Increasing advertising effectiveness through individualization approaches and cause-related marketing in online shopping: Insights from the apparel industry

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To my beloved son

Abstract

With the increasing shift of essential parts of our personal lives from the offline world to the Internet—e.g., shopping, entertainment, work and education, communication, or even finance—the number of online advertisements has increased rapidly and continuously in recent years. As a result, it is becoming increasingly challenging for companies to reach and engage their target audiences with online ads. The individualization of ads and the communication of practices that support beneficiaries other than the consumer, such as the environment or society at large, also known as corporate social responsibility (CSR) advertising, are two approaches that have the potential to break through this advertising clutter and increase the effectiveness of online advertising. The research described in this thesis aims to fill existing research gaps in the above research fields, such as considering individualized advertising across different communication channels, comparing the effectiveness of CSR advertising to traditional advertising during the COVID-19 pandemic, and examining the success of customized and personalized cause-related marketing (CRM) compared to traditional advertising. The research findings of this thesis provide both scholars and practitioners with insights to overcome advertising clutter and increase the effectiveness of advertising efforts. To this end, this dissertation features four research articles.

Research papers #1 and #2 (chapters 4 and 5) investigate consumer preferences for personalized advertising in different media channels, taking into account gender effects. The articles differ in their main research objectives, with paper #1 focusing on heterogeneous preferences and reasons for rejecting personalized product recommendations, while paper #2 on top of this discusses promising state-of-the-art recommender algorithms to enhance the perceived quality of personalized ads. Research article #3 (chapter 6) measures the importance of CSR advertising with different beneficiaries compared to traditional advertising with pure self-benefits for the respective consumer during the COVID-19 pandemic. Research paper #4 (chapter 7) examines consumer preferences for customized and personalized CRM campaigns compared to generic CRM campaigns with a single predefined cause and traditional advertising.

Finally, the thesis concludes with a summary of the insights gained, recommendations for practitioners, and a brief outlook on future research avenues.

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List of abbreviations

ABIC	Adjusted Bayesian Information Criterion
AIC	Akaike Information Criterion
ANOVA	Analysis of variance
BFI-10	Big-Five-Inventory-10
BIC	Bayesian Information Criterion
BWS	Best-Worst Scaling
CAIC	Consistent Akaike Information Criterion
CBC	Choice-based conjoint (analysis)
CBF	Content-based filtering
CF	Collaborative Filtering
CLT	Construal level theory
CRediT	Contributor Role Taxonomy
CRM	Cause-related marketing
CSR	Corporate social responsibility
DCA	Discrete choice analysis
FCHR	First choice hit rate
HB	Hierarchical Bayes
LCA	Latent class analysis
M	Mean
MaxDiff	Maximum Difference Scaling
RLH	Root likelihood
RQ	Research question
SD	Standard deviation
Tukey HSD	Tukey’s honestly significant difference post-hoc test
TURF	Total Unduplicated Reach and Frequency (analysis)

1 Introduction and research outline

As global advertising spending has steadily increased in recent decades, almost US$723 billion was spent on advertising in 2021 (Statista, 2023a, 2023c). At US$523 billion, online channels accounted for a significant and growing share of this (Statista, 2023c), with video and social media advertising showing the highest growth rates in recent years due to an increasing number of ad formats in those channels (Statista, 2023d).

This continued increase in advertising spending is accompanied by consumers being exposed to an ever-greater number of advertisements during their online interactions and experiences. Clearly, advertising effectiveness suffers as a result, as standard online ads—advertisements that do not stand out from the growing ad clutter—are less and less likely to attract consumers' attention and reinforce ad-avoidance behavior (Bauer & Lasinger, 2014; Bleier & Eisenbeiss, 2015a). Other negative effects of ad clutter, which can be described as a large number of advertisements in one medium, e.g., on a single web page, include lower recognition and recall of ads and lower perceived quality of media content (Cho & Hongsik, 2004; Ha, 2017; Ha & McCann, 2008).

Targeting advertisements to consumers' individual needs and preferences, and thereby making ads more relevant to their personal interests and more appealing to consumers, is a promising approach to increasing advertising effectiveness and breaking through the ad clutter (Bauer & Lasinger, 2014; Bleier & Eisenbeiss, 2015a, 2015b; Jung & Heo, 2021; Segijn et al., 2021). In general, such practices can be referred to as tailoring or individualization approaches, which can be differentiated into customization and personalization (Arora et al., 2008; Bleier et al., 2018; Chandra et al., 2022). Previous research has demonstrated that such approaches can significantly enhance customer relationships in several ways, such as increasing customer satisfaction, loyalty, or purchase intentions (Chandra et al., 2022; Keyzer et al., 2022; Kwiseok Kwon & Kim, 2012), as well as increasing actual sales (Goic et al., 2021; Sahni et al., 2018; Sridhar et al., 2022).

Another approach that allows brands to stand out from the media clutter and that has become very popular in recent years, especially among younger audiences, is corporate social responsibility (CSR) initiatives, which enable brands to “incorporate corporate-level intangible assets such as their identities and reputations and the goodwill associated with being a good corporate citizen into their marketing initiatives in efforts to garner sustainable competitive advantages” (Du et al., 2010; Pyle et al., 2022; Sen et al., 2006, p. 164; Taylor & Carlson, 2021). In particular, cause-related marketing (CRM), which links corporate donations to a designated cause to consumers’ purchase decisions, can be considered an effective marketing tool to capture consumers’ attention and thus penetrate online ad clutter (Chang & Chen, 2017; e Silva et al., 2020; La Ferle et al., 2013; Varadarajan & Menon, 1988). A large body of research has shown that CRM has the potential to improve attitudes (e.g., toward the brand, campaign, or product) and behaviors (e.g., purchase intentions, willingness to pay, or product choice), and some studies even suggest an increase in actual product sales (Andrews et al., 2014; Lafferty et al., 2016; Schamp et al., 2022). Key drivers of the success of such campaigns include both altruistic and egoistic benefits that consumers derive from participating in them. While CRM campaigns provide altruistic benefits to consumers by providing donations to charitable organizations, consumers may also benefit from so-called "warm-glow" feelings—an egoistic benefit that makes individuals feel better about themselves when participating in charitable giving (Arora & Henderson, 2007; Koschate-Fischer et al., 2012).

Recent research has shown that a combination of the two aforementioned approaches—individualization, particularly through customization, and CRM campaigns—can elicit very positive consumer responses and increase the effectiveness of online advertising (Arora & Henderson, 2007; Bartsch & Kloß, 2019; Christofi et al., 2019; Kim & Kim, 2022; Kull & Heath, 2016; Robinson et al., 2012).

Therefore, this thesis aims to provide a deeper investigation and understanding of consumers’ heterogeneous preferences for these marketing communication approaches—both individually and in conjunction with each other. With this objective in mind, existing research gaps in both research streams, as well as in the combined research area of individualized CRM, are addressed. To this end, four full research articles are presented that comprise the bulk of the research in this thesis.

As a complement to the existing literature that explores the success factors for designing product recommendations—as a specific type of personalized marketing—on a single communication channel (i.e., the retailer's website), research papers #1 and #2 examine the effectiveness of product recommendations on three different communication channels. Although both research papers were based on the results of the same empirical study, the two publications differ mainly in terms of their research objectives. Article #1 focuses on the investigation of heterogeneous consumer preferences in terms of gender and communication channels and elaborates on the reasons for rejecting recommendations. Additionally, article #2 also emphasizes on state-of-the-art recommender algorithms to overcome common issues of frequently used recommender systems and on approaches that have the potential to increase perceived individual recommendation quality.

In addition to the pre-pandemic research that compared the effectiveness of CSR advertising to traditional advertising, research article #3 examines this topic in the context of the COVID-19 pandemic and compares the effectiveness of CSR advertising with different types of beneficiaries. Again, sociodemographic aspects such as gender are used to look at heterogeneous consumer preferences for different types of marketing appeals such as employee-oriented CSR advertising, CRM campaigns and traditional sales promotion methods.

Research paper #4 analyzes the success of personalized CRM campaigns and customized CRM campaigns compared to traditional advertising, complementing recent research that examines the effectiveness of both types of CSR advertising separately. In addition, the drivers of heterogeneous consumer preferences are studied not only in terms of sociodemographic consumer characteristics but also in terms of psychographic consumer characteristics such as personality traits and cultural dimensions. This additional research topic arose from the fact that previous studies—including research article #3 within this thesis— had failed to sufficiently explain the heterogeneity of consumer preferences by sociodemographic aspects such as gender, age, or educational background.

The remainder of this thesis is structured as follows: Chapter 2 introduces the theoretical background for the concepts of individualized advertising, CSR advertising, and CRM campaigns, as well as the recent linkage between the two research fields.

In addition, the main research questions of this thesis are stated before chapter 3 presents the research content of each article in detail. This chapter also states the author's contributions to each article. In the following chapters (4–7), the four research articles are presented. Finally, the thesis concludes with a summary of the research findings discussed.

2 Theoretical background and main research questions

2.1 Two forms of individualization: Personalization and customization

The marketing literature distinguishes between two distinct forms of individualization based on the entity that initiates the tailoring of the firm's marketing mix to individual consumer preferences (Arora et al., 2008; Bleier et al., 2018; Chandra et al., 2022; Sundar & Marathe, 2010). Personalization refers to company-initiated tailoring of the marketing mix based on either explicitly (e.g., consumer ratings for products) or implicitly (e.g., purchase history or browsing behavior) retrieved consumer preferences (Arora et al., 2008). Customization involves consumers actively tailoring the marketing mix to their individual needs. Figure 1 illustrates the individualization possibilities of these approaches in terms of the different marketing mix instruments and the varying degrees of individualization they offer.

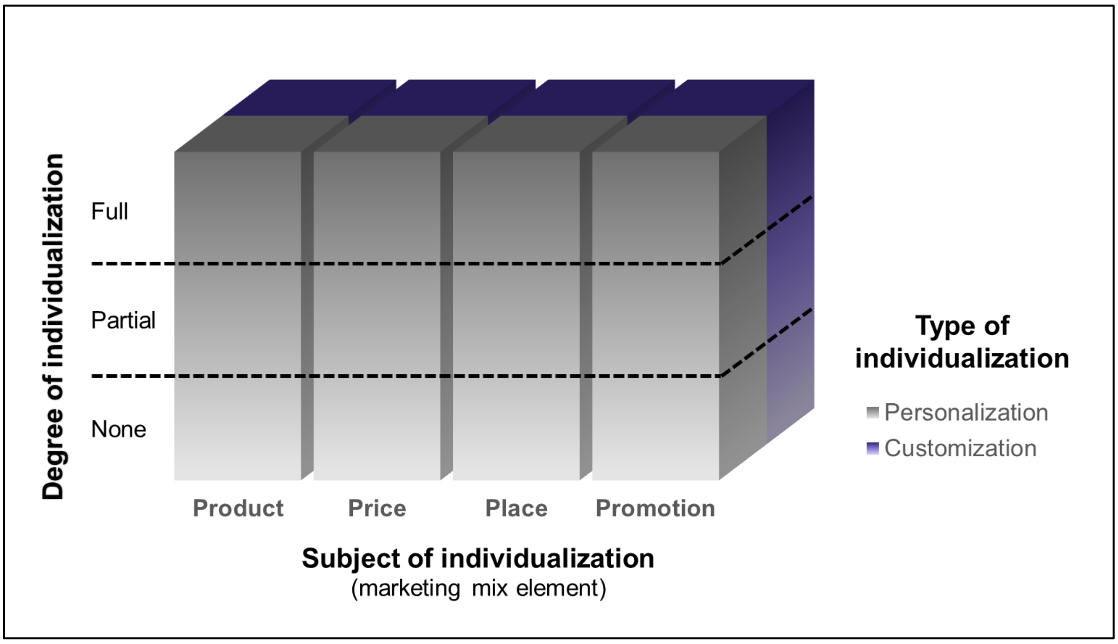

Figure 1: Individualization possibilities in marketing through personalization and customization

The degree of personalization refers to the granularity with which the marketing mix is tailored to consumers (e.g., the same marketing mix for all consumers versus an individualized marketing mix for each consumer), while the degree of customization refers to how much control or autonomy consumers are given in tailoring marketing mix elements to their preferences—e.g., customization of only a few product aspects versus quasi-fully customized products (Arora et al., 2008; Bleier et al., 2018; Montgomery & Smith, 2009; J. Zhang & Wedel, 2009).

Different marketing strategies can be made based on the four key marketing mix elements and the varying levels of individualization. For example, product-related one-to-one individualization strategies can be implemented by allowing consumers to configure a product according to their individual needs (customization) or by presenting personalized product recommendations based on their previous purchasing and browsing behavior (Arora et al., 2008). In terms of pricing, partial personalization can be realized by personalizing prices for different consumer segments according to their current location, device, or operating system (e.g., Android versus iOS). Partial customization can allow consumers to suggest a price that may be accepted by the seller if it exceeds their predefined price threshold (Bleier et al., 2018). Individualization subjects for place typically involve purchase channels and website interfaces (Bleier et al., 2018; Kwiseok Kwon & Kim, 2012). Regarding marketing communication, subjects of individualization are mainly the communication attributes, such as tailored messages or product offerings, as well as the communication channel itself, e.g., allowing or rejecting advertisements via specific channels through opting-in or opting-out behaviors (Bleier et al., 2018; Kwiseok Kwon & Kim, 2012).

Although the concepts of personalization and customization have been used and studied for decades, they remain highly relevant (Arora et al., 2008; Bleier et al., 2018; Chandra et al., 2022). On the one hand, global sales of personalization software and services are estimated to reach $9 billion in 2023, with a strong growth forecast for the following years (Statista, 2023b). On the other hand, customization practices are widespread in many industries, mainly through product configurators (cyLEDGE Media, 2022).

As a distinct sub-domain of individualized marketing communication, personalized advertising, in particular, has received much attention in recent years (Chandra et al., 2022). This refers to the tailoring of advertising messages to consumers' individual preferences by incorporating available personal information, such as demographic data, online shopping behavior, or social media data (Baek & Morimoto, 2012; Bang & Wojdynski, 2016; Bleier & Eisenbeiss, 2015b; Yu & Cude, 2009). For example, personalized advertising messages may address consumers by their real names or cater to individual preferences by providing personalized product recommendations based on past purchase behavior (Bleier & Eisenbeiss, 2015b; Lambrecht & Tucker, 2013; Sahni et al., 2018).

While much recent research has addressed the effectiveness of personalized online advertising, the effectiveness of personalized advertising across different media channels has been less well studied (Baek & Morimoto, 2012). In addition, issues related to the design of product recommendations, which are the most common way of implementing personalized advertising, have not been addressed in a multichannel environment. These research gaps are therefore addressed in research papers #1 and #2:

Research question (RQ) 1: *How can retailers maximize the effectiveness of personalized product recommendations in advertisements while considering design characteristics and advertising channels?*

Furthermore, the second research paper focuses on another key aspect of personalized product recommendations in advertising and thus addresses the following research question:

RQ 2: *How can current trends in recommender systems research be used to enhance perceived individual recommendation quality?*

Recently, research has also focused on customized advertising (Douglas Olsen & Pracejus, 2020). Unlike personalized advertising and similar to the distinction made by Arora et al. (2008), customized advertising allows consumers to pro-actively tailor certain elements of the advertising message, such as visualizations, to their preferences (Douglas Olsen & Pracejus, 2020). In three studies Douglas Olsen and Pracejus (2020) showed that this approach could significantly increase the overall impact of the ad, making it a viable alternative to personalized advertising without compromising consumer privacy by using personal data for advertising purposes.

In general, the approaches yield different benefits and drawbacks for consumers. Personalization has a positive impact on consumer responses because it is convenient and effortless, while the main benefit of customization is that consumers retain a sense of control when they actively tailor marketing mix aspects to their preferences (Aguirre et al., 2015; Sundar & Marathe, 2010; B. Zhang & Sundar, 2019). The major drawbacks of personalization are increased privacy concerns due to perceived intrusiveness and a perceived lack of control (Aguirre et al., 2015; Bleier et al., 2018; Sundar & Marathe, 2010; B. Zhang & Sundar, 2019). In contrast, customization processes may be perceived as overly complex and too effortful (Aguirre et al., 2015; Bleier et al., 2018; Sundar & Marathe, 2010; B. Zhang & Sundar, 2019).

A comparison of the effectiveness of both individualization approaches is addressed in RQ4, which is outlined in section 2.3.

2.2 Corporate social responsibility and cause-related marketing

Although there have been numerous research studies and literature reviews that address the history and evolution of approaches to defining the concept of CSR over time (e.g., the studies conducted by Agudelo et al., 2019; Carroll, 1999; Carroll & Shabana, 2010; Dahlsrud, 2008; M.-D. P. Lee, 2008), there is still no universally accepted definition of the concept (Dahlsrud, 2008; Peloza & Shang, 2011; Saeidi et al., 2015). A very popular and widely used definition of CSR was provided by Carroll (1979), who categorized different types of responsibilities (economic, legal, ethical, and discretionary) that companies are expected to fulfil for their different stakeholders. Another widely used definition developed more in the context of practitioners sees CSR as a “commitment to improve community well-being through discretionary business practices and contributions of corporate resources” (Kotler & Lee, 2005, p. 3). Another frequently cited definition comes from the Commission of the European Communities, which, in a Green Paper promoting a European strategy for CSR, described the term as “a concept whereby companies integrate social and environmental concerns in their business operations and in their interaction with their stakeholders on a voluntary basis” (Commission of the European Communities, 2001, p. 7). Common to these definitions and to the understanding of CSR in this thesis is that CSR is described as a set of corporate activities that aim to enhance or generate value for stakeholders and go beyond the goal of mere profit maximization.

In this regard, CSR can generate value for different stakeholders (Malik, 2015; Öberseder et al., 2014; Turker, 2009). Typically, internal (e.g., employees) and external stakeholders, such as customers, suppliers, investors, the community, and the environment, can be targeted as beneficiaries of CSR initiatives (Hameed et al., 2016; Schaefer et al., 2020; Turker, 2009; Verdeyen et al., 2004). In this context, cause-related marketing can be considered a popular "CSR instrument with promotional character" which mainly involves the consumer and the supported charitable organization as company stakeholders (Lafferty et al., 2016; Schamp et al., 2022, 192; Thomas et al., 2020). Thus, CRM falls into the category of CSR advertising, which basically describes the proactive communication of firms' CSR efforts (Kyeongwon Kwon & Lee, 2021; Oh et al., 2017). Unlike traditional sales promotion methods such as price discounts, CSR advertising involves benefits for other parties than the consumer. Other forms of CSR advertising, for instance, include sponsorships and philanthropy (Lii & Lee, 2012). While the focus of CSR advertising has primarily been on environmental and philanthropic efforts, more recently, in light of the COVID-19 pandemic, CSR health advertising that "encouraged people to engage in socially responsible health and safety behaviors or to highlight a company's efforts to support the community" has also been observed and researched (Mueller et al., 2022, p. 337).

In research paper #3, the effectiveness of such marketing appeals with other-benefit components is compared to traditional sales promotion methods. The setting of this research article is very specific, as the study was conducted at the beginning of the COVID-19 pandemic. Thus, the main research question for this article is the following:

RQ 3: *What types of marketing actions should online apparel retailers use to stay relevant to customers and remain digitally competitive during the COVID-19 pandemic, and beyond?*

2.3 Personalized and customized CRM

Despite the popularity of the above two approaches to overcoming the online ad clutter—individualized advertising on the one hand and CRM as a form of CSR advertising on the other—very little research has been conducted examining these approaches together.

Research combining individualized advertising and CRM campaigns has mainly been studied in the context of customized CRM, i.e., empowering consumers with choice regarding certain design elements of CRM campaigns (Arora & Henderson, 2007; Christofi et al., 2019; Howie et al., 2018; Kull & Heath, 2016; Robinson et al., 2012; Singh & Pathak, 2020). Taken together, the results of these studies point to enhanced consumer responses to such CRM campaigns with choice compared to generic CRM campaigns without consumer engagement (Arora & Henderson, 2007; Howie et al., 2018; Kull & Heath, 2016; Robinson et al., 2012). In the context of CRM campaigns, previous research mainly refers to consumer choice in terms of the supported cause, i.e., the ability for consumers to select their preferred charity supported by the CRM campaign, while other aspects such as characteristics of the supported cause or the supported organization have been addressed much less frequently (Christofi et al., 2019; Patil & Rahman, 2022).

The concept of personalization—as defined by Arora et al. (2008)— has received even less attention within CRM research. Few recent studies on CRM and the related domain of charity advertising have explored personalization by including personal details such as name, address, age, and gender in promotional messages (Bartsch & Kloß, 2019; Kim & Kim, 2022).

Consequently, the individualization options in CRM can include the tailoring of personal information, as with any type of advertising, as well as the tailoring of the main components of such a campaign and the characteristics of the supported charitable organization. More specifically, the main components of CRM campaigns that can be customized or personalized include (i) the supported cause, (ii) the proximity of the supported cause, and (iii) the donation type (Christofi et al., 2019). The determination of the supported cause refers to the type of cause, e.g., humanitarian aid or environmental protection, or to specific charities, e.g., World Vision or Greenpeace. In addition, the proximity of the supported cause, e.g., support for a local, national, or international project, can be individualized. When specifying the type of donation, a distinction can be made between monetary donations, donations in kind, and donations of time. In addition, the characteristics of the charity can be individualized, e.g., the organization’s size or its country of origin (Patil & Rahman, 2022). All possible aspects of individualizing CRM campaigns are illustrated in Figure 2.

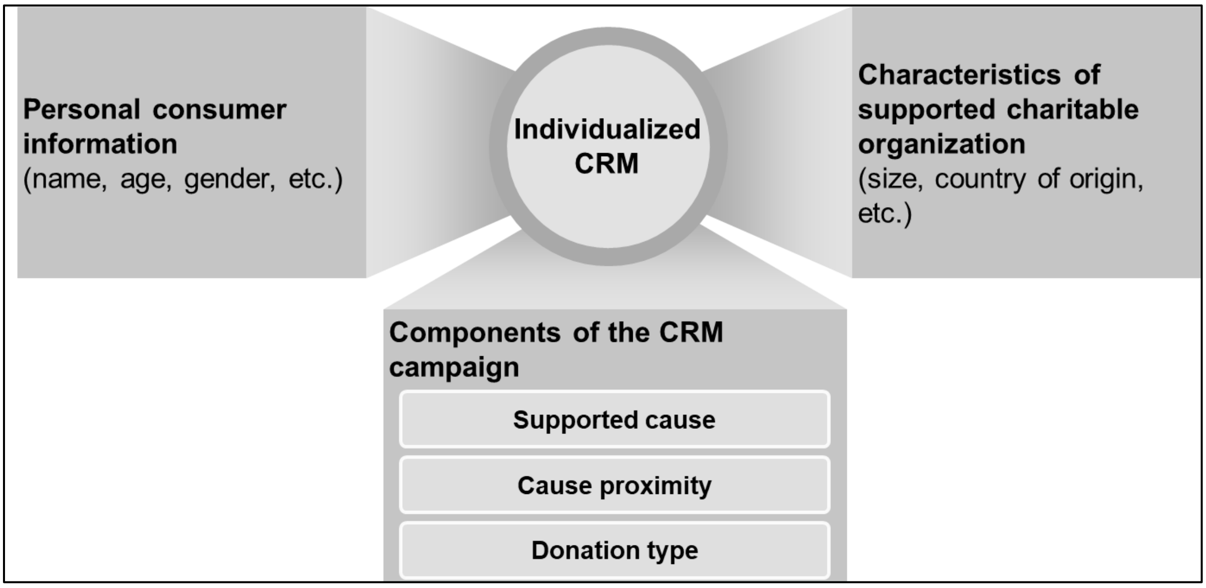

Figure 2: Individualization possibilities within CRM campaigns

While the effectiveness of customized and personalized CRM on consumer responses has already been studied independently, a comparison of the two approaches has yet to be made, leading to the following research question:

RQ 4: *How effective are customized CRM campaigns compared to personalized CRM campaigns, CRM campaigns with a predetermined baseline cause, and promotions with pure self-benefits, such as price discounts?*

Thus, the combination of individualized advertising and CRM is covered thoroughly in research article #4. The subjects of individualization in this study are the supported cause and, in the case of customized CRM, also the cause proximity. A comparison is also made with marketing efforts that provide only self-benefits to the particular consumer, i.e., price discounts, to provide some point of reference for the effectiveness of such individualized CRM campaigns.

3 Detailed overview of included research articles and author contributions

The four research articles presented below address the main research questions listed above. Although they elaborate on different research questions, all presented studies are conducted in the context of the German online apparel industry.

This allows us to obtain an in-depth and comprehensive overview of consumer preferences for attention-grabbing online advertising practices in a specific industry. The apparel industry was chosen as the field of application primarily because of its high relevance, as it was, for example, the product domain with the highest overall revenue in German online retail in 2021 (Statista, 2023e). Another common feature of the included research papers is the main methodological approach used: while choice-based conjoint analyses (CBC) were conducted in articles #1, #2, and #4, a closely related method with the best-worst scaling approach of Maximum Difference Scaling (MaxDiff) was used in research article #3. In addition to these main methods, also other methods have been used to enable an in-depth exploration of consumer preferences such as latent class analysis (LCA) or total unduplicated reach and frequency analysis (TURF). Furthermore, different consumer characteristics have been explored as potential drivers of heterogeneous consumer preferences: While research articles #1 to #3 relied on sociodemographic consumer characteristics, particularly gender differences, to describe discrepancies in consumer preferences, research paper #4 also considered psychographic consumer preferences, i.e., personality traits and cultural orientations of consumers.

By examining different types of advertising efforts that enable breaking through the increasing (online) ad clutter and by considering various impact factor on the effectiveness of these advertising efforts, this thesis covers a wide range of literature in different research streams. Research articles #1 and #2 primarily draw on previous literature in the areas of advertising and personalization research, multichannel marketing, research on human-computer interaction with a focus on recommender systems, and recommender algorithms, e.g., from the fields of machine learning and deep learning. Research article #3 mainly elaborates on literature in CSR, CRM, marketing during the COVID-19 pandemic, self-benefit compared to other-benefit promotions, and social psychology, especially construal level theory. Finally, research article #4 complements the research fields of the three previous research papers by additionally reviewing the literature on customization and personalization practices in CRM research, research on the effectiveness of customization versus personalization, and effects of aspects from intercultural communication research as well as personality dimensions on consumer responses to CRM campaigns.

Table 1 provides an overview of the included research articles, their main content, the applied methods as well as the underlying samples.

Because three of the included research articles were written by multiple authors, the individual author contributions to each article are briefly listed in Table 2 following the Contributor Role Taxonomy (CRediT) for identifying author contributions to research articles (Allen et al., 2019; Allen et al., 2014). This highlights each author's involvement in basic tasks that were relevant to each publication. In addition, for each included research article, the submission/publication status is provided with the date of online publication—if already published—in the respective journal, and the number of revisions that have been required for publication.

Table 1: Detailed overview of research articles and their research outline

Paper	Title and content / research outline	Method(s)	Sample
#1 Chapter 4	**Multichannel personalization: Identifying consumer preferences for product recommendations in advertisements across different media channels** ▪ Literature research on personalization effects across different media channels, success factors for product recommendations and gender-effects on fashion shopping behavior and motivations. ▪ Investigation of the ideal design of personalized product recommendations in advertisements. ▪ Comparison of the effectiveness of different communication channels, i.e., package inserts, email advertising and banner advertising. ▪ Investigation of gender effects as drivers for heterogeneous consumer preferences. ▪ Examination of reasons for rejecting product recommendations. ▪ Demonstration of the potential of using CBC with exclusively visual stimuli presentation.	▪ CBC	n=170 male and n=162 female German students as part of the Digital Natives
#2 Chapter 5	**Success Factors for Recommender Systems From a Customers' Perspective** ▪ Literature review on recent, popular recommender algorithms and success factors of recommender systems. ▪ Investigation of the ideal design of personalized product recommendations in advertisements. ▪ Discussion of promising future recommender algorithms for increasing the perceived recommendation quality.	▪ CBC	Same sample as in #1
#3 Chapter 6	**Online retailing during the COVID-19 pandemic: Consumer preferences for marketing actions with consumer self-benefits versus other-benefit components** ▪ Literature review on the concept of CSR and the effectiveness of marketing actions with different beneficiaries. ▪ Investigation of the importance of different types of marketing actions during the COVID-19 pandemic. ▪ Comparison of the effectiveness of marketing actions with different beneficiaries, i.e., mere self-benefit versus other-benefit components. ▪ Examination of gender-related differences in the evaluations of self-benefit versus other-benefit promotions. ▪ Application of LCA to group respondents into segments with similar preferences. ▪ Identification of combinations of marketing actions with maximum reach via TURF analysis.	▪ MaxDiff ▪ LCA ▪ TURF analysis	n=503 German consumers recruited from an online panel
#4 Chapter 7	**Balancing self-benefits and altruism in online shopping: Examining consumer preferences for customized and personalized cause-related marketing campaigns versus price discounts** ▪ Literature review on the effectiveness of different types of CRM campaigns versus price discounts and the impact of psychographic consumer characteristics on the effectiveness of CRM campaigns. ▪ Examination of the effectiveness of customized and personalized CRM campaigns to CRM campaigns with a predetermined cause and price discounts. ▪ Investigation of psychographic consumer characteristics as drivers of preferences for CRM campaigns. ▪ Examination of reasons for rejecting CRM campaigns by certain retailers. ▪ Application of LCA to group respondents into segments with similar preferences; characterization of different segments by psychographic consumer characteristics.	▪ CBC ▪ LCA	n=388 German consumers recruited from an online panel

Table 2: Overview of author contributions

Paper	Journal	Submission / publication status		CRediT-author statement (Allen et al., 2019; Allen et al., 2014)
#1 – Chapter 4	Journal of Retailing and Consumer Services	Status	Published (22.02.2019)	▪ **Timo Schreiner (11/11):** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review and editing, Visualization, Supervision, Project administration ▪ **Alexandra Rese (2/11):** Writing – original draft, Writing – review and editing ▪ **Daniel Baier (3/11):** Methodology, Writing – original draft, Writing – review and editing
		Number of revisions	1	
#2 – Chapter 5	Archives of Data Science, Series A	Status	Published (12.10.2020)	▪ **Timo Schreiner (11/11):** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review and editing, Visualization, Supervision, Project administration ▪ **Alexandra Rese (1/11):** Writing – original draft ▪ **Daniel Baier (2/11):** Methodology, Writing – original draft
		Number of revisions	1	
#3 – Chapter 6	Journal of Marketing Management	Status	Published (28.01.2022)	▪ **Timo Schreiner (11/11):** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review and editing, Visualization, Supervision, Project administration ▪ **Daniel Baier (2/11):** Methodology, Writing – review and editing
		Number of revisions	2	
#4 – Chapter 7	International Journal of Research in Marketing	Status	Under review (since 10.03.2023)	▪ **Timo Schreiner (10/10):** Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization, Supervision, Project administration

4 Research paper #1: Multichannel personalization: Identifying consumer preferences for product recommendations in advertisements across different media channels

Abstract

Nowadays, many retailers use personalization in advertising to increase customers' awareness and interest in their offers. Product recommendations are a common form of personalization used in various communication channels. However, previous studies have focussed on particular design aspects of product recommendations on a retailer's website, without considering other communication channels. Therefore, this study examines the ideal design of personalized product recommendations in advertisements from a consumer's perspective by relying on a choice-based conjoint experiment in the apparel industry. The findings of two studies for young male (n=170) and female (n=162) consumers show that the advertising channel is the most important attribute for determining the participant's intentions to adopt the respective product recommendations, followed by the number of recommendations. While banner advertising is the least preferred channel for both samples, males prefer smaller recommendation sets than females. In addition to exploring consumer preferences, the reasons for rejecting the advertisements are also analysed. Finally, design recommendations for advertisers and retailers regarding personalized product recommendations are derived.

Keywords:

Personalization – Product recommendation – Multichannel – Avoidance of advertising – Digital natives – Gender differences.

This chapter has been published in:

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4.1 Introduction

During the past decade the advertising industry has faced major changes due to the rapid and extensive diffusion of the internet. In addition to traditional media, online advertising such as display ads, search engine or social media advertising are increasingly used for promotional purposes (Danaher, 2017). As a result, consumers are constantly exposed to a multitude of advertising messages in different online and offline channels (Baek and Morimoto, 2012). Quite often the consumers' reaction to such 'advertising clutter' is characterized by behaviors of advertising avoidance (Cho and Cheon, 2004; Ha and McCann, 2008). For instance, 11% of the global Internet users already rely on 'adblock' technologies to suppress advertisements on websites (PageFair, 2017). In order to increase advertising effectiveness, many advertisers make use of personalization techniques (Bleier and Eisenbeiss, 2015a). Product recommendations are a widespread type of personalization used in ecommerce (Arora et al., 2008; Baier and Stüber, 2010; Kaptein and Parvinen, 2015) and are often integrated directly on a company's website as well as in the email communication between a firm and its customers (Linden et al., 2003). Personalized product recommendations have been related to information technology from an early stage and charged with the hope to "shift the focus of traditional mass advertising to more concentrated and focused audiences" (Pavlou and Stewart, 2000, p. 67). In addition, experiments have shown that personalized (postal) mailings, e.g. identifying a "friend" as a sender, increased advertising response rates (Howard and Kerin, 2004). While it has been expected and predicted for years that personalized product recommendations would be used more frequently in offline advertising and retailing (Linden et al., 2003), to date there have only been a few industry applications. As an example, a German apparel retailer recently reported an increase of 25% in its purchase order rates thanks to the implementation of personalized product recommendations in package inserts (Borchers, 2016).

Due to a growing number of advertising media and almost stagnating advertising budgets within firms, it is also becoming increasingly important for companies to make decisions about the allocation of their advertising spend across different media channels (Danaher, 2017).

Therefore, it is crucial to investigate the effectiveness of advertising messages and in particular of personalized advertising across different media channels in order to derive recommendations for companies on how to best approach customers.

Accordingly, the main purpose of this study is to examine the ideal design of personalized product recommendations in advertisements in terms of the preferred advertising channel, underlying recommender algorithm as well as other design characteristics from a consumer's perspective. While previous studies solely deal with design issues for product recommendations on a single communication channel, namely a retailer's website (for a recent literature overview, see e.g.: Jugovac and Jannach, 2017), the current research aims to investigate both, the impact of different properties of product recommendations on the consumers' willingness to follow the recommendations and a comparison of the effectiveness of three distinct online and offline advertising channels: package inserts, email advertising and banner advertising. Therefore, this study enhances and extends current research on personalization effects with regard to different advertising channels (Bues et al., 2017; Cheung and To, 2017; Sahni et al., 2018), and provides an initial connection between personalization research and research on the ideal design of product recommendations. In addition, gender differences are taken into account. Previous research has consistently shown that females are more involved with clothing than males (Millan and Wright, 2018; Workman and Studak, 2006). This also holds with regard to advertising involvement, e.g. paying attention to ads about clothing (O'Cass, 2000) or gathering information before purchasing (Jackson et al., 2011). However, shopping behaviour is changing over the generations e.g. with millennial males increasingly enjoying shopping (Funches et al., 2017; Shephard et al., 2016). Research calls for a "deeper understanding of each generation" (Funches et al., 2017, p. 101) as well as "understanding the mechanisms of change" (Shephard et al., 2016, p. 5). Therefore, two separate studies – one for men and one for women – are conducted and analysed in comparison.

The article is structured as follows: First, related literature regarding personalization and its effects across different media channels, literature on product recommendations as well as literature addressing gender-related issues with regard to fashion and advertising is elaborated. Based on this literature review, several research hypotheses are developed. Choice-based conjoint analysis (CBC) is used as a methodological approach for data collection and utility estimation of different attributes (and levels) identified with the help of the literature review. In addition, the reasons for rejecting the advertisements are explored. Finally, we present the empirical results, discuss their implications on retailers and conclude our research by pointing out research limitations and revealing possibilities for future research.

4.2 Literature review and hypotheses development

4.2.1 Personalization in advertising

While nowadays continuous and fast improvements in information and communication technology increasingly enable companies to provide personalized product and service offerings (Rust and Huang, 2014), personalization has been applied in direct marketing for decades (Vesanen, 2007). However, Fan and Poole (2006, p. 183) describe the concept of personalization as “intuitive but also slippery”. This is because “(m)odern personalization seems to have different kinds of meanings“ (Vesanen, 2007, p. 410). Therefore, both references criticize the lack of a common definition.

While early definitions of personalization mainly refer to a context of brick-and-mortar stores (Surprenant and Solomon, 1987), more recently the term is often described in an online context. According to the literature, one possible goal of web personalization is the provision of the right content to the right person at the right time (Ansari and Mela, 2003; Tam and Ho, 2006). Other authors refer to personalization as the tailoring of certain marketing mix instruments to an individual based on customer data (Arora et al., 2008; Chung and Wedel, 2014; Sundar and Marathe, 2010). Following the latter definition, personalization is a form of (firm-initiated) one-to-one marketing relying on “a target segment of size one” (Arora et al., 2008, p. 306). Another form is 'customization' which describes customer-initiated practices (Arora et al., 2008).

In the context of marketing communication, personalization relates to advertising messages that are tailored to an individual’s preferences and characteristics based on specific information about the respective customer (Bang and Wojdynski, 2016; White et al., 2008; Yu and Cude, 2009). Various data sources can be used for personalizing advertising messages, ranging from demographic characteristics and personally identifiable information, e.g. “including the consumer’s name and her place of work” (Sahni et al., 2018, p. 236), to “consumers’ most recent shopping behaviors in the retailer’s online store" (Bleier and Eisenbeiss, 2015a, p. 670). Increasingly, companies deploy the concept of "retargeting" by providing personalized product recommendations in banner advertisements based on their customers' individual previous browsing behaviour (Bleier and Eisenbeiss, 2015a; Lambrecht and Tucker, 2013). Although current research mainly focuses on personalized advertising in online channels, also different types of traditional media, e.g. postal direct mail or telemarketing (Baek and Morimoto, 2012; Yu and Cude, 2009), can be used for delivering personalized messages (Bang and Wojdynski, 2016).

4.2.2 Effects of personalization across different media channels

In the past, several researchers have dealt with personalization effects on consumer behaviour related to brick-and-mortar stores (Goodwin and Smith, 1990; Mittal and Lassar, 1996; Surprenant and Solomon, 1987), and this field of research continues to receive much attention especially in the context of the Internet and digital technologies (for a literature overview: Salonen and Karjaluoto, 2016). In many cases, positive effects of personalization on aspects of the customer relationship are found, such as increased customer satisfaction and loyalty (Benlian, 2015; Ha and Janda, 2014; Kim and Gambino, 2016; Kwon and Kim, 2012; Verhagen et al., 2014; Yoon et al., 2013), greater purchase intentions (Ha and Janda, 2014; Li and Liu, 2017; Pappas et al., 2014; Sahni et al., 2018), enhanced click-through-rates for banner or email advertisements (Aguirre et al., 2015; Bleier and Eisenbeiss, 2015a, 2015b; Sahni et al., 2018; Tucker, 2014; Wattal et al., 2012) as well as more favourable attitudes towards the respective advert (Tran, 2017). However, some studies also report negative customer reactions to personalization such as increased privacy concerns (Bleier and Eisenbeiss, 2015b; Song et al., 2016), feelings of vulnerability (Aguirre et al., 2015), perceived intrusiveness (van Doorn and Hoekstra, 2013) or even reactance (Bleier and Eisenbeiss, 2015b; Puzakova et al., 2015).

While most of these studies consider personalization effects solely on a single communication channel like banner or email advertising, only a few studies exist that provide cross-channel comparisons of the impacts of personalization. However, nowadays advertisers are increasingly forced "to make tough decisions about how to allocate their ad budget across the many possible media channels" (Danaher, 2017, p. 465). Those decisions are an essential part and great challenge within 'multichannel marketing' which aims to provide customers with information, products, services or support simultaneously in two or more synchronized channels (Ailawadi and Farris, 2017; Rangaswamy and van Bruggen, 2005). Whereas in prior literature the term 'multichannel' has been mainly used in the context of retailing and referred to the "design, deployment, coordination, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development" (Neslin et al., 2006, p. 96), multichannel marketing rather incorporates evaluations of aspects like "customer lifetime value, total spending across channels and cross-selling, and dynamics among media" (Li and Kannan, 2014, p. 41). Following the request of Verhoef et al. (2015) to explore "the effect of different marketing mix instruments (i.e., promotions) used across touchpoints and channels on the performance of channels" (Verhoef et al., 2015, p. 179), more and more studies now also address issues regarding the attribution of advertising spend in a multichannel context across different types of digital media (Kireyev et al., 2016; Li and Kannan, 2014) as well as between traditional and digital channels (Danaher and Dagger, 2013; Dinner et al., 2014; Zantedeschi et al., 2016). Nevertheless, remarkably few studies do so for personalized advertising.

The few studies that investigate the impacts of personalized advertising from a cross-channel approach (see Table 1) show that traditional print media such as direct mails or letters are perceived more positively than digital media (Baek and Morimoto, 2012; Yu and Cude, 2009). For instance, in a comparative study of the customers' perceptions towards personalized advertising in offline mail, email and telephone advertising, Yu and Cude (2009) found that personalization is generally perceived negatively, with personalized letters still being perceived most positively. Their study revealed that the "respondents showed comparably more favourable responses towards delivery via offline mail than the other two types of media. They were less likely to reject the mail immediately, more likely to take it seriously, less threatened by the personalized advertisement as a violation of their privacy, and somewhat more likely to view it as personal attention" (Yu and Cude, 2009, p. 511). Furthermore, Baek and Morimoto (2012) show that the relationship between perceived privacy concerns and advertising avoidance is significantly weaker for direct mail than for email advertising. Other studies into the advertising effectiveness of different media unrelated to personalization confirm the supremacy of advertising in traditional (print) media over digital communication channels (Danaher and Dagger, 2013; Zantedeschi et al., 2016). While Shephard et al. (2016) report positive influences of mass and personalized media on fashion consciousness and fashion leadership, both factors were only significant for males.

At this point, our study is added to the list as it provides, on the one hand, valuable insights into the customers' preferences regarding personalized advertising across three different types of media, and on the other hand also yields gender-specific insights.

With reference to research about the effects of personalization across different media channels, customer preferences for product recommendations in three different advertising channels are investigated in the study at hand: namely package inserts for traditional print media and banner as well as email advertisements for digital media. Based on prior findings we hypothesize:

H1a. Consumers prefer advertising in print media (package inserts) to advertising in digital communication channels (email and banner advertising).

With regard to the two digital communication channels, research has shown that overall email advertising is more effective at influencing sales compared to banner advertising with a weaker immediate, but a much stronger long-term effect (Breuer et al., 2011). Investigating a four-week advertising campaign across several media channels of an Australian retailer and relying on members of the loyalty program for respondents, Danaher and Dagger (2013) found that banner advertising had no effect on sales in contrast to email advertising. According to the results of this study "only 7% recalled having seen one or more of [the retailer's online display ads]" (Danaher and Dagger, 2013, p. 528). Li and Kannan (2014) confirmed the enduring impact of emails compared to banner ads. Based on these findings we hypothesize:

H1b. Consumers prefer email advertising to banner ads.

Table 1: Studies on personalization with a cross-channel perspective

Study	Sample	Ad Media	Constructs / measurements	Main results
Yu and Cude (2009)	192 US college students between 19 and 24 years old	Email, offline mail, phone call	General perceptions, actual responses, attitude towards advertiser, privacy concerns, purchase intentions	There were significant differences with regard to purchase intentions between ad media. Personalized offline mail was considered more favourable. Personalized advertising had a significantly negative effect on purchase intentions. Females evaluated personalized advertising more negatively than males.
Baek and Morimoto (2012)	442 US college students between 18 and 31 years, average age 20.4 years, 27.5% male and 72.5% female	Email, offline mail, phone call, wireless text message	Ad avoidance - AVV (dependent), ad scepticism - ASK (mediator), privacy concerns - PVC, ad irritation - IRR, perceived personalization - PSL (antecedents)	PSL directly decreases ASK and AAV. ASK has a partially mediating role. The direct negative effect of PSL on AAV was highest for emails, but lowest and not significant for wireless text messages. The direct negative effect of PSL on ASK was highest for offline mail and wireless text messages. ASK has a fully mediating role for PSL on AAV for wireless text messages.
Shephard et al. (2016)	408 US college student participants (232 male and 176 female), 97.8% between 18 and 29 years old	Mass media: television, billboard, store display, worn by persons on television programs, in music videos. Personalized media: catalogue, magazine, recommended by a sales associate	Mass media, personalized media, fashion consciousness, fashion leadership, traditional store patronage, non-traditional store patronage	Mass media had a positive effect on fashion consciousness regardless of gender. The effect of personalized media on fashion leadership was only positively significant for males. Fashion leadership had a positive effect on non-traditional over traditional retail channels for both male and female consumers.
Present study	Two distinct (gender-specific) samples: 170 male and 162 female German college students, average age 21.9 years	Package inserts (offline), email, banner ads	Part-worth utilities / importance via CBC/HB for different levels of • Advertising channels • Recommender algorithm of product recommendations • Explanation for the recommended products • Number of recommendations • Provider of advertisement, Reasons for rejecting product recommendations	For both samples, the advertising channel is the most important attribute for the respondents' intention to adopt product recommendations. Banner advertisements provide a comparably low utility to female as well as male students. Email advertising provides the greatest utility to females and ads in package inserts are preferred most by males. While female respondents prefer a set of twelve product recommendations, male participants favour considerably smaller recommendation sets. Females do more often reject product recommendations due to privacy concerns and a minor recommendation quality.

4.2.3 Identification of relevant design characteristics of product recommendations for personalized advertising

Several empirical and literature-based, conceptual studies identify various success factors of recommender systems (Jugovac and Jannach, 2017; Knijnenburg et al., 2012; Schafer et al., 2001; Xiao and Benbasat, 2007). Based on those studies, potential success factors of recommender systems can be divided into different categories such as system-related aspects or personal characteristics. We focus on system-related aspects of product recommendations as these factors can be easily controlled and modified by companies.

Product recommendations as a specific personalization tool can be based on different recommendation sources ranging from user-generated content such as customer reviews to automatic recommender systems (Lin, 2014; Senecal and Nantel, 2004). Since personalization refers to firm-initiated practices, the focus is exclusively on recommender systems as a recommendation source. The term ‘recommender system’ refers to any system that proposes a personalized subset of interesting or useful objects from a large number of options to a user (Burke, 2002). While recommender systems can significantly improve the decision-making quality of consumers in ecommerce and reduce information overload as well as search costs (Xiao and Benbasat, 2007), the primary goal of recommender systems from a firm’s point of view is an increase in product sales or conversion rates (Aggarwal, 2016). Based on different underlying data sources such as product ratings of other customers or a specific customer’s purchase history, different recommendation techniques are distinguished (Burke, 2002; for an overview: Table 2).

Collaborative Filtering (CF) is by far the most widespread and popular recommendation technique and Amazon’s item-to-item CF approach (Linden et al., 2003) is the best-known and most influential example of CF in ecommerce. In contrast to the user-based CF approach described in Table 2, the item-based CF approach by Amazon generates its recommendations based on similar items, i.e. products that are often purchased together (Linden et al., 2003). While content-based filtering approaches are also used quite frequently, hybrid recommender systems nowadays represent the state of the art. For instance, Netflix uses a combination of various algorithms to generate video recommendations. Their recommender systems include e.g. not personalized recommendations from the most popular videos, recommendations based on similar videos, as well as personalized recommendations based on the movie genre (Gomez-Uribe and Hunt, 2016). By applying several recommendation techniques at a time, 80% of hours streamed at Netflix are triggered by its own recommender systems (Gomez-Uribe and Hunt, 2016).

Table 2: Overview of recommendation techniques (Adomavicius and Tuzhilin, 2005; Burke, 2002; Ricci et al., 2015)

Technique	**Description/approach**
Collaborative-filtering (CF)	Recommendations are based on the ratings of other users with similar profiles.
Content-based filtering	Recommendations are based on specific product features that were included in previously preferred items.
Demographic filtering	Recommendations are based on the sociodemographic user profiles.
Knowledge-based/ utility-based filtering	Recommendations are based on specific domain knowledge about how a particular item meets a specific user need.
Community-based/ social	Recommendations are based on the preferences of a user's friends.
Hybrid methods	Combination of two or more of the previous methods in order to compensate for the disadvantages of a single technique by making use of the advantages of another technique.

Previous research has shown that the success of recommender systems highly depends on the underlying recommender algorithm. In particular, several studies confirmed for various domains such as video clips and movies (Knijnenburg et al., 2010, 2012; Said et al., 2013) or cultural events (Dooms et al., 2011) that personalized algorithms outperform random recommendations or recommendations of the generally most popular items from a customer's point of view. Therefore, we propose:

H2. Consumers prefer product recommendations generated by a CF algorithm to product recommendations of bestselling products.

Beyond algorithms, but with reference to system-related aspects, many recent studies identify several other aspects, e.g. the number of product recommendations (Beierle et al., 2017; Bollen et al., 2010; Ozok et al., 2010; Tam and Ho, 2005; Willemsen et al., 2016) or the explanation style for the recommended items (Nilashi et al., 2016; Papadimitriou et al., 2012; Symeonidis et al., 2009; Vig et al., 2009; Wang et al., 2016; Zanker,

2012) as major drivers for the success and customer perception of product recommendations (see Table 3).

Table 3: Success factor analysis of product recommendations for personalized advertising

Success factor	(Main) results	Corresponding references
Algorithm	Recommendations using a **personalized algorithm** are to a much higher extent positively correlated with user choice satisfaction than **random recommendations of products** or **best-selling items**.	Dooms et al. (2011); Knijnenburg et al. (2010); Knijnenburg et al. (2012); Said et al. (2013)
Number of recommendations	Mixed results:	
	On the one hand, a large number of recommendations leads to **higher click-through rates and positive consumer perception** (multiple recommendations).	Bollen et al. (2010); Tam and Ho (2005); Willemsen et al. (2016)
	On the other hand, a large number of recommendations also makes the **selection decision difficult**, which in turn can have a negative impact on consumer behaviour due to choice overload, e.g. lower click through rates, choice deferral, or a decrease in satisfaction.	Beierle et al. (2017); Bollen et al. (2010); Willemsen et al. (2016)
Explanation	The provision of explanations **positively affects** for example **the perceived usefulness and confidence** in the system and **increases the transparency** of the recommender system.	Nilashi et al. (2016); Wang et al. (2016); Zanker (2012)
	Hybrid statements, that are combinations of three basic styles of explanation (human, item or feature), **are perceived as the most positive** by consumers.	Papadimitriou et al. (2012); Symeonidis et al. (2009); Vig et al. (2009)
Display of customer ratings	A **better average (star) rating** and **a higher number of ratings** have a **positive effect on the attitude and behaviour** of the consumers, as well as on their **willingness to pay.**	Adomavicius et al. (2016); Adomavicius et al. (2017); Kim and Gambino (2016)
Layout / arrangement	A **structured arrangement of recommendations** by genre or product properties **is perceived more positively** than just unstructured list displays. **Consumers significantly look at more recommendations** if they are presented in a category structure.	Chen and Pu (2014); Nanou et al. (2010); Pu and Chen (2007)

Explanations for the recommended items can be regarded as a critical success factor of product recommendations as they create transparency about the functionality of recommender systems and reinforce customers' trust in the recommendations (Herlocker et al., 2000). Various researchers have shown that the usage of explanations in recommender systems significantly enhances customers' perceptions of the recommended products (Nilashi et al., 2016; Wang et al., 2016; Zanker, 2012). There are several types of classifications for explanations in recommender systems (Papadimitriou et al., 2012). Based on Tintarev and Masthoff's (2012) findings which revealed that specific explanations can lead to higher customer satisfaction, we suggest the following hypothesis:

H3. Consumers prefer an item style of explanation to an unspecific explanation.

While several researchers indicate that a higher number of product recommendations can increase click-through rates or enhance customer perceptions (Beierle et al., 2017; Bollen et al., 2010; Tam and Ho, 2005; Willemsen et al., 2016), others observe that larger recommendation sets can also impede the decision between the different alternatives (Bollen et al., 2010; Willemsen et al., 2016) by creating so-called 'choice overload' which describes the phenomenon that too many options can significantly reduce customers' willingness to buy a certain product (Gourville and Soman, 2005; Iyengar and Lepper, 2000). Because of a potential cognitive overload and the related choice overload phenomenon, we hypothesize:

H4. Consumers prefer smaller recommendation sets to larger ones.

In the current research, further system-related aspects such as the display of customer ratings or the layout/arrangement of recommendations are not included. The layout/arrangement of product recommendations is not taken into account as this design issue is mainly addressed by prior research with reference to long lists of product recommendations presented on a website. Thus, this issue seems to be less relevant for the concise presentation of product recommendations in advertisements. Furthermore, the display of customer ratings is also excluded because incorporating star ratings in the visual depiction of the product recommendations could considerably increase the cognitive load of study participants.

Instead, the type of advertising channel is included since it is the main object of interest. In addition, the provider of the advertisement is also incorporated in the current study. Research has demonstrated the important role of the credibility of the advertiser in terms of the company's "perceived expertise and trustworthiness" (Goldsmith et al., 2000, p. 44) with regard to the customer's (positive) attitude towards advertisements and brands. Accordingly, we modify the provider of the product recommendations by using a well-known and highly credible online retailer (Amazon), a local mail-order company (Baur) as well as a fictitious company (Vestes Deis) that has been created for the research object. Past research revealed that an advertiser's reputation (Goldberg and Hartwick, 1990; Kim and Choi, 2012) and credibility (Goldsmith et al., 2000; Lafferty and Goldsmith, 1999) can be a major driver of advertising effectiveness. Contrary to these findings, Senecal and Nantel (2004) examined the effect of provider credibility on consumers' propensity to follow the recommendations in the area of product recommendations and determined no significant differences. Nevertheless, a positive relationship between provider credibility and the intention to use product recommendations is assumed:

H5. Consumers prefer advertisements from retailers with high credibility (Amazon>Baur>Vestes Deis).

Table 4 summarizes the attributes and levels used in the CBC, as well as the research hypotheses and their sources.

Table 4: Attributes, attribute levels and research hypotheses

Research hypothesis		References	Examination in the current CBC study	
			Attribute	Level
H1a	Consumers prefer advertising in print media (package inserts) to advertising in digital communication channels (email and banner advertising).	Baek and Morimoto (2012); Danaher and Dagger (2013); Yu and Cude (2009); Zantedeschi et al. (2016)	**Advertising channel**	Package inserts
H1b	Consumers prefer email advertising to banner ads.	Breuer et al. (2011); Danaher and Dagger (2013); Li and Kannan (2014)		Email advertising Banner advertising
H2	Consumers prefer product recommendations generated by a CF algorithm to product recommendations of bestselling products.	Dooms et al. (2011); Knijnenburg et al. (2010); Knijnenburg et al. (2012) Said et al. (2013)	**Algorithm**	CF
				Recommendations of best-selling products
H3	Consumers prefer an item style of explanation to an unspecific explanation.	Tintarev and Masthoff (2012)	**Explanation**	Item style of explanation: *Individual recommendations for you based on items you recently purchased*
				Unspecific: *Our recommendations for you*
H4	Consumers prefer smaller recommendation sets to larger ones.	Beierle et al. (2017); Ozok et al. (2010); Willemsen et al. (2016)	**Number of recommendations**	4
				8
				12
H5	Consumers prefer advertisements from retailers with high credibility (Amazon > Baur > Vestes Deis).	Goldberg and Hartwick (1990); Goldsmith et al. (2000); Kim and Choi (2012); Lafferty and Goldsmith (1999)	**Provider**	Amazon
				Baur
				Vestes Deis

4.2.4 Gender-related issues with regard to fashion and (personalized) advertising

A product in the apparel industry was chosen as field of application for our study as the apparel industry is currently the sector with the highest revenue within the German ecommerce market (Bundesverband E-Commerce und Versandhandel e.V, 2017). In addition, personalization in ecommerce is in particular applied to experience goods such as apparel where customers need relatively much specific information in the pre-purchase stage (Guan et al., 2016; Lee and Park, 2009). Due to the selection of a product from the apparel industry, it is crucial to also consider gender-specific differences regarding the customers' preferences for personalized advertisements as previous literature points to clear differences between men and women in terms of their fashion shopping behaviour and motivations.

Basing on development psychology, e.g. socialization/upbringing (Thompson, 1975), theories on expectancy or stereotype confirmation (Eagly and Wood, 1999), as well as theories on mate selection (Marcus and Miller, 2003), research has argued for a strong significance of appearance for the self-definition of females and in consequence a high importance of fashionability (Millan and Wright, 2018; Thompson and Haytko, 1997; Workman and Studak, 2006). Therefore, in contrast to men, women more often purchase clothes not to satisfy needs, e.g. replacing clothes not fit to wear, but due to the desire for "pleasure and sensory gratification" (Cho and Workman, 2011, p. 367). In a more recent study, males were found to be "more functional in their multichannel shopping behaviour, searching for information online […] and comparing information online" (Blázquez, 2014, p. 105) while females "appeared to be more experiential, looking for inspiration in blogs and social networks more than men" (Blázquez, 2014, p. 105). Fashion consumers can be even finer categorized into four groups (Hirschman and Adcock, 1978): (want-based) fashion innovators, fashion opinion leaders, innovative communicators more often seeking variety and changes as well as (need-based) fashion followers (Workman and Studak, 2006). "Feminine" shopping behaviour is characterized by interacting with others, e.g. "shopping together" or "consumer socialization" (Otnes and McGrath, 2001, p. 119). Relying on theories such as social cognitive theory (Bandura, 2001) or symbolic interaction theory (Solomon, 1983) research has shown that the influence of different types of media is to the most part higher on females than on males (Apeagyei, 2011) and that they are more involved in advertising (O'Cass, 2000), and "seek information more actively before making purchases" (Jackson et al., 2011, p. 2). However, in terms of personalized advertising via email or telephone females were more concerned with regard to their privacy (Yu and Cude, 2009). While studies often highlight differences between males and females (Workman and Cho, 2012; Otnes and McGrath, 2001; Millan and Wright, 2018), increasingly similarities are found (Shephard et al., 2016), e.g. due to millennial men "redefining masculinity and finding it possible for them to engage in shopping behaviour" (Funches et al., 2017, p. 101).

4.3 Empirical investigation

4.3.1 Research method

For the investigation of effects of personalization, in current literature often a (2 × 2) between-subjects full factorial design is deployed (e.g. Aguirre et al., 2015; Benlian, 2015; Kim and Gambino, 2016; van Doorn and Hoekstra, 2013), requiring a distinct subsample for each condition. However, for the identification of individual preferences regarding different alternatives such an experiment is not well suited as each subject is only exposed to one specific condition (Gunawardana and Shani, 2015). Instead of conducting such a between-subject experiment, hierarchical Bayes choice-based conjoint analysis (CBC) was applied as a user-centric evaluation method to identify consumer preferences regarding product recommendations. In contrast to the traditional conjoint analysis approach which derives customers' preference structures from rank-order response data or ratings-based data (Green et al., 2001), in CBC respondents are asked to select their favourite option from a set of alternatives (choice set) – also called stimuli - in repetitive choice tasks (Cohen, 1997; Louviere and Woodworth, 1983). Besides various product alternatives, respondents can also choose a "none" option, indicating their aversion to all other presented stimuli (Cohen, 1997). Those decisions between different choice alternatives are very similar to real-world decisions in the marketplace (Cohen, 1997), and thus allow consumer preferences to be collected in a realistic way.

In this study all stimuli are represented visually. This is due to certain attributes of product recommendations such as the underlying algorithm or the number of recommendations which can only be evaluated properly in combination, e.g. with “several system aspects (and personal and situational characteristics)” (Knijnenburg et al., 2012, p. 486). The few studies in marketing research that present alternatives exclusively by visual means, primarily deal with related topics such as the optimization of landing pages (Tamimi and Sebastianelli, 2015) or website interfaces (Kwon and Kim, 2012) and with the evaluation of the effectiveness of advertisements in various contexts (Hing et al., 2017; Meulenaer et al., 2015; van der Rest et al., 2016). Similar to the approach of Tamimi and Sebastianelli (2015), various fictitious ads were designed featuring personalized product recommendations. However, here, CBC is used because this method allows for the selection of a “none” option as we also want to identify reasons for rejecting the advertisements. The CBC just features one product recommendation and a “none” option per choice task. This so-called single product CBC is a special type of CBC (Chrzan, 2015) and allows for an even more realistic evaluation of product recommendations in advertisements.

4.3.2 Experimental design

Prior to the CBC exercise, respondents were shown a pullover. They were asked to imagine that they had recently purchased this pullover from an ecommerce retailer. In the following choice tasks, subjects were asked whether they would follow the presented product recommendations - e.g. by clicking on or searching for the recommended items. Two separate CBC exercises were created for males and females which featured the respectively bestselling pullover at amazon.de on November 21st, 2017.

The ***advertising channel*** was visualized by integrating the product recommendations in the image of a package insert, an email interface of a renowned German email provider or in the banner advertisement of a German news portal. The CF ***product recommendations*** were based on Amazon’s item-to-item CF algorithm which has been used extensively in various domains of the Web due to its simplicity, scalability, recommendation quality and rapid data updating (Smith and Linden, 2017). Product recommendations via CF were derived from Amazon’s recommendations for the corresponding pullover listed under the label “Customers who bought this item also bought” and non-personalized recommendations were deduced from other bestselling products from the pullover category. Following prior research (Bilgic and Mooney, 2005; Papadimitriou et al., 2012; Tintarev and Masthoff, 2012), we include an item style of ***explanation*** as well as an unspecific baseline explanation without explicit explanatory power. The item style of explanation is represented by the label “Individual recommendations for you based on items you recently purchased”. By contrast, “Our recommendations for you” is used as an unspecific explanation. The two explanations were varied as captions. With regard to the ***number of recommendations*** we use a small (four), medium (eight) and large (twelve) set of recommendations. The ***provider*** (advertiser) was illustrated by using the retailer’s logo and in the case of email advertising by adding the retailer’s name as the message sender.

Overall, the attributes and levels led to a total of 108 possible stimuli. As the evaluation of all 108 stimuli would lead to fatigue by the subjects, a reduced design was created using the ‘Balanced Overlap’ method which allows a moderate degree of level overlap and provides particularly reliable estimates of the main effects (Orme, 2009). Hence, we constructed each exercise with 16 choice tasks of which twelve were used for utility estimation as four holdout tasks had been included. The holdout tasks which are used to assess the predictive validity of a conjoint analysis were designed in the same way.

After completing all twelve choice tasks and the four holdout tasks, respondents that had chosen the none option “I would not use these product recommendations” more than three times, were asked for the reasons for refusing the product recommendations. The answers in this multiple-choice question were based on prior research on advertising avoidance and user evaluations of recommender systems (Table 5).

Table 5: Possible reasons for refusing to use product recommendations

Item/reason	**Construct**	**Source**
I basically ignore any personalized advertising.	Advertising avoidance	Baek and Morimoto (2012); Cho and Cheon (2004)
I basically ignore any email advertising.	Advertising avoidance	Baek and Morimoto (2012)
I basically ignore any banner advertising.	Advertising avoidance	Baek and Morimoto (2012)
I basically ignore any advertising in package inserts.	Advertising avoidance	Baek and Morimoto (2012)

Item/reason	Construct	Source
It bothers me that the firm can access my private data.	Privacy concerns	Bleier and Eisenbeiss (2015b); Sheng et al. (2008)
When I receive personalized advertising, I think it is irritating.	Irritation	Baek and Morimoto (2012); Edwards et al. (2002); van Doorn and Hoekstra (2013)
I did not like the recommended products.	Perceived recommendation quality	Knijnenburg et al. (2012); Nilashi et al. (2016); Pu et al. (2011)
All the recommended products were similar to each other.	Perceived recommendation variety	Knijnenburg et al. (2012); Nilashi et al. (2016); Pu et al. (2011)
I did not understand why the products were recommended to me.	Transparency	Nilashi et al. (2016); Pu et al. (2011)

4.3.3 Sample and data collection

Students at a medium-sized German university were recruited for the CBC study. A student population was considered to be well suited for the research, as students are part of the so-called Digital Natives who were born after 1980 and have grown up with digital technologies as an integral part of everyday life (Palfrey and Gasser, 2008; Prensky, 2001). In addition, emerging adults have been identified as “key trendsetters for fashion” (Workman and Studak, 2006, p. 76). Due to their great affinity to digital media (Palfrey and Gasser, 2008) and personalized marketing (Smith, 2011) it is very promising to compare their preferences for product recommendations in traditional and digital advertising channels, e.g. to generate concrete recommendations for designing product recommendations for personalized advertising across channels. In order to add to prior literature dealing with gender-differences in terms of apparel shopping, we also control for differences between males and females regarding their preferences for personalized product recommendations in advertisements.

The computer-aided survey took place at the faculty of law, business and economics at a medium-sized German university on four days in November and December 2017. A random sample was drawn from the population of all students who attended the faculty of law, business and economics during the survey period. To assure that all students had an equal probability of taking part in the sample, a survey area with four laptops was set up in the entrance hall of the faculty building and posters as well as a wheel of fortune drew attention to the survey. As an incentive to participate in the survey, respondents could spin the wheel of fortune and win vouchers for a café in the building as well as candy.

A total of 334 students completed the survey and after elimination of two respondents who completed the survey significantly faster than the average or were older than 37 and thus not Digital Natives, 170 male (51.2%) and 162 female (48.8%) participants remained for analysis. Most of the respondents were aged between 18 and 23 (76.2%) and an overwhelming majority were undergraduates (74.1%), representing the population of students in the faculty well in terms of gender and their level of qualification. Nevertheless, it is noteworthy that our samples might suffer from minor sampling biases as the study programs of the university were not all very well represented.

The *Analysis Manager* of Sawtooth's *Lighthouse Studio* was used for utility estimation. A total of 20,000 iterations were executed for the hierarchical Bayes estimation of which 10,000 so-called burn-in iterations were used to achieve convergence. In addition, *IBM SPSS Statistics version 21* was used for the analysis of demographic aspects and for conducting t-tests for the comparison of the means of the male and female samples.

4.4 Research results

4.4.1 Assessment of goodness of fit and predictive validity

The mean root likelihood (RLH) values which measure the goodness of fit of the model data (Sawtooth Software, 2009) clearly exceed the expected RLH value for a random model of 0.5 for both samples at the aggregate as well as at the individual level. In addition, the mean first choice hit rates (FCHR) indicate a good predictive validity: The choice decision was correctly predicted in 79.12% of cases for the male and 77.62% of cases for the female sample. Consequently, predictive accuracy increases by 58% ($\frac{0.7912-0.5}{0.5}$) for the male and by 55% ($\frac{0.7762-0.5}{0.5}$) for the female sample compared to the random model. Therefore, CBC with exclusively visual presentation of stimuli can be considered a suitable approach for measuring advertising preferences (Table 6).

Table 6: Internal and predictive validity of the utility estimations

	Male (n = 170)	**Female (n = 162)**
RLH		
Aggregate	0.727	0.707
Individual	0.736	0.724
FCHR		
Holdout task 1	74.12%	74.07%
Holdout task 2	79.41%	70.37%
Holdout task 3	77.06%	83.95%
Holdout task 4	85.88%	82.10%
Mean	79.12%	77.62%

4.4.2 CBC/HB results and hypotheses testing

The results from the HB estimate for both samples - the average importance of the attributes and the zero-centred part-worth utilities for the respective attribute levels - indicate that the willingness to use certain product recommendations is mainly influenced by the advertising channel. For both male and female respondents, the advertising channel is by far the most important attribute (47%/43%), while being even significantly more important to men. Male students prefer product recommendations in package inserts much more than ads in digital media, whereas email advertising provides the greatest utility to female students (see Table 7).

Table 7: Part-worth utilities and attribute importance for both samples in comparison

Attribute / level	Importance (%) / part-worth utility (Standard deviation)			
	Male (n = 170)		**Female (n = 162)**	
Advertising channel**	47.06%	(18.5383)	42.52%	(16.4170)
Package inserts	41.6981	(86.9194)	27.2990	(92.1058)
Email advertising*	18.3888	(91.8203)	35.3836	(62.6270)
Banner advertising	-60.0869	(119.8352)	-62.6827	(100.2497)
Algorithm***	11.47%	[8.0500]	18.52%	[13.3744]
CF***	-20.0924	(28.7406)	5.8049	(56.9336)
Bestselling products ***	20.0924	(28.7406)	-5.8049	(56.9336)
Explanation	7.41%	[5.4502]	6.69%	[4.7139]
Item style***	-1.9414	(22.9594)	-9.3738	(18.2219)
Unspecific***	1.9414	(22.9594)	9.3738	(18.2219)
Number of recommendations	20.49%	[12.8676]	18.89%	[9.0242]
4***	41.3089	(51.9067)	-8.7204	(47.2899)
8	-22.7051	(29.5661)	-21.3111	(26.8464)
12***	-18.6038	(43.8844)	30.0315	(41.8294)
Provider	13.57%	[7.2459]	13.38%	[7.0440]
Amazon	23.4981	(33.0486)	25.5799	(29.1617)
Baur	-13.2115	(27.4731)	-17.1631	(19.9480)
Vestes Deis	-10.2866	(24.9089)	-8.4169	(29.0588)
“None” option***	169.5986	(220.7524)	100.1100	(121.5072)
***, **, * indicate two-sided significant differences of importance or part-worth utilities between both groups at $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively.				

Thus, H1a is only supported for males and H1b is supported for both samples as banner advertising is preferred least by both groups.

The recommender algorithm is significantly more important for women than for men. Female respondents prefer recommendations based on the CF algorithm, supporting H2 for this group. In contrast, men prefer recommendations of bestselling products rather than recommendations from the CF algorithm. Therefore, H2 is only supported for the female sample. Contrary to our expectations, the unspecific explanation is preferred by both groups to an item style of explanation, rejecting H3 for both groups. Nevertheless, the type of explanation only plays a minor part for the respondents’ preferences.

The number of product recommendations is the second most important attribute for males (20%) and females (19%). However, there are significant differences between the part-worth utilities between both samples. The smallest set of four product recommendations is preferred most by males, whereas the largest number of twelve recommendations provides the greatest utility to females. H4 cannot be supported as the medium number of eight recommendations scores worst for both groups.

There are no significant differences for the importance of the provider of the product recommendations between men and women. Both prefer Amazon the most, followed by the fictitious retailer Vestes Deis and, surprisingly, the local mail-order company Baur is preferred least. Hence, H5 is rejected for both samples. It is also notable that the “none” option provides a significantly greater utility for males than for females, indicating that males reject product recommendations in a greater fashion. Table 8 summarizes the results of hypotheses testing.

Table 8: Results of hypotheses testing

Research hypothesis	Male (n = 170)	Female (n = 162)
H1a: Consumers prefer advertising in print media (package inserts) to advertising in digital communication channels (email and banner advertising).	√	x
H1b: Consumers prefer email advertising to banner ads.	√	√
H2: Consumers prefer product recommendations generated by a CF algorithm to product recommendations of bestselling products.	x	√
H3: Consumers prefer an item style of explanation to an unspecific explanation.	x	x
H4: Consumers prefer smaller recommendation sets to larger ones.	x	x
H5: Consumers prefer advertisements from retailers with high credibility (Amazon > Baur > Vestes Deis).	x	x

4.4.3 Ideal design of product recommendations and market simulations

With reference to the part-worth utilities presented in Table 7, our study suggests that a set of four product recommendations of the bestselling products with an unspecific explanation provided by Amazon in a package insert provides the highest utility for men. However, the added utility value for this ideal design of product recommendations is lower than the utility value of the “none” option (128.5389 <169.5986). A market simulation of the ideal design shows that a share of 50.5 per cent would use these product recommendations.

The ideal set of product recommendations for females consists of twelve recommendations, generated by the CF algorithm with an unspecific explanation presented by Amazon in an email advertisement. The added utility value of this design slightly exceeds the utility value of the “none” option (106.1737 >100.1100), providing a market share of 54.5 per cent. Consequently, more than half of the respondents would use this set of product recommendations.

The results of the market simulations indicate that a large number of male and female respondents refuse product recommendations in advertisements in general. However, the market shares of the ideal designs represent a tremendous increase in advertising effectiveness compared to previously determined click-through rates of product recommendations in email or banner advertising, which have been at a maximum of twelve per cent (Bleier and Eisenbeiss, 2015a; Sahni et al., 2018; Wattal et al., 2012).

4.4.4 Reasons for rejecting product recommendations

On average, the respondents decided in approximately one-third of the 16 choice tasks (including the four holdout tasks) to pursue the presented product recommendations $\bar{x} = 5.33; \frac{5.33}{16} = 33.31\%$). Accordingly, in more than two-thirds of the choice tasks respondents rejected the use of product recommendations. Those study participants who chose the “none” option in three or more of the 16 choice tasks - overall 331 respondents - were asked why they refused the respective product recommendations. The reasons for rejecting the product recommendations vary and there are significant differences between the two samples (see Fig. 1).

The majority of respondents (85.2%) basically ignores personalized advertising on at least one advertising channel. While advertising avoidance is most pronounced in email advertising (58%) and banner advertisements are rejected in almost the same manner (52%), advertising in package inserts is still considered most commonly. Besides a basic refusal of product recommendations in specific channels, the perceived recommendation quality and privacy concerns are major drivers for rejecting product recommendations, especially for female respondents who stated those aspects significantly more frequently as reasons for dismissing product recommendations. Such increased privacy concerns of women have already been determined in prior research (Hoy and Milne, 2010; Sheehan, 1999; Yu and Cude, 2009), though no solid explanation or interpretation has been provided so far.

Other aspects such as perceived recommendation variety, irritation or transparency are less pronounced. In addition to the illustrated reasons, several, mainly male study participants indicated that they would generally disregard product recommendations after purchasing a certain item due to no further interest or need. In line with these statements, a study by Bleier and Eisenbeiss (2015a) found that product recommendations in banner advertisements lose effectiveness with an increasing amount of time between buying or visiting the online store and receiving the product recommendations.

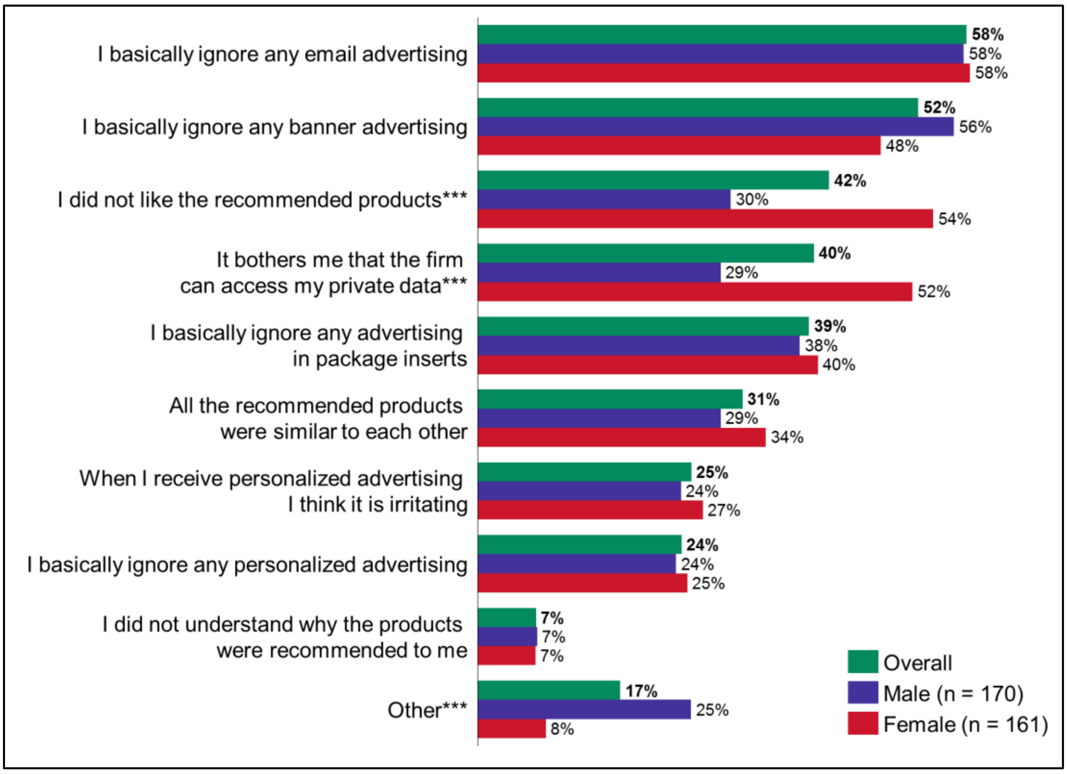

Fig. 1: Reasons for rejecting product recommendations

4.5 Discussion and managerial implications

The empirical results and hypotheses testing clearly show that the literature-based success factors for the design of recommender systems on websites are not necessarily applicable to product recommendations in other advertising media. For instance, while explanations are an important factor for the success of web recommender systems, they only play a minor part in consumers' preferences regarding product recommendations in advertisements.

This finding is especially interesting considering findings from a previous study by Wattal et al. (2012) comparing the effectiveness of different types of personalization in email advertisements. In their study, the use of personalized product recommendations was in general accompanied by more positive reactions, e.g. in terms of click-through rates and purchase probability, whereas the usage of personalized greetings was considered mainly negative (Wattal et al., 2012). Previous research also indicates that the effectiveness of using personalized product recommendations in banner advertisements might also depend on consumers' level of trust in a specific retailer (Bleier and Eisenbeiss, 2015b). Whereas more trusted retailers can benefit from deploying personalized product recommendations in banner ads, less trusted retailers "should refrain from closely tailoring their banners to consumers" (Bleier and Eisenbeiss, 2015b, p. 403). Therefore, in order to increase click-through rates, retailers should not only consider the design advices for personalized product recommendations in ads provided by the results of our study, but also "carefully assess consumers' trust in them" (Bleier and Eisenbeiss, 2015b, p. 403) as well as consider the degree of personalization of the text accompanying the product recommendations. E.g., while it might be effective to provide a personalized greeting using the customer's first name for younger customers, it might not compulsory be the case for elderly customers.

Furthermore, the results of this study contribute to previous research on the user-centric evaluation of recommender systems by illustrating again that the recommender algorithm can only be considered as one of several aspects for successfully designing product recommendations. Surprisingly, the CF-algorithm did not perform well as recommendations generated by CF were less preferred in the male sample and only slightly preferred to bestselling products in the female sample. A possible explanation for this gender-related difference might be the utilitarian, need-based approach of men to apparel shopping (Workman and Studak, 2006). Otnes and McGrath (2001, p. 122) found that men enjoy "comparison-shop for items". The CF-recommendations are more in support of the variety seeking approach (want-based) of females. Another explanation for the general poor performance of the CF-algorithm can be derived from comments of some students to an open question on further suggestions, wishes or other remarks for the design of personalized product recommendations: About one-fifth of responses (3.9% of all study participants) was based on respondents' desire to receive more recommendations for complementary products or suggestions for entire outfits. Consumers are critical of algorithms that simply generate recommendations based on the similarity of items and thus only present products from the same product category. Therefore, apparel retailers should also incorporate recommendations for entire outfits “from head to toe” into their personalized advertisements.

The results of our study significantly enhance the controversial findings of previous research regarding the ideal number of recommendations by conducting a gender-specific analysis. Due to our findings male subjects suffer much earlier from choice overload than female respondents. Besides the significantly different part-worth utilities, this also becomes evident when examining the male answers regarding the reasons for rejecting product recommendations in the “other” section. 4.7% of all male respondents explicitly expressed that they would not follow the illustrated product recommendations because the number of recommended items was too large. This finding corresponds to the qualitative results of Otnes and McGrath (2001), indicating that the search for clothes among female customers was on a higher level than among male customers. Due to a higher level of fashion-consciousness, women are more likely to obtain more information about fashion sources than men (Shephard et al., 2016). For this reason, we recommend strictly differentiating the design of product recommendations for men and women: Personalized product recommendations for men should contain as few relevant items as possible (up to a maximum of four), whereas the recommendation set for women should entail significantly more products (at least twelve). However, apparel retailers should also consider that both females and males might not only shop apparel products for themselves but also for their partners, other family members or friends. Hence, a gender-specific adaptation of the number of product recommendations should only be implemented based on the users’ profile data and not due to an unregistered user’s previous or recent browsing behaviour. In order to ensure that products that have been purchased as a gift or for another person are not used for the generation of product recommendations, online retailers could include an additional option within the login area similarly to Netflix's "Who's watching" filter query. Amazon already makes use of such a function, e.g. by stating to "don't use for recommendations" or that "this was a gift". However, this has to be selected manually for each product in the aftermath.

The results of the HB estimate also show that the effectiveness of personalization for banner advertising is the lowest compared to other advertising media. Consequently, retailers should increasingly focus on designing personalized product recommendations in email advertising and package inserts. The relatively high part-worth utilities for advertising in package inserts illustrate that traditional (print) advertising media must not be neglected for Digital Natives and younger audiences as it still really matters to them.

Our results confirm the findings of previous studies with regard to gender differences. Yu and Cude (2009, p. 510) found that females responded much more positively to email advertising than males, e.g. they felt to be "treated with special care". Emails might correspond better to the interacting shopping style of females (Otnes and McGrath, 2001). For males, Shephard et al. (2016) showed a positive effect of personalized media on fashion leadership and argued for promotions in the form of package inserts or email. Those gender-specific differences between the preferences for the advertising channel or the number of recommendations reveal that product recommendations should not only be tailored to individual or segment-specific product needs by applying a personalized recommender algorithm, but rather should also be personalized to individual preferences with regard to other design aspects.

4.6 Conclusions, limitations, and future research

This study contributes to literature on personalized advertising in various ways: First of all, the application of CBC with exclusively visual presentation of stimuli has not been used frequently in the past in marketing literature. The validity criteria of our CBC/HB estimate prove that this type of conjoint analysis provides an adequate method for measuring consumer's preferences regarding advertisements. Secondly, the CBC results show that men and women differ significantly in their preferences regarding product recommendations in advertisements. Therefore, retailers and advertisers need to think about personalizing their advertisements not only in terms of the products presented, but also in terms of other design aspects such as the number of recommendations according to individual or segment-specific customer preferences. Thirdly, this study deepens the sparse research on personalization in multichannel marketing by indicating that the effectiveness of personalized advertising is significantly worse for banner ads than for advertisements in package inserts or emails.

However, the findings of this study are subject to a number of limitations that should be addressed in future research. First of all, it should be noted that the generalizability of the study results might be limited due to the usage of a student sample. Further research should investigate our findings also for non-student samples within the consumer group of Digital Natives in order to explore potential effects and biases due to the subjects' educational background.

At this point it should be also noted that a different composition of samples in terms of demographic aspects could possibly yield differing results. For instance, prior research suggests that a more educated audience engages more often in advertising avoidance behaviour regarding television advertising (Rojas-Méndez et al., 2009), or regarding advertisements in newspapers (Speck and Elliott, 1997). Therefore, future research should also explore differences in the attitudes to personalized advertising or in the advertising avoidance behaviour between different subgroups (e.g. due to their educational background) within the young cohort of Digital Natives or between different generations in order to further extend our research findings. This is in line with Shephard et al., (2016, p. 15) who have called for research "to better understand generational differences between male and female shopping behaviors". An implementation of the four different types of fashion shoppers could also provide additional insights in particular when it comes to the rejection of product recommendations.

Furthermore, additional research is needed to replicate the study at hand also for other product types and product categories that are less dependent of the gender, e.g. electronics or books, in order to confirm the superiority of personalized email advertising as well as personalized advertisements in package inserts to banner ads also within another context.

Another limitation is based on the application of CBC as research methodology, as this method only allows an investigation into a small number of attributes and levels regarding the design of personalized product recommendations. Therefore, future research should also include other design aspects such as the layout of the recommendations, the integration of customer star ratings or the time period between the product purchase and the presentation of the recommendations. In addition, other attribute levels such as other recommender algorithms providing entire outfit recommendations should be examined.

Finally, the banner advertisements were shown as part of a German news portal. For future studies it would be interesting to review our findings in other advertising contexts, e.g. by placing the advertisement on a thematically congruent website. For instance, in addition to the advertising channels examined in this work, the use of banner advertisements on the website of a fashion magazine or fashion blog could be analysed.

In the end, it is hoped that this study can provide food for thought and motivation for further research on personalized product recommendations and the effectiveness of advertising channels in multichannel marketing.

References

Adomavicius, G., Bockstedt, J., Curley, S., Zhang, J., 2016. Understanding effects of personalized vs. aggregate ratings on user preferences. In: Proceedings of the Joint Workshop on Interfaces and Human Decision Making for Recommender Systems. Joint Workshop on Interfaces and Human Decision Making for Recommender Systems, Boston, MA, USA. September 16, 2016, pp. 14–21. Retrieved from ⟨https://pdfs.semanticscholar.org/e4af/2be912a6294486065cfc91f8b5fc441f9754.pdf⟩.

Adomavicius, G., Bockstedt, J.C., Curley, S.P., Zhang, J., 2017. Effects of online recommendations on consumers' willingness to pay. Inf. Syst. Res. 1–19. https://doi.org/10.1287/isre.2017.0703.

Adomavicius, G., Tuzhilin, A., 2005. Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Trans. Knowl. Data Eng. 17 (6), 734–749. https://doi.org/10.1109/TKDE.2005.99.

Aggarwal, C.C., 2016. Recommender Systems: The Textbook. Springer, Cham, Heidelberg, New York, Dordrecht, London, pp. 498 (xxi).

Aguirre, E., Mahr, D., Grewal, D., Ruyter, K. de, Wetzels, M., 2015. Unraveling the personalization paradox: the effect of information collection and trust-building strategies on online advertisement effectiveness. J. Retail. 91 (1), 34–49. https://doi.org/10.1016/j.jretai.2014.09.005.

Ailawadi, K.L., Farris, P.W., 2017. Managing multi- and omni-channel distribution: metrics and research directions. J. Retail. 93 (1), 120–135. https://doi.org/10.1016/j.jretai.2016.12.003.

Ansari, A., Mela, C.F., 2003. E-customization. J. Mark. Res. 40 (2), 131–145. https://doi.org/10.1509/jmkr.40.2.131.19224.

Apeagyei, P.R., 2011. The impact of image on emerging consumers of fashion. Int. J. Manag. Cases 13 (4), 242–251. https://doi.org/10.5848/APBJ.2011.00133.

Arora, N., Dreze, X., Ghose, A., Hess, J.D., Iyengar, R., Jing, B., Joshi, Y., Kumar, V., Lurie, N., Neslin, S., Sajeesh, S., Su, M., Syam, N., Thomas, J., Zhang, Z.J., 2008. Putting one-to-one marketing to work: personalization, customization, and choice. Mark. Lett. 19 (3–4), 305. https://doi.org/10.1007/s11002-008-9056-z.

Baek, T.H., Morimoto, M., 2012. Stay away from me: examining the determinants of consumer avoidance of personalized advertising. J. Advert. 41 (1), 59–76. https://doi.org/10.2753/JOA0091-3367410105.

Baier, D., Stüber, E., 2010. Acceptance of recommendations to buy in online retailing. J. Retail. Consum. Serv. 17 (3), 173–180. https://doi.org/10.1016/j.jretconser.2010.03.005.

Bandura, A., 2001. Social cognitive theory of mass communication. Media Psychol. 3 (3), 265–299. https://doi.org/10.1207/S1532785XMEP0303_03.

Bang, H., Wojdynski, B.W., 2016. Tracking users' visual attention and responses to personalized advertising based on task cognitive demand. Comput. Hum. Behav. 55 (B), 867–876. https://doi.org/10.1016/j.chb.2015.10.025.

Beierle, F., Aizawa, A., Beel, J., 2017. Exploring choice overload in related-article recommendations in digital libraries. In: Proceedings of the Fifth Workshop on Bibliometric-enhanced Information Retrieval (BIR). 5th Workshop on Bibliometricenhanced Information Retrieval 2017, Aberdeen, UK. 09. April 2017, pp. 51–61. Retrieved from ⟨https://arxiv.org/abs/1704.00393⟩.

Benlian, A., 2015. Web personalization cues and their differential effects on user assessments of website value. J. Manag. Inf. Syst. 32 (1), 225–260. https://doi.org/10.1080/07421222.2015.1029394.

Bilgic, M., Mooney, R., 2005. Explaining recommendations: satisfaction vs. promotion. In: Beyond Personalization 2005. A Workshop on the Next Stage of Recommender Systems Research, San Diego. 09. Januar 2005, pp. 13–18. Retrieved from ⟨http://www.cs.utexas.edu/~ml/papers/submit.pdf⟩.

Blázquez, M., 2014. Fashion shopping in multichannel retail: the role of technology in enhancing the customer experience. Int. J. Electron. Commer. 18 (4), 97–116.https://doi.org/10.2753/JEC1086-4415180404.

Bleier, A., Eisenbeiss, M., 2015a. Personalized online advertising effectiveness: the interplay of what, when, and where. Mark. Sci. 34 (5), 669–688. https://doi.org/10.1287/mksc.2015.0930.

Bleier, A., Eisenbeiss, M., 2015b. The importance of trust for personalized online advertising. J. Retail. 91 (3), 390–409. https://doi.org/10.1016/j.jretai.2015.04.001.

Bollen, D., Knijnenburg, B.P., Willemsen, M.C., Graus, M., 2010. Understanding choice overload in recommender systems. In: Proceedings of the Fourth ACM conference on Recommender systems, Barcelona, Spanien. 26–30. September 2010, pp. 63–70. ⟨https://doi.org/10.1145/1864708.1864724⟩.

Borchers, D., 2016. Personalisieren in Print. ONEtoONE (9), 48. Retrieved from ⟨https://prudsys.de/wp-content/uploads/2016/10/ONE-toONE_Klingel_Case_09_2016.pdf⟩.

Breuer, R., Brettel, M., Engelen, A., 2011. Incorporating long-term effects in determining the effectiveness of different types of online advertising. Mark. Lett. 22 (4), 327–340. https://doi.org/10.1007/s11002-011-9136-3.

Bues, M., Steiner, M., Stafflage, M., Krafft, M., 2017. How mobile in-store advertising influences purchase intention: value drivers and mediating effects from a consumer perspective. Psychol. Mark. 34 (2), 157–174. https://doi.org/10.1002/mar.20981.

Bundesverband E-Commerce und Versandhandel e.V, 2017. Interaktiver Handel in Deutschland: Ergebnisse 2016 ⟨https://www.bevh.org/uploads/media/Auszug_aus_der_bevh-Studie_Interaktiver_Handel__in_Deutschland_2016_.pdf⟩ (Accessed 3 October 2018).

Burke, R., 2002. Hybrid recommender systems: survey and experiments. Use. Model. Use.-Adapt. Interact. 12 (4), 331–370. https://doi.org/10.1023/A:1021240730564.

Chen, L., Pu, P., 2014. Experiments on user experiences with recommender interfaces. Behav. Inf. Technol. 33 (4), 372–394. https://doi.org/10.1080/0144929X.2012.719034.

Cheung, M.F., To, W.M., 2017. The influence of the propensity to trust on mobile users' attitudes toward in-app advertisements: an extension of the theory of planned behavior. Comput. Hum. Behav. 76, 102–111. https://doi.org/10.1016/j.chb.2017.07.011.

Cho, C.-H., Cheon, H.J., 2004. Why do people avoid advertising on the Internet? J. Advert. 33 (4), 89–97. https://doi.org/10.1080/00913367.2004.10639175.

Cho, S., Workman, J., 2011. Gender, fashion innovativeness and opinion leadership, and need for touch: effects on multi-channel choice and touch/non-touch preference in clothing shopping. J. Fash. Mark. Manag. 15 (3), 363–382. https://doi.org/10.1108/13612021111151941.

Chrzan, K., 2015. Choice experiments for pharmaceutical market research ⟨https://www.sawtoothsoftware.com/download/techpap/Choice_Experiments_for_Physicians_(Chrzan).pdf⟩ (Accessed 3 October 2018).

Chung, T.S., Wedel, M., 2014. Adaptive personalization of mobile information services. In: Rust, R.T., Huang, M.-H. (Eds.), Handbook of Service Marketing Research. Edward Elgar Publishing, Cheltenham, UK, Northampton, MA, USA, pp. 395–412.

Cohen, S.H., 1997. Perfect Union: CBCA marries the best of conjoint and discrete choice models. Mark. Res. 9 (1), 12–17. (Retrieved from). ⟨https://archive.ama.org/archive/ResourceLibrary/MarketingResearch/documents/9705084855.pdf⟩.

Danaher, P.J., 2017. Advertising effectiveness and media exposure. In: Wierenga, B., van der Lans, R. (Eds.), Handbook of Marketing Decision Models, 2. Auflage. Springer International Publishing, Cham, pp. 463–481.

Danaher, P.J., Dagger, T.S., 2013. Comparing the relative effectiveness of advertising channels: a case study of a multimedia blitz campaign. J. Mark. Res. 50 (4), 517–534. https://doi.org/10.1509/jmr.12.0241.

Dinner, I.M., van Heerde, H.J., Neslin, S.A., 2014. Driving online and offline sales. The cross-channel effects of traditional, online display, and paid search advertising. J. Mark. Res. 51 (5), 527–545. https://doi.org/10.1509/jmr.11.0466.

Dooms, S., Pessemier, T. de, Martens, L., 2011. A user-centric evaluation of recommender algorithms for an event recommendation system. In: RecSys 2011 Workshop on Human Decision Making in Recommender Systems (Decisions@RecSys'11) and User Centric Evaluation of Recommender Systems and Their Interfaces - 2 (UCERSTI 2) affiliated with Proceedings of the 5th ACM Conference on Recommender Systems, Chicago, IL, USA. 23–27. Oktober 2011, pp. 67–73. Retrieved from ⟨https://biblio.ugent.be/publication/2040145⟩.

Eagly, A.H., Wood, W., 1999. The origins of sex differences in human behavior: evolved dispositions versus social roles. Am. Psychol. 54 (6), 408–423. https://doi.org/10.1037/0003-066X.54.6.408.

Edwards, S.M., Li, H., Lee, J.-H., 2002. Forced exposure and psychological reactance: antecedents and consequences of the perceived intrusiveness of pop-up ads. J. Advert. 31 (3), 83–95. https://doi.org/10.1080/00913367.2002.10673678.

Fan, H., Poole, M.S., 2006. What is personalization? Perspectives on the design and implementation of personalization in information systems. J. Organ. Comput. Electron. Commer. 16 (3–4), 179–202. https://doi.org/10.1080/10919392.2006.9681199.

Funches, V., Yarber-Allen, A., Johnson, K., 2017. Generational and family structural differences in male attitudes and orientations towards shopping. J. Retail. Consum. Serv. 37, 101–108. https://doi.org/10.1016/j.jretconser.2017.02.016.

Goldberg, M.E., Hartwick, J., 1990. The effects of advertiser reputation and extremity of advertising claim on advertising effectiveness. J. Consum. Res. 17 (2), 172–179. https://doi.org/10.1086/208547.

Goldsmith, R.E., Lafferty, B.A., Newell, S.J., 2000. The impact of corporate credibility and celebrity credibility on consumer reaction to advertisements and brands. J. Advert. 29 (3), 43–54. https://doi.org/10.1080/00913367.2000.10673616.

Gomez-Uribe, C.A., Hunt, N., 2016. The Netflix recommender system. ACM Trans. Manag. Inf. Syst. 6 (4), 1–19. https://doi.org/10.1145/2843948.

Goodwin, C., Smith, K.L., 1990. Courtesy and friendliness: conflicting goals for the service providers. J. Serv. Mark. 4 (1), 5–20. https://doi.org/10.1108/EUM0000000002500.

Gourville, J.T., Soman, D., 2005. Overchoice and assortment type: when and why variety backfires. Mark. Sci. 24 (3), 382–395. https://doi.org/10.1287/mksc.1040.0109.

Green, P.E., Krieger, A.M., Wind, Y., 2001. Thirty years of conjoint analysis: reflections and prospects. Interfaces 31 (3), S56–S73. https://doi.org/10.1287/inte.31.3s.56.9676.

Guan, C., Qin, S., Ling, W., Ding, G., 2016. Apparel recommendation system evolution: an empirical review. Int. J. Cloth. Sci. Technol. 28 (6), 854–879. https://doi.org/10.1108/IJCST-09-2015-0100.

Gunawardana, A., Shani, G., 2015. Evaluating recommender systems. In: Ricci, F., Rokach, L., Shapira, B. (Eds.), Recommender Systems Handbook. Springer, US, Boston, MA, pp. 265–308.

Ha, H.-Y., Janda, S., 2014. The effect of customized information on online purchase intentions. Internet Res. 24 (4), 496–519. https://doi.org/10.1108/IntR-06-2013-0107.

Ha, L., McCann, K., 2008. An integrated model of advertising clutter in offline and online media. Int. J. Advert. 27 (4), 569–592. https://doi.org/10.2501/S0265048708080153.

Herlocker, J.L., Konstan, J.A., Riedl, J., 2000. Explaining collaborative filtering recommendations, In: Proceedings of the 2000 ACM Conference on Computer Supported Cooperative Work. ACM, New York, NY, USA, pp. 241–250. ⟨http://doi.acm.org/10.1145/358916.358995⟩.

Hing, N., Vitartas, P., Lamont, M., 2017. Understanding persuasive attributes of sports betting advertisements: a conjoint analysis of selected elements. J. Behav. Addict. 6 (4), 658–668. https://doi.org/10.1556/2006.6.2017.062.

Hirschman, E.C., Adcock, W.O., 1978. An examination of innovative communicators, opinion leaders, and innovators for men's fashion apparel. In: Hunt, H.K. (Ed.), Advances in Consumer Research. Association for Consumer Research, Ann Arbor, MI, pp. 303–314.

Howard, D.J., Kerin, R.A., 2004. The effects of personalized product recommendations on advertisement response rates: the "Try this. It works!" Technique. J. Consum. Psychol. 14 (3), 271–279. https://doi.org/10.1207/s15327663jcp1403_8.

Hoy, M.G., Milne, G., 2010. Gender differences in privacy-related measures for young adult Facebook users. J. Interact. Advert. 10 (2), 28–45. https://doi.org/10.1080/15252019.2010.10722168.

Iyengar, S.S., Lepper, M.R., 2000. When choice is demotivating: can one desire too much of a good thing? J. Personal. Soc. Psychol. 79 (6), 995–1006. https://doi.org/10.1037/0022-3514.79.6.995.

Jackson, V., Stoel, L., Brantley, A., 2011. Mall attributes and shopping value: differences by gender and generational cohort. J. Retail. Consum. Serv. 18 (1), 1–9. https://doi.org/10.1016/j.jretconser.2010.08.002.

Jugovac, M., Jannach, D., 2017. Interacting with recommenders—overview and research directions. ACM Trans. Interact. Intell. Syst. (TiiS) 7 (3), 1–46. https://doi.org/10.1145/3001837.

Kaptein, M., Parvinen, P., 2015. Advancing e-commerce personalization: process framework and case study. Int. J. Electron. Commer. 19 (3), 7–33. https://doi.org/10.1080/10864415.2015.1000216.

Kim, J., Gambino, A., 2016. Do we trust the crowd or information system? Effects of personalization and bandwagon cues on users' attitudes and behavioral intentions toward a restaurant recommendation website. Comput. Hum. Behav. 65 (Supplement C), 369–379. https://doi.org/10.1016/j.chb.2016.08.038.

Kim, S., Choi, S.M., 2012. Credibility cues in online shopping: an examination of corporate credibility, retailer reputation, and product review credibility. Int. J. Internet Mark. Advert. 7 (3), 217–236. https://doi.org/10.1504/IJIMA.2012.047425.

Kireyev, P., Pauwels, K., Gupta, S., 2016. Do display ads influence search? Attribution and dynamics in online advertising. Int. J. Res. Mark. 33 (3), 475–490. https://doi.org/10.1016/j.ijresmar.2015.09.007.

Knijnenburg, B.P., Willemsen, M.C., Gantner, Z., Soncu, H., Newell, C., 2012. Explaining the user experience of recommender systems. Use. Model. Use.-Adapt. Interact. 22 (4–5), 441–504. https://doi.org/10.1007/s11257-011-9118-4.

Knijnenburg, B.P., Willemsen, M.C., Hirtbach, S., 2010. Receiving recommendations and providing feedback: The user-experience of a recommender system. In: Buccafurri, F., Semeraro, G. (Eds.), E-Commerce and web technologies: 11th International Conference, EC-Web 2010, Bilbao, Spain, September 1–3, 2010, Proceedings. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 207–216. ⟨https://doi.org/10.1007/978-3-642-15208-5_19⟩.

Kwon, K., Kim, C., 2012. How to design personalization in a context of customer retention: who personalizes what and to what extent? Electron. Commer. Res. Appl. 11 (2), 101–116. https://doi.org/10.1016/j.elerap.2011.05.002.

Lafferty, B.A., Goldsmith, R.E., 1999. Corporate credibility’s role in consumers' attitudes and purchase intentions when a high versus a low credibility endorser is used in the ad. J. Bus. Res. 44 (2), 109–116. https://doi.org/10.1016/S0148-2963(98)00002-2.

Lambrecht, A., Tucker, C., 2013. When does retargeting work? Information specificity in online advertising. J. Mark. Res. 50 (5), 561–576.

Lee, E.-J., Park, J.K., 2009. Online service personalization for apparel shopping. J. Retail. Consum. Serv. 16 (2), 83–91. https://doi.org/10.1016/j.jretconser.2008.10.003.

Li, C., Liu, J., 2017. A name alone is not enough: a reexamination of web-based personalization effect. Comput. Hum. Behav. 72, 132–139. https://doi.org/10.1016/j.chb.2017.02.039.

Li, H., Kannan, P.K., 2014. Attributing conversions in a multichannel online marketing environment: an empirical model and a field experiment. J. Mark. Res. 51 (1), 40–56. https://doi.org/10.1509/jmr.13.0050.

Lin, Z., 2014. An empirical investigation of user and system recommendations in ecommerce. Decis. Support Syst. 68, 111–124. https://doi.org/10.1016/j.dss.2014.10.003.

Linden, G., Smith, B., York, J., 2003. Amazon.com recommendations: item-to-item collaborative filtering. IEEE Internet Comput. 7 (1), 76–80. https://doi.org/10.1109/MIC.2003.1167344.

Louviere, J.J., Woodworth, G., 1983. Design and analysis of simulated consumer choice or allocation experiments: an approach based on aggregate data. J. Mark. Res. 20 (4), 350–367. https://doi.org/10.2307/3151440.

Marcus, D.K., Miller, R.S., 2003. Sex differences in judgments of physical attractiveness: a social relations analysis. Personal. Soc. Psychol. Bull. 29 (3), 325–335. ⟨https://doi.org/10.1177%2F0146167202250193⟩.

Meulenaer, S., de, Dens, N., Pelsmacker, P. de, 2015. Which cues cause consumers to perceive brands as more global? A conjoint analysis. Int. Mark. Rev. 32 (6), 606–626.https://doi.org/10.1108/IMR-04-2014-0144.

Millan, E., Wright, L.T., 2018. Gender effects on consumers' symbolic and hedonic preferences and actual clothing consumption in the Czech Republic. Int. J. Consum. Stud. 42 (5), 478–488. https://doi.org/10.1111/ijcs.12447.

Mittal, B., Lassar, W.M., 1996. The role of personalization in service encounters. J. Retail. 72 (1), 95–109. https://doi.org/10.1016/S0022-4359(96)90007-X.

Nanou, T., Lekakos, G., Fouskas, K., 2010. The effects of recommendations' presentation on persuasion and satisfaction in a movie recommender system. Multimed. Syst. 16 (4), 219–230. https://doi.org/10.1007/s00530-010-0190-0.

Neslin, S.A., Grewal, D., Leghorn, R., Shankar, V., Teerling, M.L., Thomas, J.S., Verhoef, P.C., 2006. Challenges and opportunities in multichannel customer management. J. Serv. Res. 9 (2), 95–112. https://doi.org/10.1177/1094670506293559.

Nilashi, M., Jannach, D., Ibrahim, Ob, Esfahani, M.D., Ahmadi, H., 2016. Recommendation quality, transparency, and website quality for trust-building in recommendation agents. Electron. Commer. Res. Appl. 19 (Suppl. C), 70–84. https://doi.org/10.1016/j.elerap.2016.09.003.

O'Cass, A., 2000. An assessment of consumers product, purchase decision, advertising and consumption involvement in fashion clothing. J. Econ. Psychol. 21 (5), 545–576. https://doi.org/10.1016/S0167-4870(00)00018-0.

Orme, B., 2009. Fine-tuning CBC and adaptive CBC questionnaires ⟨http://www.sawtoothsoftware.com/download/techpap/finetune.pdf⟩ (Accessed 3 October 2018).

Otnes, C., McGrath, M.A., 2001. Perceptions and realities of male shopping behavior. J. Retail. 77 (1), 111–137. https://doi.org/10.1016/S0022-4359(00)00047-6.

Ozok, A.A., Fan, Q., Norcio, A.F., 2010. Design guidelines for effective recommender system interfaces based on a usability criteria conceptual model: results from a college student population. Behav. Inf. Technol. 29 (1), 57–83. https://doi.org/10.1080/01449290903004012.

PageFair, 2017. The state of the blocked web: 2017 Global Adblock Report. PageFair ⟨https://pagefair.com/downloads/2017/01/PageFair-2017-Adblock-Report.pdf⟩ (Accessed 3 October 2018).

Palfrey, J., Gasser, U., 2008. Born Digital: Understanding the First Generation of Digital Natives. Basic Books, New York (381 pp).

Papadimitriou, A., Symeonidis, P., Manolopoulos, Y., 2012. A generalized taxonomy of explanations styles for traditional and social recommender systems. Data Min. Knowl. Discov. 24 (3), 555–583. https://doi.org/10.1007/s10618-011-0215-0.

Pappas, I.O., Kourouthanassis, P.E., Giannakos, M.N., Chrissikopoulos, V., 2014. Shiny happy people buying: the role of emotions on personalized e-shopping. Electron. Mark. 24 (3), 193–206. https://doi.org/10.1007/s12525-014-0153-y.

Pavlou, P.A., Stewart, D.W., 2000. Measuring the effects and effectiveness of interactive advertising: a research agenda. J. Interact. Advert. 1 (1), 61–77.

https://doi.org/10.1080/15252019.2000.10722044.

Prensky, M., 2001. Digital natives, digital immigrants part 1. Horizon 9 (5), 1–6. https://doi.org/10.1108/10748120110424816.

Pu, P., Chen, L., 2007. Trust-inspiring explanation interfaces for recommender systems. Knowl.-Based Syst. 20 (6), 542–556. https://doi.org/10.1016/j.knosys.2007.04.004.

Pu, P., Chen, L., Hu, R., 2011. A user-centric evaluation framework for recommender systems. In: Proceedings of the Fifth ACM Conference on Recommender systems. The Fifth ACM Conference, Chicago, Illinois, USA. ACM, New York, NY, pp. 157–164. ⟨https://doi.org/10.1145/2043932.2043962⟩.

Puzakova, M., Rocereto, J.F., Kwak, H., 2015. Ads are watching me. Int. J. Advert. 32 (4), 513–538. https://doi.org/10.2501/IJA-32-4-513-538.

Rangaswamy, A., van Bruggen, G.H., 2005. Opportunities and challenges in multichannel marketing: an introduction to the special issue. J. Interact. Mark. 19 (2), 5–11. https://doi.org/10.1002/dir.20037.

Ricci, F., Rokach, L., Shapira, B., 2015. Recommender systems: introduction and challenges. In: Ricci, F., Rokach, L., Shapira, B. (Eds.), Recommender Systems Handbook. Springer US, Boston, MA, pp. 1–34.

Rojas-Méndez, J.I., Davies, G., Madran, C., 2009. Universal differences in advertising avoidance behavior: a cross-cultural study. J. Bus. Res. 62 (10), 947–954. https://doi.org/10.1016/j.jbusres.2008.08.008.

Rust, R.T., Huang, M.-H., 2014. The service revolution and the transformation of marketing science. Mark. Sci. 33 (2), 206–221. https://doi.org/10.1287/mksc.2013.0836.

Sahni, N.S., Wheeler, S.C., Chintagunta, P., 2018. Personalization in email marketing: the role of noninformative advertising content. Mark. Sci. 37 (2), 236–258. https://doi.org/10.1287/mksc.2017.1066.

Said, A., Fields, B., Jain, B.J., Albayrak, S., 2013. User-centric evaluation of a K-furthest neighbor collaborative filtering recommender algorithm. In: Proceedings of the 2013 conference on Computer supported cooperative work companion, San Antonio, Texas, USA. ACM, 2441955, pp. 1399–1408. ⟨https://doi.org/10.1145/2441776.2441933⟩.

Salonen, V., Karjaluoto, H., 2016. Web personalization: the state of the art and future avenues for research and practice. Telemat. Inform. 33 (4), 1088–1104. https://doi.org/10.1016/j.tele.2016.03.004.

Sawtooth Software, 2009. The CBC/HB System for Hierarchical Bayes Estimation: Version 5.0 Technical Paper ⟨https://www.sawtoothsoftware.com/download/techpap/hbtech.pdf⟩ (Accessed 3 October 2018).

Schafer, J.B., Konstan, J.A., Riedl, J., 2001. E-commerce recommendation applications. Data Min. Knowl. Discov. 5 (1–2), 115–153.

https://doi.org/10.1023/A:1009804230409.

Senecal, S., Nantel, J., 2004. The influence of online product recommendations on consumers' online choices. J. Retail. 80 (2), 159–169. https://doi.org/10.1016/j.jretai.2004.04.001.

Sheehan, K.B., 1999. An investigation of gender differences in on-line privacy concerns and resultant behaviors. J. Interact. Mark. 13 (4), 24–38. https://doi.org/10.1002/(SICI)1520-6653(199923)13:4%3C24::AID-DIR3%3E3.0.CO;2-O.

Sheng, H., Nah, F.F.-H., Siau, K., 2008. An experimental study on ubiquitous commerce adoption: impact of personalization and privacy concerns. J. Assoc. Inf. Syst. 9 (6), 344–376. ⟨https://aisel.aisnet.org/jais/vol9/iss6/15/⟩.

Shephard, A., Pookulangara, S., Kinley, T.R., Josiam, B.M., 2016. Media influence, fashion, and shopping: a gender perspective. J. Fash. Mark. Manag. 20 (1), 4–18. https://doi.org/10.1108/JFMM-09-2014-0068.

Smith, B., Linden, G., 2017. Two decades of recommender systems at Amazon. com. IEEE Internet Comput. 21 (3), 12–18. https://doi.org/10.1109/MIC.2017.72.

Smith, K.T., 2011. Digital marketing strategies that Millennials find appealing, motivating, or just annoying. J. Strateg. Mark. 19 (6), 489–499. https://doi.org/10.1080/0965254X.2011.581383.

Solomon, M.R., 1983. The role of products as social stimuli: a symbolic interactionism perspective. J. Consum. Res. 10 (3), 319–329. https://doi.org/10.1086/208971.

Song, J.H., Kim, H.Y., Kim, S., Lee, S.W., Lee, J.-H., 2016. Effects of personalized e-mail messages on privacy risk: moderating roles of control and intimacy. Mark. Lett. 27 (1), 89–101. https://doi.org/10.1007/s11002-014-9315-0.

Speck, P.S., Elliott, M.T., 1997. Predictors of advertising avoidance in print and broadcast media. J. Advert. 26 (3), 61–76. https://doi.org/10.1080/00913367.1997.10673529.

Sundar, S.S., Marathe, S.S., 2010. Personalization versus customization: the importance of agency, privacy, and power usage. Hum. Commun. Res. 36 (3), 298–322. https://doi.org/10.1111/j.1468-2958.2010.01377.x.

Surprenant, C.F., Solomon, M.R., 1987. Predictability and personalization in the service encounter. J. Mark. 51 (2), 86–96. https://doi.org/10.2307/1251131.

Symeonidis, P., Nanopoulos, A., Manolopoulos, Y., 2009. MoviExplain: a recommender system with explanations. In: Proceedings of the Third ACM Conference on Recommender Systems. ACM, New York, NY, USA, pp. 317–320. ⟨https://doi.org/10.1145/1639714.1639777⟩.

Tam, K.Y., Ho, S.Y., 2005. Web personalization as a persuasion strategy: an elaboration likelihood model perspective. Inf. Syst. Res. 16 (3), 271–291. https://doi.org/10.1287/isre.1050.0058.

Tam, K.Y., Ho, S.Y., 2006. Understanding the impact of web personalization on user information processing and decision outcomes. MIS Q. 30 (4), 865–890. https://doi.org/10.2307/25148757.

Tamimi, N., Sebastianelli, R., 2015. The relative importance of e-tailer website attributes on the likelihood of online purchase. Internet Res. 25 (2), 169–183. https://doi.org/10.1108/IntR-07-2013-0131.

Thompson, C.J., Haytko, D.L., 1997. Speaking of fashion: consumers' uses of fashion discourses and the appropriation of countervailing cultural meanings. J. Consum. Res. 24 (1), 15–42. https://doi.org/10.1086/209491.

Thompson, S.K., 1975. Gender labels and early sex role development. Child Dev. 46 (2), 339–347. https://doi.org/10.2307/1128126.

Tintarev, N., Masthoff, J., 2012. Evaluating the effectiveness of explanations for recommender systems. Use. Model. Use.-Adapt. Interact. 22 (4), 399–439. https://doi.org/10.1007/s11257-011-9117-5.

Tran, T.P., 2017. Personalized ads on Facebook: an effective marketing tool for online marketers. J. Retail. Consum. Serv. 39, 230–242. https://doi.org/10.1016/j.jretconser.2017.06.010.

Tucker, C.E., 2014. Social networks, personalized advertising, and privacy controls. J. Mark. Res. 51 (5), 546–562. https://doi.org/10.1509/jmr.10.0355.

van der Rest, J.-P.I., Cordella, P., Loosschilder, G., Schwartz, Z., 2016. Connecting search marketing to hotel revenue management: conjoint analysis as a methodology to evaluate the optimal online travel agency commission fee. Serv. Sci. 8 (2), 169–183. https://doi.org/10.1287/serv.2016.0137.

van Doorn, J., Hoekstra, J.C., 2013. Customization of online advertising: the role of intrusiveness. Mark. Lett. 24 (4), 339–351. https://doi.org/10.1007/s11002-012-9222-1.

Verhagen, T., van Nes, J., Feldberg, F., van Dolen, W., 2014. Virtual customer service agents: using social presence and personalization to shape online service encounters. J. Comput.-Mediat. Commun. 19 (3), 529–545. https://doi.org/10.1111/jcc4.12066.

Verhoef, P.C., Kannan, P.K., Inman, J.J., 2015. From multi-channel retailing to omni-channel retailing: introduction to the special issue on multi-channel retailing. J. Retail. 91 (2), 174–181. https://doi.org/10.1016/j.jretai.2015.02.005.

Vesanen, J., 2007. What is personalization? A conceptual framework. Eur. J. Mark. 41 (5/6), 409–418. https://doi.org/10.1108/03090560710737534.

Vig, J., Sen, S., Riedl, J., 2009. Tagsplanations: explaining recommendations using tags, In: Proceedings of the 14th International Conference on Intelligent User Interfaces. ACM, New York, NY, USA, pp. 47–56. ⟨https://doi.org/10.1145/1502650.1502661⟩.

Wang, W., Qiu, L., Kim, D., Benbasat, I., 2016. Effects of rational and social appeals of online recommendation agents on cognition- and affect-based trust. Decis. Support Syst. 86, 48–60. https://doi.org/10.1016/j.dss.2016.03.007.

Wattal, S., Telang, R., Mukhopadhyay, T., Boatwright, P., 2012. What's in a “name”? Impact of use of customer information in e-mail advertisements. Inf. Syst. Res. 23 (3-part-1), 679–697. https://doi.org/10.1287/isre.1110.0384.

White, T.B., Zahay, D.L., Thorbjørnsen, H., Shavitt, S., 2008. Getting too personal: reactance to highly personalized email solicitations. Mark. Lett. 19 (1), 39–50. https://doi.org/10.1007/s11002-007-9027-9.

Willemsen, M.C., Graus, M.P., Knijnenburg, B.P., 2016. Understanding the role of latent feature diversification on choice difficulty and satisfaction. Use. Model. Use.-Adapt. Interact. 26 (4), 347–389. https://doi.org/10.1007/s11257-016-9178-6.

Workman, J.E., Cho, S., 2012. Gender, fashion consumer groups, and shopping orientation. Fam. Consum. Sci. Res. J. 40 (3), 267–283. https://doi.org/10.1111/j.1552-3934.2011.02110.x.

Workman, J.E., Studak, C.M., 2006. Fashion consumers and fashion problem recognition style. Int. J. Consum. Stud. 30 (1), 75–84. https://doi.org/10.1111/j.1470-6431.2005.00451.x.

Xiao, B., Benbasat, I., 2007. E-commerce product recommendation agents: use, characteristics, and impact. MIS Q. 31 (1), 137–209. https://doi.org/10.2307/25148784.

Yoon, V.Y., Hostler, R.E., Guo, Z., Guimaraes, T., 2013. Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty. Decis. Support Syst. 55 (4), 883–893. https://doi.org/10.1016/j.dss.2012.12.024.

Yu, J., Cude, B., 2009. 'Hello, Mrs. Sarah Jones!: we recommend this product!’ Consumers' perceptions about personalized advertising: comparisons across advertisements delivered via three different types of media. Int. J. Consum. Stud. 33 (4), 503–514. https://doi.org/10.1111/j.1470-6431.2009.00784.x.

Zanker, M., 2012. The Influence of knowledgeable explanations on users' perception of a recommender system. In: Proceedings of the Sixth ACM Conference on Recommender Systems. ACM, New York, NY, USA, pp. 269–272. ⟨https://doi.org/10.1145/2365952.2366011⟩.

Zantedeschi, D., Feit, E.M., Bradlow, E.T., 2016. Measuring multichannel advertising response. Manag. Sci. 63 (8), 2706–2728. https://doi.org/10.1287/mnsc.2016.2451.

5 Research paper #2: Success Factors for Recommender Systems From a Customers' Perspective

Abstract

Recommender systems have become an integral part of today's ecommerce landscape and are no longer only deployed on websites but also increasingly serve as a basis for the delivery of personalized product recommendations in various communication channels. Within this paper, we present a brief overview of popular and commonly used recommender algorithms as well as current cutting-edge algorithmic advances. We examine consumers' preferences regarding product recommendations in advertisements across different media channels within the apparel industry by applying choice-based conjoint analysis. The findings of studies for young male (= 170) and female (= 162) consumers show that the recommender algorithm is not necessarily of upmost importance. In contrast, the advertising channel is of highest relevance with banner advertising being the least preferred channel. Moreover, differences between male and female respondents are outlined. Finally, implications for retailers and advertisers are discussed and a brief outlook on future developments is presented.

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5.1 Introduction

Nowadays, consumers are constantly exposed to various advertisements throughout their everyday lives, both offline and online. The omnipresent exposure to advertisements forces companies and advertisers, especially in an online context, to make their ads as relevant and appealing as possible to increase the advertising effectiveness in terms of conversion (e.g. click-through rates). Therefore, personalization methods that allow for tailoring advertising messages to individual preferences, e.g. based on customers' recent online browsing behavior, are increasingly used by online advertisers and retailers (Bleier and Eisenbeiss, 2015; Estrada-Jiménez et al., 2017).

Recommender systems are a distinct and widespread method of personalization (Kaptein and Parvinen, 2015). They offer benefits for both firms and customers: On the one hand, recommender systems can help to increase product sales by enabling cross- and upselling opportunities, and thus be of great value to firms (Aggarwal, 2016). On the other hand, recommender systems can enhance consumers' decision-making quality in ecommerce and they reduce information overload as well as search costs (Xiao and Benbasat, 2007). Besides their usage on websites and within web shops, they are also used when presenting product recommendations in email campaigns (Linden et al., 2003). Such personalized product recommendations have recently even been successfully deployed in offline print mailings such as package inserts when delivering online orders (Borchers, 2016). In order to maximize the effectiveness of product recommendations in advertisements, companies have to consider several design aspects of recommender systems, such as which algorithm to use or how many recommendations to present at a time (Jugovac and Jannach, 2017; Knijnenburg et al., 2012; Xiao and Benbasat, 2007).

Motivated by the increasing usage of product recommendations within various communication channels, our research goal was to identify the ideal design of personalized product recommendations in advertisements from a customers' perspective. Therefore, we first present a classification scheme of popular, commonly used, and recent recommender algorithms as well as a brief summary of success factors for the design of recommender systems that have been researched so far (Section 2). Then, in Section 3, the research method and design as well as the investigated success factors of recommender systems (attributes and attribute levels) for the choice-based conjoint experiments are outlined, followed by the presentation of the main results. Section 4 closes with a brief discussion of results, potential implications for retailers and advertisers as well as promising future developments in the field of recommender systems.

5.2 Recommender Systems: Approaches and Success Factors

The term “recommender systems” has its origin in the early 1990s and has been mainly coined by Resnick and Varian (1997). According to a refined definition by Burke (2002, p.331) the term refers to

> *“ (. . .) any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options.”*

For achieving the overarching goal of increasing product sales, recommendations need to be relevant to the respective users (Aggarwal, 2016). Next, the recommendation of novel or serendipitous items – recommendations that are unexpected by the consumer – can also be beneficial. Moreover, recommendation sets should include diverse items instead of only similar products for increasing the probability that the consumer will like at least one object from the set: It might, for instance, be unfavorable to present movies of only one specific genre or only t-shirts with similar color and shape within a recommendation set. If users do not like the specific movie genre or rather wish for recommendations of complementary outfits, such highly similar recommendation sets will be rather unsuccessful.

The generation of product recommendations is based on the underlying data sources (Burke, 2002): Background data refers to already existing data such as preferences of other users for certain items or features of specific items. Input data refers to information that needs to be elaborated explicitly or implicitly by the user to the system (e.g. ratings of a specific user for certain items vs. purchase history). Different algorithms can be used for the generation of product recommendations by combining background and input data. On the basis of the data sources used, several recommendation techniques can be distinguished. The two most common and widely used approaches are collaborative-filtering (CF) and content-based filtering (CBF). Furthermore, hybrid recommender systems combining several particular methods are being increasingly used in order to counterbalance disadvantages of single methods by benefits of others

(Burke, 2002).

In CF, recommendations for a specific user are based on previous ratings by other users (Adomavicius and Tuzhilin, 2005). Such ratings can either refer to explicitly stated user feedback collected via e.g. numerical rating scales (1–5 star rating), or to implicitly collected user feedback e.g. via unconsciously analyzing the consumers' online shopping behavioral data (Schafer et al., 2001).

By contrast, in CBF, recommendations for a specific user are based on his previous, already known preferences (ratings) for certain features of objects (Adomavicius and Tuzhilin, 2005). In the case of a movie recommender relevant features might for instance be actors, directors or the genre of the movie.

In general, CF and CBF can be classified into heuristics-based approaches where utility predictions are calculated by heuristic methods, and model-based ones which develop – "learn" – a model predicting preferences based on the user database (Adomavicius and Tuzhilin, 2005; Breese et al., 1998).

In *heuristics-based* CF, predictions are directly based on the entire data set of user-item ratings (Breese et al., 1998). Accordingly, there are two ways how predictions of ratings can be retrieved (Aggarwal, 2016):

a) *Item-to-item CF:* Recommendations are based on similar items. Similarity scores of items might, for instance, be positively impacted when products are often purchased together (Linden et al., 2003). This approach is nowadays widely used across various domains mainly inspired by Amazon's successful item-to-item CF approach (Linden et al., 2003).
b) *User-to-user CF:* As opposed to this, recommendations are based on similar users, i.e. users with similar profiles who are providing similar ratings for multiple items (Adomavicius and Tuzhilin, 2005).

Popular algorithms used within the CF approaches include nearest-neighbor classifiers (e.g. cosine, correlation), clustering-based methods as well as graph models (Adomavicius and Tuzhilin, 2005).

Heuristics-based CBF mainly relies on information retrieval methods such as the term frequency-inverse document frequency (TF-IDF) weight which is used to determine the importance of keywords/features within documents/items (Adomavicius and Tuzhilin, 2005). User profiles are then generated by "*analyzing the content of the items previously seen and rated by the user*" (Adomavicius and Tuzhilin, 2005, p.736). Subsequently, for instance, similarity measures can be used for predicting similar items (e.g. cosine similarity measures). Despite their widespread use, these heuristics-based approaches suffer from several issues (Table 1).

Table 1: Major drawbacks of heuristics-based approaches (based on Adomavicius and Tuzhilin (2005); Bobadilla et al. (2013)).

Collaborative filtering	**Content-based filtering**
Cold start issue for new users: The recommender system cannot provide accurate recommendations to new users until the user has rated a sufficient number of items.	
Cold start issue for new items: The CF recommender system is not capable of providing recommendations for new items within the environment until the new item has been rated by a sufficient number of users.	*Limited content analysis:* A CBF recommender system is limited by features that have been explicitly associated with items (either manually or automatically).
Data sparsity / limited coverage: Especially for neighborhood-based algorithms (k Nearest Neighbors (kNN) algorithm), the recommendation quality clearly suffers in case of sparse rating data as only few neighbors (for items or users) can be used to predict ratings.	*Overspecialization:* CBF recommender systems tend to recommend items that are highly similar to previously rated items.
Scalability issues: With increasing amounts of data, especially neighborhood-based approaches become too slow.	

Model-based approaches have been developed in order to address major disadvantages of heuristics-based recommender systems. Such

> " *(…) model-based techniques calculate utility (rating) predictions based not on some ad hoc heuristic rules, but, rather, based on a model learned from the underlying data using statistical and machine learning techniques*" (Adomavicius and Tuzhilin, 2005, p.740).

While basically all model-based approaches can be classified as machine learning-based methods, deep learning-based approaches are a more specific sub-field currently receiving a great deal of attention and being widely researched within the recommender systems literature (Figure 1). Deep learning methods can be defined as

> “ *representation-learning methods with multiple levels of representation, obtained by composing simple but non-linear modules that each transform the representation at one level (starting with the raw input) into a representation at a higher, slightly more abstract level*” (LeCun et al., 2015, p. 436).

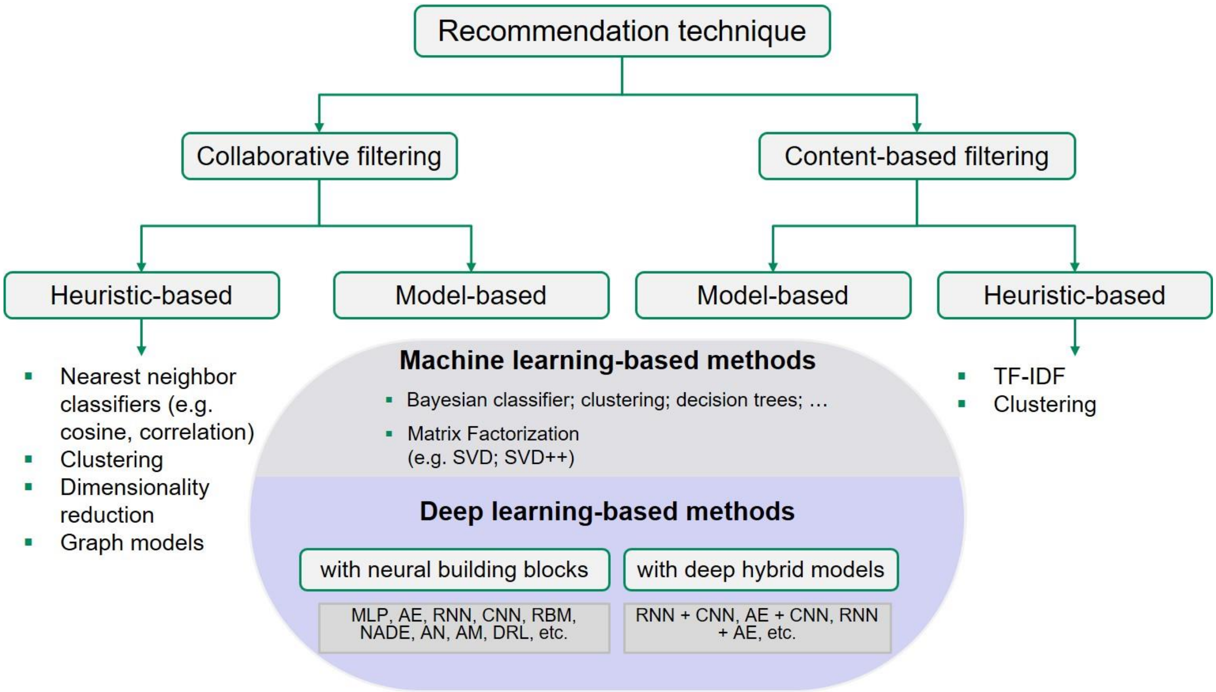

Figure 1: Classification of frequently used recommender algorithms (based on Adomavicius and Tuzhilin (2005); Zhang et al. (2019)). Abbreviations: Multilayer perceptron (MLP); autoencoder (AE); recurrent neural network (RNN); convolutional neural network (CNN); restricted Boltzmann machine (RBM); neural autoregressive distribution estimation (NADE); adversarial networks (AN); attentional models (AM); deep reinforcement learning (DRL).

For recommender systems, deep learning-based approaches can be divided into two categories (Zhang et al., 2019):

1. “*Recommender systems with neural building blocks*”:
   Here, Zhang et al. (2019) mainly differentiate between several specific methods ranging from basic feed-forward neural networks (MLP) to more recent developments tailored to specific recommendation issues such as recurrent neural

networks (RNN) which are capable of modeling temporal dynamics.

2. "*Recommendation with deep hybrid models*":
   Deep learning methods that combine several specific techniques at a time.

Various researchers have already successfully applied different types of deep learning algorithms to recommender systems in various domains (for an overview see Zhang et al., 2019). For instance, Cheng et al. (2016) created the so-called "*wide & deep*" learning model by a combination of deep neural networks (multilayer perceptrons) with wide, linear models (single layer perceptrons). By doing so, their model is capable of capturing both memorization and generalization, and thus enhancing both the accuracy as well as the diversity of the recommendations (Cheng et al., 2016). The authors evaluated their algorithm within a live environment for the context of app recommendations in Google Play and clearly demonstrated its superiority: Compared to a wide-only algorithm, app acquisitions increased by 3.9 %, while – compared to a deep-only approach – an increase of 1.0% was observed, too.

Another example of an application of deep learning within recommender systems is the session-based recommender system GRU4Rec which addresses the special issue of generating recommendations when no long-term user data is available (Hidasi and Karatzoglou, 2018; Hidasi et al., 2016). This issue is of high practical relevance, e.g. for smaller online retailers which are not tracking user ID's, when generating recommendations for first time visitors to a website or for domains in which recommendations should particularly refer to short-term user preferences within one session (e.g. news or music recommendations). As commonly used methods such as neighborhood models and matrix factorization methods

> " *are only taking into account the last click of the user, in effect ignoring the information of the past clicks*" (Hidasi et al., 2016, p. 2),

Hidasi et al. (2016) developed a session-based recommender system based on a RNN with Gated Recurrent Units (GRU). The input to the system is the item of the current event in the session and the output is the item of the next event in the session. In an offline experiment for two data sets of videos and click stream data of an ecommerce retailer the authors determined a clear accuracy gain (~ 20–30 %) of the GRU-based approach compared to the best performing baseline algorithm (item-kNN). In addition, a revised version of the GRU4Rec recommender system (using another loss function) clearly outperformed the initial algorithm in a live environment for the recommendation of online videos in terms of watch time (+ 5 %), video plays (+ 5 %) and clicks (+ 4 %; Hidasi and Karatzoglou, 2018).

Those examples clearly illustrate that the utilization of deep learning algorithms might be very beneficial for the success of recommender systems. Nevertheless, besides algorithmic advances in the field of recommender systems and the evaluation in terms of the algorithm's predictive accuracy, current research increasingly emphasizes user-centric evaluation methods (Pu et al., 2011). In user-centric evaluations, the direct interaction of users with a system is measured (Cremonesi et al., 2013; Herlocker et al., 2004). Thus, such evaluations are either based on user survey data or on the analysis of user behavior within a live environment. In user surveys, algorithms are increasingly assessed in terms of various aspects besides accuracy, often including the similarity, novelty, serendipity or diversity of recommendations (e.g. Ekstrand et al., 2014; Said et al., 2013). Moreover, recently more holistic approaches for the evaluation of recommender systems, e.g. considering the entire user experience with such systems, have been presented identifying further success factors beyond algorithms (Jugovac and Jannach, 2017; Knijnenburg et al., 2012; Pu et al., 2011; Schafer et al., 2001; Xiao and Benbasat, 2007).

An extensive literature review (for the detailed overview, see Schreiner et al., 2019) shows that, for instance, also the number of recommendations presented at a time or the provision of an explanation on why certain items are being recommended can have a major impact on the consumers' perception of and willingness to interact with recommender systems:

- As the recommender algorithm defines which products are being recommended, it is a key success factor for a recommender system. Current literature focuses greatly on state-of-the-art algorithms such as deep learning methods. Yet, in practice still rather basic, heuristic-based approaches such as CF are commonly used across websites and ecommerce companies (Smith and Linden, 2017).
- Short captions accompanying the product recommendations (e.g. "customers

who bought this item also bought") are often used to explain how recommendations have been generated, thus increasing transparency of and trust in the system (Herlocker et al., 2000).

- The amount of products presented within one recommendation set might also clearly impact the success of a recommender system. However, there is no consensus yet in the current literature whether a large or a small number of recommendations might be more beneficial (Schreiner et al., 2019).

Therefore, for the study at hand, it was of high interest to examine these success factors from a customers' perspective.

5.3 Empirical Study: Research Methods and Results

Based on previous research on success factors for designing recommender systems and also taking into account current literature dealing with the effectiveness of advertisements in different media channels (e.g. Baek and Morimoto, 2012; Yu and Cude, 2009), we deployed choice based conjoint analysis (CBC) to determine the ideal design of product recommendations in advertisements from a customers' perspective. CBC was considered to be the most suitable approach for our research as it allows for a collection of customers' preferences in a very realistic way (Cohen, 1997).

In CBC, respondents have to select their most preferred option from a set of alternatives including the possibility to select a "none" option – indicating their aversion to all other presented stimuli (Cohen, 1997; Louviere and Woodworth, 1983). This choice decision is repeated several times and the respondents' overall evaluations of objects are subsequently decomposed into part worth utilities for specific attributes as well as attribute levels (Green and Srinivasan, 1978). Besides highly relevant success factors for designing product recommendations, namely the underlying recommender algorithm (levels: CF algorithm vs. recommendation of bestselling products), the number of recommendations presented at a time (levels: 4 vs. 8 vs. 12) as well as the explanation accompanying the recommended products (levels: specific item-style explanation vs. unspecific explanation), different media channels (levels: package inserts vs. email advertising vs. banner advertising) as well as specific providers/retailers (levels: Amazon vs. a local mail-order company: Baur vs. a fictitious company: Vestes Deis) have been included as attributes for our CBC experiment.

A product in the apparel industry, i.e. the bestselling pullover at Amazon on November 21st, 2017 for males and females respectively, was chosen as field of application for our study. Choosing a product from the apparel industry seemed especially suitable for our research context as recommender systems are commonly deployed by leading apparel online retailers such as Zalando or Amazon within their online shops as well as within their communication with customers through email newsletters or banner advertisements. Two CBC experiments have been created – one for males and one for females – and have been analyzed in comparison to identify relevant differences between both genders. Such a gender-specific investigation seemed to be very promising as previous literature points to clear differences between men and women in terms of their fashion shopping behavior and motivations (Blázquez, 2014). For generating product recommendations, Amazon's recommendations for the corresponding pullover as well as other best selling pullovers were taken (Schreiner et al., 2019). All attributes and attribute levels used for the CBC have been presented solely visual by creating 108 (3^3 x 2^2) different stimuli per experiment. For instance, the advertising channel was visualized by integrating the product recommendations in the image of a package insert, an email interface of a renowned German email provider or in the banner advertisement of a German news portal.

A reduced design was created using Sawtooth Software by deploying the *balanced overlap* method which enables a moderate degree of level overlap and provides reliable estimates of main effects.

After instructing the respondents to imagine having purchased a specific, displayed pullover previously online, they had to complete 16 choice tasks in which they had to decide whether they would consider a product recommendation or not. Four so-called holdout tasks served for evaluation of validity.

The data collection took place at one faculty of a mid-sized German university on four days in November and December 2017 via an online-aided survey. The target group of the survey were students as part of the group of so-called *Digital Natives* – young adults born after 1980 that have grown up with the internet and digital technologies. After data cleaning of two respondents who either completed the survey faster than half of the average survey duration or were older than 37 (hence, not part of the target group of Digital Natives), a total of 332 students remained for analysis. 170 respondents were male (51.2 %) and 162 were female (48.8 %) representing the population of students in the faculty well in terms of gender. An overwhelming majority of study participants was aged 23 years or younger (76.2 %), thus mainly born 1994 or later. For data analysis the *Analysis Manager* of Sawtooth's Lighthouse Studio as well as IBM SPSS Statistics version 21 were used and led to the following results:

With regard to internal validity the root likelihood (RLH) values were greater than 0.5 and satisfactory for both samples. The same holds for the mean first choice hit rates (FCHR) and predictive validity near 80% (Table 2).

Table 2: Goodness of fit and predicitve validity of the utility estimation (source: Schreiner et al. (2019)).

	Male (n = 170)	**Female (n = 162)**
RLH		
Aggregate	0.727	0.707
Individual	0.736	0.724
FCHR		
	Male (n = 170)	**Female (n = 162)**
Holdout task 1	74.12%	74.07%
Holdout task 2	79.41%	70.37%
Holdout task 3	77.06%	83.95%
Holdout task 4	85.88%	82.10%
Mean	79.12%	77.62%

The results of the CBC/HB estimation illustrated in Table 3 clearly show that the advertising channel is by far the most important attribute for males and females when deciding whether to use or follow product recommendations in advertisements.

While banner advertising is least preferred by both subgroups, males prefer ads in package inserts and females email advertising the most. The second most important attribute for both samples is the number of recommendations presented at a time. For males, the smallest set of four product recommendations is of greatest utility whereas females prefer the largest set of twelve recommendations. In terms of the underlying recommender algorithm, there are also significant differences between both groups.

The algorithm is almost as important as the number of recommendations to females. However, overall, females only slightly prefer recommendations generated by the CF algorithm (with a great variance/standard deviation in utility scores on an individual level). By contrast, the utility of the product recommendations is far less influenced by the recommender algorithm for males. Beyond that, recommendations of bestselling products even outperfom recommendations generated by the item-to-item CF algorithm for the male sample.

Table 3: CBC/HB results: part-worth utilities and attribute importances for both samples in comparison (source: Schreiner et al. (2019)).

Attributes, levels	Importance (%) / part-worth utility (Standard deviation)	
	Male (n = 170)	**Female (n = 162)**
Advertising channel**	47.06% (18.5383)	42.52% (16.4170)
Package inserts	41.6981 (86.9194)	27.2990 (92.1058)
Email advertising*	18.3888 (91.8203)	35.3836 (62.6270)
Banner advertising	-60.0869 (119.8352)	-62.6827 (100.2497)
Algorithm***	11.47% (8.0500)	18.52% (13.3744)
CF***	-20.0924 (28.7406)	5.8049 (56.9336)
Bestselling products ***	20.0924 (28.7406)	-5.8049 (56.9336)
Explanation	7.41% (5.4502)	6.69% (4.7139)
Item style***	-1.9414 (22.9594)	-9.3738 (18.2219)
Unspecific***	1.9414 (22.9594)	9.3738 (18.2219)
Number of recommendations	20.49% (12.8676)	18.89% (9.0242)
4***	41.3089 (51.9067)	-8.7204 (47.2899)
8	-22.7051 (29.5661)	-21.3111 (26.8464)
12***	-18.6038 (43.8844)	30.0315 (41.8294)
Provider	13.57% (7.2459)	13.38% (7.0440)
Amazon	23.4981 (33.0486)	25.5799 (29.1617)
Baur	-13.2115 (27.4731)	-17.1631 (19.9480)
Vestes Deis	-10.2866 (24.9089)	-8.4169 (29.0588)
“None” option***	169.5986 (220.7524)	100.1100 (121.5072)

***, **, * indicate two-sided significant differences of importance or part-worth utilities between both groups at $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively.

5.4 Discussion, Implications and Outlook on Future Developments

These results lead to a few recommendations for action for advertisers and retailers:

1. First of all, personalized product recommendations for men should contain as few relevant items as possible (up to a maximum of four), whereas the recommendation set for women should entail significantly more products (at least twelve). One reason for the different preferences regarding the number of recommendations might be that females might have a higher level of involvement with apparel as males. However, it is important to note here that results might differ for other products and domains indicating promising possibilities for future research.
2. Secondly, retailers should increasingly focus on designing personalized product recommendations in email advertising and package inserts instead of only relying on banner ads. The relatively high part-worth utilities for advertising in package inserts illustrate that traditional (print) advertising media must also not be disregarded for younger, digitally-savvy audiences.
3. Thirdly, while currently a major focus is on tailoring product recommendations to individual or segment-specific product needs by applying a personalized recommender algorithm, our research demonstrates that the underlying algorithm is not necessarily of utmost importance. Accordingly, retailers and advertisers have to assure that product recommendations will also be personalized to individual preferences with regard to other design aspects such as the number of recommendations, the advertising channel or the degree of personalization of the text accompanying the product recommendations (e.g. personalized vs. unpersonalized greetings in email newsletters).

   ➔ This implication is in line with Jeff Bezos' vision of personalized online shops from more than 20 years ago. In an interview with the *Washington Post* the founder and CEO of Amazon pronounced:

“ *If we have 4.5 million customers,we shouldn't have one store. (…) We should have 4.5 million stores*” (Jeff Bezos in Walker, 1998).

Despite this early idea of personalized marketing, such an extreme form of online personalization “with a target segment of size one” is still far away from being reality (Arora et al., 2008, p.306). An early prototypical implementation of such a personalized user interface within a university context is discussed by Geyer-Schulz et al. (2001).

More recently, a state-of-the art industry example from Netflix shows that companies nowadays are already taking into account also other aspects when delivering personalized recommendations (Gomez-Uribe and Hunt, 2015): Netflix uses a combination of different recommendation algorithms on its website to deliver relevant, novel as well as diverse movie recommendations. Recommendations are presented in different rows – each deploying a different recommender algorithm. Furthermore, pages are constructed using another personalized algorithm

> “ *taking into account the relevance of each row to the member as well as the diversity of the page*” (Gomez-Uribe and Hunt, 2015, p. 4–5).

Consequently, each Netflix member sees an individually designed homepage in terms of page layout when logging into his or her Netflix account. By doing so, according to Gomez-Uribe and Hunt (2015) 80% of hours streamed at Netflix are triggered by its own recommender systems.

4. Last but not least, the widespread used item-to-item CF algorithm might not necessarily be a beneficial approach by default for all domains and use cases. For the specific sector of apparel, our research suggests that a similarity-based CF approach does not necessarily lead to ideal product recommendations from a customers’ perspective as females only slightly prefer the CF algorithm and male respondents even prefer the recommendation of bestselling products over the recommendations generated by the CF algorithm. Answers to an open question further support this finding: Approximately one-fifth of all answers referred to the desire to receive recommendations for complementary products or suggestions for entire outfits *from head to toe*. Accordingly, future research should evaluate recommendations for apparel products in advertisements generated by other algorithms that e.g. also take aspects like diversity, novelty and serendipity of recommendations more into account.
   ➔ *Complementary recommender systems* which aim at recommending items

that are not similar to the previously bought / viewed item but are often times bought together with it are a currently trending area in recommender systems addressing this specific issue (Hwangbo et al., 2018; Yu et al., 2019). The major challenge in such complementary recommender systems is to identify relevant complementary products as the pure co-purchase of items might not be sufficiently defining supplements (Hwangbo et al., 2018). For instance, some co-purchase relationships might only work unidirectional: A power bank is often times bought as a supplement to mobile phones. Yet, mobile phones are not bought as a supplement to a power bank.

➔ Another currently highly relevant development in the recommender systems literature having the potential to overcome this issue are multi- and cross-domain recommender systems which enable the recommendation of products from one domain or product category, e.g. music/shoes, also within another domain, e.g. movies/pullovers (Cantador et al., 2015; Cremonesi et al., 2011; Khan et al., 2017). Alternatively, recommendations can be generated on a joint basis of two domains (e.g. music and movies).
Transferring knowledge acquired in one domain to another might especially be beneficial for large ecommerce retailers and platforms like Amazon or eBay. Such systems might reduce cold-start issues for new users and items and help to create cross-selling opportunities for products from different domains. Crucial here is the identification of two or more highly related domains with reference to user preferences (Cantador et al., 2015; Cremonesi et al., 2011).

With an ever increasing amount of available data sources and customer information it is also becoming increasingly important to define the right composition of data and variables that should be taken into account by the recommender algorithm in order to reach the important goal of optimizing the individual recommendation quality. Context-aware recommender systems are a current development that seem to be very promising with reference to this goal. Such systems are capable of considering contextual information when generating recommendations such as user profiles, time, location, purpose of purchase, social situation, emotions, mood, etc. (Haruna et al., 2017). By adding contextual information to the traditionally used data sources (users and items) for predicting user's preferences, such approaches have the potential to increase the degree of personalization and individual fit of the recommended items tremendously. Major challenges in designing such context-aware recommender systems might be to identify the most relevant contextual information per user, product category and domain: While for the illustrated use case of apparel products gender was identified to be a relevant contextual information, this might, for instance, much less or not at all apply to other domains such as recommendations for music or articles in scientific journals.

Finally, another future challenge or rather opportunity will be to leverage new types of data sources such as speech data in conversational commerce from voice assistants (Baier et al., 2018) or user-generated content within reviews, blogs or comments in social networks (Chen et al., 2015). As illustrated by our research and current developments in the field of recommender systems, there are still a lot of open issues that need to be addressed for enhancing the efficiency and quality of recommender systems from a customers' perspective. We hope that our investigation can help to advance research on the design of product recommendations in advertisements as well as deliver some food for thought on future research directions.

References

Adomavicius G, Tuzhilin A (2005) Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. IEEE Transactions on Knowledge and Data Engineering 17(6):734–749. DOI: 10.1109/TKDE.2005.99.

Aggarwal CC (2016) Recommender Systems: The Textbook. Springer, Cham (Switzerland). ISBN: 978-3-319296-57-9, DOI: 10.1007/978-3-319-29659-3.

Arora N, Dreze X, Ghose A, Hess J, Iyengar R, Jing B, Joshi Y, Kumar V, Lurie N, Neslin S, Sajeesh S, Su M, Syam N, Thomas J, Zhang Z (2008) Putting One-to-one Marketing to Work: Personalization, Customization, and Choice. Marketing Letters 19(3-4):305–321. DOI: 10.1007/s11002-008-9056-z.

Baek TH, Morimoto M (2012) Stay Away From Me: Examining the Determinants of Consumer Avoidance of Personalized Advertising. Journal of Advertising 41(1):59–76. DOI: 10.2753/JOA0091-3367410105.

Baier D, Rese A, Röglinger M (2018) Conversational User Interfaces for Online Shops? A Categorization of Use Cases. In: Proceedings of the 39th International Conference on Information Systems (ICIS2018), Association for Information Systems, Atlanta (USA), pp. 1–17. ISBN: 978-0-996683-17-3.

Bleier A, Eisenbeiss M (2015) Personalized Online Advertising Effectiveness: The Interplay of What, When, and Where. Marketing Science 34(5):669–688. DOI: 10.1287/mksc.2015.0930.

Blázquez M (2014) Fashion Shopping in Multichannel Retail: The Role of Technology in Enhancing the Customer Experience. International Journal of Electronic Commerce 18(4):97–116. DOI: 10.2753/JEC1086-4415180404.

Bobadilla J, Ortega F, Hernando A, Gutiérrez A (2013) Recommender Systems Survey. Knowledge-Based Systems 46:109–132. DOI: 10.1016/j.knosys.2013.03.012.

Borchers D (2016) Personalisieren in Print. ONEtoONE 9(16):48. URL: https://prudsys.de/wp-content/uploads/2016/10/ONEtoONE_Klingel_Case_09_2016.pdf.

Breese JS, Heckerman D, Kadie C (1998) Empirical Analysis of Predictive Algorithms for Collaborative Filtering. In: Cooper GF, Moral S (eds.), Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence (UAI'98), Morgan Kaufmann Publishers Inc., San Francisco, pp. 43–52. ISBN: 978-1-558605-55-8.

Burke R (2002) Hybrid Recommender Systems: Survey and Experiments. User Modeling and User-Adapted Interaction 12(4):331–370. DOI: 10.1023/A:1021240730564.

Cantador I, Fernández-Tobías I, Berkovsky S, Cremonesi P (2015) Cross-Domain Recommender Systems. In: Ricci F, Rokach L, Shapira B (eds.), Recommender Systems Handbook. Springer, Boston (USA), pp. 919–959. DOI: 10.1007/978-1-4899-7637-6_27.

Chen L, Chen G, Wang F (2015) Recommender Systems Based on User Reviews:

The State of the Art. User Modeling and User-Adapted Interaction 25(2):99–154. DOI: 10.1007/s11257-015-9155-5.

Cheng HT, Koc L, Harmsen J, Shaked T, Chandra T, Aradhye H, Anderson G, Corrado G, Chai W, Ispir M, Anil R, Haque Z, Hong L, Jain V, Liu X, Shah H (2016) Wide & Deep Learning for Recommender Systems. In: Proceedings of the 1st Workshop on Deep Learning for Recommender Systems (DLRS2016), Association for Computing Machinery (ACM), New York (USA), pp. 7–10. DOI: 10.1145/2988450.2988454.

Cohen SH (1997) Perfect Union: CBCA marries the best of conjoint and discrete choice models. Marketing Research 9(1):12–17.

Cremonesi P, Tripodi A, Turrin R (2011) Cross-Domain Recommender Systems. In: 2011 IEEE 11th International Conference on Data Mining Workshops, Institute of Electrical and Electronics Engineers (IEEE), New York (USA), pp. 496–503. DOI: 10.1109/ICDMW.2011.57.

Cremonesi P, Garzotto F, Turrin R (2013) User-Centric vs. System-Centric Evaluation of Recommender Systems. In: Kotzé P, Marsden G, Lindgaard G, Wesson J, Winckler M (eds.), Human-Computer Interaction – INTERACT 2013, Springer, Berlin, Heidelberg (Germany), Lecture Notes in Computer Science, Vol. 8119, pp. 334–351. DOI: 10.1007/978-3-642-40477-1_21.

Ekstrand MD, Harper FM, Willemsen MC, Konstan JA (2014) User Perception of Differences in Recommender Algorithms. In: Proceedings of the 8thACMConference on Recommender Systems (RecSys ’14), Association for Computing Machinery (ACM), New York (USA), pp. 161–168. DOI: 10.1145/2645710.2645737.

Estrada-Jiménez J, Parra-Arnau J, Rodríguez-Hoyos A, Forné J (2017) Online Advertising: Analysis of Privacy Threats and Protection Approaches. Computer Communications 100:32–51. DOI: 10.1016/j.comcom.2016.12.016.

Geyer-Schulz A, Hahsler M, Jahn M (2001) Educational and Scientific Recommender Systems: Designing the Information Channels of the Virtual University. International Journal of Engineering Education 17(2):153–163.

Gomez-Uribe CA, Hunt N (2015) The Netflix Recommender System: Algorithms, Business Value, and Innovation. ACM Transactions on Management Information Systems 6(4):1–19. DOI: 10.1145/2843948.

Green PE, Srinivasan V (1978) Conjoint Analysis in Consumer Research: Issues and Outlook. Journal of Consumer Research 5(2):103–123. DOI: 10.1086/208721.

Haruna K, Akmar Ismail M, Suhendroyono S, Damiasih D, Pierewan AC, Chiroma H, Herawan T (2017) Context-Aware Recommender System: A Review of Recent Developmental Process and Future Research Direction. Applied Sciences 7(12). DOI: 10.3390/app7121211.

Herlocker JL, Konstan JA, Riedl J (2000) Explaining Collaborative Filtering Recommendations. In: Proceedings of the 2000 ACM Conference on Computer Supported Cooperative Work (CSCW ’00), Association for Computing Machinery (ACM), New

York (USA), pp. 241–250. DOI: 10.1145/358916.358995.

Herlocker JL, Konstan JA, Terveen LG, Riedl JT (2004) Evaluating Collaborative Filtering Recommender Systems. ACM Transactions on Information Systems (TOIS) 22(1):5–53. DOI: 10.1145/963770.963772.

Hidasi B, Karatzoglou A (2018) Recurrent Neural Networks with Top-k Gains for Session-based Recommendations. In: Cuzzocrea A, Allan J, Paton N, Divesh Srivastava RA, Broder A, et al. (eds.), Proceedings of the 27th ACM International Conference on Information and Knowledge Management (CIKM '18), Association for Computing Machinery (ACM), New York (USA), pp. 843–852. DOI: 10.1145/3269206.3271761.

Hidasi B, Karatzoglou A, Baltrunas L, Tikk D (2016) Session-based Recommendations with Recurrent Neural Networks. In: Proceedings of the International Conference on Learning Representations (ICLR '16), pp. 1–10. URL: https://arxiv.org/pdf/1511.06939.pdf. ArXiv:1511.06939.

Hwangbo H, Kim YS, Cha KJ (2018) Recommendation System Development for Fashion Retail E-Commerce. Electronic Commerce Research and Applications 28:94–101. DOI: 10.1016/j.elerap.2018.01.012.

Jugovac M, Jannach D (2017) Interacting with Recommenders-Overview and Research Directions. ACM Transactions on Interactive Intelligent Systems (TiiS) 7(3):1–46. DOI: 10.1145/3001837.

Kaptein M, Parvinen P (2015) Advancing E-Commerce Personalization: Process Framework and Case Study. International Journal of Electronic Commerce 19(3):7–33. DOI: 10.1080/10864415.2015.1000216.

Khan MM, Ibrahim R, Ghani I (2017) Cross Domain Recommender Systems: A Systematic Literature Review. ACM Computing Surveys (CSUR) 50(3):36–1-36:34. DOI: 10.1145/3073565.

Knijnenburg BP, Willemsen MC, Gantner Z, Soncu H, Newell C (2012) Explaining the User Experience of Recommender Systems. User Modeling and User-Adapted Interaction 22(4-5):441–504. DOI: 10.1007/s11257-011-9118-4.

LeCun Y, Bengio Y, Hinton GE (2015) Deep Learning. Nature 521(7553):436–444. DOI: 10.1038/nature14539.

Linden G, Smith B, York J (2003) Amazon.com Recommendations: Item-to-Item Collaborative Filtering. IEEE Internet Computing 7(1):76–80. DOI: 10.1109/MIC.2003.1167344.

Louviere JJ, Woodworth G (1983) Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data. Journal of Marketing Research 20(4):350–367. DOI: 10.1177/002224378302000403.

Pu P, Chen L, Hu R (2011) A User-centric Evaluation Framework for Recommender Systems. In: Proceedings of the 5th ACM Conference on Recommender Systems (RecSys '11), Association for Computing Machinery (ACM), New York (USA), pp. 157–164. DOI: 10.1145/2043932.2043962.

Resnick P, Varian HR (1997) Recommender Systems. Communications of the ACM 40(3):56–58. DOI: 10.1145/245108.245121.

Said A, Fields B, Jain BJ, Albayrak S (2013) User-centric Evaluation of a K-furthest Neighbor Collaborative Filtering Recommender Algorithm. In: Proceedings of the 2013 Conference on Computer Supported Cooperative Work (CSCW ’13), Association for Computing Machinery (ACM), New York (USA), pp. 1399–1408. DOI: 10.1145/2441776.2441933.

Schafer JB, Konstan JA, Riedl J (2001) E-Commerce Recommendation Applications. Data Mining and Knowledge Discovery 5(1-2):115–153. DOI: 10.1023/A:1009804230409.

Schreiner T, Rese A, Baier D (2019) Multichannel Personalization: Identifying Consumer Preferences for Product Recommendations in Advertisements Across Different Media Channels. Journal of Retailing and Consumer Services 48:87–99. DOI: 10.1016/j.jretconser.2019.02.010.

Smith B, Linden G (2017) Two Decades of Recommender Systems at Amazon.com. IEEE Internet Computing 21(3):12–18. DOI: 10.1109/MIC.2017.72.

Walker L (1998) Amazon Gets Personal With E-Commerce. The Washington Post, p. H1. URL: https://www.washingtonpost.com/wp-srv/washtech/daily/nov98/amazon110898.htm.

Xiao B, Benbasat I (2007) E-commerce Product Recommendation Agents: Use, Characteristics, and Impact. MIS Quarterly 31(1):137–209. DOI: 10.2307/25148784.

Yu H, Litchfield L, Kernreiter T, Jolly S, Hempstalk K (2019) Complementary Recommendations: A Brief Survey. In: 2019 International Conference on High Performance Big Data and Intelligent Systems (HPBD&IS), Institute of Electrical and Electronics Engineers (IEEE), New York (USA), pp. 73–78. DOI: 10.1109/HPBDIS.2019.8735479.

Yu JH, Cude B (2009) “Hello, Mrs. Sarah Jones! We recommend this product!” Consumers’ Perceptions About Personalized Advertising: Comparisons Across Advertisements Delivered via Three Different Types of Media. International Journal of Consumer Studies 33(4):503–514. DOI: 10.1111/j.1470-6431.2009.00784.x

Zhang S, Yao L, Sun A, Tay Y (2019) Deep Learning Based Recommender System: A Survey and New Perspectives. ACM Computing Surveys (CSUR) 52(1):1–38. DOI: 10.1145/3285029.

6 Research paper #3: Online retailing during the COVID-19 pandemic: Consumer preferences for marketing actions with consumer self-benefits versus other-benefit components

Abstract

In the present study, we investigate, from a consumer perspective, the importance of different types of marketing actions frequently used by online apparel retailers to serve different beneficiaries during the COVID-19 pandemic. The results of a Maximum Difference Scaling experiment among German consumers recruited from an online panel (n=503) reveal that marketing actions with other-benefit components, such as corporate social responsibility initiatives, have the potential to outperform traditional sales promotion methods, such as price discounts. By deploying latent class analysis, two consumer segments can be distinguished according to their preferences: those valuing marketing actions with other-benefits and those preferring marketing campaigns with mere self-benefits. Finally, combinations of marketing actions with maximum reach are identified, from which recommendations for action by retailers are offered.

Keywords:

corporate social responsibility – self-benefit – other-benefit – online marketing – marketing effectiveness – COVID-19.

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6.1 Introduction

Since its first identification in December 2019, the novel COVID-19 virus has drastically changed our interpersonal and societal lives at an incredibly fast pace. After the first wave of COVID-19 slowly subsided in the summer of 2020, many countries around the world were forced to reinstate drastic measures due to further COVID-19 outbreaks, such as enforcing rules for ‘social distancing’ – a term recently adopted for various practices to reduce the number of physical contacts in public places – or imposing the temporary shutdown of restaurants, cultural venues and non-essential retail stores (Buchholz, 2021; Finsterwalder, 2021; Hirsch & Furlong, 2021). In consequence, online sales channels became vital to many businesses, especially for retailers with no or limited online distribution channels prior to the pandemic, to ‘reach and engage customers who are shopping from their home, just to sustain themselves’ (Roggeveen & Sethuraman, 2020, p. 169). Recent research has shown that not only state-imposed social distancing rules, but also consumers’ self-imposed social distancing behaviours played a significant role in driving online sales, due to ‘consumers’ experienced convenience of online shopping and home delivery (e.g. time savings), reduced health risk (e.g. by making online payments), and reduced impulse buying, supporting the notion that consumers’ pandemic-based behaviors may continue in the future’ (Itani & Hollebeek, 2021, p. 10; also see: Hollebeek et al., 2021).

Therefore, particularly during the first wave of the pandemic in the spring of 2020, it was crucial for retailers to determine the type of marketing actions on which to concentrate to attract consumers to their online sales channels in order to ensure their economic survival.

In this regard, recent academic research and global market research studies pointed to an increased consumer demand for and stakeholder attention to corporate social responsibility (CSR) initiatives (Bae et al., 2021; Crane & Matten, 2021; Edelman, 2020, 2021; Havas Group, 2021; Huang & Liu, 2020; Manuel & Herron, 2020).

For instance, pandemic-related research indicated that CSR initiatives can result in enhanced firm evaluations and a strengthening of relationships with various stakeholders – for example, by increasing consumers’ brand loyalty (Huang & Liu, 2020) and brand attitudes (Liu et al., 2020), enhancing employees’ self-efficacy, hope, resilience, and optimism (Mao et al., 2020), and even by increasing stock returns and stakeholder attention (Qiu et al., 2021).

Contrary to traditional sales promotion methods, such as price discounts, that merely focus on self-benefits for consumers with the aim of maximising product sales, CSR can encompass different types of activity and serve different stakeholders such as employees, suppliers, the community, and the environment (Malik, 2015; Öberseder et al., 2014; Turker, 2009). Thus, CSR initiatives can either place emphasis on communicating a self-benefit (e.g. increased product quality by providing free education, and health insurances to local producers, and ensuring hygiene standards), as traditional sales promotion methods, or on communicating an other-benefit without any reference to self-benefits (Kim et al., 2014).

In particular, cause-related marketing (CRM) – a special form of CSR directly linking a company's donation to social causes with product sales – might present sound opportunities for companies to satisfy consumers' increasing demand for companies to tackle the pandemic and to increase product sales (Andrews et al., 2014; DiResta et al., 2020; Varadarajan & Menon, 1988). In practice, there have been various examples of these donation-based promotions, especially during the first wave of the pandemic, such as purchase-related donations to a COVID-19 emergency relief fund or to the United States Bartenders' Guild by an American gin producer (Shaw, 2020; Smith, 2020). While this suggests that the pandemic offers opportunities for firms to 'build stronger rapport among its customers and the general public' by enforcing 'genuine and authentic' CSR practices for 'combating the virus' (He & Harris, 2020, p. 177), previous research has also highlighted potential drawbacks with such practices in the case of consumers' perceived lack of fit between a brand promoting a CRM campaign (or the product featured in the campaign) and the supported social cause (e Silva et al., 2020; Hamlin & Wilson, 2004; Kim et al., 2015; Myers & Kwon, 2013; Nan & Heo, 2007; Trimble & Rifon, 2006; Yang & Mundel, 2021).

Companies should reflect carefully on which marketing strategies to employ to generate beneficial outcomes. Since the 'pandemic provides the setting for a natural experiment on the value of total CSR and different types of CSR over time that can be empirically tested', several researchers have called for an investigation into the pandemic-related effects of CSR initiatives on consumer responses (Manuel & Herron, 2020, p.

245; also see: He & Harris, 2020; Roggeveen & Sethuraman, 2020).

Following these research suggestions, the current research aims to examine the importance of different types of marketing actions by online apparel retailers from a consumer perspective during the first wave of the pandemic in the spring of 2020.

While pre-pandemic research has indicated that marketing actions with other-benefits can outperform marketing actions with mere self-benefit components (e.g. Andrews et al., 2014; Arora & Henderson, 2007; Henderson & Arora, 2010), pandemic-related effects on consumer preferences for both types of marketing actions remain unclear. In this study, we address this research gap and measure consumer preferences for both types of marketing actions in the COVID-19 context. We use traditional sales promotion methods as marketing actions with mere self-benefit components and different types of CSR as marketing actions with other-benefit components. In line with previous research, we consider CRM as a sub-form of CSR, which represents 'cause-specificity of CSR', and, therefore, the usage of the term CSR in this article encompasses CRM practices (Sheikh & Beise-Zee, 2011). Hence, we offer significant contributions to the still limited body of recent research on consumer responses to marketing efforts during the pandemic (e.g. Huang & Liu, 2020; Liu et al., 2020; Sung et al., 2020; Yang & Mundel, 2021) and to the pre-pandemic literature comparing the effectiveness of marketing actions with mere consumer self-benefits and marketing campaigns with other-benefits (e.g. Andrews et al., 2014; Arora & Henderson, 2007; Gao et al., 2020; Henderson & Arora, 2010; Ryoo et al., 2020; Yucel-Aybat & Hsieh, 2021).

Furthermore, we examine gender-related differences in the evaluations of self-benefit versus other-benefit promotions, and we reassess the findings from the pre-pandemic literature, which point to better evaluations of marketing actions with other-benefits by females compared to males (e.g. Chéron et al., 2012; Galan Ladero et al., 2015; Moosmayer & Fuljahn, 2010; Vilela & Nelson, 2016).

In addition, we extend previous CSR-related literature by comparing the effectiveness of CSR practices with different beneficiaries. For this purpose, we draw on the literature from social psychology and construal level theory. Here, the effectiveness of CSR initiatives with socially and spatially close (versus distant) beneficiaries is investigated by examining consumer preferences for CSR practices targeted at different stakeholders (e.g. Lii et al., 2013; Wiebe et al., 2017). This allows us to identify the beneficiaries to target and the marketing actions to favour during the pandemic. Consequently, we are able to extend recent pandemic-related research comparing the effectiveness of different types of CSR initiatives from a consumer perspective (Giacomini et al., 2021).

In sum, the results of our study provide clear recommendations to (apparel) retailers regarding the marketing actions they should focus on to remain relevant to customers and to stay digitally competitive during the pandemic, and beyond.

In the following section, we provide a literature review of the CSR concept, and we consider the impact on consumer responses of marketing actions that target different beneficiaries as the foundation for developing our research hypotheses. Subsequently, the best-worst scaling approach of Maximum Difference Scaling (MaxDiff), which we use as our research method, is outlined. Next, we present our study results and discuss its implications for research and practice. We conclude by detailing certain limitations in our research and suggesting potential avenues for future research.

6.2 Literature Review and Hypotheses Development

6.2.1 CSR before, during, and beyond COVID-19

Today, CSR initiatives are not just a well-established business practice among companies, but they have become an essential part of the overall corporate strategy (Carroll & Shabana, 2010; Du et al., 2007, 2011; Mishra & Modi, 2016). This development is not only driven by altruistic motives but also by positive stakeholder reactions to CSR initiatives – especially from customers – and increasing expectations of socially responsible behaviour by companies (Bhattacharya et al., 2009; Mishra & Modi, 2016). Previous academic research pointed to various positive impacts of CSR actions on customer relationships, such as an enhanced corporate image (Hur et al., 2014; Ramesh et al., 2019; Vanhamme et al., 2012), improved customer loyalty (Ailawadi et al., 2014; Du et al., 2007; Iglesias et al., 2020), increased purchase intentions, and a greater willingness to pay for products supporting a social cause (Abu Zayyad et al., 2020; Arora & Henderson, 2007; Koschate-Fischer et al., 2012; Robinson et al., 2012). More recently, even changes in actual purchase behaviour and an increase in a brand's customer profitability have been identified (Andrews et al., 2014; Ballings et al., 2018) as well as the potential of CSR activities to damage consumers' evaluations of competing brands (Tezer & Tofighi, 2021).

While the importance of CSR initiatives has been rising over recent years, consumer demand and stakeholder attention to such practices have increased during the pandemic (Bae et al., 2021; Crane & Matten, 2021; Huang & Liu, 2020; Manuel & Herron, 2020). Yet, despite the large research stream and various literature reviews clarifying the background and development of approaches that define the concept of CSR over time (Agudelo et al., 2019; Carroll, 1999; Carroll & Shabana, 2010; Dahlsrud, 2008; Lee, 2008), no common definition of the concept has thus far evolved (Dahlsrud, 2008; Peloza & Shang, 2011; Saeidi et al., 2015). Common to various popular and widely used definitional approaches (Carroll, 1979; Commission of the European Communities, 2001; Kotler & Lee, 2005), and our understanding of CSR in the study at hand, is the description of CSR as a set of corporate activities that aim to enhance or generate value for stakeholders and endeavour to go beyond the objective of mere profit maximisation.

According to the existing literature, CSR activities can either be differentiated by their orientation towards different stakeholders (Malik, 2015; Öberseder et al., 2014; Turker, 2009) or by their reference to companies' motives for engaging in socially responsible behaviours (Carroll, 1979; Dahlsrud, 2008; Maignan, 2001).

Recent empirical research during the pandemic has provided typologies for categorising CSR actions. For instance, García-Sánchez and García-Sánchez (2020) identified four main categories of CSR actions carried out by large companies listed on the Madrid Stock Exchange in response to the COVID-19 pandemic – namely commercial CSR, ethical CSR, and altruistic CSR as well as economic and legal responsibilities. According to their understanding, commercial CSR practices seek mainly to achieve competitive advantages and economic benefits (e.g. by designing COVID-19-related products or granting product discounts for consumers). In contrast, altruistic CSR initiatives are mainly directed at benefits for society at large (e.g. donations of medical products and pharmaceuticals). Distinct from altruistic CSR, ethical CSR practices are oriented more towards the well-being of a company's specific stakeholders and include actions such as special payments to employees or securing jobs for part-time employees during the pandemic. Lastly, economic and legal responsibilities represent mandatory actions that guarantee business operations and economic survival during the pandemic (e.g. strengthening the online presence, establishing remote working in administrative jobs).

Giacomini et al. (2021) investigated the effectiveness of different types of CSR activity undertaken by Italian companies during the first wave of the pandemic by categorising CSR-related tweets on Twitter from Italian news agencies and analysing public reactions to different CSR categories. The results indicate that specific COVID-19-oriented actions, such as transforming production capacities into products that help cope with the crisis (e.g. face masks, disinfecting agents), and employee-oriented CSR activities received considerable attention and were widely appreciated by the general (Twitter) public.

In line with pre-pandemic research and with our research objectives, we follow stakeholder-based categorisation approaches, which broadly distinguish between internal and external stakeholders as beneficiaries of CSR practices (Turker, 2009; Verdeyen et al., 2004). According to this classification, internal CSR activities aim to create value for employees, whereas CSR can, for instance, create value for customers, suppliers, the community, investors, and the environment as external company stakeholders (Hameed et al., 2016; Malik, 2015; Verdeyen et al., 2004).

6.2.2 Impact of CSR Activities on Consumer Behaviour

6.2.2.1 Effectiveness of Self-Benefit versus Other-Benefit Promotions

During the pandemic, the decision-making of many consumers was primarily driven by self-interest, exhibiting irritational consumption / stockpiling behaviours, such as panic purchases of essential hygiene items and food (He & Harris, 2020). However, contrary to self-interested consumption behaviours, many consumers engaged in various altruistic behaviours, such as buying groceries for vulnerable groups (He & Harris, 2020). Likewise, consumer demand for prosocial consumption and CSR initiatives was high because consumers demanded that companies support the fight against the virus and ‘contribute to addressing the most urgent global challenges’ without hidden agendas or ulterior motives (García-Sánchez & García-Sánchez, 2020, p. 4; also see: He & Harris, 2020; Manuel & Herron, 2020). Based on these contradictory consumption behaviours during the pandemic – either motivated by self-interest or altruistic considerations – an investigation of consumer responses to promotional approaches serving the consumer's self-interest versus other causes is a matter of considerable importance.

A discrete marketing research stream within the CSR sub-domain of CRM investigates the effectiveness of practices providing other-benefits compared to price discounts, which are a typical form of traditional sales promotion methods that offer self-benefits for consumers. In general, the findings from these studies suggest that promotions with other-benefits can outperform campaigns with self-benefits: Arora and Henderson (2007) showed that CRM campaigns were more effective than equal price discounts in terms of consumer evaluations and choice shares on the level of small denominations – for example, a CRM campaign for bottled water – whereas price discounts were of greater value to consumers at high promotional levels, as shown in the context of cash-back options for credit cards.

In another article, Henderson and Arora (2010) showed that, in the case of three related product categories (shampoo, body wash, and lotion), a CRM campaign for one product that included a donation to the American Red Cross not only enhanced consumer brand evaluations and product choice probability, but these positive effects also carried over to other related product categories of the same brand. Such effects were not observed for equivalent price discounts. In addition, the authors demonstrated that using CRM campaigns rather than equivalent coupons was more efficient because the return on investment of CRM campaigns was clearly higher.

More recently, Andrews et al. (2014) showed for Chinese mobile users that a real-world CRM campaign supporting newly accepted indigent college students clearly boosted cinema ticket purchases as well as revenues. The sales revenues generated by a CRM campaign were relatively higher than the sales revenues generated by comparatively higher price discounts. In the context of CSR and in a more general setting, Mohr and Webb (2005) showed that information on a company's positive CSR activities had a stronger impact on the purchase intentions of consumers than price, especially within the environmental domain.

Another research stream in marketing originating principally from (social) psychology compares self-benefits with other-benefits in terms of message framing in CSR campaigns – for example, a marketing claim focusing on the personal benefit to the consumer versus an appeal emphasising the gains for the beneficiary of a purchase-related donation. Overall, the findings from this research stream are mixed. Yet, several studies demonstrate that CSR initiatives can generate positive consumer responses based either on altruistic or self-serving motives, and that the effectiveness of such campaigns depends on the motive referenced in the marketing claim.

For instance, the results of a study by Fisher et al. (2008) suggest that marketing efforts with an other-benefit message framing are more valued by consumers than appeals focused on self-benefits. Partouche et al. (2020) demonstrated that marketing messages emphasising an other-benefit led to more positive attitudes, increased purchase intention, and willingness to pay compared to marketing campaigns without such a message, especially if hedonic (rather than utilitarian) products were used and if the message featured a promotion-focused argument (e.g. financial support of cancer research) rather than a prevention-focused argument (e.g. contribution to the reduction of cancer risks).

In contrast, Gao et al. (2020) showed that self-benefit appeals had a significantly more positive impact on consumer's CRM engagement than other-benefit appeals when certain combinations of visual design and message content were applied to the self-benefit appeal. Moreover, Kim et al. (2014) demonstrated that the communication of CSR initiatives with a self-benefit positioning was more effective, especially for identity irrelevant products, and pandemic-related research by Yu and Han (2021) indicated that self-benefit appeals led to increased purchase intentions for consumers that felt socially excluded.

Other researchers were unable to confirm a unidirectional effect in general. However, they showed that the effectiveness of CRM campaigns differed for: i) certain contextual factors such as public settings where consumers paid more attention to their self-image and the public accountability of donations, thus valuing other-benefits more (White & Peloza, 2009), ii) certain consumer groups such as materialistic consumers who showed more positive responses to CRM campaigns when self-benefit appeals were enforced (Ryoo et al., 2020), iii) consumers with growth mindsets who responded more positively to CRM campaigns centred on other-benefit appeals (Yucel-Aybat & Hsieh, 2021).

In sum, the prior literature and consumer behaviour during the pandemic highlight the importance and the potential superiority of marketing actions aimed at providing gains for other beneficiaries compared to marketing actions focused solely on self-benefits.

Therefore, we propose the following hypothesis:

H1: During a pandemic, consumers prefer marketing actions that include an other-benefit component – namely, actions supporting other company stakeholders (here: CSR initiatives) – to marketing efforts focused solely on self-benefits (here: traditional sales promotion methods).

6.2.2.2 Gender-related Differences in the Evaluation of Self-Benefit versus Other-Benefit Promotions

Previous research suggests that marketing campaigns with other-benefit components could well be of greater value to certain consumer segments. Several pre-pandemic studies point to better evaluations of CRM approaches by females compared to males, such as more positive attitudes towards brands promoting the CRM campaign (Cui et al., 2003; Ross et al., 1992), more positive attitudes to products supporting a social cause (Galan Ladero et al., 2015; Moosmayer & Fuljahn, 2010), an increased likelihood to buy and an increased willingness to pay for such products (Chéron et al., 2012; Galan Ladero et al., 2015), and a greater willingness of females to support CRM campaigns (Vilela & Nelson, 2016).

Other studies have only provided partial support for such a gender-effect (Hyllegard et al., 2010; Trimble & Rifon, 2006). Still others found no evidence for such an effect (Chaney & Dolli, 2001; Kropp et al., 1999; Marquina Feldman & Vasquez-Parraga, 2013; Pope et al., 2004; Tian et al., 2011; Vanhamme et al., 2012; Wymer & Samu, 2009).

In the light of the pandemic, studies across various countries have demonstrated that females have suffered more from negative labour market developments compared to their male counterparts – for instance, working fewer hours, working from home, or losing employment due to mandatory store closures and distancing laws, whereas simultaneously household and childcare needs have increased tremendously and females are more likely to deal with such additional responsibilities (Alon et al., 2020; Del Boca et al., 2020; Reichelt et al., 2021). Consequently, female employees may be likely to hold higher expectations of companies in terms of pandemic-related adjustments to work schedules and increased opportunities for telecommuting, extending even beyond the pandemic.

Hence, and consistent with the results of previous research, we assume:

H2: Females elicit stronger preferences for marketing campaigns with other-benefit components than males.

6.2.2.3 Social Distance between Consumers and Beneficiaries of Marketing Actions

Based on the premise that marketing actions with other-benefit components are preferred by consumers during the pandemic to marketing actions that only serve consumers' self-benefits (H1), it is essential that companies decide which other beneficiaries their marketing actions should principally address to enhance consumer evaluations.

To address this research question, we draw on marketing literature that investigates the impact of social distance on consumers' evaluations of companies. Misleadingly, the term 'social distancing' has been used throughout the pandemic as an interchangeable term for 'physical distancing' – the practice of maintaining a predefined physical distance from other individuals (Finsterwalder, 2021; Johns Hopkins Medicine, 2020). However, the term social distance arises from social psychology and construal level theory (CLT) and is viewed as one distinct facet within the broader construct of psychological distance. It describes the distinction between oneself and others – for instance, the dissimilarity versus similarity of others, or in-group versus out-group members (Kim et al., 2008; Trope et al., 2007; Trope & Liberman, 2003; Zhao & Xie, 2011).

One of the consequences of the pandemic has been the systematic reduction in physical contact, which increased the spatial distance between individuals. As a result, social closeness seemed to have attained extreme importance (Aminnejad & Alikhani, 2020; Bond, 2021; Finsterwalder, 2021).

In pre-pandemic research, some authors examined the impact of socially close versus socially distant consumer-brand relationships, indicating that socially close brands (brands with which consumers share similar values) would be perceived more favourably by consumers in terms of their attitudes to the brand, their company evaluations, and the perceived credibility of CSR initiatives (Lii et al., 2013; Park & Park, 2021). Other studies addressed the impact of socially close versus distant consumers (e.g. product reviews by own university members versus members of other universities) on company or product evaluations and reported joint interaction effects of social and temporal distance. Yet, they found no exclusive main effects of time or social distance (Huang et al., 2018; Kim et al., 2008; Zhao & Xie, 2011).

In contrast to these studies, our investigation focuses on the impact on consumer responses of the social distance between consumers and beneficiaries of CSR initiatives. To the best of our knowledge, this issue has only been addressed by Wiebe et al. (2017), who showed that socially proximal framing of CRM campaigns was more effective than distal message framing. In conclusion, the authors argued that, by focusing on something close instead of distal (e.g. by capitalising the word ‘CHILDREN’ instead of ‘AFRICA’ in a claim requesting help for children in Africa), the effectiveness of CRM campaigns could be increased (Wiebe et al., 2017).

Drawing together the previous research on CLT and social distance, the lack of physical interactions during the pandemic, and our premises underpinning H1, we hypothesise:

H3: During a pandemic, consumers prefer the targeting of socially close beneficiaries of marketing actions to socially distant ones – that is to say, consumers prefer CSR initiatives aimed at employees over marketing actions benefitting all consumers, society at large, and suppliers.

6.2.2.4 Spatial Distance between Consumers and Beneficiaries of Marketing Actions

Since the pandemic has been a huge obstacle for international companies due to the disruptions of global supply chains across various industries and the forcing of consumers to increasingly shift their consumption to local products, spatial distance between consumers and beneficiaries of marketing campaigns might be a crucial success factor in CSR initiatives during the pandemic (He & Harris, 2020). Empirical evidence for such a positive impact of spatially close versus distant beneficiaries on consumer responses in pre-pandemic research is to be found principally in the domain of CRM campaigns. For instance, previous research showed that CRM campaigns with spatially close beneficiaries resulted in an increased consumer willingness to support the campaign (Ross III et al., 1991), enhanced attitudes towards the brand (Lii et al., 2013; Wiebe et al., 2017) and towards the campaign (Grau & Folse, 2007), as well as increased purchase intentions (Hou et al., 2008; Wiebe et al., 2017).

Yet, other researchers found no statistically significant results for consumer evaluations of CRM campaigns with spatially proximal versus distal beneficiaries (Cui et al., 2003; Ross et al., 1992) .

Vanhamme et al. (2012) offered an explanation for these inconsistent findings by highlighting two opposing effects of spatially close causes on consumer responses. On the one hand, a positive effect of CRM campaigns with a local or national focus on consumer-cause identification, which in turn increased perceptions of corporate image, was reported. Yet, apart from that, a negative direct effect of cause proximity on corporate image was identified, which impeded prediction of the final effect of cause proximity on corporate image.

Since, overall, many of the aforementioned studies pointed to more positive consumer reactions to CRM campaigns with spatially close beneficiaries, we propose the following hypothesis:

H4: During a pandemic, consumers prefer CSR practices with spatially close (i.e. local) beneficiaries to CSR practices with spatially distant (i.e. national) beneficiaries.

6.3 Empirical investigation

6.3.1 Research Method

To identify the most important actions of online apparel retailers during the pandemic from a consumer perspective, we deployed Maximum Difference Scaling. MaxDiff is a measurement approach developed by Louviere and Woodworth (1990) that was first applied by Finn and Louviere (1992). The approach is closely related to discrete choice analysis (DCA) (Louviere & Hensher, 1982) or choice-based conjoint analysis (CBC) (Louviere & Woodworth, 1983) with a similar measurement objective. However, in contrast to DCA and CBC, besides a ‘best’ stimulus also a ‘worst’ stimulus must also be selected from a set of alternatives (choice sets), thus, forcing individuals to make trade-off decisions (Lee et al., 2007). This is why MaxDiff is often called Best-Worst Scaling (BWS).

MaxDiff originates from the random utility model of Thurstone (1927) and McFadden (1974), which assumes that individuals assess alternatives (objects / attributes, profiles / attribute-levels, or multi-profiles / attribute-level-combinations) on a subjective value scale and select the alternative with maximum utility.

The probability $Prob\big((j_1;j_2)|CS_{ik};i\big)$ that individual i selects stimulus pair $(j_1;j_2)$ with j_1 as the best and j_2 as the worst stimulus in choice set CS_{ik} (k=1,…,K) can be expressed in the following way:

$$\begin{aligned} &Prob\big((j_1;j_2)|CS_{ik};i\big) \\ &\qquad = Prob\Big((u_{ij_1}+\varepsilon_{ij_1})-(u_{ij_2}-\varepsilon_{ij_2}) \\ &\qquad \geq \max_{j,j'\in CS_{ik},j\neq j'}\big((u_{ij}+\varepsilon_{ij})-(u_{ij'}+\varepsilon_{ij'})\big)\Big) \end{aligned}$$

Here, expression $(u_{ij_1}+\varepsilon_{ij_1})-(u_{ij_2}-\varepsilon_{ij_2})$ constitutes the difference between the ratings of stimulus j_1 and j_2. u_{ij} is the mean evaluation of stimulus j (j=1,…,J) by individual i and ε_{ij} represents the additive random (unexplainable) error. $\max_{j,j'\in CS_{ik},j\neq j'}\big((u_{ij}+\varepsilon_{ij})-(u_{ij'}+\varepsilon_{ij'})\big)$ expresses the greatest possible difference between the ratings of all stimuli in the choice set (Finn & Louviere, 1992). To construct choice sets and measure the unknown mean subjective utility values, the following distinctions are usually made (Flynn, 2010):

- case 1: object scaling,
- case 2: profile scaling, and
- case 3: multi-profile scaling

Case 1 – object scaling – is considered the archetype of MaxDiff which has been initially described by Finn and Louviere (1992). As discussed above, object scaling involves the measurement of individual preferences for objects as stimuli in several choice tasks (Mühlbacher et al., 2016). In each of these tasks, respondents have to select their favourite (‘best’) object and their least preferred (‘worst’) object from a predefined number of alternatives (Finn & Louviere 1992).

Different techniques can be used for analysing MaxDiff best-worst data (Flynn & Marley, 2014; Mühlbacher et al., 2016; Orme, 2009). For instance, count analysis, which calculates the best-worst score as difference between the amount or percentage of best choices and worst choices for each object, is often used to receive aggregate utility scores for all respondents (Cohen, 2009; Orme, 2009). Provided that each attribute has been evaluated sufficiently often by respondents, this simple approach also allows to calculate scores at an individual-level. While utility scores from count analysis only provide information on the importance and rank order of objects, multinomial logit (MNL) also considers ‘the strength of competition within each set’ (Orme, 2009, p. 5; also see: Mühlbacher et al., 2016). Therefore, MNL is a more robust approach for fractional designs where the number of objects shown per respondent may vary slightly (Furlan & Turner, 2014; Orme, 2009). Moreover, latent class analysis (LCA) is often deployed to MaxDiff data for identifying latent segments with internally homogeneous and externally heterogeneous utility scores (Mühlbacher et al., 2016; Orme, 2009).

Today, Hierarchical Bayes (HB) is considered the ‘gold standard’ for estimating utility scores at the individual-level (Orme, 2009, p. 3). The main advantage of HB stems from the underlying two-level hierarchical model which combines individual choice data (at the lower level) with distributional assumptions of utility scores across all respondents (at the higher level) to estimate individual-level values (Sawtooth Software, 2009). Hence, HB is considered a useful approach for estimating individual-level utility scores even when there are few choice tasks per respondent (Furlan & Turner, 2014; Mühlbacher et al., 2016). After zero-centring the utility scores derived from the HB estimation, results for different segments can be analysed, e.g. by averaging the utility scores or by the use of clustering approaches.

Contrary to object-scaling, in case 2 (profile scaling) respondents are asked to evaluate levels of attributes. Here, respondents are presented with a profile of attribute-levels in choice tasks and have to select their most preferred ('best') and least preferred ('worst') stimuli (Flynn & Marley, 2014). Similar to CBC and DCA, in the third scenario – multi-profile scaling – respondents are presented with alternatives consisting of all attributes and their differing levels across various choice tasks (Mühlbacher et al., 2016). As in the other cases, respondents are required to select the most preferred and least preferred attribute-level-combination from the presented stimuli.

Due to the different points of focus as well as the strengths and weaknesses of the three cases of MaxDiff, they have different areas of application. While case 1 and case 3 are mainly used in the context of marketing, case 2 is prevalent in the health sector (Adamsen et al., 2013). In both cases, HB estimation and usage of software packages (Sawtooth Software, 2009, 2020) are standard.

MaxDiff offers several benefits compared to traditional survey methods where rating scales ranging from 'totally unimportant' to 'totally important' are used to measure aspect importances (Cohen & Neira, 2003; Louviere et al., 2015). MaxDiff repeatedly forces the respondents to select the 'most important' and the 'least important' aspects within sets of aspects. Hence, there is no opportunity for bias by respondents who give constant high / low or middle-of-the-road ratings. In contrast, respondents are forced to make discriminating choices (Cohen & Neira, 2003). Moreover, the tasks can be easily completed, and it is possible to check for order or context biases. This superiority has also been demonstrated in many comparisons. For example, Cohen (2003) demonstrated a higher validity (96% correct predictions of the best aspects) by MaxDiff object scaling compared to the importances estimated by direct evaluation on rating scales (85% correct predictions of the best aspects) when measuring the importance IT managers give to 20 aspects when purchasing or recommending hardware. Cohen and Neira (2003) also found a similar MaxDiff superiority over rating scales when estimating the importance of 13 coffee drinking benefits in another between-subjects experiment. The crucial difference between MaxDiff and traditional approaches seems to be that MaxDiff estimates the importances indirectly. Hence, the risk of possible bias in the results can be avoided (Auger et al., 2007). Consequently, object scaling is used in our survey to answer the research questions formulated. Due to the advantages of MaxDiff compared to other survey methods and the fact that the alternatives can be described by one characteristic, this case appears to be suitable.

6.3.2 Experimental Design

Prior to the MaxDiff tasks, respondents were required to answer questions about their usual purchasing behaviour for apparel products in general as well as their (adjusted) purchasing behaviour during the first wave of COVID-19 – that is to say, since the enforcement of the contact restrictions on 22nd of March 2020 in Germany. Subsequently, respondents were asked a total of nine repeating MaxDiff-BWS tasks presenting four different marketing actions by online apparel retailers aiming to encourage customers to purchase products from their online shops. In each of the tasks, participants were asked to select the most preferred as well as the least preferred marketing action. The list of actions was derived from research on frequently communicated marketing actions among the top 100 German ecommerce retailers and based on recent studies examining frequently used CSR actions and company responses to the pandemic.

Similar to pandemic-related CSR practices among Spanish companies identified by García-Sánchez and García-Sánchez (2020), the commonly communicated marketing actions of German online retailers could be broadly categorised into i) traditional sales promotions methods such as price discounts (deployed by 36% of apparel online retailers from the top 100 German online shops), free standard shipping (25%), or the extension of periods for returning items (47%), ii) ethical CSR practices such as actions ensuring employee protection and safety (28%), or the implementation of hygienic and cautionary measures for combating the spread of the virus (33%), and iii) rather generic information on the online business operations and delivery capacities during the pandemic (72%). Hence, three out of four CSR categories proposed by García-Sánchez and García-Sánchez (2020) were covered by the frequently deployed actions of German online retailers. To cover the fourth category identified in previous research – altruistic CSR – we included two CRM campaigns with a spatially close (local) and spatially distant (national) beneficiary. As a result, a list of twelve different marketing actions by online apparel retailers was developed for the investigation. In contrast to other pandemic-related research (García-Sánchez & García-Sánchez, 2020; Giacomini et al., 2021) and in line with our research objectives, we distinguished marketing actions based on their beneficiaries (Table 1). Two of the chosen actions provided benefits for various stakeholders simultaneously. To ensure that the respondents had an intuitive understanding of the actions presented, we included an exemplary implementation of each action based on real-world cases from major German online apparel retailers. Further information regarding the questioning process in the MaxDiff tasks is presented in Appendix A, and a MaxDiff task example can be found in Appendix B. After completing the MaxDiff tasks, demographic data on respondents were collected.

Table 1: List of marketing actions used in the MaxDiff experiment

Action	Example	Type of action	Beneficiaries
Support of local specialist retailers	With each order in our online shop, you can support a regional dealer: We pass on 25% of the purchase value of first-time orders directly to a local specialist retailer of your choice, who has to keep its doors closed during the COVID-19 crisis.	CSR (local CRM)	Local retailer
Financial support of a COVID-19 emergency relief	As a company we want to contribute to the fight against the spread of COVID-19. Therefore, we donate 25% of the purchase value of first-time orders to the COVID-19 emergency fund by the German Red Cross. You can also donate to COVID-19 emergency relief. Together, we will master this crisis!	CSR (national CRM)	Society at large
Actions ensuring employee protection and safety	To protect our employees, most of our employees work remotely. In addition, we have implemented preventive health measures at all our sites (e.g. more frequent cleaning; implementation of regulations regarding safety distances).	CSR (employee-oriented)	The retailer's employees
Hygienic and cautionary measures	All our employees and service partners receive comprehensive and ongoing training on the latest official hygiene and precautionary measures. We monitor compliance with these measures on a daily basis.	CSR (employee-oriented)	The retailer's employees
Textile safety masks as free giveaways	To counteract the spread of COVID-19 and to protect your health, you will receive a fashionable textile cloth face mask as a free giveaway with your first order until the 4^{th} of May 2020.	CSR (customer-oriented)	Individual consumer's self; society at large
Actions enabling customers to avoid direct contact with package deliverers	To protect your health, we are offering you a contactless delivery or transfer to a packing station by our suppliers.	CSR (customer-oriented)	Individual consumer's self; suppliers
Free standard shipping	To support you as much as possible in these difficult times, we offer free standard shipping for all purchases over 25€.	Traditional sales promotion	Individual consumer's self
Discounts for orders during the COVID-19 crisis	During these difficult times, we are currently granting you a 15€ purchase voucher for all orders starting from 40€.	Traditional sales promotion	Individual consumer's self

Action	Example	Type of action	Beneficiaries
Extension of periods for returning items	To support you during the current situation, we are extending the right to return items for orders placed before 30th of April 2020 to 60 days.	Traditional sales promotion	Individual consumer's self
Extension of the validity of coupons / campaign vouchers	All promotion vouchers can also be used for online orders. In addition, promotion vouchers that lose their validity during the period of store closures remain valid for a correspondingly longer period and can also be used once the stores are reopened.	Traditional sales promotion	Individual consumer's self
Actions ensuring the delivery capacity	Despite the currently difficult situation, we will ensure that all online orders are delivered as usual. We have sufficient products in stock, all logistic processes are still being performed, and our delivery partners are also continuing to operate at full blast.	Ensuring business operations	All consumers
Availability of customer service / contact details	Despite the current difficult situation, we ensure availability of our customer service as usual by phone, email, and via live chat.	Ensuring business operations	All consumers

6.3.3 Sample and Data Collection

For the data collection consumers were recruited from an online consumer panel in Germany at the end of April 2020 (April 22nd to 28th) while the contact restrictions imposed by the German government were still in force. The survey was conducted using an online questionnaire that had been distributed by a German online panel provider to invited participants by email. In the email invitation participants were informed about the approximate duration of the questionnaire and the amount of the monetary reward for participating in the survey. To avoid multiple completions of the questionnaire per respondent, each participant received an individual survey link that only could be completed once. Participation was restricted to consumers aged 18 years and older. In addition, consumers who had not purchased apparel products in the past 12 months were excluded to ensure that participants had some familiarity with apparel products. In total, 503 respondents completed the survey representing the overall population of Germany (in 2019) quite well in terms of major socio-demographic characteristics (Table 2). However, people holding an academic degree were clearly over-represented in our sample.

Table 2: Composition of the sample and the overall population of Germany in terms of

several socio-demographic criteria (Statista, 2020a, 2020b, 2020c; Statistisches Bundesamt, 2020)

Socio-demographic characteristics	**Germany (2019)**	**Sample**
Mean age	44.5 years	48.3 years
Female	50.7%	48.9%
Academic degree	18.5%	31.0%
Occupation status: Employed or self-employed	61.5%	63.4%
State of residence: North-Rhine-Westphalia, Bavaria, or Baden-Wuerttemberg	50.7%	45.9%

6.4 Results

6.4.1 Consumer Purchasing Behaviour before and during the Pandemic

For the purpose of identifying the impact of the pandemic in Germany on consumers' purchasing behaviour concerning apparel products, respondents were asked to specify their usual purchase frequency for apparel products employing different channels. Besides commonly used distribution channels, we included supermarkets as a distinct sales channel because of their slightly increased importance during the first wave of the pandemic in Germany and because supermarkets were the only venues where consumers could buy apparel products in person (Statista, 2021a). Subsequently, respondents were requested to state how often they used the aforementioned channels to purchase apparel products during the pandemic. Table 3 shows the results of the usual purchase frequency and the purchase frequency during the pandemic in comparison.

Table 3: Purchase frequency for apparel products usually and during the beginning of the first wave of the pandemic (~ period of 1 month)

Channel / frequency		**Never**	**Once a year**	**Every three months**	**Every month**	**Several times a month**
Internet	Usually	6.76%	17.89%	38.37%	21.07%	15.90%
	During the pandemic*	33.80%			33.20%	33.00%
Store	Usually	5.77%	20.48%	42.54%	20.68%	10.54%
	During the pandemic*	81.11%			11.53%	7.36%
Catalogue	Usually	64.41%	19.48%	12.13%	2.78%	1.19%
	During the pandemic*	89.66%			6.96%	3.38%
Teleshopping / shopping channels	Usually	88.07%	4.57%	3.98%	2.58%	0.80%
	During the pandemic*	94.83%			3.38%	1.79%
Telephone	Usually	87.87%	5.96%	3.78%	1.79%	0.60%
	During the pandemic*	93.44%			4.77%	1.79%
Supermarket	Usually	33.00%	24.25%	15.90%	8.15%	18.69%
	During the pandemic*	67.59%			13.92%	18.49%
Other	Usually	92.84%	2.39%	2.19%	1.39%	1.19%
	During the pandemic*	97.02%			1.19%	1.79%

*The purchase frequency during the pandemic was measured on a scale using the levels *never*, *once* (equivalent to *every month*) and *several times* (equivalent to *several times a month*).

Results of an in-depth analysis comparing the percentage of consumers who increased or decreased their purchase frequency showed that the Internet has clearly gained in importance for purchasing apparel products, whilst retail stores unsurprisingly have suffered from temporary closure (Figure 1). Such a decline in the purchase frequency of apparel products in German brick-and-mortar stores had already been observed – for example, the offline purchase frequency for clothing declined by 13.6 percentage points in 2018 compared to 2014 (Handelsverband Deutschland (HDE), 2019).

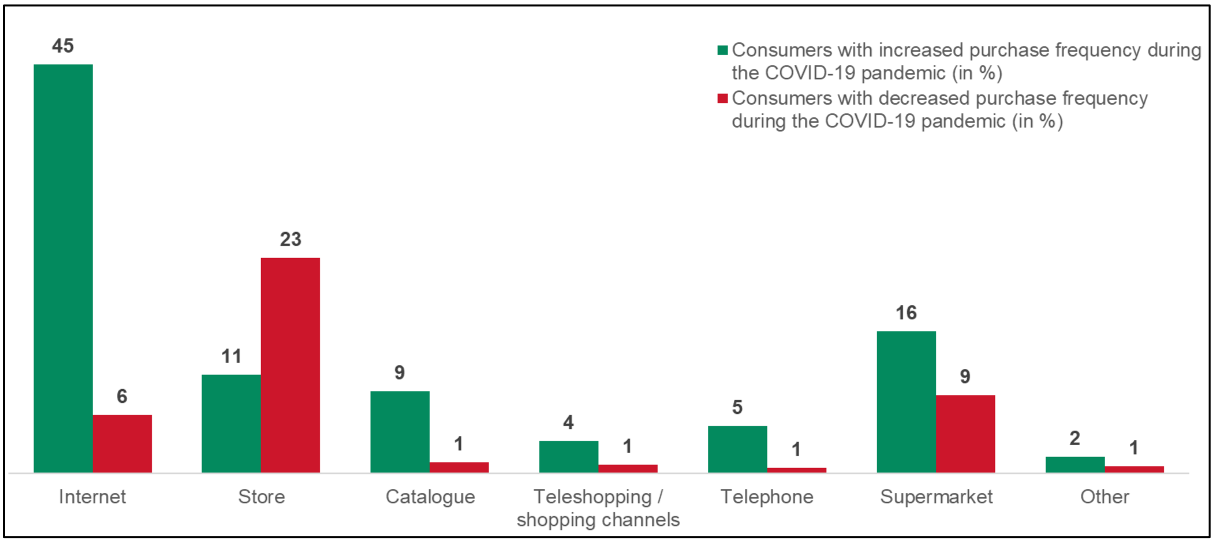

Figure 1: Percentage of consumers with an increased versus decreased purchase frequency during the first wave of the pandemic within different sales channels

Furthermore, the percentage of consumers with monthly expenses up to 50€ increased considerably during the pandemic whereas the percentage of users spending a larger amount of money clearly decreased (Table 4). Hence, more than one-third of all respondents indicated that they had reduced their expenses for apparel products, whereas only 8% stated they had increased their spending since the enforcement of the contact restrictions and distancing rules. Pure online shoppers had been slightly (yet, not significantly) more likely to increase their spending on clothing (12%). The results of our study are consistent with the findings of a global survey by McKinsey & Company (2020a) during the first wave of COVID-19, which demonstrated that, in most countries, consumers expected to reduce spending on all apparel product categories because consumers were preparing for a longer period of financial uncertainty and, consequently were shifting their consumption towards essential products.

Table 4: Respondents' expenses on apparel products usually and during the first COVID-19 wave

Expenses	**0-50€**	**51-100€**	**101-150€**	**151-200€**	**More than 200€**
Usually	43.34%	37.38%	11.33%	5.77%	2.19%
During the pandemic	68.99%	17.69%	7.16%	4.17%	1.99%

While temporary store closures seem to have clearly boosted online sales channels for apparel purchases, massive price discounts by online apparel retailers during the first wave of COVID-19 may also have played a crucial role in the sharp increase in online purchases. For instance, Zalando and H&M – two of Germany's most popular online apparel stores in terms of revenue – routinely offered rebates of up to 50% – rising even to 70% – in early April 2020 (Internet World, 2020; Statista, 2021b).

6.4.2 MaxDiff / HB Results

To measure the predictive validity of a MaxDiff experiment, hit rates are commonly calculated indicating the percentage of respondents actually choosing the item with the highest (lowest) estimated utility in a predefined holdout choice task. Since we did not include holdout tasks, we redetermined the last task as a holdout task ex-post and excluded this task from the utility estimation, using it to calculate the correctly predicted choices of respondents. By doing so, both hit rates, for the best as well as the worst choices, demonstrated good predictive validity. The best choice decision was correctly predicted in 61.43% of cases and the worst choice decision for 56.86% of respondents. This represented a clear improvement in predictive accuracy compared to the random model of 25%. In addition, no loss in internal validity could be observed when using only eight MaxDiff tasks to estimate utilities because root likelihood (RLH) values for the utility estimation without the last choice task did not decrease (aggregate level: 0.5188 versus 0.5143; individual level: 0.5380 versus 0.5332). RLH values clearly exceeded the values for a random model (RLH = 0.25) indicating that the fit between the choice model and the data set was satisfactory. Therefore, the subsequently reported results of the HB estimation refer to the first eight tasks in the MaxDiff experiment.

In Table 5, the mean zero-centred raw utility scores derived from the HB estimation and the corresponding standard deviations are depicted. The most popular marketing action for consumers during the pandemic was the CRM campaign with a local focus – namely, financially supporting local specialist retailers with each purchase. This demonstrates that marketing actions with other-benefit components have the potential to outperform self-benefit appeals, thus delivering support for H1. A two-tailed t-test for marketing actions solely serving the consumer's self and marketing actions also supporting other company stakeholders throughout the pandemic provided further statistical support for H1. Utility scores for marketing actions with other-benefits (mean zero-centred raw utility [standard deviation]: 0.1541 [2.0048]) were significantly higher than for marketing actions with mere consumer self-benefits (-0.3083 [2.2106]), t(3692,94) = 7.90, $p < 0.001$. Nevertheless, certain marketing actions with self-benefit components for consumers, such as free standard shipping (rank 3) and price discounts (rank 6), were preferred by consumers to several marketing actions with other-benefits, such as customer-oriented CSR initiatives (ranks 8 and 9) and the CRM campaign supporting the national COVID-19 emergency relief (rank 7). Hence, H1 is only partially supported.

With reference to the comparison of consumer preferences for socially proximal versus socially distal beneficiaries of marketing campaigns, the HB results provide support for H3. Marketing actions with socially close beneficiaries – namely, CSR initiatives directed at the retailer’s employees (ranks 2 and 4) – received higher utility scores than marketing efforts serving all consumers (ranks 5 and 11), the society at large (ranks 7 and 8), and suppliers (rank 9). The results of a two-tailed t-test also confirmed H3 beacuase utility scores for CSR initiatives directed at employees (0.6160 [1.6898]) were significantly higher compared to CSR initiatives supporting other beneficiaries (-0.2745 [1.9675]), t(2139.03) = 13.46, $p < 0.001$.

Moreover, since the local CRM campaign was the most preferred action, H4 is supported, indicating that marketing campaigns with spatially close beneficiaries were clearly preferred over spatially distant beneficiaries.

To check for gender-related differences and to review H2, a two-tailed t-test for independent groups was performed. Significant differences between males and females could only be found for actions ensuring the delivery capacity, which were preferred by males (0.5224 [1.6856]) to a significantly greater degree than females (0.1387 [1.5627]), t(501)=2.64, $p < 0.01$. Consequently, in contrast to previous research and contrary to our expectations, H2 was rejected.

Table 5: Results of the HB estimation

Rank	Actions	Mean zero-centred raw utility	Standard deviation	Beneficiaries
1	Support of local specialist retailers	1.3733	2.0662	Local retailer
2	Actions ensuring employee protection and safety	0.7603	1.7374	The retailer's employees
3	Free standard shipping	0.5072	1.9281	Individual consumer's self
4	Hygienic and cautionary measures	0.4716	1.6300	The retailer's employees
5	Actions ensuring the delivery capacity	0.3347	1.6363	All consumers
6	Discounts for orders during the COVID-19 crisis	0.0722	2.5194	Individual consumer's self
7	Financial support of COVID-19 emergency relief	-0.0407	1.7774	Society at large
8	Textile safety masks as free giveaways	-0.2057	2.4778	Individual consumer's self; society at large
9	Actions enabling customers to avoid direct contact with package deliverers	-0.3719	1.8073	Individual consumer's self; suppliers
10	Extension of the validity of coupons / campaign vouchers	-0.5913	1.9351	Individual consumer's self
11	Availability of customer service / contact details	-1.0888	1.7425	All consumers
12	Extension of periods for returning items	-1.2209	2.0105	Individual consumer's self

Moreover, one-way analyses of variance (ANOVA) or two-tailed t-tests for independent groups did not point to statistically significant differences in terms of utility values for almost all of the twelve marketing actions for respondents in terms of age groups, highest education level, occupation status, and respondents' levels of monthly expenses for apparel products usually and during the pandemic ($p<0.01$).

A Tukey's honestly significant difference post-hoc test was conducted for a pair-wise comparison of items used in the MaxDiff tasks (Abdi & Williams, 2010). It revealed that there are significant differences for several item-pairs (50 out of 66 item-pairs = 76%) at $p<0.05$. However, non-significant differences were strongly reported for pair-wise comparisons of the item-combinations 2-3-4-5, or 6-7-8-9, or 11-12 as numbered in Table 5.

6.4.3 Investigating heterogeneous Consumer Preferences: Latent Class Analysis

For a more granular exploration of the HB results, a latent class analysis was utilised to group respondents into segments with similar preferences for marketing actions based on the raw zero-centred utility scores derived from the HB analysis. Compared to other classification approaches, such as cluster analysis, LCA is a model-based approach deriving class membership based on a probabilistic model, assuming 'that the data are generated by a mixture of underlying probability distributions' (Vermunt & Magidson, 2002, p. 90). Deciding on the number of classes is a critical step in LCA. Similar to conventional structural equation modelling, various fit statistics are considered and jointly examined to elaborate on this decision (Nylund-Gibson & Choi, 2018). Table 6 shows different model-fit statistics for a one-class LCA model up to a ten-class solution. These model-fit indices show that the absolute model fit increased gradually with each additional latent class. Accordingly, for ten LCA models starting with a one-class model up to a ten-class model, the local maximum of the Log-likelihood value, the percent certainty, and the Chi-Square statistic were observed for the ten-class solution. If we increased the number of LCA models to 30, the maximum for these fit indices would be at the 30-class solution.

Only the relative Chi-Square, which also takes into account the number of estimated parameters pointed to a two-class model where the value reached a global maximum.

In addition to absolute fit statistics, information criteria can be used as approximate fit indices that are 'weighing between a better model fit from an increasing number of segments and the additional number of parameters to be estimated for more segments' (Paetz et al., 2019, p. 12; also see: Nylund-Gibson & Choi, 2018).

Table 6: Model fit statistics for the LCA with reference to the number of latent classes

Fit statistics / number of classes	Log-likelihood	Percent certainty	Chi-Square	Relative Chi-Square	Smallest class size
1	-10741.36	3.72	831.08	75.55	503
2	-10107.52	9.41	2098.76	**91.25**	238
3	-9892.28	11.33	2529.24	72.26	113

Fit statistics / number of classes	**Log-likeli-hood**	**Percent cer-tainty**	**Chi-Square**	**Relative Chi-Square**	**Smallest class size**
4	-9724.51	12.84	2864.77	60.95	98
5	-9597.49	13.98	3118.80	52.86	79
6	-9502.28	14.83	3309.24	46.61	70
7	-9401.94	15.73	3509.92	42.29	50
8	-9338.30	16.30	3637.20	38.29	48
9	-9257.72	17.02	3798.36	35.50	43
10	**-9202.33**	**17.52**	**3909.13**	32.85	33

We used the criteria that are reported by default by the Analysis Manager of Sawtooth Software's Lighthouse Studio. The closely related Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), consistent Akaike Information Criterion (CAIC), and the adjusted Bayesian Information Criterion (ABIC) all indicate superior model-fit with lower values. All four information criteria deployed pointed to different numbers of latent classes when estimating up to 30 LCA models (Figure 2). Despite the differences in the ideal number of latent classes, the plots shared the commonality that an 'elbow' could be detected in the curves at the two-class solution, indicating that a further increase in the number of latent classes only caused slight improvements in model fit. In practice, this 'elbow'-method is often deployed to identify the ideal number of classes (Masyn, 2013; Nylund-Gibson & Choi, 2018; Orme, 2012).

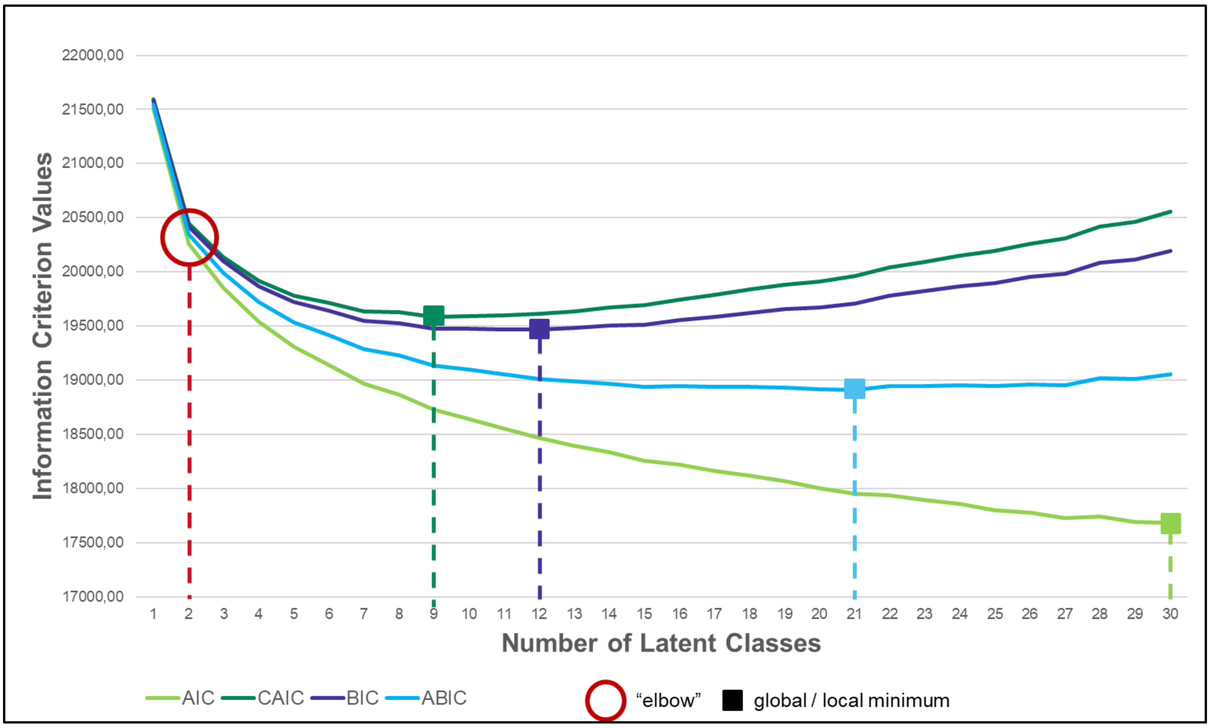

Figure 2: Information criterion values with reference to the number of latent classes

Given the comparatively low marginal gain in model fit beyond a second-class solution, using the two-class LCA model seemed to be appropriate with reference to the statistical fit criteria. These two segments could be clearly distinguished in terms of consumer preferences for online marketing actions. The first latent class (n=238) comprised consumers who particularly valued marketing actions with other-benefits whereas the slightly larger second latent class (n=265) consisted of consumers who especially favoured traditional sales promotion methods solely with self-benefits (Figure 3). Both latent classes significantly differed in terms of mean zero-centred raw utility scores for all marketing actions ($p<0.01$) except for the availability of customer service / contact details.

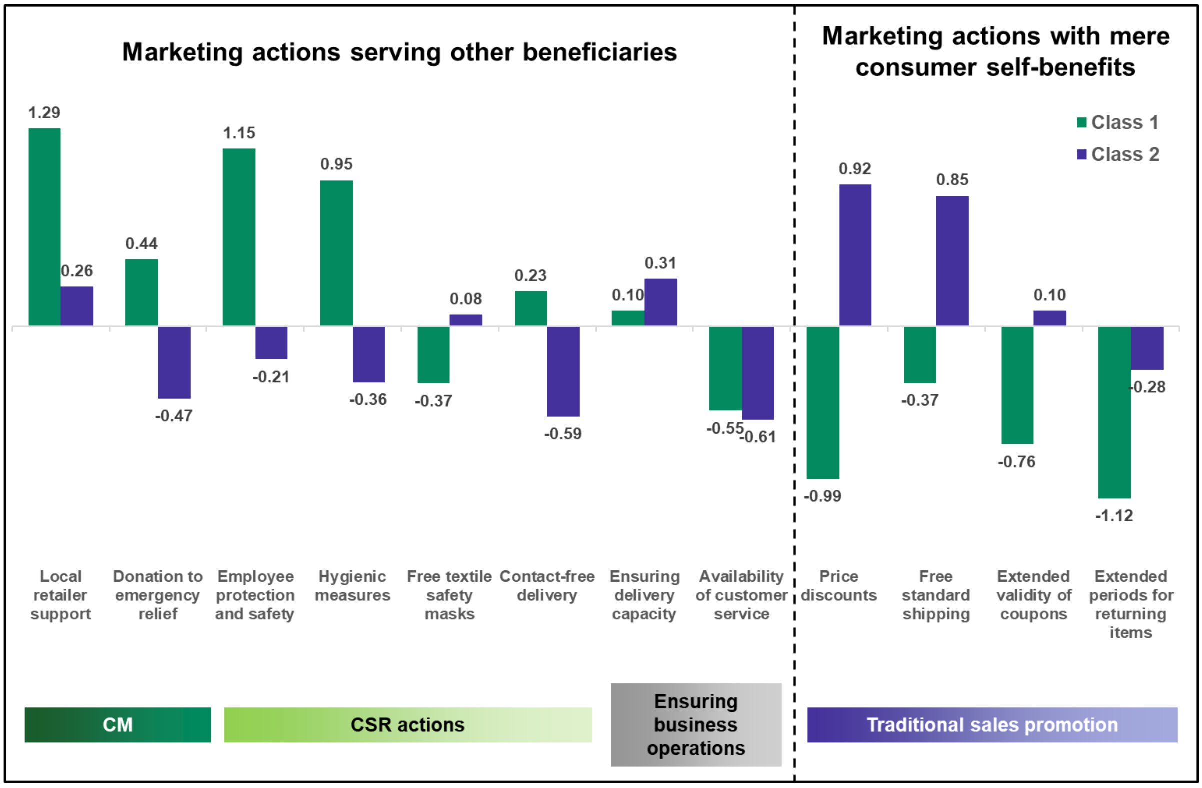

Figure 3: Differences between the two latent classes in terms of mean zero-centred raw utilities

In comparing both segments in terms of demographics only slight differences were apparent. Among consumers focusing on traditional sales promotions there were significantly more males (55.8% versus 45.8%; $p<0.05$) than in the segment of consumers placing greater emphasis on marketing actions serving other beneficiaries. Yet, there were no significant differences regarding age, education, employment status, and state of residence, which made it difficult to describe the composition of both segments.

6.4.4 Finding the ideal Combination of Marketing Actions: TURF Analysis

Since we know little about the differences in descriptive variables or characteristics of both latent classes, it might well be a crucial challenge for retailers to tailor their marketing actions to consumers from either one of the two segments. Therefore, we used TURF (Total Unduplicated Reach and Frequency) analysis to identify possible combinations of marketing actions to reach as many consumers as possible (Kreiger & Green, 2000; Miaoulis et al., 1990). TURF analysis originates from reach and frequency concepts in early media research. It calculates estimates of market potential ‘by counting the number of respondents that would choose one of the items in the portfolio and how many of the items each respondent would choose from the portfolio' (Howell, 2016, p. 1; also see: Miaoulis et al., 1990).

A prerequisite step in TURF analysis for MaxDiff experiments is discretising the data and, thus, defining reach (Howell, 2016). For instance, reach could be defined as the first choice – that is to say, a respondent will only be counted as reach if the item with the highest score personally is contained in the item-bundle (Howell, 2016). Another calculation approach that we applied in our analysis, computes reach weighted by probability – that is to say, the 'probability of each item being chosen as best from a set of typical items like those shown in the MaxDiff questionnaire' – which also considers 'strong second choices' (Howell, 2016, p. 4). Since many of the specified marketing actions involve direct or implicit costs for the retailer, a maximum of three marketing actions in a bundle was chosen. Figure 4 presents the top three item-combinations with the maximum reach of one, two, and three items.

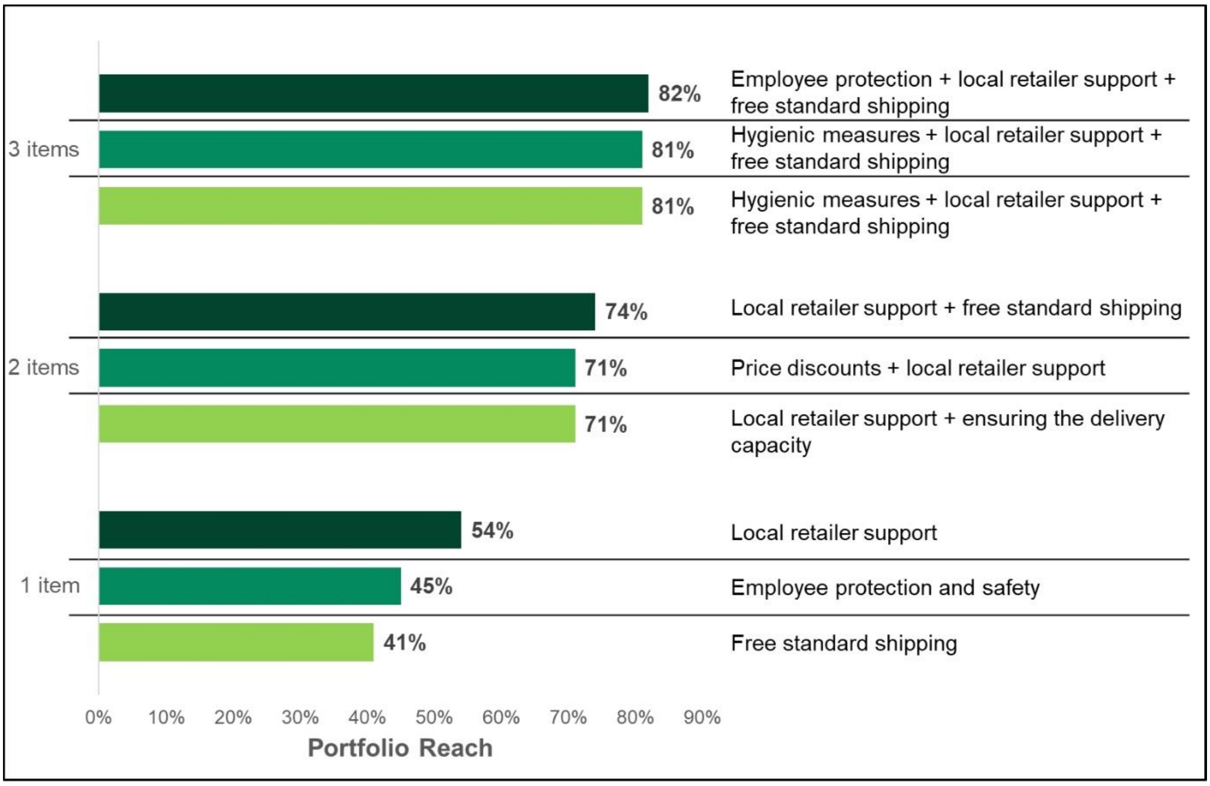

Figure 4: Results of TURF analysis for combinations of one, two, and three marketing actions

As illustrated, the local CRM campaign definitely needs to be included in any portfolio of marketing actions because the support of local retailers alone may already reach more than half of all consumers. Moreover, while a combination of CSR initiatives with traditional sales promotion methods seems to be very promising, the portfolio of actions ensuring delivery capacity and the local CRM campaign could be a potentially more cost-effective alternative that is still able to reach 71% of all consumers.

6.5 Discussion

Following recent calls for an investigation of the pandemic-related effects of different types of marketing actions and CSR practices on consumer responses, our study explores consumer preferences for different types of marketing actions by online apparel retailers during the first wave of the pandemic. In doing so, this research demonstrates in a specific online fashion retailer setting, that during the COVID-19 pandemic, consumers prefer specific marketing actions that include an other-benefit component – e.g. a local CRM campaign – to marketing efforts focused solely on self-benefits such as price discounts and free standard shipping (H1). Yet, contrary to the pre-pandemic literature (e.g. Chéron et al., 2012; Galan Ladero et al., 2015; Moosmayer & Fuljahn, 2010; Vilela & Nelson, 2016), a gender effect – whereby females elicit stronger preferences for marketing campaigns with other-benefit components than males – could not be confirmed (H2).

By drawing on the marketing literature investigating the effects of psychological distance between consumers and beneficiaries of CSR practices, we further show that consumers prefer CSR practices with socially and spatially close beneficiaries to CSR initiatives with socially and spatially distant ones (H3 and H4).

By applying MaxDiff-BWS as the research method and Hierarchical Bayes as the method for data analysis, we obtain subjective individual-level preference estimates allowing us to perform latent class analysis to identify consumer segments with similar preferences. The results of the LCA reveal that consumer preferences for marketing actions during the pandemic are not homogeneous but differ radically between two major consumer segments – those valuing marketing campaigns with other-benefit components and those favouring marketing actions serving consumer self-interests.

Lastly, the results of the TURF analysis reveal promising portfolios of marketing actions for reaching broad audiences. These results offer several important insights and implications for research and practice.

6.6 Contributions to Research

In the first place, our study contributes to pre-pandemic research by showing that certain marketing efforts with other-benefit components can outperform traditional sales promotion methods, such as price discounts, in the context of a global health and economic crisis. Yet, since not all marketing campaigns with other-benefit components are preferred to marketing actions with mere self-benefits for consumers, our research reveals that a more differentiated comparison of marketing actions is required than has been addressed by previous research.

Second, our results suggest that CSR initiatives with socially close beneficiaries (e.g. employees) are preferred over CSR practices with socially distant ones (e.g. society at large). While these findings may well be explained by an increasingly compassionate and empathetic attitude on the part of consumers in the specific setting of COVID-19, it is likely that such preferences will survive beyond the pandemic because social closeness in general may have become more meaningful due to the limited physical interaction experienced during the crisis (Aminnejad & Alikhani, 2020; Bond, 2021; Liu et al., 2020).

Third, our research provides the first valuable insights into consumer preferences based on the spatial distance between consumers and the beneficiaries of CSR initiatives. It shows that CRM campaigns are particularly successful if the campaign supports a local rather than a national cause. While this finding is in line with pre-pandemic research (Grau & Folse, 2007; Hou et al., 2008; Lii et al., 2013; Ross III et al., 1991; Vanhamme et al., 2012), the entirely favourable perception of the local CRM campaign may have also been driven by providing consumers with a degree of co-decision-making regarding the target of the CRM campaign – namely, it enabled them to select their preferred local specialist retailer. This might have been the first step towards customising the supported social cause. Previous research provides clear evidence that providing consumers with choice in CRM campaigns is a beneficial approach for increasing the effectiveness of such marketing efforts (Arora & Henderson, 2007; Christofi et al., 2019; Kull & Heath, 2016; Robinson et al., 2012). Due to an increased consumer awareness of, and a possible shift towards prosocial and responsible consumption in the context of the pandemic, consumer choice in future CRM campaigns may prove to be of even greater importance because it has the potential to satisfy heterogeneous consumer preferences (Christofi et al., 2019; He & Harris, 2020).

Fourth, the identification of two consumer segments with heterogeneous preferences for marketing actions during the pandemic provides some intellectual nourishment for future research in this field. Since the investigated demographic consumer characteristics did not account for significant deviations in consumer preferences, our research suggests that personality traits may well be a major latent factor determining consumer preferences for different types of marketing actions. Several researchers have already examined the impact of personality traits on consumer perceptions of different types of marketing actions. For instance, previous studies in the context of intercultural research indicated that consumers with rather collectivist (as opposed to individualist) orientations tend to have more positive attitudes towards a CRM campaign (Wang, 2014), or that consumers in a rather collectivist society are willing to pay more for a product supporting a prosocial cause (Vaidyanathan et al., 2013). Accordingly, a potentially promising complement to our study could be to examine the impact of personality traits on consumer preferences for different types of marketing actions.

Finally, our study provides some methodological contributions. A seldom applied methodological approach for measuring the importance of different types of marketing actions from a consumer perspective – MaxDiff-BWS – demonstrated its usefulness. Respondents were able to answer the questions posed with few discontinuations in answering the questionnaire, and so quantitative weights of all marketing campaigns at the respondent level could be validly estimated. Utilising LCA has proven to be a valuable approach for forming subgroups with internally homogeneous and externally heterogeneous preferences. Moreover, the opportunity to use TURF analysis in conjunction with MaxDiff enabled us to gain valuable insights into portfolios of marketing actions with maximum reach.

6.7 Managerial Implications

In addition to these theoretical contributions, the findings of this research offer managerial implications for retailers, especially in the apparel industry. Our results clearly emphasise the increased importance of online sales channels for apparel products during the pandemic. While the shift from offline to online sales in apparel retailing has existed as a major trend in recent years, and previous research has proven that omnichannel purchase options, such as ‘click-and-collect’ or instore returns, are attractive to consumers (Baier & Rese, 2020; Rese et al., 2019), the impact of the COVID-19 pandemic would seem to be accelerating this development and breaking purchasing habits of pure offline shoppers by transferring such consumers to online sales channels (McKinsey & Company, 2020a, 2020b). Although this rising trend of ecommerce may not be sustained across all industries and for all consumer groups in a post-COVID era when physical stores could once again operate without any pandemic-related constraints, remaining competitive in a digital landscape that is increasingly dominated by a few, large ecommerce players will be a major challenge for apparel retailers, especially those that have placed little emphasis on online sales channels in the past (OECD, 2020; Roggeveen & Sethuraman, 2020). In this regard, the results of our MaxDiff experiment provide valuable insights for apparel retailers.

Firstly, our results show that marketing campaigns with other-benefits can be very promising, so long as these efforts are directed to beneficiaries that key audiences consider apposite. In addition to selecting relevant beneficiaries, companies should thoroughly reflect on the effective public communication of such marketing actions and consider key issues, such as the message content, the message channel, and company-specific factors (e.g. corporate reputation) ‘to overcome stakeholder skepticism and to generate favorable CSR attributions’ (Du et al., 2010, p. 17). Recent research has shown that social media channels might prove helpful in effectively communicating CSR campaigns and that CSR messages should be congruently communicated to internal and external stakeholders to avoid confusing brand communications and potential negative impacts on brand perception (Carlini et al., 2019; Carlini & Grace, 2021; Dunn & Harness, 2018).

Secondly, it could prove worthwhile to deploy differing marketing strategies for different consumer segments, because heterogeneous consumer preferences for marketing actions might not be limited to the COVID context or to apparel retailing. Indeed, He and Harris (2020) argue that the pandemic might increasingly spur the growth of two disparate types of consumer group. On the one hand, consumers engaging in responsible and prosocial behaviours due to an increased consciousness on the connectedness of one's brand choice with one's self-concept; on the other, consumers focusing on hedonic gratification in order to instantly satisfy emotional and sensory needs as a reaction to the distress and harm caused by the pandemic (He & Harris, 2020). The results of the TURF analysis show that by combining at least two online marketing actions, the vast majority of consumers of both segments can still be reached. A possible approach to combining marketing actions that both consumer segments find appealing without incurring additional costs might be to allow consumers to decide on one specific perk – for instance, either a personal benefit such as a price discount or supporting a selectable local specialist retailer.

Thirdly, the strongest preference overall for the CRM campaign which allowed consumers to choose a specific local specialist retailer confirms that, when designing CRM campaigns, retailers should consider providing consumers with some degree of co-deciding on the target cause (as operationalised in our study through the local CRM campaign). This could help in overcoming existing difficulty faced by CRM campaigns in trying to identify a particular social cause capable of reaching the widest possible audience. Nevertheless, other aspects such as consumer characteristics, company-cause characteristics, and characteristics of the CRM campaign need to be considered when selecting possible social causes (Lafferty et al., 2016).

6.8 Limitations and future Research

The findings of this study are subject to certain limitations that should be addressed in future research.

Firstly, since the sample was extracted from a German online panel, the results of this study are only representative of German consumers and cannot automatically be generalised to other countries or cultures. Given that cultural dimensions, particularly those related to individualistic versus collectivistic orientations, exert a clear impact on consumer responses to CSR initiatives as suggested by prior research (Robinson et al., 2012; Wang, 2014), future studies should investigate consumer preferences for various online marketing actions in different cultures – for example, Western versus Asian countries.

Secondly, the special setting during the COVID-19 pandemic may have influenced consumer preferences for online marketing actions. Hence, a replication of our study in a setting ‘after’ the pandemic - for example, when distancing rules and the mandatory wearing of masks in brick-and-mortar stores are no longer required, and when CSR initiatives that specifically address measures coping with the pandemic are no longer deployed – could yield different results and, therefore, might offer additional insights.

Lastly, the use of MaxDiff as a method for collecting consumer preferences for different online marketing actions might be another limitation of this study, because of the so-called ‘attitude-behaviour gap’ identified in previous studies – in particular, in the field of sustainable and green consumption (ElHaffar et al., 2020; Park & Lin, 2020). This discrepancy between consumers’ (purchase) intentions and their actual (purchasing) behaviour might have impacted the results of our study. Yet, previous research has demonstrated that CSR initiatives – especially CRM campaigns – not only exert a positive impact on consumers’ attitudes but can also lead to increased real-world product sales and revenues (Andrews et al., 2014) and can strengthen a company’s profitability (Ballings et al., 2018). This suggests that the attitude-behaviour gap in CSR initiatives may not be nearly as wide as between consumer attitudes and their purchase behaviour concerning sustainable products. Nevertheless, future research should address this potential attitude-behaviour gap to augment the CSR literature.

6.9 Conclusion

The fight against the spread of the COVID-19 virus has fundamentally changed interpersonal lives, consumer behaviour, and business practices. In this article, we have offered guidance for online (apparel) retailers concerning which marketing actions to concentrate on during these unprecedented times to attract consumers to their online sales channels so that their economic survival is assured. Since it is likely that pandemic-related consumer behaviours such as increased online shopping activities will persist, the results of our study offers insights for research and practice beyond the pandemic. The deployment of CSR practices has proven to be a successful strategy to convince and encourage consumers to continue ordering products from a retailer’s online store – especially when targeting socially close and spatially close beneficiaries.

Finally, we hope that the results of our study will encourage further research on consumer responses to marketing actions with different beneficiaries.

Appendix A: Questioning process of the MaxDiff tasks

After completing the questions on the purchase frequency and expenses for apparel products in usual circumstances and since the beginning of the COVID-19 pandemic, a brief introductory text on the objective and procedure of the subsequent MaxDiff-BWS tasks was presented:

> In den folgenden Fragen werden Ihnen jeweils vier verschiedene Maßnahmen von Online-Händlern für Bekleidung als Reaktion auf die *Corona-Krise* dargestellt.
>
> Aufgrund der aktuell schwierigen Situation, müssen sich Online-Händler eventuell auf die Umsetzung von wenigen Maßnahmen beschränken. Deshalb ist es enorm wichtig, herauszufinden, welche Maßnahmen aus Kundensicht am wichtigsten sind.
>
> Bitte entscheiden Sie für jede der folgenden Fragen aufs Neue, womit Sie ein **Online-Händler für <u>Bekleidung</u>** in der derzeitigen *Krisen-Situation* **<u>am stärksten</u>** bzw. **<u>am wenigsten</u>** davon überzeugen und dazu ermutigen kann, weiterhin Produkte in seinem Online-Shop zu bestellen.
>
> Bitte lassen Sie sich nicht davon verunsichern, dass sich die dargestellten Maßnahmen in den einzelnen Fragen teilweise wiederholen.

This is the English translation of the introductory text for completing the MaxDiff tasks:

In each of the following questions, four different actions taken by online apparel retailers in response to the COVID-19 crisis are presented.

Due to the current difficult situation, online retailers might be restricted to the implementation of only a few measures. Therefore, it is extremely important to identify the most important measures from a customer's point of view.

*For each of the following tasks, please decide anew with which measures an **online apparel retailer** can **<u>most</u>** or **<u>least</u>** convince and encourage you to continue ordering products from its online store in the current crisis.*

Please note that some of the actions presented are repeated throughout the following questions.

Appendix B: Exemplarily MaxDiff task

MaxDiff task in German:

Bitte wählen Sie **jeweils eine Maßnahme** eines Online-Händlers für Bekleidung, die Sie in der derzeitigen Krisen-Situation **am wichtigsten** (👍) bzw. **am wenigsten wichtig** (👎) finden!

(6 of 9)

	👍	👎
Maßnahmen zur Unterstützung von lokalen Fachhändlern: z.B. *Mit jeder Bestellung im Online-Shop können Sie einen beliebigen Händler aus Ihrer Region unterstützen: Wir geben 25% des Einkaufswerts bei Erstbestellungen direkt an einen lokalen Fachhändler Ihrer Wahl weiter, der in der Corona-Krise seine Ladentüren geschlossen halten muss.*	○	○
Textiler Gesichtsschutz als Gratis-Zugabe: z.B. *"Um der Verbreitung des Coronavirus entgegenzuwirken und zum Schutz Ihrer Gesundheit, erhalten Sie für eine Bestellung bis zum 04.05.2020 eine modische textile Behelfsmaske als kostenlose Beilage."*	○	○
Hygiene- und Vorsichtsmaßnahmen seitens des Unternehmens: z.B. *Alle unsere Mitarbeiter und Servicepartner werden umfassend und permanent über die aktuellsten, offiziellen Hygiene- und Vorsichtsmaßnahmen geschult. Die Einhaltung der Maßnahmen kontrollieren wir täglich.*	○	○
Erreichbarkeit des Kundenservice / Kontaktmöglichkeiten: z.B. *Trotz der aktuell schwierigen Situation, stellen wir sicher, dass unser Kundenservice für Sie wie gewohnt telefonisch unter 0123456789, per Email unter kundenservice@xyz.de und per Live-Chat erreichbar ist.*	○	○

Weiter

Kontakt

English translation of the illustrated MaxDiff task:

From the following measures taken by an online apparel retailer during the current crisis, please select **one measure** that you consider **most important** and one that you consider **least important**!		
	Most important	**Least important**
Support of local specialist retailers: e.g., *with each order in our online shop, you can support a regional dealer: We pass on 25% of the purchase value of first-time orders directly to a local specialist retailer of your choice, who has to keep its doors closed during the COVID-19 crisis.*		
Textile safety masks as free giveaways: e.g., *to counteract the spread of COVID-19 and to protect your health, you will receive a fashionable textile cloth face mask as a free giveaway with your first order until the 4th of May 2020.*		
Hygienic and cautionary measures: e.g., *all our employees and service partners receive comprehensive and ongoing training on the latest official hygiene and precautionary measures. We monitor compliance with these measures on a daily basis.*		
Availability of customer service/contact details: *e.g. despite the current difficult situation, we ensure availability of our customer service as usual by phone, email, and via live chat.*		

References

Abdi, H., & Williams, L. J. (2010). Honestly Significant Difference (HSD) test. In N. J. Salkind (Ed.), Encyclopedia of research design (pp. 583–585). Sage.

Abu Zayyad, H. M., Obeidat, Z. M., Alshurideh, M. T., Abuhashesh, M., Maqableh, M., & Masa'deh, R. (2020). Corporate social responsibility and patronage intentions: The mediating effect of brand credibility. Journal of Marketing Communications, 27(5), 510–533. https://doi:10.1080/13527266.2020.1728565

Adamsen, J. M., Rundle-Thiele, S., & Whitty, J. A. (2013). Best-Worst scaling…reflections on presentation, analysis, and lessons learnt from case 3 BWS experiments. Market & Social Research, 21(1), 9–27. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.976.2866& rep=rep1&type=pdf

Agudelo, M. A. L., Jóhannsdóttir, L., & Davídsdóttir, B. (2019). A literature review of the history and evolution of corporate social responsibility. International Journal of Corporate Social Responsibility, 4(1), 1–23. https://doi:10.1186/s40991-018-0039-y

Ailawadi, K. L., Neslin, S. A., Luan, Y. J., & Taylor, G. A. (2014). Does retailer CSR enhance behavioral loyalty? A case for benefit segmentation. International Journal of Research in Marketing, 31(2), 156–167. https://doi:10.1016/j.ijresmar.2013.09.003

Alon, T., Doepke, M., Olmstead-Rumsey, J., & Tertilt, M. (2020). The Impact of COVID-19 on Gender Equality. https://www.nber.org/papers/w26947

Aminnejad, R., & Alikhani, R. (2020). Physical distancing or social distancing: that is the question. Canadian journal of anaesthesia, 67(10), 1457–1458. https://doi:10.1007/s12630-020-01697-2

Andrews, M., Luo, X., Fang, Z., & Aspara, J. (2014). Cause Marketing Effectiveness and the Moderating Role of Price Discounts. Journal of Marketing, 78(6), 120–142. https://doi:10.1509/jm.14.0003

Arora, N., & Henderson, T. (2007). Embedded Premium Promotion: Why It Works and How to Make It More Effective. Marketing Science, 26(4), 514–531. https://doi:10.1287/mksc.1060.0247

Auger, P., Devinney, T. M., & Louviere, J. J. (2007). Using Best–Worst Scaling Methodology to Investigate Consumer Ethical Beliefs Across Countries. Journal of Business Ethics, 70(3), 299–326. https://doi:10.1007/s10551-006-9112-7

Bae, K.-H., El Ghoul, S., Gong, Z., & Guedhami, O. (2021). Does CSR matter in times of crisis? Evidence from the COVID-19 pandemic. Journal of Corporate Finance, 67(3), 1–18. https://doi:10.1016/j.jcorpfin.2020.101876

Baier, D., & Rese, A. (2020). How to increase multichannel shopping satisfaction? An adapted Kano based stage-gate approach to select new technologies. Journal of Retailing and Consumer Services, 56, 102172. https://doi:10.1016/j.jretconser.2020.102172

Ballings, M., McCullough, H., & Bharadwaj, N. (2018). Cause marketing and customer profitability. Journal of the Academy of Marketing Science, 46(2), 234–251. https://doi:10.1007/s11747-017-0571-4

Bhattacharya, C. B., Korschun, D., & Sen, S. (2009). Strengthening Stakeholder–Company Relationships Through Mutually Beneficial Corporate Social Responsibility Initiatives. Journal of Business Ethics, 85(2), 257–272. https://doi:10.1007/s10551-008-9730-3

Bond, B. J. (2021). Social and parasocial relationships during COVID-19 social distancing. Journal of Social and Personal Relationships, 38(8), 2308–2329. https://doi:10.1177/02654075211019129

Buchholz, K. (2021, July 23). COVID-19 Second Wave: Europe Stays in Lockdown Mode. Statista. https://www.statista.com/chart/23330/coronavirus-restrictions-europe-map/

Carlini, J., & Grace, D. (2021). The corporate social responsibility (CSR) internal branding model: aligning employees' CSR awareness, knowledge, and experience to deliver positive employee performance outcomes. Journal of Marketing Management, 37(7-8), 732–760. https://doi:10.1080/0267257X.2020.1860113

Carlini, J., Grace, D., France, C., & Lo Iacono, J. (2019). The corporate social responsibility (CSR) employer brand process: integrative review and comprehensive model. Journal of Marketing Management, 35(1-2), 182–205. https://doi:10.1080/0267257X.2019.1569549

Carroll, A. B. (1979). A Three-Dimensional Conceptual Model of Corporate Performance. Academy of Management Review, 4(4), 497–505. https://doi:10.5465/amr.1979.4498296

Carroll, A. B. (1999). Corporate Social Responsibility: Evolution of a Definitional Construct. Business & Society, 38(3), 268–295. https://doi:10.1177/000765039903800303

Carroll, A. B., & Shabana, K. M. (2010). The Business Case for Corporate Social Responsibility: A Review of Concepts, Research and Practice. International Journal of Management Reviews, 12(1), 85–105. https://doi:10.1111/j.1468-2370.2009.00275.x

Chaney, I., & Dolli, N. (2001). Cause related marketing in New Zealand. International Journal of Nonprofit and Voluntary Sector Marketing, 6(2), 156–163. https://doi:10.1002/nvsm.143

Chéron, E., Kohlbacher, F., & Kusuma, K. (2012). The effects of brand-cause fit and campaign duration on consumer perception of cause-related marketing in Japan. Journal of Consumer Marketing, 29(5), 357–368. https://doi:10.1108/07363761211247479

Christofi, M., Vrontis, D., Leonidou, E., & Thrassou, A. (2019). Customer engagement through choice in cause-related marketing: A potential for global competitiveness. International Marketing Review, 37(4), 621-650. https://doi:10.1108/IMR-04-2018-0133

Cohen, E. (2009). Applying best-worst scaling to wine marketing. International Journal of Wine Business Research, 21(1), 8–23. https://doi:10.1108/17511060910948008

Cohen, S. & Neira, L. (2003). Measuring Preference For Product Benefits Across Countries: Overcoming scale usage bias with Maximum Difference Scaling. https://www.warc.com/fulltext/ESOMAR/79133.htm

Cohen, S. H. (2003). Maximum Difference Scaling: Improved Measures of Importance and Preference for Segmentation. https://sawtoothsoftware.com/resources/technical-papers/maximum-difference-scaling-improved-measures-of-importance-and-preference-for--segmentation

Commission of the European Communities (2001, July 18). Promoting a European Framework for Corporate Social Responsibility. https://ec.europa.eu/transparency/regdoc/rep/1/2001/EN/1-2001-366-EN-1-0.Pdf

Crane, A., & Matten, D. (2021). COVID-19 and the Future of CSR Research. Journal of Management Studies, 58(1), 280–284. https://doi:10.1111/joms.12642

Cui, Y., Trent, E. S., Sullivan, P. M., & Matiru, G. N. (2003). Cause-related marketing: how generation Y responds. International Journal of Retail & Distribution Management, 31(6), 310–320. https://doi:10.1108/09590550310476012

Dahlsrud, A. (2008). How corporate social responsibility is defined: an analysis of 37 definitions. Corporate Social Responsibility and Environmental Management, 15(1), 1–13. https://doi:10.1002/csr.132

Del Boca, D., Oggero, N., Profeta, P., & Rossi, M. (2020). Women's and men's work, housework and childcare, before and during COVID-19. Review of economics of the household, 18(4), 1001–1017. https://doi:10.1007/s11150-020-09502-1

DiResta, A. E., Williford, K. T., Cohen, D. A., & Genn, B. A. (2020). The impact of COVID-19 on your advertising and marketing campaigns: Strategic Questions Companies May Face, Regulatory Issues Companies Must Address and Governmental Agency Interests of Note. https://www.pandcglobal.com/wp-content/uploads/2020/11/042020-impactcovid19-on-advertising-marketing.pdf

Du, S., Bhattacharya, C. B., & Sen, S. (2007). Reaping relational rewards from corporate social responsibility: The role of competitive positioning. International Journal of Research in Marketing, 24(3), 224–241. https://doi:10.1016/j.ijresmar.2007.01.001

Du, S., Bhattacharya, C. B., & Sen, S. (2010). Maximizing Business Returns to Corporate Social Responsibility (CSR): The Role of CSR Communication. International Journal of Management Reviews, 12(1), 8–19. https://doi:10.1111/j.1468-2370.2009.00276.x

Du, S., Bhattacharya, C. B., & Sen, S. (2011). Corporate Social Responsibility and Competitive Advantage: Overcoming the Trust Barrier. Management Science, 57(9), 1528–1545. https://doi:10.1287/mnsc.1110.1403

Dunn, K., & Harness, D. (2018). Communicating corporate social responsibility in a social world: the effects of company-generated and user-generated social media content on CSR attributions and scepticism. Journal of Marketing Management, 34(17-18), 1503–1529. https://doi:10.1080/0267257X.2018.1536675 e Silva, S. C., Duarte, P., Machado, J. C., & Martins, C. (2020). Cause-related marketing in online environment: the role of brand-cause fit, perceived value, and trust. International Review on Public and Nonprofit Marketing, 17(2), 135–157. https://doi:10.1007/s12208-019-00237-z

Edelman (2020). Edelman Trust Barometer 2020: Special Report: Brand Trust and the Coronavirus Pandemic. https://www.edelman.de/sites/g/files/aatuss401/files/2020-04/Edelman%20Trust%20Barometer%20Special%20Report%20-%20Brand%20Trust%20and%20the%20Coronavirus%20Pandemic.pdf

Edelman (2021). Global Trust Barometer 2021. https://www.edelman.com/sites/g/files/aatuss191/files/2021-03/2021%20Edelman%20Trust%20Barometer.pdf

EHI Retail Institute (2019). Top 100 umsatzstärkste Onlineshops in Deutschland. Retrieved August 22, 2020, from https://www.ehi.org/de/top-100-umsatzstaerkste-onlineshops-in-deutschland/.

ElHaffar, G., Durif, F., & Dubé, L. (2020). Towards closing the attitude-intention-behavior gap in green consumption: A narrative review of the literature and an overview of future research directions. Journal of Cleaner Production, 275, 1–20. https://doi:10.1016/j.jclepro.2020.122556

Finn, A., & Louviere, J. J. (1992). Determining the Appropriate Response to Evidence of Public Concern: The Case of Food Safety. Journal of Public Policy & Marketing, 11(2), 12–25. https://doi:10.1177/074391569201100202

Finsterwalder, J. (2021). Social distancing and wellbeing: conceptualizing actor distance and actor safe zone for pandemics. The Service Industries Journal, 41(1-2), 9–31. https://doi:10.1080/02642069.2020.1841753

Fisher, R. J., Vandenbosch, M., & Antia, K. D. (2008). An Empathy-Helping Perspective on Consumers' Responses to Fund-Raising Appeals. Journal of Consumer Research, 35(3), 519–531. https://doi:10.1086/586909

Flynn, T. N. (2010). Valuing citizen and patient preferences in health: recent developments in three types of best–worst scaling. Expert Review of Pharmacoeconomics & Outcomes Research, 10(3), 259–267. https://doi:10.1586/erp.10.29

Flynn, T. N., & Marley, A. (2014). Best-worst scaling: theory and methods. In S. Hess & A. Daly (Eds.), Handbook of Choice Modelling (pp. 178–201). Edward Elgar Publishing Limited; Edward Elgar Publishing, Inc.

Furlan, R., & Turner, G. (2014). Maximum difference scaling: Exploring the impact of design elements on results. International Journal of Market Research, 56(3), 367–385. https://doi:10.2501/IJMR-2014-024

Galan Ladero, M. M., Galera Casquet, C., & Singh, J. (2015). Understanding factors influencing consumer attitudes toward cause-related marketing. International Journal of Nonprofit and Voluntary Sector Marketing, 20(1), 52–70. https://doi:10.1002/nvsm.1517

Gao, Y., Wu, L., Shin, J., & Mattila, A. S. (2020). Visual Design, Message Content, and Benefit Type: The Case of A Cause-Related Marketing Campaign. Journal of Hospitality & Tourism Research, 44(5), 761–779. https://doi:10.1177/1096348020911444

García-Sánchez, I.-M., & García-Sánchez, A. (2020). Corporate Social Responsibility during COVID-19 Pandemic. Journal of Open Innovation: Technology, Market, and Complexity, 6(4), 1–21. https://doi:10.3390/joitmc6040126

Giacomini, D., Martini, M., Sancino, A., Zola, P., & Cavenago, D. (2021). Corporate social responsibility actions and organizational legitimacy at the peak of COVID-19: a sentiment analysis. Corporate Governance: The International Journal of Business in Society, 21(6), 1043–1058. https://doi:10.1108/CG-09-2020-0389

Grau, S. L., & Folse, J. A. G. (2007). Cause-Related Marketing (CRM): The Influence of Donation Proximity and Message-Framing Cues on the Less-Involved Consumer. Journal of Advertising, 36(4), 19–33. https://doi:10.2753/JOA0091-3367360402

Hameed, I., Riaz, Z., Arain, G. A., & Farooq, O. (2016). How Do Internal and External CSR Affect Employees' Organizational Identification? A Perspective from the Group Engagement Model. Frontiers in Psychology, 7, 1–13. https://doi:10.3389/fpsyg.2016.00788

Hamlin, R. P., & Wilson, T. (2004). The Impact of Cause Branding on Consumer Reactions to Products: Does Product/Cause 'Fit' Really Matter? Journal of Marketing Management, 20(7-8), 663–681. https://doi:10.1362/0267257041838746

Handelsverband Deutschland (HDE) (2021, July 6). Online Monitor 2019. https://einzelhandel.de/images/publikationen/Online_Monitor_2019_HDE.pdf

Havas Group (2021). Havas' Meaningful Brands report 2021 finds we are entering the age of cynicism. https://www.havasgroup.com/press_release/havas-meaningful-brands-report-2021-finds-we-are-entering-the-age-of-cynicism/

He, H., & Harris, L. (2020). The impact of Covid-19 pandemic on corporate social responsibility and marketing philosophy. Journal of Business Research, 116, 176–182. https://doi:10.1016/j.jbusres.2020.05.030

Henderson, T., & Arora, N. (2010). Promoting Brands across Categories with a Social Cause: Implementing Effective Embedded Premium Programs. Journal of Marketing, 74(6), 41–60. https://doi:10.1509/jmkg.74.6.41

Hirsch, C. & Furlong, A. (2021, October 26). The next coronavirus wave in Europe. https://www.politico.eu/article/europe-next-coronavirus-wave/

Hollebeek, L. D., Smith, D. L., Kasabov, E., Hammedi, W., Warlow, A., & Clark, M. K. (2021). Customer brand engagement during service lockdown. Journal of Services Marketing, 35(2), 201–209. https://doi:10.1108/JSM-05-2020-0199

Hou, J., Du, L., & Li, J. (2008). Cause's attributes influencing consumer's purchasing intention: empirical evidence from China. Asia Pacific Journal of Marketing and Logistics, 20(4), 363–380. https://doi:10.1108/13555850810909704

Howell, J. (2016). A simple introduction to TURF analysis. Orem, UT, US. https://sawtoothsoftware.com/resources/technical-papers/a-simple-introduction-to-turf-analysis

Huang, H., & Liu, S. Q. (2020). “Donate to help combat COVID-19!” How typeface affects the effectiveness of CSR marketing? International Journal of Contemporary Hospitality Management, 32(10), 3315–3333. https://doi:10.1108/IJCHM-05-2020-0462

Huang, L., Tan, C.-H., Ke, W., & Wei, K. (2018). Helpfulness of Online Review Content: The Moderating Effects of Temporal and Social Cues. Journal of the Association for Information Systems, 19(06), 503–522. https://doi:10.17705/1jais.00499

Hur, W.-M., Kim, H., & Woo, J. (2014). How CSR Leads to Corporate Brand Equity: Mediating Mechanisms of Corporate Brand Credibility and Reputation. Journal of Business Ethics, 125(1), 75–86. https://doi:10.1007/s10551-013-1910-0

Hyllegard, K. H., Yan, R.-N., Ogle, J. P., & Attmann, J. (2010). The influence of gender, social cause, charitable support, and message appeal on Gen Y's responses to cause-related marketing. Journal of Marketing Management, 27(1-2), 100–123. https://doi:10.1080/02672571003683755

Iglesias, O., Markovic, S., Bagherzadeh, M., & Singh, J. J. (2020). Co-creation: A Key Link Between Corporate Social Responsibility, Customer Trust, and Customer Loyalty. Journal of Business Ethics, 163(1), 151–166. https://doi:10.1007/s10551-018-4015-y

Internet World (2020, April 17). Corona-Virus: Das müssen Händler wissen. https://www.internetworld.de/digitaler-handel/online-handel/corona-virus-haendler-wissen-2515287.html

Itani, O. S., & Hollebeek, L. D. (2021). Consumers' health-locus-of-control and social distancing in pandemic-based e-tailing services. Journal of Services Marketing, 1–19. Advance online publication. https://doi:10.1108/JSM-10-2020-0410

Johns Hopkins Medicine (2020, July 15). Coronavirus, Social and Physical Distancing and Self-Quarantine. https://www.hopkinsmedicine.org/health/conditions-and-diseases/coronavirus/coronavirus-social-distancing-and-self-quarantine

Kim, K., Cheong, Y., & Lim, J. S. (2015). Choosing the right message for the right cause in social cause advertising: type of social cause message, perceived company–cause fit and the persuasiveness of communication. International Journal of Advertising, 34(3), 473–494. https://doi:10.1080/02650487.2015.1006081

Kim, K., Zhang, M., & Li, X. (2008). Effects of Temporal and Social Distance on Consumer Evaluations. Journal of Consumer Research, 35(4), 706–713. https://doi:10.1086/592131

Kim, M. S., Kim, D. T., & Kim, J. I. (2014). CSR for Sustainable Development: CSR Beneficiary Positioning and Impression Management Motivation. Corporate Social Responsibility and Environmental Management, 21(1), 14–27. https://doi:10.1002/csr.1300

Koschate-Fischer, N., Stefan, I. V., & Hoyer, W. D. (2012). Willingness to Pay for

Cause-Related Marketing: The Impact of Donation Amount and Moderating Effects. Journal of Marketing Research, 49(6), 910–927. https://doi:10.1509/jmr.10.0511

Kotler, P., & Lee, N. (2005). Corporate social responsibility: Doing the most good for your company and your cause. John Wiley & Sons, Inc.

Kreiger, A. M., & Green, P. E. (2000). TURF Revisited: Enhancements to Total Unduplicated Reach and Frequency Analysis. Marketing Research, 12(4), 30–36. https://web.s.ebscohost.com/ehost/ pdfviewer/pdfviewer?vid=0&sid=3031934b-21d0-4f69-9cd5-c73616a45a44%40redis

Kropp, F., Holden, S. J. S., & Lavack, A. M. (1999). Cause-related marketing and values in Australia. International Journal of Nonprofit and Voluntary Sector Marketing, 4(1), 69–80. https://doi:10.1002/nvsm.57

Kull, A. J., & Heath, T. B. (2016). You decide, we donate: Strengthening consumer–brand relationships through digitally co-created social responsibility. International Journal of Research in Marketing, 33(1), 78–92. https://doi:10.1016/j.ijresmar.2015.04.005

Lafferty, B. A., Lueth, A. K., & McCafferty, R. (2016). An Evolutionary Process Model of Cause-Related Marketing and Systematic Review of the Empirical Literature. Psychology & marketing, 33(11), 951–970. https://doi:10.1002/mar.20930

Lee, J. A., Soutar, G. N., & Louviere, J. (2007). Measuring values using best-worst scaling: The LOV example. Psychology and Marketing, 24(12), 1043–1058. https://doi:10.1002/mar.20197

Lee, M.-D. P. (2008). A review of the theories of corporate social responsibility: Its evolutionary path and the road ahead. International Journal of Management Reviews, 10(1), 53–73. https://doi:10.1111/j.1468-2370.2007.00226.x

Lii, Y.-S., Wu, K.-W., & Ding, M.-C. (2013). Doing Good Does Good? Sustainable Marketing of CSR and Consumer Evaluations. Corporate Social Responsibility and Environmental Management, 20(1), 15–28. https://doi:10.1002/csr.294

Liu, F., Meng, L., Zhao, Y., & Duan, S. (2020). The influence of the corporate social responsibility disclosures on consumer brand attitudes under the impact of COVID-19. Frontiers of Business Research in China, 14(1), 1-22. https://doi:10.1186/s11782-020-00096-0

Louviere, J. J., Flynn, T. N., & Marley, A. A. J. (2015). Best-worst scaling: Theory, methods and applications. Cambridge University Press.

Louviere, J. J., & Hensher, D. A. (1982). On the design and analysis of simulated choice or allocation experiments in travel choice modelling. Transportation research record 890, 11–17. https://trid. trb.org/view/189334

Louviere, J. J., & Woodworth, G. G. (1983). Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data. Journal of Marketing Research, 20(4), 350–367. https://doi:10.1177/002224378302000403

Louviere, J. J., & Woodworth, G. G. (1990). Best-Worst Scaling: A Model for Largest Difference Judgments. Working Paper, University of Alberta.

Maignan, I. (2001). Consumers' Perceptions of Corporate Social Responsibilities: A Cross-Cultural Comparison. Journal of Business Ethics, 30(1), 57–72. https://doi:10.1023/A:1006433928640

Malik, M. (2015). Value-Enhancing Capabilities of CSR: A Brief Review of Contemporary Literature. Journal of Business Ethics, 127(2), 419–438. https://doi:10.1007/s10551-014-2051-9

Manuel, T., & Herron, T. L. (2020). An ethical perspective of business CSR and the COVID-19 pandemic. Society and Business Review, 15(3), 235–253. https://doi:10.1108/SBR-06-2020-0086

Mao, Y., He, J., Morrison, A. M., & Andres Coca-Stefaniak, J. (2020). Effects of tourism CSR on employee psychological capital in the COVID-19 crisis: from the perspective of conservation of resources theory. Current Issues in Tourism, 24(19), 2716–2734. https://doi:10.1080/13683500.2020.1770706

Marquina Feldman, P., & Vasquez-Parraga, A. Z. (2013). Consumer social responses to CSR initiatives versus corporate abilities. Journal of Consumer Marketing, 30(2), 100–111. https://doi:10.1108/07363761311304915

Masyn, K. E. (2013). Latent class analysis and finite mixture modeling. In T. D. Little (Ed.), Oxford library of psychology. The Oxford handbook of quantitative methods: Statistical analysis, Vol. 2 (pp. 551–611). Oxford University Press.

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behavior. In P. Zarembka (Ed.), Economic theory and mathematical economics. Frontiers in econometrics (pp. 105–142). Academic Press.

McKinsey & Company (2020a). Perspectives on retail and consumer goods. https://www.mckinsey.com/~/media/McKinsey/Industries/Retail/Our%20Insights/Perspectives%20on%20retail%20and%20consumer%20goods%20Number%208/Perspectives-on-Retail-and-Consumer-Goods_Issue-8.pdf

McKinsey & Company (May 2020b). Consumer sentiment on sustainability and fashion in the COVID crisis. https://www.mckinsey.de/~/media/McKinsey/Locations/Europe%20and%20Middle%20East/Deutschland/Publikationen/2020-06-03%20Covid-19%20Sustainability%20in%20Fashion/COVID19%20Sustainability%20Apparel%20Consumer%20Survey%20Germany.pdf

Miaoulis, G., Free, V., & Parsons, H. (1990). Turf: A New Planning Approach for Product Line Extensions. Marketing Research, 2(1), 28–40. http://search.ebscohost.com/login.aspx?direct=true&db= buh&AN=7665661&site=ehost-live

Mishra, S., & Modi, S. B. (2016). Corporate Social Responsibility and Shareholder Wealth: The Role of Marketing Capability. Journal of Marketing, 80(1), 26–46. https://doi:10.1509/jm.15.0013

Mohr, L. A., & Webb, D. J. (2005). The effects of corporate social responsibility and price on consumer responses. Journal of Consumer Affairs, 39(1), 121–147. https://doi:10.1111/j.1745-6606.2005.00006.x

Moosmayer, D. C., & Fuljahn, A. (2010). Consumer perceptions of cause related marketing campaigns. Journal of Consumer Marketing, 27(6), 543–549. https://doi:10.1108/07363761011078280

Mühlbacher, A. C., Kaczynski, A., Zweifel, P., & Johnson, F. R. (2016). Experimental measurement of preferences in health and healthcare using best-worst scaling: an overview. Health economics review, 6(1), 2. https://doi:10.1186/s13561-015-0079-x

Myers, B., & Kwon, W.-S. (2013). A model of antecedents of consumers' post brand attitude upon exposure to a cause-brand alliance. International Journal of Nonprofit and Voluntary Sector Marketing, 18(2), 73–89. https://doi:10.1002/nvsm.1439

Nan, X., & Heo, K. (2007). Consumer Responses to Corporate Social Responsibility (CSR) Initiatives: Examining the Role of Brand-Cause Fit in Cause-Related Marketing. Journal of Advertising, 36(2), 63–74. https://doi:10.2753/JOA0091-3367360204

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. Translational Issues in Psychological Science, 4(4), 440–461. https://doi:10.1037/tps0000176

Öberseder, M., Schlegelmilch, B. B., Murphy, P. E., & Gruber, V. (2014). Consumers' Perceptions of Corporate Social Responsibility: Scale Development and Validation. Journal of Business Ethics, 124(1), 101–115. https://doi:10.1007/s10551-013-1787-y

OECD (2020, October 7). OECD Policy Responses to Coronavirus (COVID-19): E-commerce in the time of COVID-19. https://www.oecd.org/coronavirus/policy-responses/e-commerce-in-the-time-of-covid-19-3a2b78e8/

Orme, B. (2009). MaxDiff Analysis: Simple Counting, Individual-Level Logit, and HB. Sequim, WA, US. https://sawtoothsoftware.com/resources/technical-papers/maxdiff-analysis-simple-counting-individual-level-logit-and-hb

Orme, B. (September 2012). Latent Class v4.5: Software for Latent Class Estimation for CBC Data. Orem, UT, US. https://sawtoothsoftware.com/resources/technical-papers/latent-class-technical-paper

Paetz, F., Hein, M., Kurz, P., & Steiner, W. (2019). Latent Class Conjoint Choice Models: A Guide for Model Selection, Estimation, Validation, and Interpretation of Results. Marketing ZFP, 41(4), 3–20. https://doi:10.15358/0344-1369-2019-4-3

Park, G., & Park, H. S. (2021). Communicating Sustainability to Ethnocentric Consumers in China: Focusing on Social Distance from Foreign Corporations. Sustainability, 13(1), 1–15. https://doi:10.3390/su13010047

Park, H. J., & Lin, L. M. (2020). Exploring attitude–behavior gap in sustainable consumption: comparison of recycled and upcycled fashion products. Journal of Business Research, 117, 623–628. https://doi:10.1016/j.jbusres.2018.08.025

Partouche, J., Vessal, S., Khelladi, I., Castellano, S., & Sakka, G. (2020). Effects of cause-related marketing campaigns on consumer purchase behavior among French millennials. International Marketing Review, 37(5), 923–943. https://doi:10.1108/IMR-12-2018-0348

Peloza, J., & Shang, J. (2011). How can corporate social responsibility activities create value for stakeholders? A systematic review. Journal of the Academy of Marketing Science, 39(1), 117–135. https://doi:10.1007/s11747-010-0213-6

Pope, N. K. L., Voges, K. E., & Brown, M. R. (2004). The effect of provocation in the form of mild erotica on attitude to the ad and corporate image: Differences Between Cause-Related and Product-Based Advertising. Journal of Advertising, 33(1), 69–82. https://doi:10.1080/00913367.2004.10639154

Qiu, S., Jiang, J., Liu, X., Chen, M.-H., & Yuan, X. (2021). Can corporate social responsibility protect firm value during the COVID-19 pandemic? International Journal of Hospitality Management, 93(1), 102759. https://doi:10.1016/j.ijhm.2020.102759

Ramesh, K., Saha, R., Goswami, S., Sekar, & Dahiya, R. (2019). Consumer's response to CSR activities: Mediating role of brand image and brand attitude. Corporate Social Responsibility and Environmental Management, 26(2), 377–387. https://doi:10.1002/csr.1689

Reichelt, M., Makovi, K., & Sargsyan, A. (2021). The impact of COVID-19 on gender inequality in the labor market and gender-role attitudes. European Societies, 23(sup1), S228-S245. https://doi:10.1080/14616696.2020.1823010

Rese, A., Schlee, T., & Baier, D. (2019). The need for services and technologies in physical fast fashion stores: Generation Y’s opinion. Journal of Marketing Management, 35(15-16), 1437–1459. https://doi:10.1080/0267257X.2019.1665087

Robinson, S. R., Irmak, C., & Jayachandran, S. (2012). Choice of Cause in Cause-Related Marketing. Journal of Marketing, 76(4), 126–139. https://doi:10.1509/jm.09.0589

Roggeveen, A. L., & Sethuraman, R. (2020). How the COVID-19 Pandemic May Change the World of Retailing. Journal of Retailing, 96(2), 169–171. https://doi:10.1016/j.jretai.2020.04.002

Ross, J. K., Patterson, L. T., & Stutts, M. A. (1992). Consumer Perceptions of Organizations that Use Cause-Related Marketing. Journal of the Academy of Marketing Science, 20(1), 93–97. https://doi:10.1177/009207039202000110

Ross III, J. K., Stutts, M. A., & Patterson, L. (1991). Tactical Considerations For The Effective Use Of Cause-Related Marketing. Journal of Applied Business Research, 7(2), 58–65. https://doi:10.19030/jabr.v7i2.6245

Ryoo, Y., Sung, Y., & Chechelnytska, I. (2020). What makes materialistic consumers more ethical? Self-benefit vs. other-benefit appeals. Journal of Business Research, 110, 173–183. https://doi:10.1016/j.jbusres.2020.01.019

Saeidi, S. P., Sofian, S., Saeidi, P., Saeidi, S. P., & Saaeidi, S. A. (2015). How does corporate social responsibility contribute to firm financial performance? The mediating role of competitive advantage, reputation, and customer satisfaction. Journal of Business Research, 68(2), 341–350. https://doi:10.1016/j.jbusres.2014.06.024

Sawtooth Software (2009). The CBC/HB System for Hierarchical Bayes Estimation: Version 5.6. Sequim, WA, US. https://sawtoothsoftware.com/resources/technical-papers/cbc-hb-technical-paper

Sawtooth Software (October 2020). The MaxDiff System Technical Paper: Version 9. Provo, UT, US. https://sawtoothsoftware.com/resources/technical-papers/maxdiff-technical-paper

Shaw, L. (2020, March 26). Ryan Reynolds donates gin proceeds to bartenders. https://www.thedrinksbusiness.com/2020/03/ryan-reynolds-donates-gin-proceeds-to-bartenders/

Sheikh, S.-R., & Beise-Zee, R. (2011). Corporate social responsibility or cause-related marketing? The role of cause specificity of CSR. Journal of Consumer Marketing, 28(1), 27–39. https://doi:10.1108/07363761111101921

Smith, W. (2020, July 2). 4 Brands Embracing Cause Marketing In The COVID-19 Era. GlobalGiving. https://www.globalgiving.org/learn/covid-19-cause-marketing

Statista (2020a, September 17). Average age of the population in Germany from 2011 to 2019. https://www.statista.com/statistics/1127805/population-average-age-germany/

Statista (2020b, September 28). Population in Germany as of December 2019, by federal state. https://www.statista.com/statistics/1127686/population-by-federal-state-germany/

Statista (2020c, December 7). Population of Germany from 1990 to 2019, by gender. https://www.statista.com/statistics/454338/population-by-gender-germany/

Statista (2021a). Anteil der Vertriebsformen am Textil- und Bekleidungsumsatz in Deutschland in den Jahren 2007 bis 2020. https://de.statista.com/statistik/daten/studie/6199/umfrage/anteil-des-textil--und-bekleidungsumsatzes-in-2007/

Statista (2021b, March 23). Most popular online stores in the clothing segment in Germany in 2018, by e-commerce net sales. https://www.statista.com/forecasts/871108/top-online-stores-germany-clothing-ecommercedb

Statistisches Bundesamt (2020, November 25). Educational attainment of the population in Germany. https://www.destatis.de/EN/Themes/Society-Environment/Education-Research-Culture/Educational-Level/Tables/educational-attainment-population-germany.html

Sung, K., Tao, C.-W., & Slevitch, L. (2020). Restaurant chain's corporate social responsibility messages on social networking sites: The role of social distance. International Journal of Hospitality Management, 85(3), 102429. https://doi:10.1016/j.ijhm.2019.102429

Tezer, A., & Tofighi, M. (2021). CSR spillover effect: the influence of a brand's corporate social responsibility activity on competing brands. Journal of Marketing Management, 37(7-8), 651–670. https://doi:10.1080/0267257X.2020.1865430

Thurstone, L. L. (1927). A law of comparative judgment. Psychological Review, 34(4), 273–286. https://doi:10.1037/h0070288

Tian, Z., Wang, R., & Yang, W. (2011). Consumer Responses to Corporate Social Responsibility (CSR) in China. Journal of Business Ethics, 101(2), 197–212. https://doi:10.1007/s10551-010-0716-6

Trimble, C. S., & Rifon, N. J. (2006). Consumer perceptions of compatibility in cause-related marketing messages. International Journal of Nonprofit and Voluntary Sector Marketing, 11(1), 29–47. https://doi:10.1002/nvsm.42

Trope, Y., & Liberman, N. (2003). Temporal construal. Psychological Review, 110(3), 403–421. https://doi:10.1037/0033-295x.110.3.403

Trope, Y., Liberman, N., & Wakslak, C. (2007). Construal Levels and Psychological Distance: Effects on Representation, Prediction, Evaluation, and Behavior. Journal of Consumer Psychology, 17(2), 83–95. https://doi:10.1016/S1057-7408(07)70013-X

Turker, D. (2009). Measuring Corporate Social Responsibility: A Scale Development Study. Journal of Business Ethics, 85(4), 411–427. https://doi:10.1007/s10551-008-9780-6

Vaidyanathan, R., Aggarwal, P., & Kozłowski, W. (2013). Interdependent self-construal in collectivist cultures: Effects on compliance in a cause-related marketing context. Journal of Marketing Communications, 19(1), 44–57. https://doi:10.1080/13527266.2011.551833

Vanhamme, J., Lindgreen, A., Reast, J., & van Popering, N. (2012). To Do Well by Doing Good: Improving Corporate Image Through Cause-Related Marketing. Journal of Business Ethics, 109(3), 259–274. https://doi:10.1007/s10551-011-1134-0

Varadarajan, P. R., & Menon, A. (1988). Cause-Related Marketing: A Coalignment of Marketing Strategy and Corporate Philanthropy. Journal of Marketing, 52(3), 58–74. https://doi:10.1177/002224298805200306

Verdeyen, V., Put, J., & van Buggenhout, B. (2004). A social stakeholder model. International Journal of Social Welfare, 13(4), 325–331. https://doi:10.1111/j.1468-2397.2004.00328.x

Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. In J. A. Hagenaars & A. L. McCutcheon (Eds.), Applied latent class analysis (pp. 89–106). Cambridge Univ. Press.

Vilela, A. M., & Nelson, M. R. (2016). Testing the Selectivity Hypothesis in cause-related marketing among Generation Y: [When] Does gender matter for short- and long-term persuasion? Journal of Marketing Communications, 22(1), 18–35. https://doi:10.1080/13527266.2013.841272

Wang, Y. (2014). Individualism/collectivism, charitable giving, and cause-related marketing: a comparison of Chinese and Americans. International Journal of Nonprofit and Voluntary Sector Marketing, 19(1), 40–51. https://doi:10.1002/NVSM.1486

White, K., & Peloza, J. (2009). Self-Benefit versus Other-Benefit Marketing Appeals: Their Effectiveness in Generating Charitable Support. Journal of Marketing, 73(4), 109–124. https://doi:10.1509/jmkg.73.4.109

Wiebe, J., Basil, D. Z., & Runté, M. (2017). Psychological distance and perceived consumer effectiveness in a cause-related marketing context. International Review on Public and Nonprofit Marketing, 14(2), 197–215. https://doi:10.1007/s12208-016-0170-y

Wymer, W., & Samu, S. (2009). The influence of cause marketing associations on product and cause brand value. International Journal of Nonprofit and Voluntary Sector Marketing, 14(1), 1–20. https://doi:10.1002/NVSM.348

Yang, J., & Mundel, J. (2021). “Are We All in This Together?”: Brand Opportunism in COVID-19 Cause Related Marketing and the Moderating Role of Consumer Skepticism. Journal of Promotion Management, 27(1), 1–23. https://doi:10.1080/10496491.2021.1888181

Yu, A., & Han, S. (2021). Social Exclusion and Effectiveness of Self-Benefit versus Other-Benefit Marketing Appeals for Eco-Friendly Products. Sustainability, 13(9), 5034. https://doi:10.3390/su13095034

Yucel-Aybat, O., & Hsieh, M.-H. (2021). Consumer mindsets matter: Benefit framing and firm–cause fit in the persuasiveness of cause-related marketing campaigns. Journal of Business Research, 129, 418–427. https://doi:10.1016/j.jbusres.2021.02.051

Zhao, M., & Xie, J. (2011). Effects of Social and Temporal Distance on Consumers' Responses to Peer Recommendations. Journal of Marketing Research, 48(3), 486–496. https://doi:10.1509/jmkr.48.3.486

7 Research paper #4: Balancing self-benefits and altruism in online shopping: Examining consumer preferences for customized and personalized cause-related marketing campaigns versus price discounts

Abstract

Recently, the well-established marketing concepts of personalization and customization have also been applied to cause-related marketing (CRM) to empower consumers and overcome issues of such campaigns with a specific, predetermined cause. This study examines the effectiveness of customized and personalized CRM for apparel products compared to price discounts. The results of a choice based conjoint experiment among German consumers (n = 388) showed that consumers prefer customized CRM to other types of CRM campaigns and price discounts. While personalized CRM is also perceived as more effective than price discounts, CRM campaigns with a baseline cause are outperformed by price discounts. The study also found that psychographic consumer characteristics, i.e., consumers’ personality structures and cultural orientations can be used to explain consumers' heterogeneous preferences for different marketing appeals. Finally, three consumer segments were identified – pro-social consumers, price-sensitive consumers, and Amazon enthusiasts – that retailers can target with tailored marketing strategies.

Keywords:

cause-related-marketing – customization – personalization – marketing effectiveness – corporate social responsibility.

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7.1 Introduction

In today's digital era, brands are constantly interacting with consumers through a multiplicity of communication channels, such as different types of social media platforms. Social media channels enable brands to establish a certain degree of connectedness due to interpersonal interactions which can be used to enhance customer relationships, e.g., by increasing their customers' profitability (Maecker et al., 2016). However, poor brand communications on such social media platforms, e.g., by conveying false or unclear information, offensive messages or deleting criticism in comments, can backfire and result in considerable reputational damage (Hansen et al., 2018; Rauschnabel et al., 2016). Apart from that, previous research has shown that engagement in corporate social responsibility (CSR) initiatives has the potential to increase positive word-of-mouth and reduce negative reactions on social media channels, especially if the company has been involved in CSR activities relatively long and if the CSR engagement has been intrinsically motivated (Ham & Kim, 2019; Vo et al., 2019). A continuous engagement and communication in CSR initiatives might therefore diminish the risk of becoming the goal of so-called social media firestorms – i.e., sudden surges of negative comments, messages and reactions on social media platforms (Pfeffer et al., 2014). Moreover, CSR practices can mitigate negative consumer responses in case of service failures – e.g., overly long waiting times or slow and inattentive service – or defective products (Alhouti et al., 2021; Bolton & Mattila, 2015; Joireman et al., 2015; Klein & Dawar, 2004). With reference to the recent COVID-19 pandemic, research also showed that genuine CSR activities offered opportunities for companies to strengthen their customer relationships (Giacomini et al., 2021; He & Harris, 2020; Schreiner & Baier, 2022) while unauthentic practices could have led to undesirable outcomes since "[c]orporate reputations can be built or destroyed through the crisis" (Eagar et al., 2020, p. 19).

Hence, engaging in CSR practices seems to be vital for brands to foster or even enhance their brand image. While there are many different types of CSR practices, especially cause-related marketing (CRM) has become a valuable and popular marketing tool especially throughout the last two decades (Lafferty et al., 2016; Schamp et al., 2022; Thomas et al., 2020). Since CRM is linking consumer purchases of products and services with a company's contribution to a specified cause (Varadarajan & Menon, 1988), this concept offers direct benefits for both consumers and retailers. From a consumer's perspective CRM campaigns offer the benefits of purchasing a product to fulfill an unmet consumer need, thus providing a "self-benefit" and, at the same time, providing intrinsic rewards by supporting a good cause, hence also providing an "other-benefit" (Ballings et al., 2018; Robinson et al., 2012; Schamp et al., 2022). From the advertiser's perspective CRM campaigns have the potential to enhance customer relationships in various ways, e.g., by increasing consumers' purchase intentions and willingness to pay for products (Arora & Henderson, 2007; Koschate-Fischer et al., 2012; Robinson et al., 2012). CRM might also be a cost-effective type of sales promotion since the campaign-related additional sales might clearly exceed the incurring costs of donating to a cause (Arora & Henderson, 2007; Ballings et al., 2018).

The selection of the "right" cause is a fundamental challenge in CRM campaigns. In this regard, numerous research showed that ensuring a beneficial company-cause fit, brand-cause fit and product-cause fit – i.e., the perceived congruency between the supported cause and the brand, firm or product – are crucial success factors for CRM campaigns (Fan et al., 2020; Lafferty et al., 2016; Schamp et al., 2022). Providing consumers with choice regarding the supported cause seems to overcome this issue of choosing the best fitting cause. Research demonstrated that CRM campaigns with choice resulted in an increased purchase likelihood of and willingness to pay for products, enhanced attitudes towards the company (Robinson et al., 2012), and increased choice probabilities (Arora and Henderson, 2007). In the last decade, such CRM campaigns with choices have been successfully deployed by online retailers. For instance, since its launch in 2013 Amazon has donated more than $377 million to charitable causes globally through its CRM-with-choice platform termed AmazonSmile which allows consumers to select a cause to be supported by their purchase from a broad range of public charitable organizations registered on the platform (Amazon, 2022a, 2022b). The supported causes ranged from humanitarian aid, consumer rights, animal protection, health to sports clubs or youth organizations. Several other shopping platforms have emerged where consumers can select their preferred charitable cause while shopping at various online shops involving no additional costs (e.g., Gooding, 2022; ShopRaise, 2022).

While the special form of CRM with choice has already evolved one decade ago and has been used by companies ever since, only very limited research exists regarding such CRM campaigns with choice, also referred to in this article as customized CRM (Arora & Henderson, 2007; Christofi et al., 2019). As a main reason for the superior effectiveness of CRM campaigns with choice compared to CRM campaigns with a pre-defined cause, previous research suggests that providing consumers with choice “increases engagement and suggests a power shift from the firm to the consumer” (Lafferty et al., 2016, p. 966). Hence, CRM with choice provides consumers with a greater sense of empowerment and enables consumers to co-create a brand’s meaning (Kull & Heath, 2016).

Existing research investigating consumer responses to customized CRM campaigns mainly focus on comparisons of CRM with choice versus CRM campaigns with a pre-defined cause (Howie et al., 2018; Kull & Heath, 2016; Lucke & Heinze, 2015; Robinson et al., 2012; Tao & Ji, 2020), whereas research on the effectiveness of CRM with choice versus traditional sales promotion methods such as price discounts remains sparse (Arora & Henderson, 2007; Schreiner & Baier, 2022). Beyond that, only few is known about factors explaining an increased preference for CRM campaigns compared to price discounts. While previous studies have shown that certain sociodemographic aspects, especially gender, might result in more or less favorable consumer responses towards CRM campaigns (Arora & Henderson, 2007), recent research indicated that such aspects did not sufficiently cover heterogeneous consumer preferences for different types of marketing actions (Schreiner & Baier, 2022). Hence, psychographic consumer characteristics such as personality traits might be well-suited to describe the heterogeneity of consumer preferences for CRM campaigns compared to price discounts and might offer additional guidance for characterizing different consumer segments.

Moreover, research comparing the effectiveness of customized CRM versus personalized CRM campaigns has not been a focus of academic studies so far, even though there is a distinct research stream comparing the effectiveness of customization versus personalization approaches in (CRM-unrelated) marketing literature (Kwon & Kim, 2012; B. Zhang & Sundar, 2019). Derived from the concepts of customization and personalization in marketing literature, we define customized CRM as practices that enable consumers to actively choose their preferred charitable cause, and personalized

CRM campaigns as the firm-initiated pre-selection of charitable causes based on implicitly retrieved individual preferences such as likes or follows of social media pages of charitable organizations.

To address these research gaps this study aims to (1) examine the effectiveness of customized CRM campaigns compared to other types of CRM campaigns (CRM with personalized or predetermined baseline causes) and traditional types of sales promotion such as price discounts of different online apparel retailers; (2) determine potential drivers of consumers preferences for CRM campaigns rooted in consumers' personality structure or cultural dimensions; (3) identify and characterize different consumer segments based on sociodemographic and psychographic consumer characteristics.

Accordingly, the findings of this study contribute to the still limited literature on exploring the effectiveness of CRM campaigns with choice (Arora & Henderson, 2007; Christofi et al., 2019; Howie et al., 2018; Kull & Heath, 2016; Lucke & Heinze, 2015; Robinson et al., 2012; Ruiz de Maya et al., 2015; Singh & Pathak, 2020; Tao & Ji, 2020) and offer a comparison of consumer preferences for CRM campaigns with choice to preferences for non-participatory CSR approaches such as CRM campaigns with a predefined cause as well as CRM campaigns with a personalized cause inferred from implicit consumer data. Secondly, the study at hand adds to existing research measuring the effectiveness of marketing efforts with mere self-benefits compared to marketing actions with benefits for other stakeholders (Andrews et al., 2014; Arora & Henderson, 2007; Henderson & Arora, 2010; Schreiner & Baier, 2022). Lastly, by studying the effect of psychographic consumer variables on consumer preferences for CRM campaigns and price discounts, this study provides additional insights into drivers for heterogeneous consumer preferences for such marketing efforts and enables (apparel) retailers to derive effective promotional strategies for attracting different segments of apparel consumers.

In the following sections, a literature review of studies on the effectiveness of different types of CRM campaigns versus price discounts, the impact of psychographic consumer characteristics on the effectiveness of CRM campaigns, and the impact of retailer reputation on consumer preferences for different types of marketing actions is provided. Next, choice-based conjoint analysis is introduced as research method and the experimental design is outlined. Then the results of the study are presented and discussed in terms of their contributions to research and practice, followed by limitations of the study and avenues for future research.

7.2 Literature review and hypotheses development

7.2.1 CRM with choice: possibilities of customizing CRM campaigns

7.2.1.1 CRM with choice versus generic CRM campaigns

In general, existing research on CRM campaigns with choice still is sparse (Christofi et al., 2019; Kull & Heath, 2016; Lafferty et al., 2016).

Arora and Henderson (2007) were the first to investigate the effectiveness of CRM campaigns with choice – back then termed as a customization strategy for embedded premium. They showed that CRM campaigns with choice regarding the supported charity were clearly preferred by consumers to CRM campaigns with one predetermined cause in the context of credit card offerings (Arora & Henderson, 2007).

Several years later, the research by Robinson et al. (2012) indicated that providing consumers with choice regarding the donation cause increased consumers' purchase likelihood of and willingness to pay for products and enhanced consumers' attitudes towards the company within the context of candy, calculators, notebooks and shampoo. According to this study, some moderating variables might enhance the positive effects of CRM campaigns with choice, such as collectivistic orientations or the perceived fit between the company and cause types (e.g., environmental causes versus educational causes) (Robinson et al., 2012).

In a similar vein, Howie et al. (2018) demonstrated that CRM campaigns with choice led to more favorable consumer responses, especially when the perceived effort for supporting a cause through a CRM campaign was high. In the context of COVID-19 Schreiner and Baier (2022) pointed out that CRM with choice was of greater utility to apparel consumers than the support of a predefined cause.

Kull and Heath (2016) showed that CRM campaigns with choice clearly enhanced relationships of brands and their consumers – especially if the choice was unrestricted, i.e., consumers could choose any potential cause rather than choosing from a predefined list of causes. Moreover, it was demonstrated that CRM campaigns with choice were particularly effective for brands with neutral or positive consumer perceptions whereas choice in CRM campaigns of brands with a negative prior image might even elicit more unfavorable consumer responses.

In contrast to the aforementioned studies, Tao and Ji (2020) found that corporate reputation rather than choice-of-cause options within CRM campaigns determined consumers' evaluations of CRM campaigns and Lucke and Heinze (2015) even detected an overall negative effect of customization options within CRM campaigns for travel insurances upon consumers' purchase intentions. More specifically, the authors found that choice in CRM campaigns directly negatively affected consumers' involvement with the advertised product which in turn led to decreased purchase intentions. As a possible explanation for these findings the authors referred to potential methodological limitations of their study due to a "relative low monetary amount of the donation issued" (Lucke & Heinze, 2015, p. 651).

Overall, customized CRM campaigns seem to be a promising approach for increasing engagement and enabling "a power shift from the firm to the consumer" which also has been demonstrated in recent research (Christofi et al., 2019; Lafferty et al., 2016, p. 966; Singh & Pathak, 2020). According to a framework exploring the role of customer engagement for the success of CRM campaigns proposed by Christofi et al. (2019) choice-possibilities could trigger positive word-of-mouth persuasion behaviors. Within the context of CRM customer engagement is defined as "the conditions in which consumers are allowed to choose: the cause that receives the donation; the cause proximity; and the type of donation in a CRM campaign." (Christofi et al., 2018, p. 516). Hence, customization possibilities include decisions about which charitable cause to support in a CRM campaign, the proximity of the supported cause to the respective consumer – e.g., local, national, international – as well as the type of donation, e.g. money versus donation in kind versus time.

Based on the mainly positive effects of choice options in CRM campaigns identified by previous research and considering the positive effects of consumer empowerment through choice, we hypothesize:

H1a: *Consumers prefer CRM campaigns with choice (in this study conceptualized as cause type and cause proximity) to CRM campaigns with a predefined baseline cause.*

In the present study, only the most common type of donation – a monetary donation – is investigated alongside with the cause proximity.

7.2.1.2 CRM campaigns with different levels of cause proximity

Providing consumers with choice regarding the proximity of the supported cause, e.g., supporting a local versus national versus international cause, is another major facet of customizing CRM campaigns (Christofi et al., 2019). Previous research demonstrated that spatially close beneficiaries of CRM campaigns led to increased consumer support for the campaign (Ross III et al., 1991), more favorable attitudes towards the brand (Lii et al., 2013; Wiebe et al., 2017) and the campaign (Grau & Folse, 2007), and greater purchase intentions (Hou et al., 2008; Wiebe et al., 2017).

The results of a recent study in the context of the COVID-19 pandemic also showed that CRM campaigns with spatially close (local) beneficiaries are more valued by consumers than CRM campaigns with a more distant (national) beneficiary (Schreiner & Baier, 2022). Although some other studies have found no statistically significant effects of CRM campaigns with spatially close compared to distant beneficiaries (Cui et al., 2003; Ross et al., 1992), we propose the following hypothesis, consistent with the above mentioned prior studies:

H1b: *Consumers prefer CRM campaigns with spatial close beneficiaries to distant ones (in this study: local > national > international).*

7.2.2 Comparison of the effectiveness of customization and personalization approaches in marketing literature

7.2.2.1 Personalized CRM campaigns versus generic CRM campaigns

In previous studies, CRM with choice is also referred to as customized CRM (Arora & Henderson, 2007; Christofi et al., 2019). Within marketing literature customization is described as one distinct form of one-to-one marketing – i.e., practices tailoring a company's marketing mix according to individual customer preferences (Arora et al., 2008; Chandra et al., 2022). While customization describes customer-initiated practices, personalization refers to firm-initiated practices tailoring its marketing mix to consumer's individual needs (Arora et al., 2008; Chandra et al., 2022; B. Zhang & Sundar, 2019).

In the context of CRM and the related domain of charity advertising, personalization has been studied by including personal information such as name, residence, age or gender in promotional messages (Bartsch & Kloß, 2019; Jihye Kim & Kim, 2022; Masthoff et al., 2013). Other personalization objects within CRM campaigns could, for instance, correspond to the aforementioned facets of customization – cause type, cause proximity and type of donation. Extending previous research on personalized CRM campaigns, we define personalized CRM as the firm-initiated tailoring of charitable causes to individual consumer preferences based on consumers' interactions with social media pages of charitable organizations, e.g. likes and follows.

While the research on consumer responses to personalization approaches in CRM is limited, vast research has identified various positive effects of personalized advertising on consumer behavior in general, including enhanced customer satisfaction and loyalty (Benlian, 2015; Ha & Janda, 2014; Jinyoung Kim & Gambino, 2016; Kwon & Kim, 2012; Verhagen et al., 2014; Yoon et al., 2013), increased purchase intentions (Ha & Janda, 2014; Li & Liu, 2017; Pappas et al., 2014; Sahni et al., 2018) and click intentions (Keyzer et al., 2022), more favorable consumer attitudes (Keyzer et al., 2022; Tran, 2017), and actual increases in sales (Goic et al., 2021; Sridhar et al., 2022). Yet, also negative effects of personalized advertising have been reported mainly due to increased privacy concerns (Bleier & Eisenbeiss, 2015; Schreiner et al., 2019; Song et al., 2016), and perceived intrusiveness (Aguirre et al., 2015; van Doorn & Hoekstra, 2013).

With reference to personalized CRM Jihye Kim and Kim (2022) found that such campaigns resulted in significantly lower social engagement intentions compared to a general CRM campaign when using a photo of a single child in need supported by the CRM campaign whereas personalization marginally increased the effectiveness of CRM campaigns when presenting a photo of a group of children in need. Personalized charity advertising was found to indirectly enhance attitudinal and behavioral responses to the campaign through increased levels of self-reference and empathy (Bartsch & Kloß, 2019). In sum, both studies show that at least under some conditions personalized CRM can spur favorable consumer responses.

Accordingly, and due to the positive effects of personalized marketing approaches suggested by previous marketing literature we hypothesize:

H2: *Consumers prefer personalized CRM campaigns to CRM campaigns with a pre-defined baseline cause.*

7.2.2.2 Customized versus personalized CRM campaigns

Research comparing the effectiveness of customized and personalized marketing approaches is mainly found within the domain of human-computer interaction (e.g., adaptation of web user interfaces or content). While some studies within this research stream point to an overall higher effectiveness of customization approaches compared to personalization (Kwon & Kim, 2012; Laban & Araujo, 2022), other studies report mixed findings (Sundar & Marathe, 2010; B. Zhang & Sundar, 2019) or even a general superiority of personalization approaches (Frias-Martinez et al., 2009; Orji et al., 2017; X. Sun et al., 2016).

In general, both customization and personalization approaches offer different benefits for consumers beyond delivering tailored content, offers or experiences: Customization was found to empower users to make adaptations according to their preferences, which gives them some sense of control, but also requires some effort when actively customizing their preferences (Sundar & Marathe, 2010; B. Zhang & Sundar, 2019). By contrast, main benefits of personalization include the low effort for consumers and the convenient usage, whereas potential drawbacks might be a perceived intrusiveness, which can lead to increased privacy concerns and result in a perceived loss of control (Aguirre et al., 2015; Sundar & Marathe, 2010; B. Zhang & Sundar, 2019).

Drawing on previous literature, a general superiority of one of these approaches cannot be assumed. Instead, the effectiveness of both approaches seems to depend on the context and the topic to which they are applied. Accordingly, some researchers propose a hybrid approach that combines personalization and customization to balance the weaknesses of one approach with the strengths of the other (Orji et al., 2017; X. Sun et al., 2016; B. Zhang & Sundar, 2019), for example, by offering customization options for consumers' privacy settings (B. Zhang & Sundar, 2019). Yet, previous research has shown that unrestricted choice in CRM campaigns had no negative effect on consumer responses to the brand, despite resulting in an increased choice difficulty (Kull & Heath, 2016). Hence, the complexity of choosing a preferable cause within CRM campaigns seems to be negligible, which might attenuate the major drawback of customization. Following these considerations, we propose the following hypothesis:

H3: *Consumers prefer customized CRM campaigns to personalized CRM campaigns.*

7.2.3 Comparison of the effectiveness of price discounts and CRM campaigns

While the comparison of personalized and customized CRM campaigns is still an under-researched domain and therefore beckons investigation, it is also important to define a reference point for comparing the effectiveness of such marketing campaigns with benefits for multiple stakeholders beyond the consumers' self. For this purpose, price discounts have already been used in the past as a form of traditional marketing approaches providing benefits solely for the respective consumer (Arora & Henderson, 2007; Schreiner & Baier, 2022).

Previous research comparing the effectiveness of price discounts to CRM campaigns in general suggests that CRM campaigns might outperform such traditional marketing approaches with mere self-benefits (Andrews et al., 2014; Arora & Henderson, 2007; Henderson & Arora, 2010; Schreiner & Baier, 2022), especially for campaigns with comparatively small price discounts or donation amounts (Arora & Henderson, 2007) and when consumers are granted some level of choice regarding the supported cause (Schreiner & Baier, 2022).

In line with these previous findings as well as taking into account H1a, H2 and H3, we assume:

H4: *Consumers prefer CRM campaigns to price discounts (in this study: customized CRM > personalized CRM > CRM with a predefined baseline cause > price discounts).*

7.2.4 Impact of retailer reputation on consumer preferences

Previous research has shown that, in general, an advertiser's reputation can be a substantial success factor for advertising campaigns (Akdeniz et al., 2013; Goldberg & Hartwick, 1990; S. Kim & Choi, 2012). Within the research domain of CRM a brand's "pre-reputation", which can be described as consumers' perceived reputation of a brand previous to its engagement in a CRM campaign, has also been identified as a potential driver of the campaign's effectiveness (Fan et al., 2020; Lafferty et al., 2016).

For instance, perceptions of brand credibility have been found to positively impact consumer responses (Bigné et al., 2012; Lafferty, 2007).

Accordingly, we propose the following hypothesis:

H5: *High pre-reputational evaluations of a retailer positively influence consumer preferences for marketing appeals provided by this specific retailer.*

7.2.5 Impact of psychographic consumer characteristics on preferences for CRM campaigns

7.2.5.1 Collectivistic versus individualistic orientations

Previous research indicates that consumers with rather collectivist orientations compared to consumers with rather individualist orientations tend to show more positive responses towards CRM campaigns. For instance, Wang (2014) found that collectivist orientations – especially horizontal collectivism which is primarily characterized by interdependence, i.e., the perceived similarity to others – had a positive impact on attitudes towards CRM campaigns in both rather collectivist as well as rather individualist societies. Other researchers also identified positive perceptions of CRM campaigns by consumers with collectivist orientations on attitudinal responses (Schamp et al., 2022), such as decreased consumer skepticism towards CRM campaigns (Chang & Cheng, 2015), a willingness to pay higher prices (Vaidyanathan et al., 2013), and a generally higher purchase intention for social-cause products (J.-E. Kim & Johnson, 2013), especially if the company promoting a CRM campaign was a national firm (Choi et al., 2016; Fan et al., 2020). Moreover, Robinson et al. (2012) showed that consumers with collectivist orientations were more likely to purchase products advertised by customized CRM campaigns compared to CRM campaigns with a predefined cause.

In line with existing CRM research within the context of intercultural communication we suggest the following hypothesis:

H6a: *Consumers who score high on collectivism show an increased preference for CRM campaigns.*

Beyond the exploration of impacts of collectivistic orientations, only few studies explicitly examine the influence of individualistic orientations on the effectiveness of CRM campaigns. Those few studies suggest a negative effect of individualistic orientations: Chang and Cheng (2015) showed that an individualistic mindset increased skepticism toward advertising which in turn impaired purchase intentions. Deb and Amawate (2019) demonstrated for the consumer group of Millennials that higher levels of individualism resulted in increased perceptions of skepticism towards the company promoting the CRM campaign.

Based on these previous findings and since an individualistic mindset might increase skepticism toward advertising in general as shown by Chang and Cheng (2015), the following hypothesis is proposed:

H6b: *Consumers who score high on individualism show a decreased preference for CRM campaigns.*

7.2.5.2 Big five personality traits

While the impact of consumer characteristics such as moral identity or cultural orientations on the effectiveness of CRM campaigns has already been well studied, the influence of another type of psychographic consumers characteristics – personality traits – remains under-researched (Fan et al., 2020; J. Lee & Lee, 2021).

According to a popular definition provided by R. R. McCrae and John (1992) – that is also followed within this research article – personality traits are described as the characterization of individuals “in terms of relatively enduring patterns of thoughts, feelings, and actions” (Costa & McCrae, 1999, p. 140). Over the past decades the “five-factor-model”, also known as the “big five personality dimensions”, has evolved as the predominant model for assessing personality structures (Barrick & Mount, 1991; Robert R. McCrae & Costa, 2008; R. R. McCrae & John, 1992). This “five-factor structure has generalized across measures, cultures, and sources of ratings” and has been applied in numerous studies (Costa & McCrae, 1999; Judge et al., 2002, p. 530). It describes personality along the five dimensions of extraversion, agreeableness, conscientiousness, neuroticism, and openness (R. R. McCrae & John, 1992). In brief, high levels of agreeableness represent friendliness or generosity, whereas high scores of openness (to experience) reflect imaginativeness or exploratory tendencies (Robert R. McCrae & Costa, 2008; Poropat, 2009). High scores of extraversion mainly portray sociability, whereas high levels of conscientiousness stand for dependability and high levels of neuroticism represent anxiety (Robert R. McCrae & Costa, 2008; Poropat, 2009).

The impact of these personality traits upon consumer responses to CRM campaigns is not well researched. Only one recent study investigated the impact of consumers' personality traits on their attitudes towards a CRM campaign by a sports company. J. Lee and Lee (2021) found that agreeableness had a significant direct positive effect on consumer attitudes whereas neuroticism had a significant negative impact. As a rationale for these findings the authors argue that individuals who score high on agreeableness might place a greater value on altruism and helping others which is a great fit with the other-benefit-component entailed in CRM campaigns (J. Lee & Lee, 2021). The negative relationship between high levels of neuroticism and attitudes towards CRM is explained by an increased level of consumer skepticism regarding the motivation of CRM campaigns.

Similarly, Paetz (2020) investigated consumer preferences in the related domain of social consumption, specifically in terms of consumer preferences for apparel products featuring a fair trade label. While the authors hypothesized positive effects for all of the five personality traits on consumer preferences for fair trade labelled apparel products, the results revealed that consumers with high scores on the personality dimensions extraversion, neuroticism, openness and agreeableness showed increased preferences for products with such a label. The reasons suggested for these effects are that i), extraverts tend to be sociable and pursuing social jobs, ii), neurotic individuals feel guilt which drives ethical consumption behaviors, iii), open persons are receptive to other cultures, and iv), agreeable individuals exhibit altruistic and caring behaviors.

Y. Sun et al. (2018) showed that extraversion, agreeableness, openness and conscientiousness positively affected consumers' attitudes towards buying green products. Again, the positive relationship between high levels of agreeableness and buying green products was explained by tendencies to engage in altruistic behaviors. The positive impact of extraversion was accounted for an increased willingness to helping others whereas the positive influence of conscientiousness was attributed to a strong sense of self-discipline, responsibility, and compliance with rules and social norms. Lastly, the positive effect of openness was explained by curious and creative mindsets.

Since all of these studies revealed a positive relationship between high levels of agreeableness and responses to pro-social product offerings and due to the definition of agreeableness as personality trait encompassing altruistic and caring characteristics, we suggest the following hypothesis (Digman, 1990):

H7a: *Consumers who score high on agreeableness show an increased preference for CRM campaigns.*

Moreover, and in line with previous research, we also suggest a positive effect of openness and extraversion on consumer preferences for CRM campaigns.

H7b: *Consumers who score high on extraversion show an increased preference for CRM campaigns.*

H7c: *Consumers who score high on openness show an increased preference for CRM campaigns.*

For the remaining two personality traits contradictory effects have been reported. Therefore, it is unclear how these personality traits might impact consumer preferences for CRM campaigns.

7.3 Empirical investigation

7.3.1 Method

For investigating these hypotheses and measuring consumer preferences for distinct types of marketing appeals we applied hierarchical Bayes choice-based conjoint analysis (CBC) using Sawtooth Software's Lighthouse Studio version 9.13.1. Dating back to Louviere and Woodworth (1983), CBC combines traditional conjoint analysis and discrete choice analysis and asks respondents to repeatedly choose their most preferred (product) alternative from a set of options (Cohen, 1997; Green et al., 2001). A specific advantage of the CBC approach is its inquiry of consumer preferences in a comparatively realistic way by simulating (purchase) decisions (Desarbo et al., 1995). Hence, CBC is the most widely used variant of conjoint analyses which are among the most popular methods for preference measurement (Eggers et al., 2022; Orme, 2019; Selka et al., 2014). CBC has already been applied in previous studies with a similar research focus to examine consumer preferences for CRM campaigns (Arora & Henderson, 2007; Kulshreshtha et al., 2019; Schreiner & Baier, 2022). In comparison to prior studies involving a between-subjects design (Andrews et al., 2014; Kull & Heath, 2016; e.g., Robinson et al., 2012), the within-subject design of conjoint experiments enables the examination of causal effects of various aspects simultaneously (Knudsen & Johannesson, 2019).

In CBC part-worth utilities for each attribute level are typically estimated employing the Multinomial Logit model developed by McFadden (1974) to model discrete choice decisions (Green et al., 2001). Hierarchical Bayes (HB) models allow for individual-level analysis in addition to utility estimation at an aggregate level (Green et al., 2001; Sawtooth Software, 2009a). Accordingly, HB is considered a robust method for estimating utility scores also in case of relatively small numbers of choice tasks and has also been used for calculating utility scores in this study (Sawtooth Software, 2016).

7.3.2 Experimental design

Prior to the CBC exercise, respondents had to answer the extra-short BFI-10 scale – a 10-item abbreviated version of the established Big Five Inventory – to measure their personality structure with two distinct items per personality dimension (for detailed information about the BFI-10 scale, see: Beatrice Rammstedt et al., 2020; Beatrice Rammstedt & John, 2007). For measuring collectivistic versus individualistic orientations of consumers selected items from already existing and validated scales by Sharma (2010) and McCarty and Shrum (2001) have been used. These scales enable a generic survey of collectivistic and individualistic orientations on relatively short scales which have been used by researchers in the context of CRM (Chang & Cheng, 2015) and green marketing (Leonidou et al., 2010; Mo et al., 2018). The items building the dimensions of collectivism and individualism have been chosen by considering the classification approach of individualism and collectivism components by Oyserman et al. (2002) and by ensuring that items mainly contributing to the four dimensions of horizontal/vertical individualism/collectivism were represented (Singelis et al., 1995; Triandis & Gelfand, 1998; see Appendix A). All items measuring personality traits and cultural dimensions have been measured on a scale ranging from strongly disagree (1) to strongly agree (5).

Next, respondents' input for the personalization condition in the subsequent CBC exercise has been collected. Respondents were asked to select all organizations from a list of 14 charitable organizations whose content they were most likely to follow on a regular basis, e.g., via social media or email newsletter. The list of 14 selectable charitable organizations was derived by analyzing popular social media pages (Facebook and Twitter) of non-governmental organizations in Germany in March 2021 using freely accessible social media statistics (SocialBakers, 2021a, 2021b) [1]. Similarly to previous academic research (Kotler & Lee, 2008; Lafferty & Edmondson, 2014; Vanhamme et al., 2012; A. Zhang et al., 2020), charitable organizations supporting various popular categories of social causes such as health, humanitarian aid, animal protection and environmental protection have been included. Moreover, relevant charitable organizations falling into other less frequently listed categories, such as anti-corruption, consumer rights, human rights, and freedom of information have been added due to their popularity among German social media users. All 14 organizations could be selected, but at least one organization had to be chosen. All charitable organizations were illustrated by the image of their current Facebook logo to simulate a genuine like/follow process on social media pages (see Appendix B). One of the chosen charitable organizations of the respective respondent was then randomly assigned to the personalization condition in the CBC (see Appendix F; stimulus #1).

Subsequently, respondents were asked to select one specific organization they would be most likely to support financially (e.g., by making a donation) as input for the customized CRM campaign. The basis for this choice was the list of the previously selected organizations. In addition, respondents could also specify any other organization of their own choice via a free text field, enabling an unrestricted choice (see Appendix C). Respondents then had to indicate the preferred cause proximity, i.e., they had to decide whether a local, national, or international project of their chosen charity should be supported (see Appendix D). Both selections – the most preferred charitable organization for donations as well as the donation proximity – were used as input for the customization condition in the CBC (see Appendix F; stimulus #2).

[1] The freely accessible interactive social media statistics in Germany for non-governmental organizations have been removed end of 2021 and, thus, are no longer accessible.

Still prior to the CBC tasks, respondents were required to specify their usual purchasing behavior for apparel products – that is to say, their purchasing frequency in different sales channels within the last twelve months as well as their average monthly expenses on apparel products. Next, three different online apparel retailers were presented and briefly described (the short descriptions can be found in Appendix E). After reading these descriptions, respondents had to answer three questions regarding the perceived pre-reputation of each retailer on a scale ranging from one to five anchored by the levels very negative / very positive. The items used for evaluating consumers' overall impression of the portrayed online apparel retailers have been retrieved from previous studies investigating consumers' perceptions of corporate credibility or company evaluations (Goldsmith et al., 2000; Lafferty & Goldsmith, 1999; Öberseder et al., 2014). Moreover, we also queried the perceived social contribution, as well as the perceived contribution to sustainability of the respective retailers to include evaluations of perceived CSR – similarly to previous studies investigating the moderating impact of CSR (reputation) on consumer attitudes and behavior (Lichtenstein et al., 2004; Lii & Lee, 2012).

Thereafter, subjects were repeatedly asked to select their most preferred additional offer from online apparel retailers in the CBC experiment. Respondents had to complete a total of twelve choice tasks and had to choose between three alternatives in each case. Ten out of these twelve choice tasks were used for utility estimation and two so-called holdout choice tasks were included to assess the predictive validity, and thus, were excluded from the utility estimation. Overall, 36 stimuli were created from the possible attribute-level-combinations as depicted by Table 1 (an exemplary choice task can be found in Appendix F).

Table 1: Overview of attributes and attribute levels used in the CBC experiment

Attribute	**Level**
Promotion type	CRM campaign with a baseline cause
	CRM campaign with a personalized cause
	CRM campaign with a customized cause and customized cause proximity
	Price discount
Promotion depth	10% (low)
	20% (medium)
	50% (strong)

Attribute	Level
Retailer	Global market leader in online retailing (Amazon)
	Fast-fashion retailer (H&M)
	Sustainable fashion retailer (Wijld)

Besides a personalized and a customized cause, also a baseline cause and a price discount have been used as levels of the campaign type attribute. The baseline cause was implemented by the financial support of the World Health Organization (WHO), which has received corporate donations from numerous companies during the recent COVID-19 pandemic "to help prevent, detect, and manage the spread of COVID-19" (Mahmud et al., 2021, p. 11) and which has already been used in previous research as baseline charitable organization (Arora & Henderson, 2007). As levels of promotion depths, we chose 10% off the regular price as a relatively low discount, 30% off as moderate discount and 50% off as comparatively deep discount. These promotion depths are in line with some previous studies (Andrews et al., 2014; Arora & Henderson, 2007) and not uncommon within the apparel industry (K. Kim et al., 2019; J. E. Lee & Chen-Yu, 2018).

Upon completion of the twelve CBC tasks, respondents that had chosen CRM campaigns by one specific apparel retailer in less than two choice tasks were asked about reasons for their aversion to these offers for that retailer. The items of this multiple-choice question were based on previous research on consumer perceptions of corporate motives for engaging in CRM campaigns, the fit between a brand and its CRM campaigns as well as consumers' evaluations of a brand's credibility in terms of its commitment to charitable causes (Lafferty et al., 2016; also see Appendix G). Lastly, demographic data were collected.

7.3.3 Sample and Data Collection

The survey was conducted during April 2021 using an online questionnaire distributed by a German online panel provider by email to invited participants aged 18 years and older. A total of 398 respondents completed the online survey. Three respondents were eliminated due to straight-lining behavior in the CBC tasks. Moreover, seven other respondents were excluded as they indicated to be willing to support a custom charitable organization but did not provide a valid input in the text field for the 'customization' condition. Accordingly, the final sample comprised 388 respondents representing the German overall population (in 2019) quite well in terms of most sociodemographic characteristics (Table 2). Yet, people holding an academic degree were clearly overrepresented.

Table 2: Composition of the sample and the German overall population in terms of several sociodemographic criteria (Statista, 2020a, 2020b, 2021a, 2021b, 2021c; Statistisches Bundesamt, 2020)

	Germany (2019/2020)	**Sample** (n = 388)
Mean age (2020)	44.6 years	49.1 years
Female (2019)	50.7%	49.7%
Monthly household income < 2.600 € (2019)	55.0%	51.6% (n=349)[2]
Academic degree (2019)	18.5%	34.3%
Household size < 5 persons (2020)	96.5%	97.7% (n=387)[2]
State of residence: North-Rhine-Westphalia, Bavaria, or Baden-Württemberg (2020)	50.7%	50.0%

7.4 Results

7.4.1 Personality traits, cultural dimensions, purchasing behavior and retailer pre-reputation

For the analysis of the respondents self-assessment regarding the big five personality traits, we followed the recommended procedure for analysis of the extra-short BFI-10 scale as described by B. Rammstedt et al. (2012). Thus, measures for the five personality dimensions are determined by adding and averaging individual responses to the respective two questions for each dimension. The results are presented in Table 3 and

[2] A reduced sample size for specific questions is due to the response option “prefer not to specify” which has been coded as missing value in the aftermath.

compared to reference values of a representative random sample of the German population reported by B. Rammstedt et al. (2012). In comparison to reference values, respondents of our study score clearly lower on extraversion, conscientiousness, and agreeableness, whereas average scores for neuroticism and openness are similar to the reported reference values.

Table 3: Respondents' personality structure compared to reference values by B. Rammstedt et al. (2012)

	Mean	**Standard deviation (SD)**	**Reference values (mean)**	**Reference values (SD)**
Extraversion	3.12	1.01	3.47	0.95
Conscientious-ness	3.87	0.82	4.15	0.79
Neuroticism	2.60	1.00	2.42	0.88
Agreeableness	3.18	0.81	3.45	0.80
Openness	3.49	0.98	3.41	0.93

Mean individualistic and collectivist orientations were calculated in an equivalent manner, averaging responses on the corresponding four items. The mean score for collectivistic orientations (3.74; SD: 0.68) was slightly higher than the mean score for individualistic orientations (3.54; SD: 0.64).

In terms of respondents' purchase frequency, online sales channels were of greatest relevance to consumers during the last twelve months with 90 percent of respondents indicating to having used the internet at least once for purchasing apparel during this period. Unsurprisingly, brick-and-mortar stores were less frequently used for purchasing apparel products due to temporary closure, distancing rules, and mandatory mask-wearing during the COVID-19 pandemic (usage by 74% of respondents during the last twelve months). Supermarkets were the third most popular sales channel used by 55 percent of consumers at least once during the last twelve months. This is in line with findings from previous pandemic-related research on apparel retailing (Schreiner & Baier, 2022). The majority of all respondents (56%) reported spending less than €50 per month on apparel products, while only 15% of consumers reported monthly spending of more than €100.

With reference to retailer pre-reputation the small fashion start-up Wijld that has been introduced as an apparel retailer offering EU-made clothing products made from wood fibers (see also Appendix E) received highest mean consumer ratings (general impression: 3.83 – SD: 1.03; social impact: 3.83 – SD 1.04; sustainability impact: 4.07 – SD: 1.00). Amazon (general impression: 3.58 – SD: 1.12; social impact: 2.75 – SD 1.19; sustainability impact: 2.75 – SD: 1.17) and H&M (general impression: 3.23 – SD: 1.08; social impact: 2.83 – SD 1.03; sustainability impact: 2.76 – SD: 1.06) were evaluated less positive, particularly in terms of its social and sustainability impact.

7.4.2 CBC-HB results

7.4.2.1 Internal and predictive validity

For the utility estimation of attributes and attribute levels in the CBC, we used ten random choice tasks and considered two holdout tasks. The mean root likelihood (RLH) values at the aggregate (0.66) and the individual level (0.68) clearly surpassed values of a random model (RLH = 0.33) indicating a satisfactory fit between the estimates and the data (Sawtooth Software, 2009b). The first choice hit rates which are most frequently used for assessing the predictive validity of the estimated choice model, i.e., calculating the percentage of respondents actually selecting the concept with the highest predicted part-worth utility in a predefined holdout task (Steiner & Meißner, 2018), proved that respondents' choices were predicted correctly in 74.74% of all cases. Accordingly, the predictive accuracy for both holdout tasks was 124% higher compared to the random model ((0,7474-0,3333)/0,3333)).

7.4.2.2 CBC/HB results

The results of the HB estimation illustrate that consumer preferences for apparel retailers' marketing appeals were predominantly driven by the promotion type as well as the promotion depth. On average, the apparel retailer was least important for consumers' choice (Table 4).

In terms of the promotion type, customized CRM campaigns were preferred most followed by personalized CRM campaigns and price discounts. CRM campaigns supporting the WHO as the baseline cause provided the lowest utility to respondents. Hence H1a, H2, and H3 can be fully supported. Due to the overall greater part-worth utility of price discounts compared to CRM campaigns with the baseline cause, H4 is dismissed.

Unsurprisingly, there was a linear relation between the part-worth utilities of ascending promotion depths: The lowest promotion depth of 10% was less preferred than the medium promotion depth of 20%, while the strong promotion depth of 50% received the highest utility scores. With reference to the retailer, Amazon was preferred most followed by the sustainable fashion retailer Wijld. H&M received the lowest utility scores.

Table 4: Attribute importances and part-worth utilities of attribute-level combinations

Attribute / Level	**Importance (%) / part-worth utility**	**Standard deviation**
Promotion type	40.29%	(14.5031)
Price discount	-3.4457	(64.4036)
Customized CRM campaign	37.5236	(30.4814)
Personalized CRM campaign	6.2512	(27.3346)
CRM campaign with a baseline cause	-40.3318	(31.4264)
Promotion depth	33.01%	(16.1473)
10%	-40.8814	(32.4262)
20%	-4.5981	(10.5607)
50%	45.4795	(36.1474)
Retailer	26.70%	(17.2080)
Amazon	10.0915	(45.9718)
H&M	-11.8573	(34.1506)
Wijld	1.7658	(39.9912)

According to the CBC/HB results, the overall most promising marketing appeal in our study would be a customized CRM campaign by Amazon passing on 50% of the purchase value to a custom charitable organization.

To test hypothesis H1b a simple count analysis of consumers choosing to support a local versus national versus international cause of their preferred cause has been performed: 45.6 percent of respondents selected the support of a local cause. 17.8 percent selected to prefer the support of a national cause and the remaining 36.6 percent preferred to support an international cause. Hence, H1b cannot be supported.

For testing H5, the spearman's rank-order correlation between consumers' perceived pre-reputation of the three retailers and the utility scores of each retailer was analyzed. For all three retailers, little to medium positive correlations were detected [Amazon: i), general impression: $\rho = .367$, $p < .001$; ii), social impact: $\rho = .277$, $p < .001$; iii), sustainability impact: $\rho = .253$, $p < .001$; H&M: i): $\rho = .287$, $p < .001$; ii): $\rho = .197$, $p < .001$; iii): $\rho = .198$, $p < .001$; Wijld: i): $\rho = .301$, $p < .001$; ii): $\rho = .261$, $p < .001$; iii): $\rho = .190$, $p < .001$]. These results support H5, indicating that consumers' perceived pre-reputation of an apparel retailer positively influenced their preferences for marketing appeals provided by this specific retailer.

7.4.3 Impact of psychographic consumer characteristics on consumer preferences

For an analysis of the impact of psychographic consumer characteristics on preferences for CRM campaigns (H6a, H6b, H7a, H7b and H7c) we compared utility scores for CRM campaigns for different groups of consumers similarly to the procedure described by Robinson et al. (2012): i) respondents with utility scores at least one standard deviation above the mean for the respective construct, ii) respondents with scores at least one standard deviation below the respective mean score. Two tailed t-tests were performed to identify significant differences between these groups. Each group consisted of between 52 and 92 respondents.

In line with H6a, consumers who scored high on collectivism showed increased preferences for all types of CRM campaigns (customized cause: $M = 51.03$, $SD = 29.82$; personalized cause: $M = 17.89$, $SD = 21.07$; baseline cause: $M = -35.78$, $SD = 32.47$) compared to respondents with low collectivism scores (customized cause: $M = 36.06$, $SD = 30.07$; $t(128) = 2.85$ $p < .005$; personalized cause: $M = 2.11$, $SD = 30.64$; $t(115.51) = 3.43$ $p < .001$; baseline cause: $M = -50.00$, $SD = 26.31$; $t(128) = 2.75$ $p < .01$). By contrast, utility scores for price discounts were significantly lower for consumers with high collectivism ratings ($M = -33.15$, $SD = 55.51$) compared to those with low scores ($M = 11.83$, $SD = 62.07$), $t(128) = -4.35$ $p < .001$. There were no statistically significant differences between respondents with comparatively high versus low individualism scores. Hence, H6b was not supported.

With reference to hypotheses H7a, b, and c, only support for H7c was found since respondents who scored high on openness placed greater utility on CRM campaigns with a customized cause ($M = 41.34$, $SD = 30.71$) and CRM campaigns with a personalized caused ($M = 7.42$, $SD = 27.76$) compared to respondents with low openness ratings (customized: $M = 30.48$, $SD = 29.06$; $t(170) = 2.38$ $p < .05$; personalized: $M = -1.71$, $SD = 24.58$; $t(170) = 2.27$ $p < .05$. While tendencies of greater utility scores for CRM campaigns with a baseline cause have also been found for consumers who scored high on openness ($M = -39.00$, $SD = 34.44$) compared to those with low scores ($M = -47.15$, $SD = 24.05$), this difference was not statistically significant at $p < .05$, $t(161.18) = 1.81$ $p = .07$. By contrast, those who scored low on openness placed a significantly higher emphasis on price discounts ($M = 18.37$, $SD = 52.85$) compared to those with high openness scores ($M = -9.76$, $SD = 68.07$), $t(167.01) = -3.04$ $p < .01$.

H7a has to be rejected since significant differences in utility scores between those who scored high on agreeableness versus those with relatively low scores have only been found for the retailer offering the promotion, $t(88.44) = -2.57$ $p < .05$, and the promotion depth, $t(142) = 3.14$ $p < .01$. In terms of extraversion, significantly greater utility scores for those who scored low on extraversion were reported for price discounts (low extraversion scores: $M = 4.82$, $SD = 62.38$; high extraversion scores: $M = -16.55$, $SD = 60.06$), $t(141) = -2.04$ $p < .05$. Although higher utility scores for consumers with high scores on extraversion have been reported for customized ($M = 44.57$, $SD = 30.72$) and personalized CRM campaigns ($M = 12.82$, $SD = 25.15$) compared to consumers with low extraversion ratings (customized: $M = 35.32$, $SD = 30.54$; $t(141) = 1.77$ $p = .08$; personalized: $M = 3.70$, $SD = 28.28$; $t(141) = 1.97$ $p = .05$), these results were not statistically significant at $p < .05$. Hence, H7b has to be dismissed. The other two personality dimensions, neuroticism and conscientiousness, did not lead to any statistically divergent consumer preferences at $p < .05$.

7.4.4 Reasons for rejecting CRM campaigns by certain apparel retailers

Respondents that had selected CRM campaigns by one of the three apparel retailers in less than two choice tasks were asked to provide reasons for their aversion to CRM campaigns of the respective retailer. The reasons for rejecting CRM campaigns by specific retailers varied between the retailers (see Figure 1). CRM campaigns by Amazon were rejected by 22% of respondents mainly due to a perceived lack of altruistic motivations for supporting a charitable cause (46%). In case of H&M 35% of respondents refused CRM campaigns. The main reasons for refusing these offers were twofold: On the one hand, many consumers did not prefer these offers due to a greater attractiveness of other offers (31%) or since they generally preferred price discounts with self-benefits to marketing campaigns with other-benefit components (37%). On the other hand, several consumers did not select CRM campaigns due to a perceived lack of H&M's corporate credibility (30%) or a perceived lack of altruistic motivations (32%) in terms of its commitment to charitable causes. Respondents that refused CRM campaigns by Wijld (29%) mainly did so due to the superior attractiveness of other offers (38%) or their general preference for price discounts (38%). By contrast to the other two retailers, a considerable percentage of consumers also claimed other reasons (16%) – here, respondents predominantly stated that they would not know Wijld, and thus would not consider offers by this unknown retailer – or no reason (17%) – i.e., don't know / prefer not to answer.

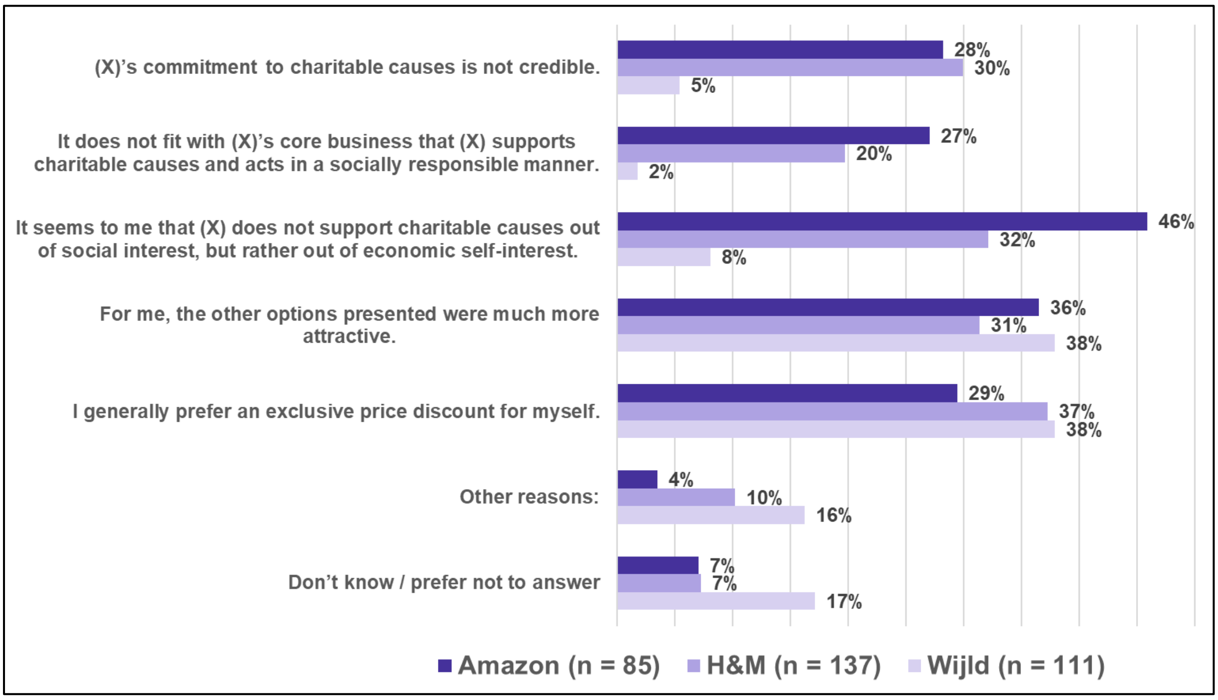


Figure 1: Reasons for rejecting CRM campaigns of the portrayed online apparel retailers

7.4.5 Identification of consumer segments with different preferences: latent

class analysis

For segmenting respondents into groups with similar preferences, which allows us to derive recommendations for dedicated marketing strategies for different audiences, a latent class analysis (LCA) was performed. This model-based approach classifies subjects based on a probabilistic model (Vermunt & Magidson, 2002). For each respondent probabilities of belonging to each of the latent classes are calculated. Hence, the main difference to clustering approaches is that respondents are not fully assigned to segments (Sawtooth Software, 2021).

To identify the ideal number of latent classes for LCA models, information criteria are often used (Nylund-Gibson & Choi, 2018; Paetz et al., 2019; Weller et al., 2020). Among the most frequently used information criteria are the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the consistent Akaike Information Criterion (CAIC), and the adjusted Bayesian Information Criterion (ABIC). For all these information criteria lower values indicate a superior model-fit (Sawtooth Software, 2021). When evaluating these information criteria, often an 'elbow plot' is used depicting the marginal gains in model fit from LCA models with additional segments (Nylund-Gibson & Choi, 2018; Weller et al., 2020). For our sample, the information criteria pointed to different LCA model solutions (Figure 2). Yet, the most salient 'elbow' was at the LCA model with three classes.

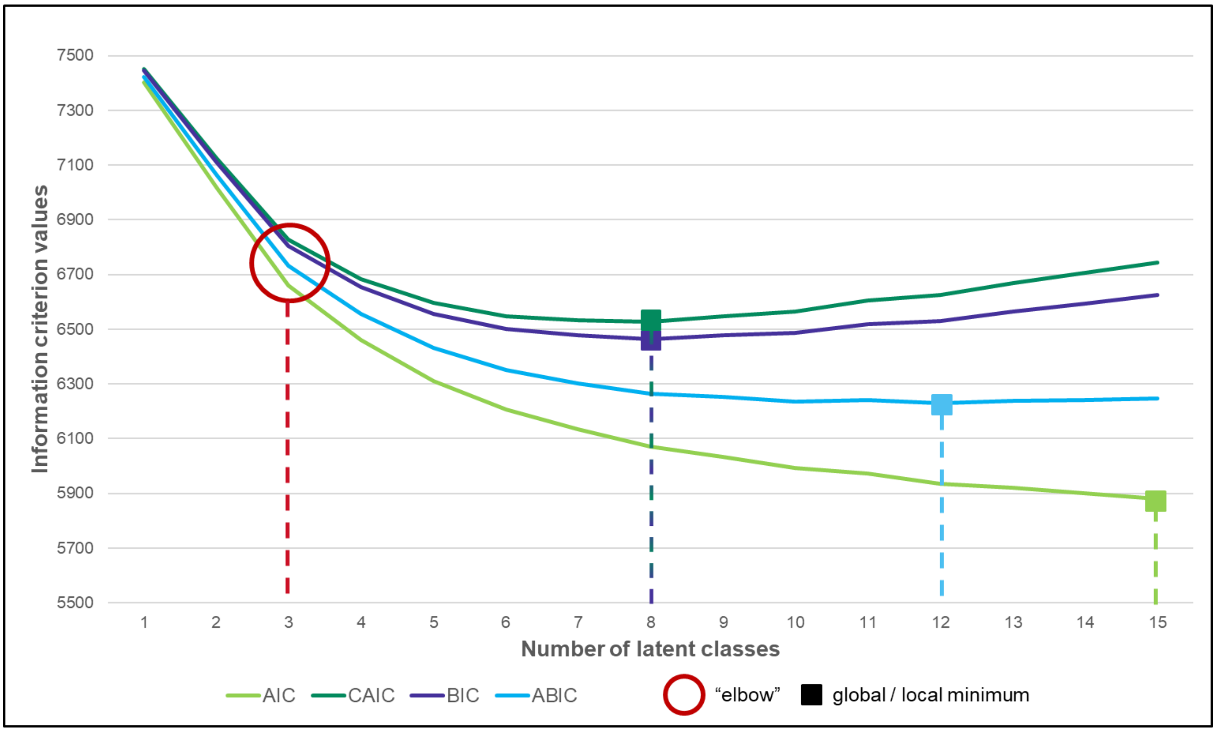


Figure 2: Information criteria plot

Beyond, statistical criteria also the number of respondents per segment as well as "noticeable differences in estimated part-worth structures and/or attribute importances across segments" should be taken into account when deciding on the ideal number of segments (Paetz et al., 2019, p. 11; Weller et al., 2020). Considering the aforementioned information criteria as well as other aspects (segment sizes and interpretability of the LCA models), either a three-model solution or an eight-model solution seemed promising. Yet, due to relatively small segments (five groups with only 8-11% of respondents per group) and partially limited unique interpretability of the groups (segments with similar preference structures), we decided against the eight-model solution and in favor for the LCA model with three segments.

For calculating average utility scores for different latent classes, either LCA can be used "to detect segments, and use the segment membership information as "banner points" (filters) applied to simulations using underlying HB utility runs" (Sawtooth Software, 2021, p. 17) or "to convert the segment-based results into individual-level estimates" (Sawtooth Software, 2021, p. 8). While the latter option – using the pseudo individual-level estimations from the latent class solution – will have relatively poor representation of true respondent heterogeneity, using HB estimates does not take into account respondents' true probabilities of belonging to different latent classes, since respondents are fully assigned to the segment with their highest membership likelihood. In line with the utility estimation of our overall sample (see Table 4), we follow the approach of calculating utility scores from HB estimates based on segment memberships derived from LCA.

The resulting three segments yield clearly different preference structures (Figure 3). Segment one (n=181) mainly comprises respondents who attach comparatively great utility to all types of CRM campaigns and this is the only group with the overall lowest utility score for price campaigns. Moreover, it is the only segment with the strongest preference for the sustainable fashion retailer Wijld. Therefore, this segment could be characterized as “pro-social consumers”. Respondents in segment two (n=119) strongly prefer price discounts to any other promotion type. Accordingly, in brief, this group could be termed “price-sensitive consumers”. By contrast, respondents in segment three (n=88) place great importance on the apparel retailer: In particular, these consumers strongly prefer offers by Amazon to the other two apparel retailers. Hence, consumers belonging to this segment could be described as “Amazon enthusiasts”.

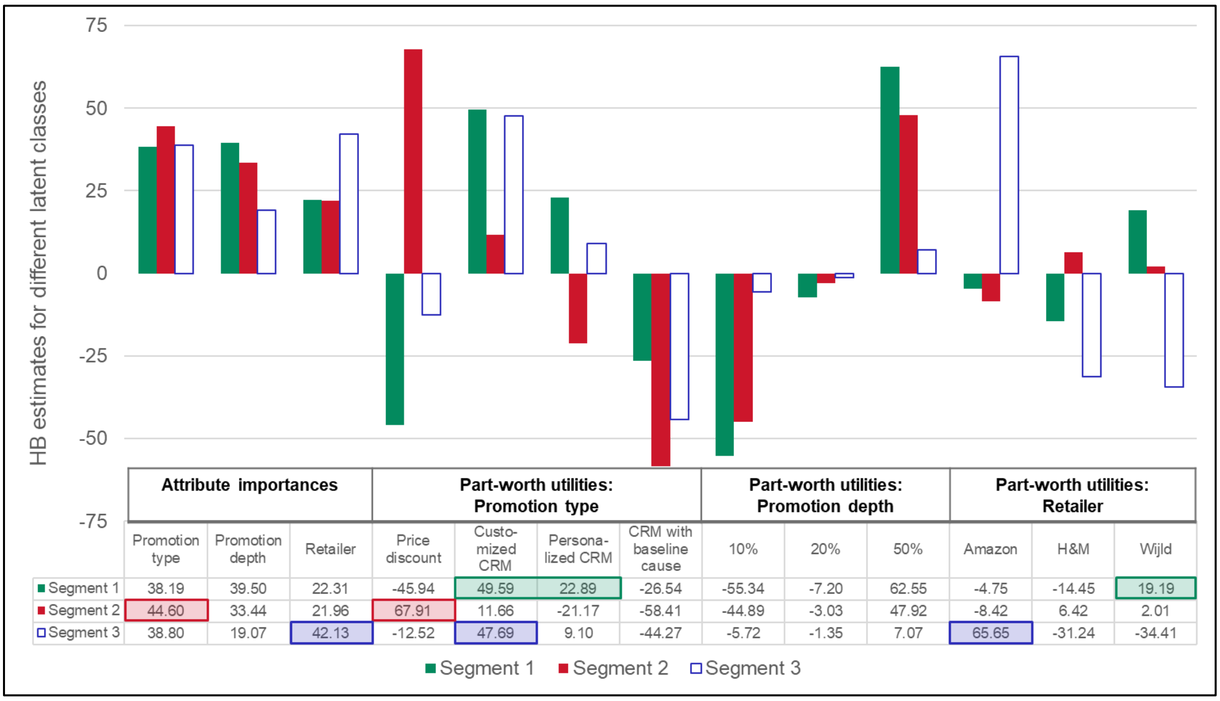


Figure 3: Part-worth utilities (HB estimates) for the three latent classes

7.4.6 Exploration of impact factors determining segment membership

For characterizing segments, we conducted one-way ANOVA with respondents' sociodemographic and psychographic characteristics and respondents' perceived pre-reputation of the three apparel retailers. The results of the ANOVA for sociodemographic characteristics did not point to statistically significant differences between the three segments (at $p < 0.05$). With reference to psychographic consumer characteristics the three segments differed significantly for different levels of openness, $F(2, 209.12) = 3.54$, $p < 0.05$, and agreeableness, $F(2, 385.00) = 3.59$, $p < 0.05$. A Tukey's honestly significant difference post-hoc test (Tukey HSD) and a Games-Howell post-hoc test were conducted for a pair-wise comparison of psychographic consumer characteristics between the three segments. Significant differences were only found for ratings of agreeableness between segments one (mean: 3.28) and three (mean: 3.01) at $p < .05$. Accordingly, individuals within the segment of pro-social consumers tend to yield a significantly greater agreeable personality structure than consumers within the segment of Amazon enthusiasts. Moreover, significant differences between the three segments were detected for each of the three facets of respondents' perceived retailer pre-reputation concerning Amazon and Wijld, but not for H&M ($p < 0.01$). A Tukey HSD revealed that significant differences particularly existed between segment one and three and segment two and three, but rarely between segment one and two ($p < 0.01$). This seems reasonable provided that preference structures of the three segments as stated in Figure 3 differed decisively between segment one and three as well as segment two and three with reference to the preferred apparel retailer.

7.5 Discussion

With an increasing consumer demand for socially responsible behaviors of companies – even during the COVID-19 pandemic (Bae et al., 2021; Manuel & Herron, 2020; Vătămănescu et al., 2021), retailers are nowadays embracing CSR initiatives as a supplementary tool in their marketing portfolios, alongside existing traditional sales promotion methods such as price discounts. Previous research indicated that especially CRM with co-creative features – e.g., allowing consumers to customize the supported cause – is a highly effective marketing approach. Hence, this study investigates the effectiveness of CRM campaigns with choice compared to other types of CRM campaigns and price discounts as a form of traditional sales promotion in the online apparel industry.

The results reveal that, in general, consumers prefer CRM campaigns with choice to other types of CRM campaigns with less co-creative features (H1a, H3) as well as to price discounts. In addition, we find that personalized CRM campaigns – that is, CRM campaigns supporting a pre-selected charitable organization based on implicitly retrieved individual preferences such as page likes or follows on social media – are more effective than CRM campaigns with a predefined cause (H2) and price discounts. Nevertheless, not all types of CRM campaigns are considered more effective than traditional sales promotion, since price discounts outperform generic CRM campaigns with a predefined cause (H4). Unlike findings of previous research (Grau & Folse, 2007; Hou et al., 2008; Ross III et al., 1991; Schreiner & Baier, 2022; Wiebe et al., 2017) and our expectations, projects with spatially closer beneficiaries (e.g., local or national projects) are not generally preferred to more distant ones (international projects) in customized CRM campaigns (H1b).

By examining consumers' personality traits and collectivist versus individualistic orientations we also demonstrated that consumers who score high on openness, and collectivism show an increased preference for CRM campaigns (in support of H6a and H7c), while hypothesized effects of individualism, agreeableness and extraversion could not be confirmed (H6b, H7a and H7b).

Applying LCA to the utility values derived from CBC/HB yields three heterogeneous segments: i), "pro-social consumers", that is, consumers with comparatively strong preferences for CRM campaigns of any type and the strongest preference for the sustainable fashion retailer Wijld; ii), "price-sensitive consumers", i.e., consumers with the overall and comparatively highest utility score for price discounts; iii), "Amazon enthusiasts", i.e., consumers who attach the greatest importance to the apparel retailer and, more precisely, strongly prefer offers by Amazon to the other two apparel retailers. By analyzing potential variables predicting segment membership, we point out that the consideration of psychographic consumer characteristics – more specifically, personality traits – and consumers perceived pre-reputation of a retailer might be more helpful than sociodemographic aspects in categorizing consumers into different segments enabling online apparel retailers to tailor their marketing appeals accordingly.

These results yield various implications for research and practice.

7.5.1 Theoretical contributions and managerial implications

The present work enriches the still limited body of research on CRM with choice by comparing the effectiveness of such campaigns with other types of CRM campaigns as well as price discounts as form of traditional sales promotion, following recent suggestions for future research directions in the field of CRM with choice (Tao & Ji, 2020). In line with prior research, we find that CRM with choice outperforms CRM campaigns with single, predetermined causes (Arora & Henderson, 2007; Howie et al., 2018; Kull & Heath, 2016; Lucke & Heinze, 2015; Robinson et al., 2012; Tao & Ji, 2020). With reference to customized CRM, we also provide insights into consumers' preferences regarding cause proximity – another facet besides the type of cause that can be customized in CRM campaigns with choice (Christofi et al., 2019). Contrary to previous findings for CRM campaigns with generic, firm-determined causes spatially close beneficiaries are not basically favored to spatially distant ones. As previous research showed, a possible explanation for this finding could be that preferences for cause proximity depend on consumers' collectivistic versus individualistic orientations (Christofi et al., 2019; Fan et al., 2020).

Moreover, by comparing customized CRM to other forms of CRM and price discounts, we establish comparability between the effectiveness of price discounts and various types of CRM campaigns. Our results prove, that while customized CRM and also personalized CRM is, in general, of greater utility to consumers than equivalent price discounts, generic CRM campaigns with a predefined cause are not. Ergo, retailers should carefully reflect on the selection of a suitable type of CRM campaign. Especially the decision between personalized and customized CRM campaigns seems to be challenging: On the one hand, the findings of our study indicate that CRM campaigns with unrestricted choice are more effective than personalized CRM campaigns. On the other hand, personalized CRM campaigns might be the more cost-effective and feasible approach in practice. While building own CRM-with-choice platforms like AmazonSmile enabling the support of numerous registered charitable organizations is too cumbersome for many retailers, especially for small and medium-sized enterprises, the collaboration with other independent shopping platforms such as Gooding (2022) or ShopRaise (2022) requires consumers to start their purchase via the dedicated shopping website or app. Hence, such CRM campaigns might not be communicated prominently enough directly on the retailers' websites as they require consumers to re-enter the website via the third-party shopping platform, and thus might prevent customers in proceeding with a transaction due to additional steps within their customer journey and interruptions of the customer experience. In addition, recently, Amazon (2023) announced to close their CRM-with-choice platform because product sales-related donations were spread across too many charitable organizations – more than one million globally – and, hence failed to make the intended powerful impact. Thus, the more feasible approach of customized CRM campaigns seems to be CRM with restricted choice, i.e., allowing consumers to select a preferred charitable organization from a predefined list with a moderate number of charitable organizations (Kull & Heath, 2016). In this regard, however, personalized CRM campaigns can be used in a more targeted manner: With a personalized CRM approach retailers can engage in cooperations with popular charitable organizations among their existing customers either derived explicitly, for instance, via previously conducted customer surveys, or collected implicitly from their customers' social media data, e.g., likes or interactions with charitable organizations.

This leads to the next contribution of our research: By examining personalization as type of one-to-one marketing in the field of CRM we enrich existing research and illustrate personalization possibilities of CRM campaigns beyond tailoring marketing messages by using personal information (Bartsch & Kloß, 2019; Jihye Kim & Kim, 2022; Masthoff et al., 2013). The results of this study reveal that retailers can apply such personalization strategies in CRM to overcome the difficulty of finding an appealing cause for broad audiences (e Silva et al., 2020; Lafferty, 2009; Lafferty et al., 2016): Selecting relevant charitable organizations for different customer segments might enhance the perceived cause-brand fit for all target groups contributing to the extant literature on cause-brand fit which suggests that CRM campaigns with a predefined single cause can result in negative evaluations for certain consumer groups (Sheikh & Beise-Zee, 2011).

The current research also enriches literature regarding the effects of consumers' perceived pre-reputation of a brand engaging in CRM campaigns on consumer responses. In line with previous literature, we prove that companies perceived as credible ex ante to the CRM campaign can positively impact consumer preferences for CRM campaigns (Bigné et al., 2012; Koschate-Fischer et al., 2016; Lafferty, 2007). We show that this effect is not limited to CRM campaigns but also applies to marketing appeals with mere self-benefits. Accordingly, building a positive brand reputation among potential customers seems to be pivotal for marketing campaigns in general. For this purpose, the brand's overall and CSR reputation might be enhanced by implementing and promoting strategic CSR initiatives (Koschate-Fischer et al., 2016).

Another contribution to existing CRM literature is made by exploring the reasons why consumers generally reject CRM campaigns by certain apparel retailers. For the well-known online retailer Amazon consumers refuse CRM campaigns because they don't believe that the brand supports charitable causes out of altruism. This might be attributed to findings of recent research suggesting that CRM campaigns are frequently used for greenwashing and bluewashing purposes, i.e., portraying exaggerated or unsubstantiated claims of environmental or social commitment to enhance the corporate image, which might lead to unfavorable consumer responses (Sailer et al., 2022). Moreover, the rejection of CRM by Wijld due to a lack of familiarity with the brand also supports findings of previous studies (Fan et al., 2020; Lafferty & Goldsmith, 2005). These results suggest that established retailers can make use of their customers' familiarity with the brand when designing CRM campaigns but should consider the cause-brand-fit when selecting charitable causes to avoid perceptions of greenwashing or bluewashing. Again, CRM with unrestricted choice can help to redress this issue and personalized CRM might overcome a lacking brand-cause-fit if suitable causes have been selected taking into account preferences of different consumer segments.

By identifying three consumer segments with heterogeneous preferences for marketing appeals guidance for online apparel retailers can be provided. While consumers within segments one (pro-social consumers) and two (price-sensitive consumers) can be addressed with offering either attractive and relevant CRM campaigns or price discounts, consumers in segment three (Amazon enthusiasts) may be difficult to win over with offers from retailers other than Amazon. Consumers within the latter segment might already have an existing customer relationship with Amazon, and since they also strongly prefer customized CRM campaigns, they might have already been using Amazon's CRM-with-choice shopping platform AmazonSmile. Nevertheless, a beneficial marketing approach for targeting a vast majority of consumers can be to enable further consumer choice beyond consumer engagement in CRM campaigns: Allowing consumers to choose between a self-benefit (price discount) and an other-benefit (CRM campaign) could equally appeal to the preferences of consumers from segments one and two, thus helping to attract a broader audience.

The research at hand offers additional insights into consumer evaluations of CRM campaigns by exploring psychographic consumer characteristics as possible drivers for consumer preferences of different types of CRM campaigns versus price discounts. Particularly, we extend previous literature on cultural effects of collectivistic versus individualistic orientations on CRM effectiveness. As hypothesized, any type of CRM campaigns is of significantly greater utility to consumers with high versus low collectivistic orientations. These results contribute to previous literature comparing the effectiveness of CRM campaigns in rather collectivistic versus individualistic cultures (Vaidyanathan et al., 2013; Wang, 2014). For customized CRM campaigns our results confirm previous findings suggesting that positive perceptions of CRM campaigns with choice are greater among collectivists who attribute value to such marketing practices due to their perceived role in helping charitable organizations than among non-collectivists, who value such customized CRM campaigns due to opportunities of personal choice (Robinson et al., 2012). Retailers can use this information in a similar manner to meet the needs of different consumer segments by offering consumers' the choice between price discounts and the support for a charity. Especially in rather individualistic cultures this might be a beneficial approach to cater to the needs of consumers with greater individualistic orientations and their preferences for personal choices (Iyengar & Lepper, 1999).

Finally, the current study extends the still limited body of research on personality traits as drivers for consumer responses to CRM campaigns (J. Lee & Lee, 2021). In line with previous research in the domain of pro-social consumption, we found that openness has an overall positive impact on consumer preferences for CRM campaigns (Paetz, 2020; Y. Sun et al., 2018). Moreover, while different levels of agreeableness did not lead to significantly different utility scores for CRM campaigns in general, consumers within the pro-social segment scored significantly higher on the personality dimension of agreeableness than Amazon enthusiasts which seems reasonable since this personality dimension has been connected to altruistic behaviors in previous studies (Paetz, 2020; Y. Sun et al., 2018). Retailers can utilize these findings for developing marketing campaigns for different consumer groups based on different tendencies in personality structures. For German consumers a feasible approach might be to differentiate between consumers in different regions: For instance, Paetz (2020) suggested that such a segmentation approach might be beneficial, since east Germans have been reported to be less open than western Germans, whereas Southern Germans were more agreeable than Northern Germans (Obschonka et al., 2019). Beyond that, Götz et al. (2020) demonstrated that people living in mountainous areas in the US differed in their personality structures compared to those living in flatter areas.

7.5.2 Limitations and future research

Some limitations of the present study provide food for thought for future research opportunities. First, the results of the study are limited to the German apparel market and cannot be generalized to products in other industries or other countries and cultures without further research. While the approach of considering personality traits and cultural dimensions of consumers might already indicate tendencies of consumer responses to price discounts versus CRM campaigns in other cultures, further research is needed to replicate these findings for other products and to analyze these relationships in comparative studies between rather collectivistic versus individualistic markets.

Moreover, the list of selectable charitable organizations in the input for the personalization condition has been restricted to 14, whereas shopping platforms like AmazonSmile enable users to choose from a considerably larger number of charities. However, since this selection of preferred charitable organizations from a predefined list was used to simulate consumer likes on social media platforms it seems reasonable to restrict the choice list to well-known charitable organizations that retailers are likely to cooperate with in CRM campaigns. Likewise previous research suggested that an increased number of choice options in customized CRM does not lead to enhanced consumer evaluations due to an increased decision difficulty and choice overload (Kull & Heath, 2016). However, general marketing research on the effects of personalization has found that female consumers value larger sets of personalized product recommendations, while their male counterparts prefer smaller recommendation sets (Schreiner et al., 2019). Hence, further research should investigate the impact of varying levels of choice options in personalized CRM campaigns on consumer evaluations to identify the ideal number of charitable causes for different consumer segments. Additionally, more research regarding the effectiveness and ideal design of personalized CRM is required. Previous research in the field of personalized marketing identified negative effects of such marketing campaigns due to increased privacy concerns, feelings of vulnerability or perceived intrusiveness leading to reactance behavior (Aguirre et al., 2015; Bleier & Eisenbeiss, 2015; Puzakova et al., 2015; Song et al., 2016; van Doorn & Hoekstra, 2013). Therefore, future studies could address the following issues: Can such negative effects also impair the success of personalized CRM campaigns? For which consumer segments are such negative perceptions more likely or unlikely to occur? What type of personalization strategy – e.g., using personal information or personalizing the supported charities – should retailers employ to achieve utmost efficacy?

Avenues for future research also include different objects of personalization or customization within CRM campaigns as outlined by Christofi et al. (2019): Researchers could examine the effectiveness of customized or personalized CRM campaigns with other types of donation such as donations in kind or donations of employee time for the respective charity versus monetary donations and price discounts.

Finally, the present study only offers results on consumer preferences for specific types of marketing campaigns. These preferences might not fully translate into actual purchasing behavior due to the previously studied ‘attitude-behavior-gap’ indicating a discrepancy between consumers attitudinal responses and their actual behaviors (Eastman et al., 2019; ElHaffar et al., 2020; Schamp et al., 2022). Such a gap has mainly been identified in the fields of sustainable consumption (ElHaffar et al., 2020; Nguyen et al., 2019; Park & Lin, 2020). However, some researchers also suggested such an effect in CRM, especially with reference to specific consumer groups such as Millennials (Eastman et al., 2019), whereas others also reported enhanced behavioral consumer responses such as increased product sales (Andrews et al., 2014). Since CRM does not involve additional costs to consumers, it seems reasonable that the ‘attitude-behavior-gap’ might be less pronounced in such campaigns. Yet, future research should address this issue, particularly with reference to customization and personalization practices.

Appendix A

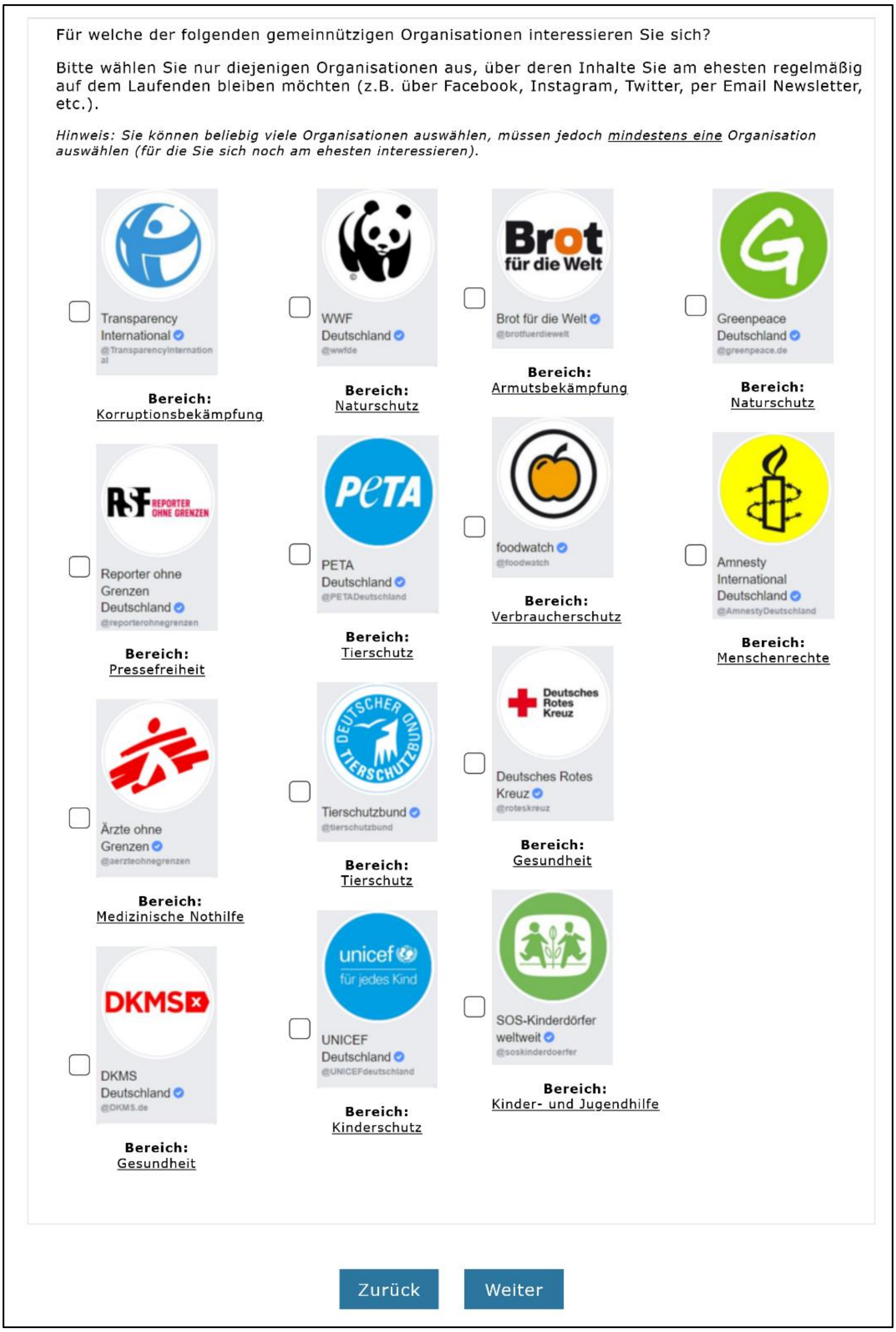
Overview of items used for measuring collectivism and individualism

German	English	Construct	Collectivism / individualism category retrieved from Oyserman et al. (2002)	Sources
Ich betrachte mich selbst als einzigartig und anders als andere in vielerlei Hinsicht.	I consider myself to be unique, different from others in many respects.	Individualism	Unique	McCarty and Shrum (2001); Triandis and Gelfand (1998)
Ich arbeite normalerweise selbstbestimmt und unabhängig von anderen.	I usually work independently from others.	Individualism	Independent	McCarty and Shrum (2001)
Ich verlasse mich lieber auf mich selbst als auf andere.	I would rather depend on myself than others.	Individualism	Independent	Triandis and Gelfand (1998); Sharma (2010)
Es ist mir wichtig, dass ich meine Arbeit besser mache als andere.	It is important that I do my job better than others.	Individualism	Goals	Triandis and Gelfand (1998); Sharma (2010)
Ich fühle mich wohl, wenn ich mit anderen zusammenarbeite.	I feel good when I cooperate with my group members.	Collectivism	Belong	Triandis and Gelfand (1998); Sharma (2010)
Ich arbeite in der Regel hart für die Ziele einer Gruppe, auch wenn ich dadurch keine persönliche Anerkennung erhalte.	I usually work hard for the goals of a group even if it doesn't result in personal recognition.	Collectivism	Duty	McCarty and Shrum (2001)
Das Wohlbefinden meiner Kollegen ist mir wichtig.	The well-being of my group members is important for me.	Collectivism	Related	Triandis and Gelfand (1998); Sharma (2010)
Familienmitglieder sollten zusammenhalten, auch wenn sie nicht einer Meinung sind.	Family members should stick together, even if they do not agree.	Collectivism	Harmony	Triandis and Gelfand (1998); Sharma (2010)

Appendix B

Selection of preferred charitable organizations (personalization input)

German task (survey language):



Für welche der folgenden gemeinnützigen Organisationen interessieren Sie sich?

Bitte wählen Sie nur diejenigen Organisationen aus, über deren Inhalte Sie am ehesten regelmäßig auf dem Laufenden bleiben möchten (z.B. über Facebook, Instagram, Twitter, per Email Newsletter, etc.).

Hinweis: Sie können beliebig viele Organisationen auswählen, müssen jedoch mindestens eine Organisation auswählen (für die Sie sich noch am ehesten interessieren).

Transparency International @TransparencyInternational
Bereich: Korruptionsbekämpfung

WWF Deutschland @wwfde
Bereich: Naturschutz

Brot für die Welt @brotfuerdiewelt
Bereich: Armutsbekämpfung

Greenpeace Deutschland @greenpeace.de
Bereich: Naturschutz

Reporter ohne Grenzen Deutschland @reporterohnegrenzen
Bereich: Pressefreiheit

PETA Deutschland @PETADeutschland
Bereich: Tierschutz

foodwatch @foodwatch
Bereich: Verbraucherschutz

Amnesty International Deutschland @AmnestyDeutschland
Bereich: Menschenrechte

Ärzte ohne Grenzen @aerzteohnegrenzen
Bereich: Medizinische Nothilfe

Tierschutzbund @tierschutzbund
Bereich: Tierschutz

Deutsches Rotes Kreuz @roteskreuz
Bereich: Gesundheit

DKMS Deutschland @DKMS.de
Bereich: Gesundheit

UNICEF Deutschland @UNICEFdeutschland
Bereich: Kinderschutz

SOS-Kinderdörfer weltweit @soskinderdoerfer
Bereich: Kinder- und Jugendhilfe

Zurück Weiter

Translated English task:

Which of the following charitable organizations are you interested in?

Please select the organizations you are most likely to receive regular updates about (e.g., via Facebook, Instagram, Twitter, email newsletters, etc.).

Please note: You can select as many organizations as you like, but you must select at least one organization (that you are most interested in).

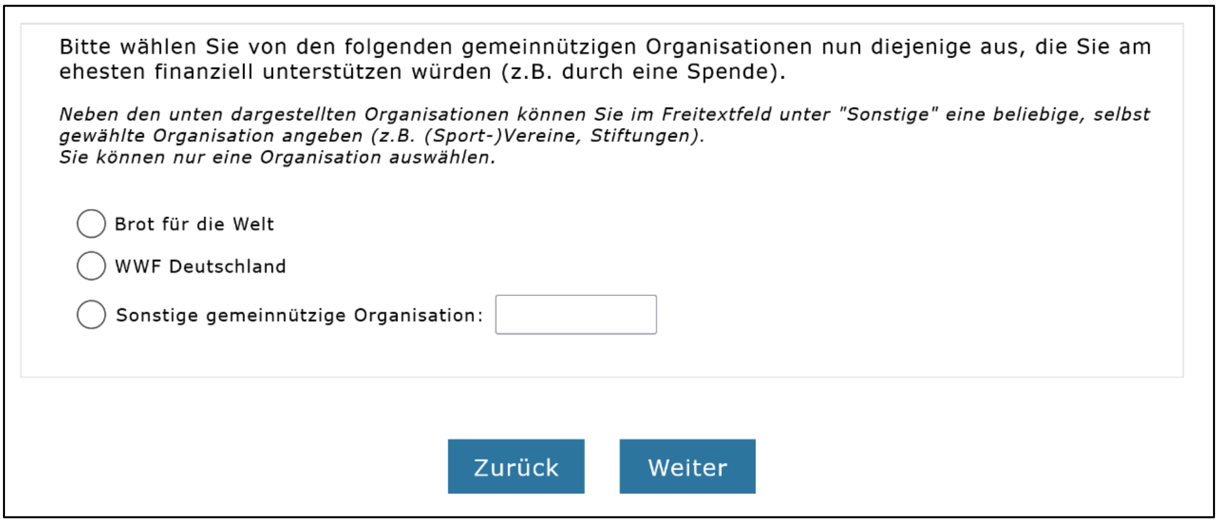
Name of the organization	**Category**
DKMS Germany	Health
PETA Germany	Animal protection
WWF Germany	Environmental protection
Greenpeace Germany	Environmental protection
Transparency International	Anti-corruption
foodwatch	Consumer rights
Amnesty International Germany	Human rights
German Red Cross	Health
German Animal Welfare Federation	Animal protection
Reporters Without Borders	Freedom of press
UNICEF Germany	Humanitarian aid for children
Bread for the world	Fight against poverty
SOS Children's Villages Germany	Humanitarian aid for children
Doctors without borders	Humanitarian aid

Appendix C

Selection of preferred donation cause (customization input part 1)

Selection of the preferred donation cause. In this case, “Brot für die Welt” and “WWF Deutschland” have been selected previously as charitable organizations of interest.

German task (survey language):



Bitte wählen Sie von den folgenden gemeinnützigen Organisationen nun diejenige aus, die Sie am ehesten finanziell unterstützen würden (z.B. durch eine Spende).

Neben den unten dargestellten Organisationen können Sie im Freitextfeld unter "Sonstige" eine beliebige, selbst gewählte Organisation angeben (z.B. (Sport-)Vereine, Stiftungen).
Sie können nur eine Organisation auswählen.

- Brot für die Welt
- WWF Deutschland
- Sonstige gemeinnützige Organisation:

Zurück Weiter

Translated English task:

From the following charitable organizations, please select the one that you would be most likely to support financially (e.g., by donating).

In addition to the listed organizations below, you can enter any organization of your choice in the “other” field (e.g., (sports) clubs, foundations).

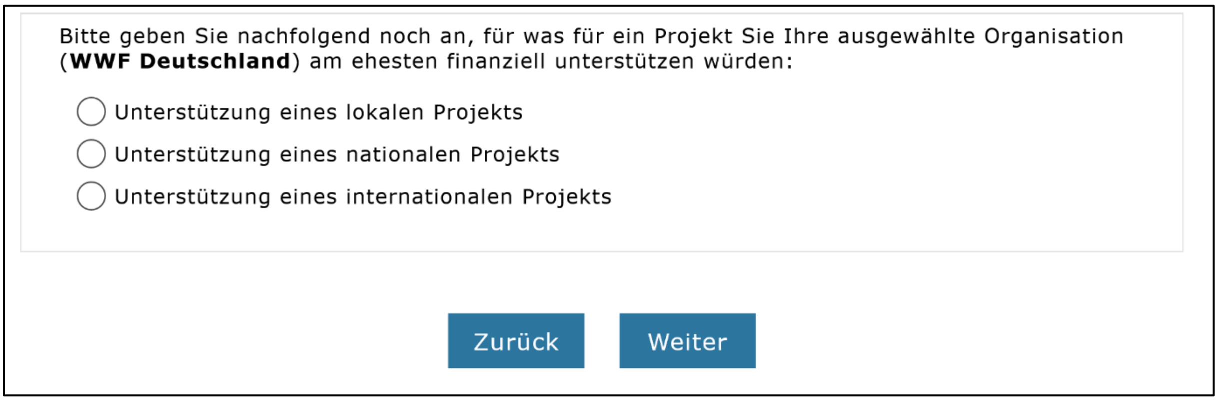
You can only select one organization.

Appendix D

Selection of preferred cause proximity (customization input part 2)

Selection of the preferred proximity of the supported cause. In this case, "WWF Deutschland" has been selected previously as preferred donation cause.

German task (survey language):


Bitte geben Sie nachfolgend noch an, für was für ein Projekt Sie Ihre ausgewählte Organisation (**WWF Deutschland**) am ehesten finanziell unterstützen würden:

- Unterstützung eines lokalen Projekts
- Unterstützung eines nationalen Projekts
- Unterstützung eines internationalen Projekts

Zurück Weiter

Translated English task:

Please indicate below for which kind of project you would most likely support your selected organization (**WWF Germany**) financially:

- Support of a local project
- Support of a national project
- Support of an international project

Appendix E

Description of online retailers for apparel products

Online apparel retailer	Original (German) brief description	English (translated) brief description
Amazon	Amazon ist ein Online-Versandhändler-Generalist mit einer breit gefächerten Produktpalette und der weltweite Marktführer im Online-Handel.	Amazon is a generalist online retailer with a diversified product range and the global market leader in online retailing.
H&M	H&M ist ein schwedisches Textilhandelsunternehmen, das Kleidung, Accessoires und Schuhe über Ladengeschäfte und den Onlineshop anbietet.	H&M is a Swedish textile retailer offering clothing, accessories and footwear through brick-and-mortar stores and its online store.
Wijld	Wijld ist ein Mode „Start-Up“, das in der EU aus Holzfasern produzierte Kleidung über den Onlineshop anbietet.	Wijld is a fashion "start-up" offering clothing made in the EU from wood fibers via its online store.

Appendix F

Exemplarily CBC tasks

Original choice task in German language:

English translation of the depicted choice task:

Imagine that you have found a new piece of clothing on the websites of the following three retailers:

All three retailers offer the products of your choice for the same price.

Which of the following offers would you be most likely to choose when purchasing apparel online?

Stimulus #1: *Personalized CRM campaign*	**Stimulus #2:** *Customized CRM campaign*	**Stimulus #3:** *Price discount*
With your purchase at **Wijld**, **10 percent** of your purchase value will directly be passed on to “**PETA Germany”**. You will receive a donation receipt in the follow-up.	With you purchase at **Amazon**, **50 percent** of your purchase value will directly be passed on to your chosen organization “**WWF Germany**” to **support a local project**. You will receive a donation receipt in the follow-up.	With your purchase at **H&M**, you will receive a **10% price discount** on your order.
Select	Select	Select

Appendix G

List of reasons for refusing offers of a particular apparel retailer to financially support charitable organizations

(German) item	**Translated item**	**Construct**	**Source**
Das Engagement von *(X)* für gemeinnützige Zwecke ist nicht glaubwürdig.	*(X)'s* commitment to charitable causes is not credible.	Corporate credibility	Pérez and Bosque (2013)
Es passt nicht zum Kerngeschäft von *(X)*, dass *(X)* gemeinnützige Zwecke unterstützt und Verantwortung für die Gesellschaft übernimmt.	It does not fit with *(X)'s* core business that *(X)* supports charitable causes and acts in a socially responsible manner.	Cause-brand fit	Pérez and Bosque (2013) Bigné et al. (2012); Bigné-Alcañiz et al. (2009)
Ich habe den Eindruck, dass *(X)* gemeinnützige Zwecke nicht aus gesellschaftlichem Interesse, sondern eher aus wirtschaftlichen Eigeninteressen unterstützt.	It seems to me that *(X)* does not support charitable causes out of social interest, but rather out of economic self-interest.	Altruistic motivations	Pérez and Bosque (2013) Bigné et al. (2012)
Die anderen dargestellten Optionen waren deutlich attraktiver.	For me, the other options presented were much more attractive.	n/a	n/a
Ich bevorzuge grundsätzlich einen exklusiven Rabatt für mich.	I generally prefer an exclusive price discount for myself.	n/a	n/a
Sonstige Gründe	Other reasons: *[free text field]*	n/a	n/a
Weiß nicht / keine Angabe	Don't know / prefer not to answer	n/a	n/a

References

Aguirre, E., Mahr, D., Grewal, D., Ruyter, K. de, & Wetzels, M. (2015). Unraveling the Personalization Paradox: The Effect of Information Collection and Trust-Building Strategies on Online Advertisement Effectiveness. Journal of Retailing, 91(1), 34–49. https://doi.org/10.1016/j.jretai.2014.09.005

Akdeniz, B., Calantone, R. J., & Voorhees, C. M. (2013). Effectiveness of Marketing Cues on Consumer Perceptions of Quality: The Moderating Roles of Brand Reputation and Third-Party Information. Psychology and Marketing, 30(1), 76–89. https://doi.org/10.1002/mar.20590

Alhouti, S., Wright, S. A., & Baker, T. L. (2021). Customers need to relate: The conditional warm glow effect of CSR on negative customer experiences. Journal of Business Research, 124, 240–253. https://doi.org/10.1016/j.jbusres.2020.11.047

Amazon. (2022a). About AmazonSmile. https://smile.amazon.com/charity/smile/about

Amazon. (2022b). AmazonSmile. https://www.aboutamazon.com/impact/community/amazonsmile

Amazon. (2023). Amazon closing AmazonSmile to focus its philanthropic giving to programs with greater impact. https://www.aboutamazon.com/news/company-news/amazon-closing-amazonsmile-to-focus-its-philanthropic-giving-to-programs-with-greater-impact

Andrews, M., Luo, X., Fang, Z., & Aspara, J. (2014). Cause Marketing Effectiveness and the Moderating Role of Price Discounts. Journal of Marketing, 78(6), 120–142. https://doi.org/10.1509/jm.14.0003

Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., Joshi, Y., Kumar, V., Lurie, N., Neslin, S., Sajeesh, S., Su, M., Syam, N., Thomas, J., & Zhang, Z. J. (2008). Putting one-to-one marketing to work: Personalization, customization, and choice. Marketing Letters, 19(3-4), 305. https://doi.org/10.1007/s11002-008-9056-z

Arora, N., & Henderson, T. (2007). Embedded Premium Promotion: Why It Works and How to Make It More Effective. Marketing Science, 26(4), 514–531. https://doi.org/10.1287/mksc.1060.0247

Bae, K.-H., El Ghoul, S., Gong, Z., & Guedhami, O. (2021). Does CSR matter in times of crisis? Evidence from the COVID-19 pandemic. Journal of Corporate Finance, 67(3), 1–18. https://doi.org/10.1016/j.jcorpfin.2020.101876

Ballings, M., McCullough, H., & Bharadwaj, N. (2018). Cause marketing and customer profitability. Journal of the Academy of Marketing Science, 46(2), 234–251. https://doi.org/10.1007/s11747-017-0571-4

Barrick, M. A., & Mount, M. K. (1991). The big five personality dimensions and job performance: a meta-analysis. Personnel Psychology, 44(1), 1–26. https://doi.org/10.1111/j.1744-6570.1991.tb00688.x

Bartsch, A., & Kloß, A. (2019). Personalized charity advertising. Can personalized pro-social messages promote empathy, attitude change, and helping intentions toward stigmatized social groups? International Journal of Advertising, 38(3), 345–363. https://doi.org/10.1080/02650487.2018.1482098

Benlian, A. (2015). Web Personalization Cues and Their Differential Effects on User Assessments of Website Value. Journal of Management Information Systems, 32(1), 225–260. https://doi.org/10.1080/07421222.2015.1029394

Bigné, E., Currás-Pérez, R., & Aldás-Manzano, J. (2012). Dual nature of cause-brand fit: Influence on corporate social responsibility consumer perception. European Journal of Marketing, 46(3/4), 575–594. https://doi.org/10.1108/03090561211202620

Bigné-Alcañiz, E., Currás-Pérez, R., & Sánchez-García, I. (2009). Brand credibility in cause-related marketing: The moderating role of consumer values. Journal of Product & Brand Management, 18(6), 437–447. https://doi.org/10.1108/10610420910989758

Bleier, A., & Eisenbeiss, M. (2015). The Importance of Trust for Personalized Online Advertising. Journal of Retailing, 91(3), 390–409. https://doi.org/10.1016/j.jretai.2015.04.001

Bolton, L. E., & Mattila, A. S. (2015). How Does Corporate Social Responsibility Affect Consumer Response to Service Failure in Buyer–Seller Relationships? Journal of Retailing, 91(1), 140–153. https://doi.org/10.1016/j.jretai.2014.10.001

Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalization in personalized marketing: Trends and ways forward. Psychology and Marketing, 9(8), 1529–1562. https://doi.org/10.1002/mar.21670

Chang, C.-T., & Cheng, Z.-H. (2015). Tugging on Heartstrings: Shopping Orientation, Mindset, and Consumer Responses to Cause-Related Marketing. Journal of Business Ethics, 127(2), 337–350. https://doi.org/10.1007/s10551-014-2048-4

Choi, J., Chang, Y. K., Jessica Li, Y., & Jang, M. G. (2016). Doing Good in Another Neighborhood: Attributions of CSR Motives Depend on Corporate Nationality and Cultural Orientation. Journal of International Marketing, 24(4), 82–102. https://doi.org/10.1509/jim.15.0098

Christofi, M., Vrontis, D., Leonidou, E., & Thrassou, A. (2019). Customer engagement through choice in cause-related marketing: A potential for global competitiveness. International Marketing Review, 37(4), 621–650. https://doi.org/10.1108/IMR-04-2018-0133

Cohen, S. H. (1997). Perfect union. Marketing Research, 9(1), 12–17.

Costa, P., & McCrae, R. R [R. R.]. (1999). A five-factor theory of personality. In L. A. Pervin & O. P. John (Eds.), Handbook of personality: Theory and Research (2nd ed., pp. 139–153). Guilford Press.

Cui, Y., Trent, E. S., Sullivan, P. M., & Matiru, G. N. (2003). Cause-related marketing:

How generation Y responds. International Journal of Retail & Distribution Management, 31(6), 310–320. https://doi.org/10.1108/09590550310476012

Deb, M., & Amawate, V. (2019). Extending the knowledge on cause-related marketing (CrM) campaign with focus on skepticism. VINE Journal of Information and Knowledge Management Systems, 50(2), 329–348. https://doi.org/10.1108/VJIKMS-05-2019-0061

Desarbo, W. S., Ramaswamy, V., & Cohen, S. H. (1995). Market segmentation with choice-based conjoint analysis. Marketing Letters, 6(2), 137–147. https://doi.org/10.1007/BF00994929

Digman, J. M. (1990). Personality Structure: Emergence of the Five-Factor Model. Annual Review of Psychology, 41(1), 417–440. https://doi.org/10.1146/annurev.ps.41.020190.002221

e Silva, S. C., Duarte, P., Machado, J. C., & Martins, C. (2020). Cause-related marketing in online environment: the role of brand-cause fit, perceived value, and trust. International Review on Public and Nonprofit Marketing, 17(2), 135–157. https://doi.org/10.1007/s12208-019-00237-z

Eagar, R., Teixeira, T., Taga, K., & Caldani, S. (2020). Leading businesses through the COVID-19 crisis: First learnings from Hong Kong, Italy and Singapore (1 / 2020). Arthur D. Little PRISM. https://www.adlittle.com/sites/default/files/prism/covid19_ceokeylearnings_prism_specialreport.pdf

Eastman, J. K., Smalley, K. B., & Warren, J. C. (2019). The Impact of Cause-Related Marketing on Millennials' Product Attitudes and Purchase Intentions. Journal of Promotion Management, 25(6), 799–826. https://doi.org/10.1080/10496491.2018.1536625

Eggers, F., Sattler, H., Teichert, T., & Völckner, F. (2022). Choice-Based Conjoint Analysis. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), Handbook of Market Research (pp. 781–819). Springer International Publishing. https://doi.org/10.1007/978-3-319-57413-4_23

ElHaffar, G., Durif, F., & Dubé, L. (2020). Towards closing the attitude-intention-behavior gap in green consumption: A narrative review of the literature and an overview of future research directions. Journal of Cleaner Production, 275, Article 122556, 1–20. https://doi.org/10.1016/j.jclepro.2020.122556

Fan, X., Deng, N., Qian, Y., & Dong, X. (2020). Factors Affecting the Effectiveness of Cause-Related Marketing: A Meta-Analysis. Journal of Business Ethics, 175, 339–360. https://doi.org/10.1007/s10551-020-04639-6

Frias-Martinez, E., Chen, S. Y., & Liu, X. (2009). Evaluation of a personalized digital library based on cognitive styles: Adaptivity vs. adaptability. International Journal of Information Management, 29(1), 48–56. https://doi.org/10.1016/j.ijinfomgt.2008.01.012

Giacomini, D., Martini, M., Sancino, A., Zola, P., & Cavenago, D. (2021). Corporate social responsibility actions and organizational legitimacy at the peak of COVID-19: a sentiment analysis. Corporate Governance: The International Journal of Business in Society, 21(6), 1043–1058. https://doi.org/10.1108/CG-09-2020-0389

Goic, M., Rojas, A., & Saavedra, I. (2021). The Effectiveness of Triggered Email Marketing in Addressing Browse Abandonments. Journal of Interactive Marketing, 55, 118–145. https://doi.org/10.1016/j.intmar.2021.02.002

Goldberg, M. E., & Hartwick, J. (1990). The effects of advertiser reputation and extremity of advertising claim on advertising effectiveness. Journal of Consumer Research, 17(2), 172–179.

Goldsmith, R. E., Lafferty, B. A., & Newell, S. J. (2000). The Impact of Corporate Credibility and Celebrity Credibility on Consumer Reaction to Advertisements and Brands. Journal of Advertising, 29(3), 43–54. https://doi.org/10.1080/00913367.2000.10673616

Gooding. (2022). gooding.de. https://www.gooding.de/

Götz, F. M., Stieger, S., Gosling, S. D., Potter, J., & Rentfrow, P. J [Peter J.] (2020). Physical topography is associated with human personality. Nature Human Behaviour, 4(11), 1135–1144. https://doi.org/10.1038/s41562-020-0930-x

Grau, S. L., & Folse, J. A. G. (2007). Cause-Related Marketing (CRM): The Influence of Donation Proximity and Message-Framing Cues on the Less-Involved Consumer. Journal of Advertising, 36(4), 19–33. https://doi.org/10.2753/JOA0091-3367360402

Green, P. E., Krieger, A. M., & Wind, Y. (2001). Thirty Years of Conjoint Analysis: Reflections and Prospects. Interfaces, 31(3_supplement), S56-S73. https://doi.org/10.1287/inte.31.3s.56.9676

Ha, H.-Y., & Janda, S. (2014). The effect of customized information on online purchase intentions. Internet Research, 24(4), 496–519. https://doi.org/10.1108/IntR-06-2013-0107

Ham, C.-D., & Kim, J [Jeesun] (2019). The Role of CSR in Crises: Integration of Situational Crisis Communication Theory and the Persuasion Knowledge Model. Journal of Business Ethics, 158(2), 353–372. https://doi.org/10.1007/s10551-017-3706-0

Hansen, N., Kupfer, A.-K., & Hennig-Thurau, T. (2018). Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands. International Journal of Research in Marketing, 35(4), 557–574. https://doi.org/10.1016/j.ijresmar.2018.08.001

He, H., & Harris, L. (2020). The impact of Covid-19 pandemic on corporate social responsibility and marketing philosophy. Journal of Business Research, 116, 176–182. https://doi.org/10.1016/j.jbusres.2020.05.030

Henderson, T., & Arora, N. (2010). Promoting Brands across Categories with a Social Cause: Implementing Effective Embedded Premium Programs. Journal of Marketing, 74(6), 41–60. https://doi.org/10.1509/jmkg.74.6.41

Hou, J., Du, L., & Li, J [Jianfeng] (2008). Cause's attributes influencing consumer's purchasing intention: Empirical evidence from China. Asia Pacific Journal of Marketing and Logistics, 20(4), 363–380. https://doi.org/10.1108/13555850810909704

Howie, K. M., Yang, L., Vitell, S. J., Bush, V., & Vorhies, D. (2018). Consumer Participation in Cause-Related Marketing: An Examination of Effort Demands and Defensive Denial. Journal of Business Ethics, 147(3), 679–692. https://doi.org/10.1007/s10551-015-2961-1

Iyengar, S. S., & Lepper, M. R. (1999). Rethinking the value of choice: A cultural perspective on intrinsic motivation. Journal of Personality and Social Psychology, 76(3), 349–366. https://doi.org/10.1037/0022-3514.76.3.349

Joireman, J., Smith, D., Liu, R. L., & Arthurs, J. (2015). It's All Good: Corporate Social Responsibility Reduces Negative and Promotes Positive Responses to Service Failures among Value-Aligned Customers. Journal of Public Policy & Marketing, 34(1), 32–49. https://doi.org/10.1509/jppm.13.065

Judge, T. A., Heller, D., & Mount, M. K. (2002). Five-factor model of personality and job satisfaction: A meta-analysis. Journal of Applied Psychology, 87(3), 530–541. https://doi.org/10.1037/0021-9010.87.3.530

Keyzer, F. de, Dens, N., & Pelsmacker, P. de (2022). How and When Personalized Advertising Leads to Brand Attitude, Click, and WOM Intention. Journal of Advertising, 51(1), 39–56. https://doi.org/10.1080/00913367.2021.1888339

Kim, J.-E., & Johnson, K. K. P. (2013). The Impact of Moral Emotions on Cause-Related Marketing Campaigns: A Cross-Cultural Examination. Journal of Business Ethics, 112(1), 79–90. https://doi.org/10.1007/s10551-012-1233-6

Kim, J [Jihye], & Kim, M. (2022). Using personalization for cause-related marketing beyond compassion fade on social media. Journal of Research in Interactive Marketing. Advance online publication. https://doi.org/10.1108/JRIM-10-2021-0242

Kim, J [Jinyoung], & Gambino, A. (2016). Do we trust the crowd or information system? Effects of personalization and bandwagon cues on users' attitudes and behavioral intentions toward a restaurant recommendation website. Computers in Human Behavior, 65(Supplement C), 369–379. https://doi.org/10.1016/j.chb.2016.08.038

Kim, K., Kim, S [Sujin], Corner, G., & Yoon, S. (2019). Dollar-Off or Percent-Off? Discount Framing, Construal Levels, and Advertising Appeals. Journal of Promotion Management, 25(3), 314–327. https://doi.org/10.1080/10496491.2019.1557808

Kim, S [Sojung], & Choi, S. M. (2012). Credibility cues in online shopping: an examination of corporate credibility, retailer reputation, and product review credibility. International Journal of Internet Marketing and Advertising, 7(3), 217–236. https://doi.org/10.1504/IJIMA.2012.047425

Klein, J., & Dawar, N. (2004). Corporate social responsibility and consumers' attributions and brand evaluations in a product–harm crisis. International Journal of Research in Marketing, 21(3), 203–217. https://doi.org/10.1016/j.ijresmar.2003.12.003

Knudsen, E., & Johannesson, M. P. (2019). Beyond the Limits of Survey Experiments: How Conjoint Designs Advance Causal Inference in Political Communication Research. Political Communication, 36(2), 259–271. https://doi.org/10.1080/10584609.2018.1493009

Koschate-Fischer, N., Huber, I. V., & Hoyer, W. D. (2016). When will price increases associated with company donations to charity be perceived as fair? Journal of the Academy of Marketing Science, 44(5), 608–626. https://doi.org/10.1007/s11747-015-0454-5

Koschate-Fischer, N., Stefan, I. V., & Hoyer, W. D. (2012). Willingness to Pay for Cause-Related Marketing: The Impact of Donation Amount and Moderating Effects. Journal of Marketing Research, 49(6), 910–927. https://doi.org/10.1509/jmr.10.0511

Kotler, P., & Lee, N. (2008). Corporate social responsibility: Doing the most good for your company and your cause. John Wiley & Sons.

Kull, A. J., & Heath, T. B. (2016). You decide, we donate: Strengthening consumer–brand relationships through digitally co-created social responsibility. International Journal of Research in Marketing, 33(1), 78–92. https://doi.org/10.1016/j.ijresmar.2015.04.005

Kulshreshtha, K., Bajpai, N., Tripathi, V., & Sharma, G. (2019). Cause-related marketing: an exploration of new avenues through conjoint analysis. Benchmarking: An International Journal, 26(6), 2017–2050. https://doi.org/10.1108/BIJ-05-2018-0131

Kwon, K., & Kim, C. (2012). How to design personalization in a context of customer retention: Who personalizes what and to what extent? Electronic Commerce Research and Applications, 11(2), 101–116. https://doi.org/10.1016/j.elerap.2011.05.002

Laban, G., & Araujo, T. (2022). Don't Take it Personally: Resistance to Individually Targeted Recommendations from Conversational Recommender Agents. In C. Bartneck, T. Kanda, M. Obaid, & W. Johal (Eds.), International Conference on Human-Agent Interaction (pp. 57–66). ACM. https://doi.org/10.1145/3527188.3561929

Lafferty, B. A. (2007). The relevance of fit in a cause–brand alliance when consumers evaluate corporate credibility. Journal of Business Research, 60(5), 447–453. https://doi.org/10.1016/j.jbusres.2006.09.030

Lafferty, B. A. (2009). Selecting the right cause partners for the right reasons: The role of importance and fit in cause-brand alliances. Psychology and Marketing, 26(4), 359–382. https://doi.org/10.1002/mar.20277

Lafferty, B. A., & Edmondson, D. R. (2014). A note on the role of cause type in cause-related marketing. Journal of Business Research, 67(7), 1455–1460. https://doi.org/10.1016/j.jbusres.2013.07.021

Lafferty, B. A., & Goldsmith, R. E. (1999). Corporate Credibility's Role in Consumers' Attitudes and Purchase Intentions When a High versus a Low Credibility Endorser Is Used in the Ad. Journal of Business Research, 44(2), 109–116. https://doi.org/10.1016/S0148-2963(98)00002-2

Lafferty, B. A., & Goldsmith, R. E. (2005). Cause–brand alliances: does the cause help the brand or does the brand help the cause? Journal of Business Research, 58(4), 423–429. https://doi.org/10.1016/j.jbusres.2003.07.001

Lafferty, B. A., Lueth, A. K., & McCafferty, R. (2016). An Evolutionary Process Model of Cause-Related Marketing and Systematic Review of the Empirical Literature. Psychology & Marketing, 33(11), 951–970. https://doi.org/10.1002/mar.20930

Lee, J., & Lee, M [Minkyo] (2021). The Role of Personality in Consumer Attitudes Toward Cause-Related Sport Marketing. International Journal of Human Movement Science, 15(3), 23–45. https://doi.org/10.23949/ijhms.2021.12.15.3.2

Lee, J. E., & Chen-Yu, J. H. (2018). Effects of price discount on consumers' perceptions of savings, quality, and value for apparel products: mediating effect of price discount affect. Fashion and Textiles, 5(1). https://doi.org/10.1186/s40691-018-0128-2

Leonidou, L. C., Leonidou, C. N., & Kvasova, O. (2010). Antecedents and outcomes of consumer environmentally friendly attitudes and behaviour. Journal of Marketing Management, 26(13-14), 1319–1344. https://doi.org/10.1080/0267257X.2010.523710

Li, C., & Liu, J. (2017). A name alone is not enough: A reexamination of web-based personalization effect. Computers in Human Behavior, 72, 132–139. https://doi.org/10.1016/j.chb.2017.02.039

Lichtenstein, D. R., Drumwright, M. E., & Braig, B. M. (2004). The Effect of Corporate Social Responsibility on Customer Donations to Corporate-Supported Nonprofits. Journal of Marketing, 68(4), 16–32. https://doi.org/10.1509/jmkg.68.4.16.42726

Lii, Y.-S., & Lee, M [Monle] (2012). Doing Right Leads to Doing Well: When the Type of CSR and Reputation Interact to Affect Consumer Evaluations of the Firm. Journal of Business Ethics, 105(1), 69–81. https://doi.org/10.1007/s10551-011-0948-0

Lii, Y.-S., Wu, K.-W., & Ding, M.-C. (2013). Doing Good Does Good? Sustainable Marketing of CSR and Consumer Evaluations. Corporate Social Responsibility and Environmental Management, 20(1), 15–28. https://doi.org/10.1002/csr.294

Louviere, J. J., & Woodworth, G. (1983). Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data. Journal of Marketing Research, 20(4), 350–367. https://doi.org/10.2307/3151440

Lucke, S., & Heinze, J. (2015). The Role of Choice in Cause-related Marketing – investigating the Underlying Mechanisms of Cause and Product Involvement. Procedia - Social and Behavioral Sciences, 213, 647–653. https://doi.org/10.1016/j.sbspro.2015.11.466

Maecker, O., Barrot, C., & Becker, J. U. (2016). The effect of social media interactions on customer relationship management. Business Research, 9(1), 133–155. https://doi.org/10.1007/s40685-016-0027-6

Mahmud, A., Ding, D., & Hasan, M. M. (2021). Corporate Social Responsibility: Business Responses to Coronavirus (COVID-19) Pandemic. SAGE Open, 11(1). https://doi.org/10.1177/2158244020988710

Manuel, T., & Herron, T. L. (2020). An ethical perspective of business CSR and the COVID-19 pandemic. Society and Business Review, 15(3), 235–253. https://doi.org/10.1108/SBR-06-2020-0086

Masthoff, J., Langrial, S., & van Deemter, K. (2013). Personalizing Triggers for Charity Actions. In D. Hutchison, T. Kanade, J. Kittler, J. M. Kleinberg, F. Mattern, J. C. Mitchell, M. Naor, O. Nierstrasz, C. Pandu Rangan, B. Steffen, M. Sudan, D. Terzopoulos, D. Tygar, M. Y. Vardi, G. Weikum, S. Berkovsky, & J. Freyne (Eds.), Lecture Notes in Computer Science. Persuasive Technology (Vol. 7822, pp. 125–136). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-37157-8_16

McCarty, J. A., & Shrum, L. J. (2001). The Influence of Individualism, Collectivism, and Locus of Control on Environmental Beliefs and Behavior. Journal of Public Policy & Marketing, 20(1), 93–104. https://doi.org/10.1509/jppm.20.1.93.17291

McCrae, R. R [R. R.], & John, O. P [O. P.] (1992). An introduction to the five-factor model and its applications. Journal of Personality, 60(2), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

McCrae, R. R [Robert R.], & Costa, P. T. (2008). Empirical and Theoretical Status of the Five-Factor Model of Personality Traits. In G. Boyle, G. Matthews, & D. Saklofske (Eds.), The SAGE Handbook of Personality Theory and Assessment: Volume 1 — Personality Theories and Models (pp. 273–294). SAGE Publications Ltd. https://doi.org/10.4135/9781849200462.n13

McFadden, D. (1974). Chapter Four: Conditional Logit Analysis of Qualitative Choice Behavior. In P. Zarembka (Ed.), Frontiers in Econometrics. Academic Press.

Mo, Z., Liu, M. T., & Liu, Y. (2018). Effects of functional green advertising on self and others. Psychology and Marketing, 35(5), 368–382. https://doi.org/10.1002/mar.21092

Nguyen, H. V., Nguyen, C. H., & Hoang, T. T. B. (2019). Green consumption: Closing the intention-behavior gap. Sustainable Development, 27(1), 118–129. https://doi.org/10.1002/sd.1875

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. Translational Issues in Psychological Science, 4(4), 440–461. https://doi.org/10.1037/tps0000176

Öberseder, M., Schlegelmilch, B. B., Murphy, P. E., & Gruber, V. (2014). Consumers' Perceptions of Corporate Social Responsibility: Scale Development and Validation. Journal of Business Ethics, 124(1), 101–115. https://doi.org/10.1007/s10551-013-1787-y

Obschonka, M., Wyrwich, M., Fritsch, M., Gosling, S. D., Rentfrow, P. J [P. Jason], & Potter, J. (2019). Von unterkühlten Norddeutschen, gemütlichen Süddeutschen und aufgeschlossenen Großstädtern: Regionale Persönlichkeitsunterschiede in Deutschland. Psychologische Rundschau, 70(3), 173–194. https://doi.org/10.1026/0033-3042/a000414

Orji, R., Oyibo, K., & Tondello, G. F. (2017). A Comparison of System-Controlled and

User-Controlled Personalization Approaches. In M. Bielikova (Ed.), Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization (pp. 413–418). ACM. https://doi.org/10.1145/3099023.3099116

Orme, B. (2019). Results of the Sawtooth Software User Survey. https://sawtoothsoftware.com/resources/blog/posts/results-of-the-sawtooth-software-user-survey

Oyserman, D., Coon, H. M., & Kemmelmeier, M. (2002). Rethinking individualism and collectivism: Evaluation of theoretical assumptions and meta-analyses. Psychological Bulletin, 128(1), 3–72. https://doi.org/10.1037/0033-2909.128.1.3

Paetz, F. (2020). Personality traits as drivers of social preferences: a mixed logit model application. Journal of Business Economics. Advance online publication. https://doi.org/10.1007/s11573-020-01001-0

Paetz, F., Hein, M., Kurz, P., & Steiner, W. (2019). Latent Class Conjoint Choice Models: A Guide for Model Selection, Estimation, Validation, and Interpretation of Results. Marketing ZFP, 41(4), 3–20. https://doi.org/10.15358/0344-1369-2019-4-3

Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2014). Shiny happy people buying: the role of emotions on personalized e-shopping. Electronic Markets, 24(3), 193–206. https://doi.org/10.1007/s12525-014-0153-y

Park, H. J., & Lin, L. M. (2020). Exploring attitude–behavior gap in sustainable consumption: comparison of recycled and upcycled fashion products. Journal of Business Research, 117, 623–628. https://doi.org/10.1016/j.jbusres.2018.08.025

Pérez, A., & Bosque, I. R. d. (2013). Extending on the Formation Process of CSR Image. Social Marketing Quarterly, 19(3), 156–171. https://doi.org/10.1177/1524500413489287

Pfeffer, J., Zorbach, T., & Carley, K. M. (2014). Understanding online firestorms: Negative word-of-mouth dynamics in social media networks. Journal of Marketing Communications, 20(1-2), 117–128. https://doi.org/10.1080/13527266.2013.797778

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. Psychological Bulletin, 135(2), 322–338. https://doi.org/10.1037/a0014996

Puzakova, M., Rocereto, J. F., & Kwak, H. (2015). Ads are watching me. International Journal of Advertising, 32(4), 513–538. https://doi.org/10.2501/IJA-32-4-513-538

Rammstedt, B [B.], Kemper, C., Klein, M. C., Beierlein, C., & Kovaleva, A. (2012). Eine kurze Skala zur Messung der fünf Dimensionen der Persönlichkeit: Big-Five-Inventory-10 (BFI-10). https://pub.uni-bielefeld.de/record/2575688

Rammstedt, B [Beatrice], Danner, D., Soto, C. J., & John, O. P [Oliver P.] (2020). Validation of the Short and Extra-Short Forms of the Big Five Inventory-2 (BFI-2) and Their German Adaptations. European Journal of Psychological Assessment, 36(1), 149–161. https://doi.org/10.1027/1015-5759/a000481

Rammstedt, B [Beatrice], & John, O. P [Oliver P.] (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. Journal of Research in Personality, 41(1), 203–212. https://doi.org/10.1016/j.jrp.2006.02.001

Rauschnabel, P. A., Kammerlander, N., & Ivens, B. S. (2016). Collaborative Brand Attacks in Social Media: Exploring the Antecedents, Characteristics, and Consequences of a New Form of Brand Crises. Journal of Marketing Theory and Practice, 24(4), 381–410. https://doi.org/10.1080/10696679.2016.1205452

Robinson, S. R., Irmak, C., & Jayachandran, S. (2012). Choice of Cause in Cause-Related Marketing. Journal of Marketing, 76(4), 126–139. https://doi.org/10.1509/jm.09.0589

Ross, J. K., Patterson, L. T., & Stutts, M. A [M. A.] (1992). Consumer Perceptions of Organizations that Use Cause-Related Marketing. Journal of the Academy of Marketing Science, 20(1), 93–97. https://doi.org/10.1177/009207039202000110

Ross III, J. K., Stutts, M. A [Mary Ann], & Patterson, L. (1991). Tactical Considerations For The Effective Use Of Cause-Related Marketing. Journal of Applied Business Research (JABR), 7(2), 58–65. https://doi.org/10.19030/jabr.v7i2.6245

Ruiz de Maya, S., Lardín-Zambudio, R., & López-López, I. (2015). I Will Do It If I Enjoy It! The Moderating Effect of Seeking Sensory Pleasure When Exposed to Participatory CSR Campaigns. Frontiers in Psychology, 6, 1940. https://doi.org/10.3389/fpsyg.2015.01940

Sahni, N. S., Wheeler, S. C., & Chintagunta, P. (2018). Personalization in Email Marketing: The Role of Noninformative Advertising Content. Marketing Science, 37(2), 236–258. https://doi.org/10.1287/mksc.2017.1066

Sailer, A., Wilfing, H., & Straus, E. (2022). Greenwashing and Bluewashing in Black Friday-Related Sustainable Fashion Marketing on Instagram. Sustainability, 14(3), 1494. https://doi.org/10.3390/su14031494

Sawtooth Software. (2009a). The CBC/HB System for Hierarchical Bayes Estimation: Version 5.6. Sequim, WA, US. https://sawtoothsoftware.com/resources/technical-papers/cbc-hb-technical-paper

Sawtooth Software. (2009b). The CBC/HB System for Hierarchical Bayes Estimation: Version 5.0 Technical Paper. https://www.sawtoothsoftware.com/download/techpap/hbtech.pdf

Sawtooth Software, I. (2016). CBC/HB v5: Software for Hierarchical Bayes Estimation for CBC Data. https://content.sawtoothsoftware.com/assets/276545e9-0445-474c-b01c-f5b24c3eba6d

Sawtooth Software, I. (2021). The Latent Class Technical Paper: Version 4.8. https://content.sawtoothsoftware.com/assets/2ef6d992-1c7d-4e30-b442-2bc2e6eb88d4

Schamp, C., Heitmann, M., Bijmolt, T. H., & Katzenstein, R. (2022). The Effectiveness of Cause-Related Marketing: A Meta-Analysis on Consumer Responses. Journal of

Marketing Research, 60(1), 189–215. https://doi.org/10.1177/00222437221109782

Schreiner, T., & Baier, D. (2022). Online retailing during the COVID-19 pandemic: consumer preferences for marketing actions with consumer self-benefits versus other-benefit components. Journal of Marketing Management, 1–37. https://doi.org/10.1080/0267257X.2022.2030784

Schreiner, T., Rese, A., & Baier, D. (2019). Multichannel personalization: Identifying consumer preferences for product recommendations in advertisements across different media channels. Journal of Retailing and Consumer Services, 48, 87–99. https://doi.org/10.1016/j.jretconser.2019.02.010

Selka, S., Baier, D., & Kurz, P. (2014). The Validity of Conjoint Analysis: An Investigation of Commercial Studies Over Time. In M. Spiliopoulou, L. Schmidt-Thieme, & R. Janning (Eds.), Studies in Classification, Data Analysis, and Knowledge Organization. Data Analysis, Machine Learning and Knowledge Discovery (pp. 227–234). Springer International Publishing. https://doi.org/10.1007/978-3-319-01595-8_25

Sharma, P. (2010). Measuring personal cultural orientations: scale development and validation. Journal of the Academy of Marketing Science, 38(6), 787–806. https://doi.org/10.1007/s11747-009-0184-7

Sheikh, S.-R., & Beise-Zee, R. (2011). Corporate social responsibility or cause-related marketing? The role of cause specificity of CSR. Journal of Consumer Marketing, 28(1), 27–39. https://doi.org/10.1108/07363761111101921

ShopRaise. (2022). shopraise.com. https://shopraise.com/supporters#choose-your-cause

Singelis, T. M., Triandis, H. C., Bhawuk, D. P. S., & Gelfand, M. J. (1995). Horizontal and Vertical Dimensions of Individualism and Collectivism: A Theoretical and Measurement Refinement. Cross-Cultural Research, 29(3), 240–275. https://doi.org/10.1177/106939719502900302

Singh, A., & Pathak, G. S. (2020). The quest for consumer engagement via cause-related marketing: A mixed method study in an emerging economy. Journal of Retailing and Consumer Services, 55, 102128. https://doi.org/10.1016/j.jretconser.2020.102128

SocialBakers. (2021a). Facebook stats in Germany - NGO. https://www.socialbakers.com/statistics/facebook/pages/total/germany/society/ngo/page-6-10

SocialBakers. (2021b). Twitter statistics in Germany - NGO. https://www.socialbakers.com/statistics/twitter/profiles/germany/society/ngo/page-6-10

Song, J. H., Kim, H. Y., Kim, S [Sahangsoon], Lee, S. W., & Lee, J.-H. (2016). Effects of personalized e-mail messages on privacy risk: Moderating roles of control and intimacy. Marketing Letters, 27(1), 89–101. https://doi.org/10.1007/s11002-014-9315-0

Sridhar, K., Kumar, A., & Bezawada, R. (2022). Investigating cross-media effects in a multichannel marketing environment: the role of email, catalog, television, and radio. Marketing Letters, 33(2), 189–201. https://doi.org/10.1007/s11002-021-09592-6

Statista. (2020a). Distribution of private households based on monthly household net income in Germany in 2019. https://www.statista.com/statistics/750827/private-household-income-distribution-in-germany/

Statista. (2020b). Population of Germany from 1990 to 2019, by gender.

Statista. (2021a). Average age of the population in Germany from 2011 to 2020. https://www.statista.com/statistics/1127805/population-average-age-germany/

Statista. (2021b). Number of households in Germany from 2000 to 2020, by size. https://www.statista.com/statistics/464187/households-by-size-germany/

Statista. (2021c). Population in Germany as of December 2020, by federal state. https://www.statista.com/statistics/1127686/population-by-federal-state-germany/

Statistisches Bundesamt. (2020). Educational attainment of the population in Germany. https://www.destatis.de/EN/Themes/Society-Environment/Education-Research-Culture/Educational-Level/Tables/educational-attainment-population-germany.html

Steiner, M., & Meißner, M. (2018). A User's Guide to the Galaxy of Conjoint Analysis and Compositional Preference Measurement. Marketing: ZFP – Journal of Research and Management, 40(2), 3–25. https://doi.org/10.15358/0344-1369-2018-2-3

Sun, X., May, A., & Wang, Q. (2016). The impact of user- and system-initiated personalization on the user experience at large sports events. Applied Ergonomics, 54, 1–9. https://doi.org/10.1016/j.apergo.2015.11.001

Sun, Y., Wang, S., Gao, L., & Li, J [Jun] (2018). Unearthing the effects of personality traits on consumer's attitude and intention to buy green products. Natural Hazards, 93(1), 299–314. https://doi.org/10.1007/s11069-018-3301-4

Sundar, S. S., & Marathe, S. S. (2010). Personalization versus Customization: The Importance of Agency, Privacy, and Power Usage. Human Communication Research, 36(3), 298–322. https://doi.org/10.1111/j.1468-2958.2010.01377.x

Tao, W., & Ji, Y. G. (2020). Firm-Determined or Consumer-Determined Corporate Social Responsibility (CSR)? Examining the Effects of Choice-of-Cause in Cause-Related Marketing. International Journal of Business Communication, 232948842091839. https://doi.org/10.1177/2329488420918397

Thomas, S., Kureshi, S., & Vatavwala, S. (2020). Cause-Related Marketing Research (1988–2016): An Academic Review and Classification. Journal of Nonprofit & Public Sector Marketing, 32(5), 488–516. https://doi.org/10.1080/10495142.2019.1606757

Tran, T. P. (2017). Personalized ads on Facebook: An effective marketing tool for online marketers. Journal of Retailing and Consumer Services, 39, 230–242. https://doi.org/10.1016/j.jretconser.2017.06.010

Triandis, H. C., & Gelfand, M. J. (1998). Converging measurement of horizontal and vertical individualism and collectivism. Journal of Personality and Social Psychology, 74(1), 118–128. https://doi.org/10.1037/0022-3514.74.1.118

Vaidyanathan, R., Aggarwal, P., & Kozłowski, W. (2013). Interdependent self-construal in collectivist cultures: Effects on compliance in a cause-related marketing context. Journal of Marketing Communications, 19(1), 44–57. https://doi.org/10.1080/13527266.2011.551833

van Doorn, J., & Hoekstra, J. C. (2013). Customization of online advertising: The role of intrusiveness. Marketing Letters, 24(4), 339–351. https://doi.org/10.1007/s11002-012-9222-1

Vanhamme, J., Lindgreen, A., Reast, J., & van Popering, N. (2012). To Do Well by Doing Good: Improving Corporate Image Through Cause-Related Marketing. Journal of Business Ethics, 109(3), 259–274. https://doi.org/10.1007/s10551-011-1134-0

Varadarajan, P. R., & Menon, A. (1988). Cause-Related Marketing: A Coalignment of Marketing Strategy and Corporate Philanthropy. Journal of Marketing, 52(3), 58–74. https://doi.org/10.1177/002224298805200306

Vătămănescu, E.-M., Dabija, D.-C., Gazzola, P., Cegarro-Navarro, J. G., & Buzzi, T. (2021). Before and after the outbreak of Covid-19: Linking fashion companies' corporate social responsibility approach to consumers' demand for sustainable products. Journal of Cleaner Production, 321, 128945. https://doi.org/10.1016/j.jclepro.2021.128945

Verhagen, T., van Nes, J., Feldberg, F., & van Dolen, W. (2014). Virtual Customer Service Agents: Using Social Presence and Personalization to Shape Online Service Encounters. Journal of Computer-Mediated Communication, 19(3), 529–545. https://doi.org/10.1111/jcc4.12066

Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. In J. A. Hagenaars & A. L. McCutcheon (Eds.), Applied latent class analysis (Vol. 11, pp. 89–106). Cambridge Univ. Press.

Vo, T. T., Xiao, X., & Ho, S. Y. (2019). How Does Corporate Social Responsibility Engagement Influence Word of Mouth on Twitter? Evidence from the Airline Industry. Journal of Business Ethics, 157(2), 525–542. https://doi.org/10.1007/s10551-017-3679-z

Wang, Y. (2014). Individualism/collectivism, charitable giving, and cause-related marketing: a comparison of Chinese and Americans. International Journal of Nonprofit and Voluntary Sector Marketing, 19(1), 40–51. https://doi.org/10.1002/NVSM.1486

Weller, B. E., Bowen, N. K., & Faubert, S. J. (2020). Latent Class Analysis: A Guide to Best Practice. Journal of Black Psychology, 46(4), 287–311. https://doi.org/10.1177/0095798420930932

Wiebe, J., Basil, D. Z., & Runté, M. (2017). Psychological distance and perceived consumer effectiveness in a cause-related marketing context. International Review on Public and Nonprofit Marketing, 14(2), 197–215. https://doi.org/10.1007/s12208-016-0170-y

Yoon, V. Y., Hostler, R. E., Guo, Z., & Guimaraes, T. (2013). Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty. Decision Support Systems, 55(4), 883–893. https://doi.org/10.1016/j.dss.2012.12.024

Zhang, A., Saleme, P., Pang, B., Durl, J., & Xu, Z. (2020). A Systematic Review of Experimental Studies Investigating the Effect of Cause-Related Marketing on Consumer Purchase Intention. Sustainability, 12(22), 9609. https://doi.org/10.3390/su12229609

Zhang, B., & Sundar, S. S. (2019). Proactive vs. reactive personalization: Can customization of privacy enhance user experience? International Journal of Human-Computer Studies, 128, 86–99. https://doi.org/10.1016/j.ijhcs.2019.03.002

8 Conclusion

In response to the current challenge of increasing clutter in online advertising, this thesis highlights two promising approaches to capture consumer attention and thus increase advertising effectiveness. While research articles #1 and #2 investigated consumer preferences for personalized product recommendations in advertisements, research paper #3 focused on examining consumer preferences for corporate social responsibility initiatives, such as cause-related marketing campaigns, versus marketing campaigns with pure consumer self-benefits. As a combination of these two approaches, research article #4 compared consumer preferences for customized and personalized CRM campaigns with those for generic CRM campaigns and price discounts.

Overall, the results of the four research papers show that both approaches—individualization through personalized or customized advertising and CSR advertising, especially in the form of CRM campaigns—can help make online advertising in the apparel sector more effective and cut through the advertising clutter. Against this backdrop, the combination of both approaches—i.e., customized CRM and personalized CRM—seems particularly promising. In order to meet the needs of different consumer segments with externally heterogeneous consumer preferences, taking into account sociodemographic consumer characteristics, especially gender, and psychographic consumer characteristics, e.g., personality traits or cultural orientations, could provide retailers with guidance in identifying different customer groups and developing corresponding segment-specific marketing approaches.

With respect to RQ1—examining consumer preferences for personalized product recommendations in advertisements—papers #1 and #2 demonstrated that the advertising channel and the number of product recommendations presented are of greater importance to consumers than the actual recommender algorithm used to generate the recommendations. This finding is significant because recent research efforts in personalization are still focused on algorithmic advances. Therefore, tailoring advertisements with product recommendations for apparel products to consumers' preferences in terms of the advertising channel and the number of product recommendations presented at the same time seems to be more promising than focusing only on the recommender algorithm. In addition to identifying individual preferences for ads with product recommendations, different design approaches for male and female consumers were also identified, allowing retailers to apply group-specific personalization strategies. Men preferred smaller sets of product recommendations for apparel, and women felt more attracted to email ads than to package inserts and banner ads, while male consumers saw the most value in package inserts, followed by email advertising.

As a complement to RQ1 and in response to RQ2, the literature review in research article #2 provided insights into promising recommendation algorithms for improving perceived individual recommendation quality. In this context, (i) complementary recommendation systems that enable the recommendation of complementary products such as power banks as supplement to mobile phones, (ii) multi- and cross-domain recommender systems that enable recommendations to be made across different product domains, and (iii) context-aware recommender systems that are able to take contextual information into account were described as promising future approaches.

RQ3 addressed the comparison of the effectiveness of marketing campaigns with different beneficiaries by online apparel retailers during the COVID-19 pandemic. Consistent with previous research, marketing campaigns with altruistic components were shown to have the potential to outperform traditional sales promotion methods during the pandemic. In particular, CRM campaigns and employee-oriented CSR advertising performed comparatively well. In addition, a CRM campaign that offered consumers some degree of choice regarding the beneficiary of the campaign was strongly preferred by consumers compared to a CRM campaign with a predetermined beneficiary. It was also highlighted that CSR advertising with socially and spatially proximate beneficiaries was preferred over CSR initiatives with socially and spatially distant beneficiaries. In contrast with previous findings, no gender effect was found in the preference for marketing campaigns with other-benefit components. Using LCA, two consumer segments with contrasting preferences were identified: those who particularly value CSR advertising with benefits to themselves versus consumers who place greater value on CSR advertising with benefits to other stakeholders. Sociodemographic consumer traits were unlikely to characterize the two distinct consumer segments, suggesting the inclusion of psychographic consumer characteristics in research article #4.

RQ4 addressed the investigation of the effectiveness of individualized CRM campaigns—personalized and customized CRM—compared to CRM campaigns with a predetermined cause and price discounts. The results of this study revealed that customized CRM campaigns—which allow consumers to select any charitable organization to support through their purchase—were more valued by consumers than other types of CRM campaigns and discounts. In addition, personalizing the cause supported by a CRM campaign based on consumers' interactions with charitable organizations on social media was more effective than CRM campaigns with both a predefined cause and price discounts. It was shown that psychographic consumer characteristics such as personality traits and cultural orientations could be used to some extent to explain consumers' heterogeneous preferences for different marketing appeals. Again, LCA was applied, and three consumer segments with fundamentally different preferences emerged. While sociodemographic consumer characteristics were not useful in describing the different segments, it was shown that personality traits, as well as consumers perceived pre-reputation of a retailer, can be used, to a certain degree, to characterize the different consumer groups.

Beyond the thematic research contributions, this thesis also offers some methodological insights by validating the applicability of CBC with merely visual stimuli presentation (research papers #1 and #2) to measure consumer preferences for advertisements. Furthermore, MaxDiff has been shown to be an appropriate method to investigate the importance of different types of marketing actions (research paper #3).

While this thesis highlights two distinct and highly relevant approaches to overcoming the ad clutter in online media, there are other forms of advertising that have evolved in response to an increasingly cluttered online environment that also call for a (further) investigation. Of particular note in this context are native advertising—advertisements that resemble in form and appearance organic content within a specific online medium—and influencer marketing as a special form of celebrity endorsement (Jung & Heo, 2021; S. Lee & Kim, 2020; Taylor & Carlson, 2021). Combinations of these approaches with the CRM and individualization approaches presented in this thesis may also be promising avenues for future research.

Finally, it is hoped that the results presented in this thesis can serve as inspiration for future research efforts in the areas of individualized advertising, CSR advertising, and

CRM campaigns and can guide practitioners in designing advertising campaigns.

9 References

Agudelo, M. A. L., Jóhannsdóttir, L., & Davídsdóttir, B. (2019). A literature review of the history and evolution of corporate social responsibility. *International Journal of Corporate Social Responsibility*, *4*(1), 1–23. https://doi.org/10.1186/s40991-018-0039-y

Aguirre, E., Mahr, D., Grewal, D., Ruyter, K. de, & Wetzels, M. (2015). Unraveling the Personalization Paradox: The Effect of Information Collection and Trust-Building Strategies on Online Advertisement Effectiveness. *Journal of Retailing*, *91*(1), 34–49. https://doi.org/10.1016/j.jretai.2014.09.005

Allen, L., O'Connell, A., & Kiermer, V. (2019). How can we ensure visibility and diversity in research contributions? How the Contributor Role Taxonomy (CRediT) is helping the shift from authorship to contributorship. *Learned Publishing*, *32*(1), 71–74. https://doi.org/10.1002/leap.1210

Allen, L., Scott, J., Brand, A., Hlava, M., & Altman, M. (2014). Publishing: Credit where credit is due. *Nature*, *508*(7496), 312–313. https://doi.org/10.1038/508312a

Andrews, M., Luo, X., Fang, Z., & Aspara, J. (2014). Cause Marketing Effectiveness and the Moderating Role of Price Discounts. *Journal of Marketing*, *78*(6), 120–142. https://doi.org/10.1509/jm.14.0003

Arora, N., Dreze, X., Ghose, A., Hess, J. D., Iyengar, R., Jing, B., Joshi, Y., Kumar, V., Lurie, N., Neslin, S., Sajeesh, S., Su, M., Syam, N., Thomas, J., & Zhang, Z. J. (2008). Putting one-to-one marketing to work: Personalization, customization, and choice. *Marketing Letters*, *19*(3-4), 305. https://doi.org/10.1007/s11002-008-9056-z

Arora, N., & Henderson, T. (2007). Embedded Premium Promotion: Why It Works and How to Make It More Effective. *Marketing Science*, *26*(4), 514–531. https://doi.org/10.1287/mksc.1060.0247

Baek, T. H., & Morimoto, M. (2012). Stay away from me: Examining the Determinants of Consumer Avoidance of Personalized Advertising. *Journal of Advertising*, *41*(1), 59–76. https://doi.org/10.2753/JOA0091-3367410105

Bang, H., & Wojdynski, B. W. (2016). Tracking users' visual attention and responses to personalized advertising based on task cognitive demand. *Computers in Human Behavior*, *55*(B), 867–876. https://doi.org/10.1016/j.chb.2015.10.025

Bartsch, A., & Kloß, A. (2019). Personalized charity advertising. Can personalized prosocial messages promote empathy, attitude change, and helping intentions toward stigmatized social groups? *International Journal of Advertising*, *38*(3), 345–363. https://doi.org/10.1080/02650487.2018.1482098

Bauer, C., & Lasinger, P. (2014). Adaptation strategies to increase advertisement effectiveness in digital media. *Management Review Quarterly*, *64*(2), 101–124. https://doi.org/10.1007/s11301-014-0101-0

Bleier, A., & Eisenbeiss, M. (2015a). The Importance of Trust for Personalized Online Advertising. *Journal of Retailing*, *91*(3), 390–409. https://doi.org/10.1016/j.jretai.2015.04.001

Bleier, A., & Eisenbeiss, M. (2015b). Personalized Online Advertising Effectiveness: The Interplay of What, When, and Where. *Marketing Science*, *34*(5), 669–688. https://doi.org/10.1287/mksc.2015.0930

Bleier, A., Keyser, A. de, & Verleye, K. (2018). Customer Engagement Through Personalization and Customization. In R. W. Palmatier, V. Kumar, & C. M. Harmeling (Eds.), *Customer Engagement Marketing* (pp. 75–94). Springer International Publishing. https://doi.org/10.1007/978-3-319-61985-9_4

Carroll, A. B. (1979). A Three-Dimensional Conceptual Model of Corporate Performance. *Academy of Management Review*, *4*(4), 497–505. https://doi.org/10.5465/amr.1979.4498296

Carroll, A. B. (1999). Corporate Social Responsibility: Evolution of a Definitional Construct. *Business & Society*, *38*(3), 268–295. https://doi.org/10.1177/000765039903800303

Carroll, A. B., & Shabana, K. M. (2010). The Business Case for Corporate Social Responsibility: A Review of Concepts, Research and Practice. *International Journal of Management Reviews*, *12*(1), 85–105. https://doi.org/10.1111/j.1468-2370.2009.00275.x

Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalization in personalized marketing: Trends and ways forward. *Psychology and Marketing*, *9*(8), 1529–1562. https://doi.org/10.1002/mar.21670

Chang, C.-T., & Chen, P.-C. (2017). Cause-related marketing ads in the eye tracker: it depends on how you present, who sees the ad, and what you promote. *International Journal of Advertising*, *36*(2), 336–355.

https://doi.org/10.1080/02650487.2015.1100698

Cho, C.-H., & Hongsik, J. C. (2004). Why do people avoid advertising on the internet? *Journal of Advertising*, *33*(4), 89–97. https://doi.org/10.1080/00913367.2004.10639175

Christofi, M., Vrontis, D., Leonidou, E., & Thrassou, A. (2019). Customer engagement through choice in cause-related marketing: A potential for global competitiveness. *International Marketing Review*, *37*(4), 621–650. https://doi.org/10.1108/IMR-04-2018-0133

Commission of the European Communities. (2001, July 18). *Promoting a European Framework for Corporate Social Responsibility*. https://ec.europa.eu/transparency/regdoc/rep/1/2001/EN/1-2001-366-EN-1-0.Pdf

cyLEDGE Media. (2022). *Configurator Database*. https://www.configurator-database.com/

Dahlsrud, A. (2008). How corporate social responsibility is defined: An analysis of 37 definitions. *Corporate Social Responsibility and Environmental Management*, *15*(1), 1–13. https://doi.org/10.1002/csr.132

Douglas Olsen, G., & Pracejus, J. W. (2020). Customized advertising: Allowing consumers to directly tailor messages leads to better outcomes for the brand. *Journal of Business Research*, *116*, 245–257. https://doi.org/10.1016/j.jbusres.2020.04.054

Du, S., Bhattacharya, C. B., & Sen, S. (2010). Maximizing Business Returns to Corporate Social Responsibility (CSR): The Role of CSR Communication. *International Journal of Management Reviews*, *12*(1), 8–19. https://doi.org/10.1111/j.1468-2370.2009.00276.x

e Silva, S. C., Duarte, P., Machado, J. C., & Martins, C. (2020). Cause-related marketing in online environment: the role of brand-cause fit, perceived value, and trust. *International Review on Public and Nonprofit Marketing*, *17*(2), 135–157. https://doi.org/10.1007/s12208-019-00237-z

Goic, M., Rojas, A., & Saavedra, I. (2021). The Effectiveness of Triggered Email Marketing in Addressing Browse Abandonments. *Journal of Interactive Marketing*, *55*, 118–145. https://doi.org/10.1016/j.intmar.2021.02.002

Ha, L. (2017). Digital Advertising Clutter in an Age of Mobile Media. In E. T. Shelly Rodgers (Ed.), *Digital advertising: Theory and research* (pp. 69–85).

Routledge. https://doi.org/10.4324/9781315623252-5

Ha, L., & McCann, K. (2008). An integrated model of advertising clutter in offline and online media. *International Journal of Advertising*, *27*(4), 569–592. https://doi.org/10.2501/S0265048708080153

Hameed, I., Riaz, Z., Arain, G. A., & Farooq, O. (2016). How Do Internal and External CSR Affect Employees' Organizational Identification? A Perspective from the Group Engagement Model. *Frontiers in Psychology*, *7*, Article 788, 1–13. https://doi.org/10.3389/fpsyg.2016.00788

Howie, K. M., Yang, L., Vitell, S. J., Bush, V., & Vorhies, D. (2018). Consumer Participation in Cause-Related Marketing: An Examination of Effort Demands and Defensive Denial. *Journal of Business Ethics*, *147*(3), 679–692. https://doi.org/10.1007/s10551-015-2961-1

Jung, A.-R., & Heo, J. (2021). Does cluttered social media environment hurt advertising effectiveness? The moderation of ad types and personalization. *Journal of Research in Interactive Marketing*, *15*(4), 592–606. https://doi.org/10.1108/JRIM-11-2020-0238

Keyzer, F. de, Dens, N., & Pelsmacker, P. de (2022). How and When Personalized Advertising Leads to Brand Attitude, Click, and WOM Intention. *Journal of Advertising*, *51*(1), 39–56. https://doi.org/10.1080/00913367.2021.1888339

Kim, J., & Kim, M. (2022). Using personalization for cause-related marketing beyond compassion fade on social media. *Journal of Research in Interactive Marketing.* Advance online publication. https://doi.org/10.1108/JRIM-10-2021-0242

Koschate-Fischer, N., Stefan, I. V., & Hoyer, W. D. (2012). Willingness to Pay for Cause-Related Marketing: The Impact of Donation Amount and Moderating Effects. *Journal of Marketing Research*, *49*(6), 910–927. https://doi.org/10.1509/jmr.10.0511

Kotler, P., & Lee, N. (2005). *Corporate social responsibility: Doing the most good for your company and your cause*. John Wiley & Sons, Inc.

Kull, A. J., & Heath, T. B. (2016). You decide, we donate: Strengthening consumer–brand relationships through digitally co-created social responsibility. *International Journal of Research in Marketing*, *33*(1), 78–92. https://doi.org/10.1016/j.ijresmar.2015.04.005

Kwon, K [Kwiseok], & Kim, C. (2012). How to design personalization in a context of customer retention: Who personalizes what and to what extent? *Electronic Commerce Research and Applications*, *11*(2), 101–116. https://doi.org/10.1016/j.elerap.2011.05.002

Kwon, K [Kyeongwon], & Lee, J. (2021). Corporate social responsibility advertising in social media: a content analysis of the fashion industry's CSR advertising on Instagram. *Corporate Communications: An International Journal*, *26*(4), 700–715. https://doi.org/10.1108/CCIJ-01-2021-0016

La Ferle, C., Kuber, G., & Edwards, S. M. (2013). Factors impacting responses to cause-related marketing in India and the United States: Novelty, altruistic motives, and company origin. *Journal of Business Research*, *66*(3), 364–373. https://doi.org/10.1016/j.jbusres.2011.08.017

Lafferty, B. A., Lueth, A. K., & McCafferty, R. (2016). An Evolutionary Process Model of Cause-Related Marketing and Systematic Review of the Empirical Literature. *Psychology & Marketing*, *33*(11), 951–970. https://doi.org/10.1002/mar.20930

Lambrecht, A., & Tucker, C. (2013). When Does Retargeting Work? Information Specificity in Online Advertising. *Journal of Marketing Research*, *50*(5), 561–576. https://doi.org/10.1509/jmr.11.0503

Lee, M.-D. P. (2008). A review of the theories of corporate social responsibility: Its evolutionary path and the road ahead. *International Journal of Management Reviews*, *10*(1), 53–73. https://doi.org/10.1111/j.1468-2370.2007.00226.x

Lee, S., & Kim, E. (2020). Influencer marketing on Instagram: How sponsorship disclosure, influencer credibility, and brand credibility impact the effectiveness of Instagram promotional post. *Journal of Global Fashion Marketing*, *11*(3), 232–249. https://doi.org/10.1080/20932685.2020.1752766

Lii, Y.-S., & Lee, M. (2012). Doing Right Leads to Doing Well: When the Type of CSR and Reputation Interact to Affect Consumer Evaluations of the Firm. *Journal of Business Ethics*, *105*(1), 69–81. https://doi.org/10.1007/s10551-011-0948-0

Malik, M. (2015). Value-Enhancing Capabilities of CSR: A Brief Review of Contemporary Literature. *Journal of Business Ethics*, *127*(2), 419–438. https://doi.org/10.1007/s10551-014-2051-9

Montgomery, A. L., & Smith, M. D. (2009). Prospects for Personalization on the Internet. *Journal of Interactive Marketing*, *23*(2), 130–137.

https://doi.org/10.1016/j.intmar.2009.02.001

Mueller, S., Diehl, S., Taylor, C. R., Terlutter, R., & Mueller, B. (2022). Do CSR Ads with Public Health Messages Pertaining to COVID-19 Actually Help Consumers, Advertisers, and Society? Insights from the United States and Germany. *Journal of Current Issues & Research in Advertising*, *43*(4), 337–359. https://doi.org/10.1080/10641734.2022.2079025

Öberseder, M., Schlegelmilch, B. B., Murphy, P. E., & Gruber, V. (2014). Consumers' Perceptions of Corporate Social Responsibility: Scale Development and Validation. *Journal of Business Ethics*, *124*(1), 101–115. https://doi.org/10.1007/s10551-013-1787-y

Oh, H., Bae, J., & Kim, S.-J. (2017). Can Sinful Firms Benefit from Advertising Their CSR Efforts? Adverse Effect of Advertising Sinful Firms' CSR Engagements on Firm Performance. *Journal of Business Ethics*, *143*(4), 643–663. https://doi.org/10.1007/s10551-016-3072-3

Patil, T., & Rahman, Z. (2022). Mapping the Cause-Related Marketing (CRM) field: document co-citation and bibliographic coupling approach. *International Review on Public and Nonprofit Marketing.* Advance online publication. https://doi.org/10.1007/s12208-022-00347-1

Peloza, J., & Shang, J. (2011). How can corporate social responsibility activities create value for stakeholders? A systematic review. *Journal of the Academy of Marketing Science*, *39*(1), 117–135. https://doi.org/10.1007/s11747-010-0213-6

Pyle, E., Furnham, A., & McClelland, A. (2022). Corporate social and environmental responsibility advertising: Advertising effectiveness as a function of viewing context. *Journal of Brand Management*, *29*(3), 301–310. https://doi.org/10.1057/s41262-021-00269-z

Robinson, S. R., Irmak, C., & Jayachandran, S. (2012). Choice of Cause in Cause-Related Marketing. *Journal of Marketing*, *76*(4), 126–139. https://doi.org/10.1509/jm.09.0589

Saeidi, S. P [Sayedeh Parastoo], Sofian, S., Saeidi, P., Saeidi, S. P [Sayyedeh Parisa], & Saaeidi, S. A. (2015). How does corporate social responsibility contribute to firm financial performance? The mediating role of competitive advantage, reputation, and customer satisfaction. *Journal of Business Research*, *68*(2), 341–350. https://doi.org/10.1016/j.jbusres.2014.06.024

Sahni, N. S., Wheeler, S. C., & Chintagunta, P. (2018). Personalization in Email Marketing: The Role of Noninformative Advertising Content. *Marketing Science*, *37*(2), 236–258. https://doi.org/10.1287/mksc.2017.1066

Schaefer, S. D., Terlutter, R., & Diehl, S. (2020). Talking about CSR matters: employees' perception of and reaction to their company's CSR communication in four different CSR domains. *International Journal of Advertising*, *39*(2), 191–212. https://doi.org/10.1080/02650487.2019.1593736

Schamp, C., Heitmann, M., Bijmolt, T. H., & Katzenstein, R. (2022). The Effectiveness of Cause-Related Marketing: A Meta-Analysis on Consumer Responses. *Journal of Marketing Research*, *60*(1), 189–215. https://doi.org/10.1177/00222437221109782

Segijn, C. M., Voorveld, H. A. M., & Vakeel, K. A. (2021). The Role of Ad Sequence and Privacy Concerns in Personalized Advertising: An Eye-Tracking Study into Synced Advertising Effects. *Journal of Advertising*, *50*(3), 320–329. https://doi.org/10.1080/00913367.2020.1870586

Sen, S., Bhattacharya, C. B., & Korschun, D. (2006). The Role of Corporate Social Responsibility in Strengthening Multiple Stakeholder Relationships: A Field Experiment. *Journal of the Academy of Marketing Science*, *34*(2), 158–166. https://doi.org/10.1177/0092070305284978

Singh, A., & Pathak, G. S. (2020). The quest for consumer engagement via cause-related marketing: A mixed method study in an emerging economy. *Journal of Retailing and Consumer Services*, *55*, 102128. https://doi.org/10.1016/j.jretconser.2020.102128

Sridhar, K., Kumar, A., & Bezawada, R. (2022). Investigating cross-media effects in a multichannel marketing environment: the role of email, catalog, television, and radio. *Marketing Letters*, *33*(2), 189–201. https://doi.org/10.1007/s11002-021-09592-6

Statista. (2023a). *Advertising spending worldwide from 2000 to 2024*. https://www.statista.com/statistics/1174981/advertising-expenditure-worldwide/

Statista. (2023b). *Customer experience personalization and optimization software and services revenue worldwide from 2020 to 2026*. https://www.statista.com/statistics/1333448/cx-personalization-optimization-revenue-worldwide/

Statista. (2023c). *Digital advertising spending worldwide from 2021 to 2026*. https://www.statista.com/statistics/237974/online-advertising-spending-worldwide/

Statista. (2023d). *Internet advertising spending worldwide from 2007 to 2024, by format*. https://www.statista.com/statistics/276671/global-internet-advertising-expenditure-by-type/

Statista. (2023e). *Product groups ranked by online retail revenue in Germany from 2019 to 2022*. https://www.statista.com/statistics/451868/best-selling-product-groups-by-revenue-in-online-retail-in-germany/

Sundar, S. S., & Marathe, S. S. (2010). Personalization versus Customization: The Importance of Agency, Privacy, and Power Usage. *Human Communication Research*, *36*(3), 298–322. https://doi.org/10.1111/j.1468-2958.2010.01377.x

Taylor, C. R., & Carlson, L. (2021). The future of advertising research: new directions and research needs. *Journal of Marketing Theory and Practice*, *29*(1), 51–62. https://doi.org/10.1080/10696679.2020.1860681

Thomas, S., Kureshi, S., & Vatavwala, S. (2020). Cause-Related Marketing Research (1988–2016): An Academic Review and Classification. *Journal of Nonprofit & Public Sector Marketing*, *32*(5), 488–516. https://doi.org/10.1080/10495142.2019.1606757

Turker, D. (2009). Measuring Corporate Social Responsibility: A Scale Development Study. *Journal of Business Ethics*, *85*(4), 411–427. https://doi.org/10.1007/s10551-008-9780-6

Varadarajan, P. R., & Menon, A. (1988). Cause-Related Marketing: A Coalignment of Marketing Strategy and Corporate Philanthropy. *Journal of Marketing*, *52*(3), 58–74. https://doi.org/10.1177/002224298805200306

Verdeyen, V., Put, J., & van Buggenhout, B. (2004). A social stakeholder model. *International Journal of Social Welfare*, *13*(4), 325–331. https://doi.org/10.1111/j.1468-2397.2004.00328.x

Yu, J., & Cude, B. (2009). ?Hello, Mrs. Sarah Jones! We recommend this product!????Consumers' perceptions about personalized advertising: comparisons across advertisements delivered via three different types of media. *International Journal of Consumer Studies*, *33*(4), 503–514. https://doi.org/10.1111/j.1470-6431.2009.00784.x

Zhang, B., & Sundar, S. S. (2019). Proactive vs. reactive personalization: Can customization of privacy enhance user experience? *International Journal of Human-Computer Studies*, *128*, 86–99. https://doi.org/10.1016/j.ijhcs.2019.03.002

Zhang, J., & Wedel, M. (2009). The Effectiveness of Customized Promotions in Online and Offline Stores. *Journal of Marketing Research*, *46*(2), 190–206. https://doi.org/10.1509/jmkr.46.2.190