other measures. Before evaluating the complete structural model, we examined the measurements to determine the reliability of the observed variables as measures of their respective latent constructs and to check for validity. As is evident in Table 3, the reliability analysis reveals high internal consistency among the concerned items. The lowest Cronbach’s alpha value ($\alpha$) is 0.84 for pizza and 0.85 for smartphones. All $\alpha$’s are well in excess of the 0.70 cut-off-value proposed by Nunnally (1978) and the threshold of 0.80 recommended by Rossi- ter (2002) suggesting an adequate reliability. Moreover, the results of a confirmatory factor analysis indicate that all composite reliabilities ($\rho_c$) meet the recommended level of 0.70 (Bagozzzi/Edwards 1998). We assessed convergent validity by exploring the magnitude and significance of the factor loadings and their associated t-values as well as inspecting the average variances extracted (AVE) by each construct. All items significantly and positively load on their corresponding construct. Furthermore, all AVEs are well above the suggested minimum value of 0.50 (Fornell/Larcker 1981) demonstrating reasonable convergent validity. Following procedures outlined by Fornell/Larcker (1981), the results provide evidence for discriminant validity since the AVEs are substantially in excess of all shared variances by any of the
constructs in both categories. Summing up, we can employ the measures for model testing purposes as they are satisfactory in terms of reliability and validity.

4.2. Manipulation Checks

NAE. Before discussing the results of the structural model, we demonstrate the occurrence of a NAE on an aggregate level by means of (1) nominal choice data and (2) constant sum ratio scale data (see Tab. 4). In the first choice task, 71.89 percent (67.76 percent) of participants selected the target brand C (brand B) in the frozen pizza (smartphone) category. While the Luce axiom and the IIA assumption predict a choice share of the target of 80.11 percent for pizza and 71.81 percent for smartphones in the second choice task, the actually observed values 76.60 and 68.94 percent are significantly smaller (with \( \chi^2 = 4.595, df = 1, p = 0.032 \) and \( \chi^2 = 3.108, df = 1, p = 0.078 \)). Since expected choice probabilities exceed real choice probabilities, a NAE is shown supporting the findings of Sivakumar/Cherian (1995) and Wiebach/Hildebrandt (2012). With respect to ratio data, we find support for the phenomenon in the smartphone sample (\( E_{P(B|A,B)} = 62.95, P(B|A,B) = 60.79 \) with \( t = 3.290, df = 762 \) and \( p = 0.001 \)) whereas the mean of the distributed preference points to the target in the pizza category (\( P(C|A,C) = 69.98 \)) does not deviate significantly from the predicted value (\( E_{P(C|A,C)} = 69.95 \)).

Similarity. In both product categories, we constructed the decoy as being more similar to the target than to the competitor. This is essential for the occurrence of a NAE. To confirm the manipulation, we applied participants’ answers regarding the perceived similarity of the respective decoy and the other two brands. The results of a paired sample t-test reveal that participants rated the target and the decoy to be substantially more similar (\( M_{pizza\text{SIM}_{CB}} = 5.28, M_{smartphone\text{SIM}_{BC}} = 5.22 \)) than the competitor and the decoy (\( M_{pizza\text{SIM}_{AB}} = 2.49, M_{smartphone\text{SIM}_{AC}} = 2.17 \)) with \( t_{pizza}(593) = 36.311, p = 0.000 \) and \( t_{smartphone}(762) = 40.153, p = 0.000 \). We retained the minority of participants (less than 5 percent) who did not rate the similarity according to the manipulation in the analysis, since we integrated the similarity construct in the Lisrel model.

Decoy popularity. In contrast to Mishra/Umesh/Stem (1993) who distinguished three levels of decoy popularity our study covered two different conditions: (1) control group and (2) 40 percent market share indicated for the decoy. To check the success of decoy popularity manipulation, we compared the values of the respective items and their underlying factor for both conditions. Respondents perceived the decoy as being significantly more popular if its market share is announced to be 40 percent. A one-way ANOVA supports this result across categories (\( F_{pizza} = 5.281, df = 1, p = 0.022; F_{smartphone} = 78.893, df = 1, p = 0.000 \)).

Information relevance. To check whether participants evaluated the information given in the elaborated stimuli description setting as more relevant than in the original setting, we compared their responses to the information relevance measure (INF) by means of a one-way ANOVA. The results indicate that the manipulation is not successful for pizza. The mean of the factor scores for the elaborated setting \( M_{elaborated\text{INF}} = -0.09 \) is smaller than respective value for the original setting \( M_{original\text{INF}} = 0.08 \) with \( F(1,592) = 4.347, p = 0.038 \). When deciding on a frozen pizza, individuals obviously do not consider a detailed description of the available alternatives to be more meaningful. Probably, they perceive the original description including merely the respective attribute levels as being more useful to decide on one of the presented repeat purchase products. By contrast, for the high involvement category smartphones, participants considered a detailed description of the available alternatives to be more relevant and useful. Respondents who faced the elaborated stimuli description rated the given information as significantly more relevant than the participants who answered the questionnaire including the original stimuli description (\( M_{smartphone\text{INF}} = 0.10, M_{smartphone\text{elaborated\text{INF}}} = -0.10 \)) with \( F(1,761) = 7.984, p = 0.005 \).

Tab. 4: Choice shares and choice shifts (nominal and ratio data)
4.3. Model Estimation

We used the Lisrel 8.8 (Jöreskog/Sörbom 2006) structural equations program and the Maximum Likelihood (ML) method to estimate the model presented earlier in Fig. 2. We primarily focus the subsequent analysis on the relationships between the constructs and the test of the discussed hypotheses.

**Measurement model.** The estimated standardized factor loadings of the measurement model for the multiple-item constructs are highly significant (p<0.01, see Tab. 5). Each parameter is greater than 0.70 supporting the high reliability of the measures. The consistent results across categories indicate the constructs’ stability.

<table>
<thead>
<tr>
<th>Antecedent</th>
<th>Measures</th>
<th>Pizza</th>
<th>Smartphone</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXP</td>
<td>$x_1^r$</td>
<td>0.757</td>
<td>0.843</td>
</tr>
<tr>
<td></td>
<td>$x_2$</td>
<td>0.911</td>
<td>0.930</td>
</tr>
<tr>
<td></td>
<td>$x_3$</td>
<td>0.783</td>
<td>0.880</td>
</tr>
<tr>
<td></td>
<td>$x_4^r$</td>
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<td>0.937</td>
</tr>
<tr>
<td>POP</td>
<td>$x_6^r$</td>
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<td>0.773</td>
</tr>
<tr>
<td></td>
<td>$x_7$</td>
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<td>0.855</td>
</tr>
<tr>
<td></td>
<td>$x_8$</td>
<td>0.958</td>
<td>0.955</td>
</tr>
<tr>
<td></td>
<td>$x_9$</td>
<td>0.914</td>
<td>0.916</td>
</tr>
<tr>
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<td>$x_{10}^r$</td>
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<td>1.000</td>
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<td>$x_{11}$</td>
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<td>0.736</td>
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<td>$y_2$</td>
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<td>0.888</td>
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<tr>
<td></td>
<td>$y_3$</td>
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<td>0.911</td>
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<tr>
<td></td>
<td>$y_4$</td>
<td>0.906</td>
<td>0.902</td>
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<tr>
<td>INF</td>
<td>$y_{5}^r$</td>
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<tr>
<td></td>
<td>$y_6$</td>
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<td>0.845</td>
<td>0.840</td>
</tr>
<tr>
<td></td>
<td>$y_8$</td>
<td>0.958</td>
<td>0.962</td>
</tr>
<tr>
<td></td>
<td>$y_9$</td>
<td>0.917</td>
<td>0.951</td>
</tr>
</tbody>
</table>

All the measurement model paths are significant at p < 0.01. For single item constructs the path loadings were fixed to 1. *These path loadings were set equal to 1 for fixing the metric of the measure.*

**Tab. 5: Measurement model and standardized factor loadings**

**Fit assessment.** We assessed the model’s overall fit using different criteria. The estimation results indicate a significant $\chi^2$-statistic ($\chi^2 = 384.46$, df = 193, p<0.01 for the pizza model and $\chi^2 = 531.80$, df = 194, p<0.01 for the smartphone model) suggesting a high discrepancy between the model-based covariance matrix $\Sigma$ and the observed covariance matrix $\Sigma$ and accordingly a poor model fit. However, this outcome is due to the large sample sizes which typically lead to low p-values (Bagozzi/Baumgartner 1994; Bentler/Bonner 1980). Since the measure is known to be overly sensitive to sample size (MacCallum/Austin 2000), it is recommended instead to utilize the Chi-square over degrees of freedom ratio ($\chi^2$/df) as descriptive goodness-of-fit measure. The ratio for the pizza model is 1.99, for the smartphone model it amounts to 2.74 suggesting an adequate model fit. In addition, absolute and incremental goodness-of-fit indicators support a good model fit. The RMSEA (Browne/Cudeck 1993) is 0.041 and 0.048 (smaller than the suggested 0.05) and the SRMR (Jöreskog/Sörbom 1982) is 0.050 and 0.061 (smaller than the recommended 0.08 by Hu/Bentler 1999) for pizza and smartphones, respectively, indicating marginal discrepancies. The GFI (Jöreskog/Sörbom 1982) and CFI (Bentler 1990) for the pizza model are 0.944 and 0.982, respectively. For the smartphone model, the GFI amounts to 0.940 and the CFI to 0.979. Both indices are consistently greater than 0.900, the recommended value for reasonable fit. To sum up, the model conceptualized in Fig. 2 yields a good overall fit.

**Hypotheses testing.** This part, primarily concentrates on the relationships between the included constructs and the NAE to test the hypotheses. The different antecedent variables can have both a direct and an indirect influence on the examined phenomenon. To improve the knowledge about drivers of the NAE, we consider both types of effects are considered in the subsequent analysis. **Tab. 6** illustrates the standardized values of the coefficient estimates.

We find no support for H1 in the estimated model. There is no significant influence of expertise on the NAE. Apparently, the respondent’s product class expertise level does not determine the stability of preference structure in different categories.

**Tab. 6: Standardized effect decomposition for the negative attraction effect**

<table>
<thead>
<tr>
<th>Antecedent</th>
<th>Pizza</th>
<th>Smartphone</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXP</td>
<td>-0.001</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>0.001</td>
<td>-0.002</td>
</tr>
<tr>
<td>SIM</td>
<td>-0.039</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.017</td>
</tr>
<tr>
<td>POP</td>
<td>-0.033</td>
<td>0.047</td>
</tr>
<tr>
<td></td>
<td>-0.067</td>
<td>-0.051</td>
</tr>
<tr>
<td>PRE</td>
<td>0.017</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>0.090***</td>
<td>0.094***</td>
</tr>
<tr>
<td>INV</td>
<td>0.038</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>-0.017</td>
<td>-0.002</td>
</tr>
<tr>
<td>INF</td>
<td>-0.074</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.005</td>
</tr>
<tr>
<td>DS</td>
<td>-0.136</td>
<td>-0.267</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.267</td>
</tr>
</tbody>
</table>

*p<0.1, ** p<0.05, *** p<0.01
the analyzed sample. This finding can be due to the fact that the respondents exhibit rather high values of expertise in the considered categories. In addition, the presented attributes (price and quality for pizza; MB and MP for smartphones) and attribute levels are very clear and familiar to the target group. Respondents can easily use them to evaluate the available options without resorting to special skills and knowledge. They rather base their decision on the particular characteristics of the presented attributes in each choice set. Accordingly, the influence on the NAE is negligible.

In contrast to the finding of Huber/Payne/Puto (1982), in the present model we do not find a significant influence of perceived decoy-target similarity (H2). While previous research on product introduction has claimed that decoys which are very similar to the target option increase the target’s attractiveness and accordingly the magnitude of the attraction effect, the overall model applied in this study does not confirm this relationship for product exit. Obviously, the similarity is important for the entry of a decoy resulting in an attraction effect but of no relevance for the removal of the decoy. The predicted negative impact of perceived decoy popularity is significant for both product groups confirming H3. Decoy share mediates the effect. Thus, the indirect effect is dominant here. Thus, we conclude that individuals who perceive the decoy to be very popular exhibit a lower NAE. Accordingly, the target’s relative choice share is higher after the removal of the decoy. This finding delivers valuable insights for brand managers or retailers who decide on the deletion of brands.

The estimation results for smartphones show that higher preference strength will result in a lower NAE (H4). The magnitude of preference shifts for respondents with a clear and stable preference structure is significantly lower than for indifferent or unsure respondents. Our results do not confirm this finding for the pizza category. Here, choices of respondents with higher preference strength lead to a stronger NAE although the direct effect is not significant. While for high-involvement goods an existing stable preference structure in the initial choice scenario is also prevalent in the reduced choice task, low-involvement products apparently lead to preference shifts according to a NAE, even if preference strength is initially rather high. A possible explanation for this phenomenon includes typical characteristics of decision-making in low- vs. high-involvement categories: in high-involvement categories individuals tend to spend a lot of effort on a decision task. They precisely compare the different alternatives by taking into account any available information. If they clearly prefer one option, they will revert to this decision-making in the second choice task. This results in a comparable preference rating and thus, a diminished NAE. By contrast, low-involvement situations usually involve spontaneous decisions without checking each option’s characteristics with the attributes of each other option. If individuals explicitly favor one alternative, they probably more easily adjust their preferences in the modified choice task by just splitting the decoy’s preference points on the remaining alternatives which results in a stronger NAE.

We further expected that individuals who are more involved with the choice task exhibit a smaller NAE since they better assimilate the presented information (H5). This effect operates through perceived information relevance. For this assumption, we find support for both product categories; the estimated parameters show a negative sign. However, the effect is not significant for smartphones.

According to H6, our results provide evidence for a negative influence of information relevance in the pizza sample. The NAE decreases if participants perceive the presented information as being more relevant. This result is in line with the assumption that on the basis of meaningful information consumers do rarely build their decisions on simplifying dominance structures. For smartphones, the effect is also in the supposed direction but smaller and not significant. Again, decision-making on the low-involvement good pizza is much easier than deciding on the high-involvement product smartphone. In accordance to that, individuals reported higher information relevance for pizza as the given information is more easily considered to be sufficiently meaningful to make a selection. High information relevance in low-involvement categories consequently lead to stable preferences and a significantly diminished NAE. The effect decreases for the smartphone sample because, if these respondents consider the given information as being very relevant, they more likely include it in each new decision situation.

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<table>
<thead>
<tr>
<th>Antecedent</th>
<th>Pizza</th>
<th>Smartphone</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXP</td>
<td>-0.001</td>
<td>0.016</td>
</tr>
<tr>
<td>SIM</td>
<td>-0.039</td>
<td>0.17</td>
</tr>
<tr>
<td>POP</td>
<td>-0.033</td>
<td>0.047</td>
</tr>
<tr>
<td>PRE</td>
<td>0.017</td>
<td>-0.108***</td>
</tr>
<tr>
<td>INV</td>
<td>0.038</td>
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<tr>
<td>INF</td>
<td>-0.074</td>
<td>-0.005</td>
</tr>
<tr>
<td>DS</td>
<td>-0.136***</td>
<td>-0.267***</td>
</tr>
</tbody>
</table>

Tab. 7: Direct effects of the causal model
As expected in H7, the share captured by the decoy has a negative influence on the NAE in both product categories. The estimated parameters indicate that decoy share has a considerable impact on preference shifts. In the estimated model, it proves to be the major construct in determining the magnitude of the NAE. For instance, for smartphones the impact is more than twice as high as for the next antecedent variable preference strength. A higher choice probability of the decoy comes along with increasing choice probabilities of the target brand in the initial choice set which results in a smaller NAE.

Overall, the results indicate that the hypotheses originally tested by Mishra/Umesh/Stem (1993) for product introduction are in part identical and supported for the market exit case (the negative influence of preference strength, task involvement and information relevance), some effects are inverted (the impact of decoy popularity and decoy share) and some hypothesized effects do not exist at all (expertise and perceived decoy-target similarity) (see Tab. 8). To account for further relationships in the structural model, the next part of the paper covers all other predicted effects between the included exogenous and endogenous constructs which Tab. 7 clarifies.

Other effects. Firstly, as supposed perceived decoy popularity positively influences decoy share. The results demonstrate the significant effect for pizza and smartphones. If individuals consider a decoy as being more popular, they tend to allocate more preference points to it. Secondly, we find support for the assumption that preference strength has a negative influence on the share captured by the decoy across categories. Higher preference strength consistently leads to lower decoy shares since, typically, we observe high choice probabilities for the target or the competitor brand. Thirdly, expertise has a significant positive effect on task involvement for smartphones. For pizza, the parameter estimate is also positive but not significant. The results show that individuals with higher levels of expertise are more involved with the decision task. Fourthly, we expected task involvement to have a positive impact on information relevance. The displayed results in Tab. 7 provide evidence for this assumption. In both product categories a significant positive effect is observable. Accordingly, individuals who are more involved in the choice task deem information as more relevant and helpful.

The estimations on modification indices and residuals as well as theoretical considerations gave us directions for possible structural changes of the model of Mishra/Umesh/Stem (1993). In this regard, we re-ran the analysis after including an additional path which we had neglected in the original model but expect to cover a significant effect.

4.4. Adapted Model

Conceptualization. Since decoy share is the most important antecedent of the NAE in the initial model, it is essential to comprise each influential factor and relationship referring to this construct. We predict that information relevance is an additional driver of decoy share and adjust the original model by adding a path between information relevance and decoy share ($\beta_{5}$). Generally, there is the recommendation to have some supportive theoretical justification when revising the original model (Hayduk 1996). Individuals who perceive the presented information as being relevant and meaningful take notice of the existing dominance structure with higher probability. In accordance to that, they easier detect the inferiority of the decoy and assign a lower preference rating to this option. Therefore, we assume a negative influence of information relevance on decoy share. To test this postulation, we again estimate the adapted model by means of Lisrel 8.8 employing Maximum Likelihood estimation.

Results. The goodness of fit measures are slightly improved and suggest a good model fit. The $\chi^2$/df is 1.98 (2.66) for pizza (smartphones). The RMSEA amounts to 0.041 (0.047), the SRMR to 0.050 (0.059), the GFI to 0.945 (0.942) and the CFI to 0.982 (0.980). Tab. 9 and Tab. 10 include the parameter estimates. The results indicate that the discussed conclusions for the original model can be maintained. Though some of the estimated path coefficients slightly deviate from the outcomes of the original model (bold figures), directions and significance levels stay unaffected. Considering the direct effects of the model in Tab. 10, the added path reveals to cover a significant relationship. As expected, information relevance has a negative influence on decoy share across categories. Consequently, we should include this effect in the overall model when analyzing antecedents of the NAE.

Tab. 8: Comparison of the results on the attraction effect (Mishra/Umesh/Stem 1993) and on the negative attraction effect

<table>
<thead>
<tr>
<th>Antecedent</th>
<th>Expected sign</th>
<th>Products with significant results</th>
<th>Hypothesis</th>
<th>Expected sign</th>
<th>Products with significant results</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXP</td>
<td>-</td>
<td>Beer</td>
<td>H1</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>SIM</td>
<td>+</td>
<td>Beer, Cars</td>
<td>H2</td>
<td>+</td>
<td></td>
</tr>
<tr>
<td>POP</td>
<td>+</td>
<td>Beer, Cars, TV sets</td>
<td>H3</td>
<td>-</td>
<td>Pizza, Smartphones</td>
</tr>
<tr>
<td>PRE</td>
<td>-</td>
<td>Beer, Cars, TV sets</td>
<td>H4</td>
<td>-</td>
<td>Smartphones</td>
</tr>
<tr>
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<td>-</td>
<td>Beer, Cars, TV sets</td>
<td>H5</td>
<td>-</td>
<td>Pizza</td>
</tr>
<tr>
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<td>H6</td>
<td>-</td>
<td>Pizza</td>
</tr>
<tr>
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<td>+</td>
<td>Beer, Cars</td>
<td>H7</td>
<td>-</td>
<td>Pizza, Smartphones</td>
</tr>
</tbody>
</table>

*Mishra/Umesh/Stem (1993) included experience in the two-dimensional construct knowledge*
Wiebach/Hildebrandt, Antecedents of the Negative Attraction Effect: An Information-Processing Approach

4.5. Reduced Model

Conceptualization. To increase explanatory power, we will next analyze a reduced model which simply comprises the influential constructs and the significant paths. Thereby, we provide an alternative conceptual model which future research can easier adapt to other categories and research questions by including all relevant relationships and drivers of the NAE. In a first step, we eliminated the construct decoy similarity from the model since it neither showed an effect in the original model nor in the adapted model. Obviously, the perceived similarity of the decoy and the target in comparison to the similarity between the decoy and the competitor does not affect the magnitude of the NAE for product exits. In addition, we remove several irrelevant paths to increase validity and informative value of the estimation results. Fig. 3 depicts the reduced model which we test subsequently.

Results. The fit statistics suggest that the reduced model provides a good fit with the data: For the pizza model $\chi^2$/$df = 1.95$, RMSEA = 0.040, SRMR = 0.050, GFI = 0.947 and CFI = 0.984; for the smartphone model $\chi^2$/$df = 2.28$, RMSEA = 0.041, SRMR = 0.058, GFI = 0.952 and CFI = 0.986. Further examination of the structural path coefficients demonstrated in Tab. 11 and Tab. 12 reveals that of the eight hypothesized paths tested, only two are insignificant for pizza (EXP $\rightarrow$ INV and PRE $\rightarrow$ NAE) and only one is insignificant for smartphones (INF $\rightarrow$ NAE). Hence, we find support for H6 and H7 for pizza and corroborate H4 and H7 for smartphones. These findings reinforce the particular importance of decoy share as driver of the NAE. In addition, our results sustain the expected positive influence of decoy popularity as well as the negative impact of preference strength on decoy share. We further verify the assumption that higher expertise yields in a significant increase in task involvement for smartphones. In contrast to decision-making in low-involvement categories, decisions in high-involvement product groups (such as smartphones) are deliberate and include prior experience and skills. Accordingly, higher expertise levels will increase the consideration with the choice task and thus, the involvement with the choice task. We further show that task involvement positively influences information relevance. At the same time, information relevance exhibits the hypothesized negative impact on decoy share.

5. Discussion

The purpose of this research was to increase knowledge about the phenomenon of a NAE when brands are removed from choice sets. By building on the conceptual work of Mishra/Umesh/Stem (1993) for product introductions, our study empirically tested an adapted holistic framework of factors that associate with the NAE for product exits. In particular, we considered the removal of an asymmetrically dominated decoy and the resulting preference shifts at an individual level in two product groups. We estimated the same model across categories...
to compare the importance of different antecedents and their interrelationships. Our findings indicate that product group moderates the impacts on the NAE and provide significant implications for marketing academics and practitioners.

5.1. Theoretical Contributions

The current study makes several contributions to marketing literature. First, by synthesizing literature from different research domains and perspectives, this study delivers valuable insights on the relevance of context ef-

Tab. 11: Standardized effect decomposition for the NAE – Reduced model

<table>
<thead>
<tr>
<th>Antecedent</th>
<th>direct</th>
<th>indirect</th>
<th>total</th>
<th>direct</th>
<th>indirect</th>
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</tr>
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<td>-0.039**</td>
<td>-0.044**</td>
<td>-0.044**</td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.085*</td>
<td>-0.087**</td>
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<td>0.014</td>
<td>-0.010</td>
<td>0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DS</td>
<td>-0.256***</td>
<td>-0.256***</td>
<td>-0.256***</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Bold values signify different estimates compared to the original model.
*p<0.1, ** p<0.05, *** p<0.01

Tab. 12: Direct effects of the causal model – reduced model

<table>
<thead>
<tr>
<th>Antecedent</th>
<th>NAE</th>
<th>INV</th>
<th>INF</th>
<th>DS</th>
<th>NAE</th>
<th>INV</th>
<th>INF</th>
<th>DS</th>
</tr>
</thead>
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<tr>
<td>EXP</td>
<td>-0.072</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.152***</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>POP</td>
<td>-</td>
<td>-</td>
<td>0.261***</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.171***</td>
<td>-</td>
</tr>
<tr>
<td>PRE</td>
<td>-0.006</td>
<td>-</td>
<td>-0.530***</td>
<td>-</td>
<td>0.087**</td>
<td>-</td>
<td>-0.413***</td>
<td>-</td>
</tr>
<tr>
<td>INV</td>
<td>-</td>
<td>-0.229***</td>
<td>-</td>
<td>-</td>
<td>0.336***</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>INF</td>
<td>-0.071*</td>
<td>-</td>
<td>-0.064*</td>
<td>-</td>
<td>-0.000</td>
<td>-</td>
<td>-0.114***</td>
<td>-</td>
</tr>
<tr>
<td>DS</td>
<td>-0.148***</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.256***</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Bold values signify different estimates compared to the original model.
*p<0.1, ** p<0.05, *** p<0.01

Fig. 3: Reduced model
effects for market exits. Second, by combining a conceptu-
al model for product entry with theory on choice set re-
ductions, our research provides a first theoretical ap-
proach to analyze influencing factors of “negative” con-
text effects. Third, by undertaking the first integrated
survey-based study, we empirically document important
drivers of theory-based choice modifications.

While research on the context-dependence of choice has
so far concentrated on new product introductions (Hu-
ber/Payne/Puto 1982; Dhar/Glazer 1996; Pan/Lehmann
1993; Tversky 1972), this research emphasizes prefer-
ence shifts as a result of product exit. In this regard, we
verify the existence of a NAE and empirically test an
overall framework to account for influencing factors of
context-dependent preference-shifts for brand removals
which, to date, has been lacking. Numerous studies on
the introduction of decoys have highlighted the relevance
of the product-decoy combination for the attraction ef-
fect phenomenon (Huber/Payne/Puto 1982; Moran/Mey-
er 2006). On the one hand, the current study demonstra-
mates comparable outcomes for decoy eliminations
while on the other hand, some findings expose essential
differences.

Similar to Mishra/Umesh/Stem (1993), we find support
for the negative influence of preference strength on the
NAE in high-involvement categories. Individuals with a
clear preference structure in the initial three-brand core-
set are less likely to exhibit the NAE. Future choice ex-
periments can only control this impact in within-subjects
designs. Whereas in the basic study preference strength
emerges as most important driver of the attraction effect,
in the present model, decoy share exhibits the strongest
influence on the NAE. A high decoy share causes a low
NAE. This negative relationship is significant across cat-
egories for reduced choice sets contrasting the findings
of Mishra/Umesh/Stem (1993) which show a positive ef-
fect of decoy share on the attraction effect. We further
detect that decreasing decoy popularity intensifies the
NAE, while the product entry case supports the reversed
relationship.

Past research has suggested that context effects are less
pronounced under conditions that facilitate decision-
making (Simonson 1989). The current results reinforce
this assumption by revealing a negative influence of in-
formation relevance on the NAE. In accordance to theo-
ry, consumers who classify the given information as re-
levant and include it in their decision process are less in-
clined to react in dependence of an altering context.

5.2. Managerial Contributions

This research also offers significant insight to retailers
and managers. In general, it becomes evident that after
the elimination of a brand, preferences and choice behav-
or are predictable using context theory. Retailers can ap-
ply the findings when deciding on the delisting of brands
which typically represent inferior options in the assort-
ment. They further can assess the impact of an out-of-
stock. From a supplier perspective, portfolio decisions
can be based on some key findings of the presented study.

The theoretical analysis of the covered phenomenon indi-
cates that after the removal of an inferior option, the
target’s brand share is higher if the NAE is reduced. Ac-
cordingly, practitioners with the aim to increase a target’s
choice share, can utilize the results to answer the ques-
tion: how to reduce the NAE?

First, in high-involvement categories, the removal of in-
ferior brands pays off for customers with an inherently
strong conviction in the target brand since the NAE de-
creases for higher preference strength. Accordingly,
choice probability of the target brand increases. On the
other hand, the total effect of preference strength for low-
involvement categories is positive. Therefore, to
strengthen a target brand, retailers or brand managers
should only remove dominated items if consumers are
rather indifferent to the initially available options. Sec-
ond, the estimation results indicate that a high decoy
share results in a limited NAE. Thus, it can be profitable
to eliminate brands even if they generate moderate sales.
Retailers should also take those brands into consideration
for a removal which hold a non-negligible market share.
Third, the findings show that decoy popularity negative-
ly influences the magnitude of the NAE. Consequently,
managers should present the inferior brand which should
be deleted as being popular, for instance by adding a tag
which indicates that many people like this brand ("third
most bought brand in 2013"). Fourth, this study reveals
that information relevance decreases the NAE. Retailers
can utilize the outcome by enhancing the perceived
meaningfulness of the information presented at the point
of sale. For instance, they should present appropriate in-
formation in a useful way for customers, introduce more
precise price tags, educate customers or promote the re-
levance of a product group can by increasing shelf space.
Thereby, they can manipulate consumers deciding on the
reduced choice set to perceive the target brand as being
attractive anymore.

Overall, to minimize the NAE, marketers should simpli-
fy decision-making. In practical terms, retailers should
adjust their shelves by clearly arranging the available op-
tions, add precise information and displays or keep cus-
omers involved in the choice task, e.g. by presenting the
available items at a secondary display.

5.3. Limitations and Avenues for Future Research

The contributions of this research are bounded by limita-
tions that, in turn, underline potentially promising ave-
ues for further studies. One limitation arises from the
application of a survey method to collect data which nor-
mally tends to result in measurement errors. However,
analyzing the measurement model revealed no problem
concerning this matter. Moreover, the collection of data
from a student sample from Germany limits the general-
izability of the findings to this group of respondents and
beyond this country. We encourage future research to validate the results across different target groups and geographical regions. With regard to the involved alternatives and attribute levels, we build on previous context effect research. Accordingly, the selectable options of the three-item core set differed in only two dimensions reducing generalizability. Further research can extend the model to larger choice sets with alternatives characterized by more attributes. Probably, different results will emerge since we can assume that in larger choice sets choice heuristics are used more easily (Shugan 1980).

The presented model includes a limited number of influencing factors. Several other antecedent variables could determine the NAE. For instance, future studies could add loss aversion as possible driver of the NAE to the model since it is typically mentioned as one explanation for context effects (Simonson/Tversky 1992). Research on phantoms (Farquhar/Pratkanis 1993; Hedgcock/Rao/Chen 2009; Pettibone/Wedell 2007) has revealed that the type of the decoy affects preferences. “Known” and “unknown phantoms” can be differentiated describing the respondent’s knowledge about the unavailability of the item prior to the decision process (Pratkanis/Farquhar 1992). Both types of phantoms lead to differences in resulting preferences (Doyle et al. 1999). Doyle et al. (1999) further distinguished between “amenable phantoms” and “not so amenable phantoms”. The unavailability of the “amenable” option is due to high demand whereas a “not so amenable” option was deleted with intent by the supplier. Their study uncovered different effects for both types of phantoms. Additionally, the timing of notification about product unavailability and the personal concern of the elimination can be considered as relevant for altered decision-making (Fitzsimons 2000; Kim 2004).

By testing a structural equation model for the NAE, this study focused on one particular “negative” context effect. Following Wiebach/Hildebrandt (2012) who demonstrated the existences of additional negative context effects (a negative similarity effect as well as a negative compromise effect), a fruitful approach for further research includes the development and the test of drivers of these phenomena.

Notes

[1] Against the basic model of Mishra/Unmesh/Stem (1993), familiarity is not included as exogenous construct in the presented model due to a lack of validity of the underlying measurement model.

[2] The quality of frozen pizza was tested in a recent study conducted by a grocery testing company. Among others, they have tested the following characteristic: valuable ingredients, richness of the topping and the contribution to a well-balanced food. On the results of these tests, points for quality on a scale of 0–100 (100 corresponds to the highest quality) were allocated.

[3] “Given that you had to buy one brand based on the given information alone, which one would it be? Please assume that the brands are identical with regard to any other attribute.”

[4] “Please distribute 100 points among the brands in proportion to the probability of choice for these brands, giving most points to the brand you prefer most. Make sure that the allocated points add up to 100.”

[5] The use of a constant sum scale to rate preferences involves respondents to not only report a prior choice. Instead, they have to consciously adapt and alter their ratings reflecting their preferences based on the exit of the brand (Sivakumar/ Cherian 1995).

[6] NAE = NAE of respondent i: \( E_i \{ P(T|T, C), D \} = \) expected share captured by target brand in the reduced choice set of respondent i under the Luce model; \( P(T|T, C), D \) = observed share captured by the target brand in the reduced choice set of respondent i; and \( P(T|T, C), D \) = respondent i’s choice probability of the target brand in the complete choice set \{T, C, D\} (T = target brand, C = competitor brand, D = decoy): 

\[
E_i \{ P(T|T, C), D \} = \frac{P(T|T, C, D)}{\sum_i P_i(T|T, C, D)} + \frac{P_i(T|T, C, D)}{\sum_i P(T|T, C, D)} \cdot \frac{P_i(D|T, C, D)}{\sum_i P_i(D|T, C, D)} + \frac{P_i(D|T, C, D)}{\sum_i P_i(D|T, C, D)} = 1
\]

[7] \( \text{PRE}_i = P(X|T, C, D) \)

\[
X = \begin{cases} 
T, & \text{if } T \text{ has the highest choice probability for respondent } i \ 
C, & \text{if } C \text{ has the highest choice probability for respondent } i \ 
D, & \text{if } D \text{ has the highest choice probability for respondent } i 
\end{cases}
\]

\[
\text{PRE}_2 = 1 - P(X|T, C, D) 
\]

\[
Y = \begin{cases} 
T, & \text{if } T \text{ has the lowest choice probability for respondent } i \ 
C, & \text{if } C \text{ has the lowest choice probability for respondent } i \ 
D, & \text{if } D \text{ has the lowest choice probability for respondent } i 
\end{cases}
\]

References


Keywords
consumer decisions, negative attraction effect, context effects, preferences, structural equation modeling