

Personalized Product Recommendations: Evidence from the Field

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Abstract

Targeting personalized product recommendations to individual customers has become a mainstream activity in online stores as it has been shown to increase click-through rate and sales. However, as personalization becomes increasingly commonplace, customers may feel personalized content intrusive and therefore not responding or even avoiding them. Many studies have investigated advertising intrusiveness and avoidance but a research gap on the effect of degree of personalization on customer responses based on field evidence exists. In this paper, 27,175 recommendation displays from five different online stores are analyzed. The results show that the further the customer is in the purchasing process, the more effective personalization is if it is based on information about the present rather than past browsing session. Moreover, recommendations in passive form are more effective than recommendations in active form suggesting the need to dispel the perception of intrusiveness.

1. Introduction

Personalized elements have become an essential part of online stores. Elements that can be personalized include for example welcome messages, store layout, sales arguments or product recommendations [5, 6, 14, 15]. The aim of personalization is to increase sales through more persuasive, suited and relevant content, and, in general, personalization has been shown to increase click-through rates [e.g., 21] and sales [e.g., 14, 15].

However, personalized advertisements may result in advertisement reactance and ultimately avoidance among consumers because targeted recommendations may be perceived as too intrusive [4, 11]. Advertising literature has extensively studied advertisement intrusiveness [e.g., 12, 18] but research on intrusiveness of personalized online content with field data is limited. White and colleagues [30] and van Doorn and Hoekstra [28] have studied the degree of personalization in e-mail messages and online advertisements but both studies utilize hypothetical scenario-based data. Field data is particularly valuable because in actual purchase situations consumers may

not always recognize that some content is personalized. In laboratory experiments personalized elements are usually highlighted with various cues and therefore create a negative mindset.

The aim of this study is to provide an understanding on how the degree of personalization in product recommendations affects consumer responses in different stages of buying. In addition, the purpose is to measure perceived intrusiveness of personalized product recommendations. The study is conducted by using data from five different online stores and ten different personalized product recommendation advertisements. The decisions regarding the advertisements – their wording, their placement, the base of their personalization – were natural in a sense that the researchers did not have any influence over them. Thus, the present paper contributes to the literature on personalization by showing how the degree of personalization affects consumers' actual clicking behavior in online shopping context.

2. Theoretical background

2.1. Online personalization and recommender systems

Customer information can be used to tailor products, services and consumption experiences to fit the specific needs and tastes of customers [6]. Kaptein and Parvinen [15] define online personalization as the act of specifically selecting content for individual customers based on properties of the customer with the goal of increasing business outcomes for an e-commerce platform. In practice, this requires identifying the customer, gathering information about him or her and processing data to provide recommendations [6]. According to Chellappa and Sin [6], availability of potential customer information is largely affected by how willing customers are to share their personal information and use personalized services.

In online stores, there are different things that can be personalized. Lee and Park [17] identify three areas for personalization: offer, recognition and personal advice. Offer includes options for personalizing wish lists as well as personalized rewards and promotion reminders. Recognition stands for using the customer's name, and providing options to save

personal and financial information. Personal advice consists of personalized shopping and search features. On the other hand, personalization can be based on a variety of factors. Van Doorn and Hoekstra [28] suggest that online content can be personalized based on browsing data, personal data, and/or transaction data.

Online personalization can be argued to increase information search process efficiency because it aids customers in making decisions and prevents information overload. [3, 6]. As a consequence, personalization can lead to increased sales [3, 21]. For example, Postma and Brokke [21] showed that personalized e-mail messages generate higher click-through rates than non-personalized messages.

Personalized product recommendations form one category of online personalization. Recommender systems generate recommendations based on customers' browsing history and previously developed data sources [5]. The systems are applied to help customers in making purchase decisions and prevent information overload by matching the customer's needs and preferences with suitable product recommendations [1, 22]. Therefore, recommender systems often succeed in influencing the choices consumers make [13].

As in the case of general online personalization, there are various ways how product recommendations are generated. Typically, recommendations are made based on customers' expressed preferences, personal information or past behavior [2, 5, 27]. In practice, this would mean for example suggestions on what to buy based on already selected products or on what other consumers expressing similar needs have bought. Schafer et al. [23] propose that there are four different forms of recommendations: Suggesting products to customers, providing personalized product information, summarizing community opinion, and providing community critiques. Cheung et al. [8] categorize recommender systems into content-based and collaborative systems based on the technology that is used. Content-based recommendations are made based on the interests and preferences of a consumer without taking information collected on other consumers into consideration. Collaborative recommendations are based on the preferences of other similar consumers.

2.2. Advertising intrusiveness, reactance and avoidance

When discussing advertising, sales promotions or other persuasive communications, customer's perspective should also be considered, and sometimes customers dislike the communication they are targeted with. Thus, advertising is sometimes perceived as intrusive. Li and colleagues [18] define intrusiveness as "a perception or psychological consequence that occurs when an audience's cognitive processes are interrupted". In the

advertising context, advertisements can be considered intrusive when a person perceives them as interrupting his or her goals. A typical emotional consequence of advertisement intrusiveness is irritation [19]. Typical causes for increased intrusiveness and irritation are loud and disturbing advertisements or advertisements that are placed in a distracting way [18]. E-mail marketing and pop-up advertisements are frequent examples of intrusive online advertising [4, 12].

In behavioral terms, advertising intrusiveness can cause consumers to react negatively to the advertisement and start avoiding it. According to Edwards and colleagues [12], theory of reactance describes the effect the loss of freedom or a threatened loss of freedom has on people. It suggests that when faced with a threat of losing freedom, reactance creates a motivational state in an individual for regaining freedom. Reactance behavior has also been observed in the case personalized online advertising [28, 30].

Advertising avoidance, on the other hand, is defined as the actions of media users for intentionally reducing exposure to advertisements [26]. There are different ways that consumers use to avoid advertisements. Television commercials have been a popular subject of study, and Clancey [10] suggests that there are three ways for avoiding television commercials: cognitive avoidance (ignoring the ad), physical avoidance (leaving room) and mechanical avoidance (switching channel). These ways can also be applied to online advertising: ignoring the ad, closing browser, and using programs that block online advertisements, such as Adblock.

Cho [9] argues that advertising avoidance in the Internet is a result of previous negative experiences, perceived hindrance to achieving a goal and perceived clutter of ads. A more recent study by Baek and Morimoto [4] suggest that there are three determinants of advertisement avoidance: privacy concerns, advertisement irritation and perceived personalization. Privacy concerns and ad irritation increase advertisement avoidance whereas increased personalization was found to decrease avoidance. In addition, privacy concerns are an extensive concern among consumers as companies use their personal information when providing personalized online services [6, 27]. Personalized messages may create reactance if individuals perceive them as too personal and feel that they do not have control over how their personal information is used [4].

3. Research model and hypotheses

Based on the literature review, it is clear that there exists a trade-off between personalization of online content and feelings of irritation that are due to perceived advertisement intrusiveness. Baek and Morimoto [4] found that increased personalization can decrease advertisement avoidance, while Van

Doorn and Hoekstra [28] found that higher degrees of personalization increase perceived intrusiveness, which in turn affects buying intentions negatively. White and colleagues [30], on the other hand, showed that high degrees of personalization in e-mail messages results in reactance. The results suggest that justification and perceived utility are factors that decrease reactance.

However, previous literature has not considered the effect the *stage* of buying might have on the effectiveness of personalized online content, or the *basis* on which the content has been personalized. These are typical variants in the realm of online stores, and more often than not, they are not explicitly recognized by consumers. This is a notable difference to previous research that often uses recipient names as one personalization aspect [e.g., 28]. However, research has not considered the effect of *form* of the messages has – are consumers addressed directly using active form or indirectly using passive form. Next, we construct hypotheses based on these variables.

3.1. Stage of buying

Literature on online personalization is limited in terms of the effect the stage of a customer's purchase process has on the effectiveness of the recommendations. In sales literature, the point at which a sales call is made has been seen to affect customer response [e.g., 20, 25]. Similarly, we believe that customer reactions on personalized product recommendations in online stores vary in terms of the stage of buying process; in the beginning, a customer might have a product in mind that he or she wants to find and is less responsive to the seller's recommendations. Later, however, the immediate need to visit the store has more likely been fulfilled (e.g., find information about a specific product [11]) and the customer is more open towards the seller's suggestions. Thus, we make a distinction between product recommendations shown on the front page of an online store and product recommendations shown on pages further in the shopping process, such as category, product and purchase pages, and hypothesize the following:

H1: Recommendations on the front page generate fewer clicks than recommendations on later pages.

3.2. Message form

Wattal and colleagues [29] distinct between implicit and explicit personalization. The distinction can be also referred to as passive and active message form. A recommendation using active form speaks to the customer explicitly by using wordings such as “we recommend for you”. Passive form refers to recommendations such as “others who viewed this also bought” or “the most popular right now”. Passive

form is also often used when recommendations are made by the company such as “picks of the day”. In practice, recommendations in passive form are typically based on information on other users and recommendations in active form on information on the current user. However, it is not necessarily so, and recommendations in passive form can be based on information on the current user, and vice versa.

The assumption on the basis of the recommendation is nevertheless easily made by a consumer based on the form of the recommendation. Active message form represents product recommendations that imply that the recommendations are made specifically for the customer. A message in passive form may not seem personalized and does not imply that the recommendation is a suggestion for a particular customer. Thus, active message form represent a higher level of personalization in the eyes of the customer. As research shows that using the customer's name in personalized advertisements increases perceived intrusiveness and thereby decreases purchase intentions [28, 29], we hypothesize that consumers respond better to recommendations in passive rather than active form:

H2: Recommendations in passive form generate more clicks than recommendations in active form.

3.3. Interaction of stage of buying and message form

White and colleagues [28] show that click-through intentions are lower for personalized messages that use explicit customer data and when the fit between the advertisement and the customer need is low. Prior research also suggests that e-mail advertisements that do not mention the use of customer information are perceived as more attractive, while customers react negatively to advertisements that explicitly use personal information, such as ones name in a personalized greeting [28, 29]. According to Wattal and colleagues [29], the negative reaction is mostly due to the concerns of the sources and uses of personal information. Also Baek and Morimoto [4] have shown that too explicitly personal messages are easily perceived negatively by consumers.

Most consumers are often aware that promotions and offers made by marketers come with an agenda [7]. Moreover, product recommendations that customers perceive as if they have been made to fit their needs by a company are less attractive than product recommendations that fit their preferences without the company's meaning [24]. Sela et al. [24] further propose that telling consumers that an offer is tailored for them can lower the degree to which consumers perceive the offers as bargains. The researchers explain the finding by the idea of a competitive relationship between consumers and marketers, according to which a gain of either side is

thought to come at the expense of the other side. Thus, in this study, it is proposed that product recommendations using a passive rather than active message form are more effective particularly in later stages of a buying process. This is because in the later stages the customer becomes more aware of the seller's intent to persuade the customer to buy. Thus, we hypothesize:

H3: Recommendations on later pages generate more clicks if they are in passive form rather than active form.

3.4. Interaction of stage of buying and base of personalization

In this study, base of personalization describes what information has been used in making a product recommendation. Personalization can be based on the present browsing session, past browsing session or it can be a random product recommendation. Past session-based product recommendations are used when an online store has acquired browsing information from a customer's previous visit, and uses this data in making a product recommendation the next time the same customer visits the store. Present session-based and random product recommendations do not use previously acquired customer data. Random product recommendations are items selected by the company, and they can be for example campaign products or the store's most popular products. Present session-based product recommendations, on the other hand, are recommendations that are typically shown after the front page and they are based on the customer's current shopping visit. These can be product recommendations shown to a customer based on an item the customer is currently viewing.

Van Doorn and Hoekstra [28] anticipate that intrusiveness is influenced by the degree of personalization, and using only browsing data is considered more acceptable than using transaction or other personal data. This study is based on product recommendations that use only browsing data, thus the degree of personalization is determined based on whether the product recommendation uses historical browsing data or not. Some research shows that personalized recommendations based on previous purchases are perceived as valuable and increase customer retention [1]. However, as Van Doorn and Hoekstra [28] found that high fit between a personalized advertisement and a customer need increases purchase intentions and decreases the negative effect perceived intrusiveness, it is proposed that personalization that is based on one's present browsing session creates a better fit between the recommendation and the need. Similarly, Li and colleagues [18] found that useful and informative advertisements are considered less irritating and therefore less likely to be avoided, which is proposed

to the be case in recommendations based on present rather than past browsing session.

Even though advertisements with a high fit with customer needs provide relevant information and therefore usually increase purchase intentions, a high fit may also increase perceived intrusiveness, and thus, particularly high fit can also reduce the positive effect of the fit because it reveals to the customer that personal information has been used [28]. On the other hand, Kivetz and Simonson [16] show that customers perceive offers that fit their own needs and preferences as more valuable than offers that fit the needs of other customers better. Also, White and colleagues [30] argue that justified product recommendations increase purchase intentions, but if the recommendations are not justified, they may lead to reactance. We believe that customers perceive present session-based product recommendations as more justified than past session-based product recommendations because they are more fitted to their current need.

Based on these considerations, we propose that product recommendations based on a customer's current activity have a higher fit than product recommendations based on a customer's past activity. Further, we assume that product recommendations based on a customer's previous activity have a higher fit than randomly chosen product recommendations. We therefore hypothesize:

H4: Recommendations on the front page generate more clicks if they are based on the customer's past visit rather than if they are chosen at random.

H5: Recommendations on the later pages generate more clicks if they are based on the customer's current visit rather than past visit.

4. Methodology

4.1. Data

The research data was collected from five different online stores ranging from June 2015 to June 2016, and it consists of a total of 27,175 true displays of product recommendations. Four of the online stores operate in Finland, and one in the United Kingdom. The types of the stores were general supermarket, outdoor apparel and clothing store, consumer electronics store, ticket agent, and children's wear store. The data was acquired from a company that provides a software to personalize websites, and the online stores included in the analysis were clients of the company.

Ten different types of product recommendations were included in the data, and they were categorized based on their message form (active, passive), base of personalization (present session, past session, random) and page (front page, further pages). The

actual products that were recommended varied between individual users. Table 1 presents the different product recommendations.

4.2. Pre-test

A pre-test was conducted to investigate the perceived intrusiveness of the different types of product recommendations. 159 university students participated in a 3 (base of personalization – present session, past session, random) x 2 (message form – passive, active) between-subjects factorial experiment. Based on a random selection, respondents were sent an online survey that included a picture of an online store layout and one of the studied product recommendation type. Also, there was a text above the picture, which introduced a scenario of a purpose to visit the store. We used the look and feel of the hypermarket’s online store that was included in the main study and the products in the recommendations were kept constant (tableware). The questionnaire consisted of claims regarding perceived intrusiveness [18], degree of interest, loss of privacy [4], and probability to click. A seven-point Likert-type scale was used in the questionnaire for all of the items ranging from “strongly disagree” to “strongly agree”.

59% of the respondents were male, and average age was 22 years. Neither age nor sex explained variance of perceived intrusiveness. Mean score of perceived intrusiveness (measured on items “This advertisement is forced”, “...is distracting” and “... is intrusive”) was 3.67. An ANOVA test reveals that both base of personalization ($F = 6.256, p < .01$) and message form ($F = 3.017, p < .10$) had an effect on perceived intrusiveness, but no interaction effect emerged ($F = .119, p = .888$).

The lowest mean score appeared in the advertisement that recommended products based on the customer’s current browsing session and stated in passive form “others who viewed this, viewed also” ($M = 2.89, SD = 1.45, N = 28$). The highest level of intrusiveness was perceived in the advertisement that was based on past browsing session and stated in active form “we recommend for you” ($M = 4.23, SD$

$= 1.38, N = 27$). Figure 1 presents the mean scores of the different treatment groups.

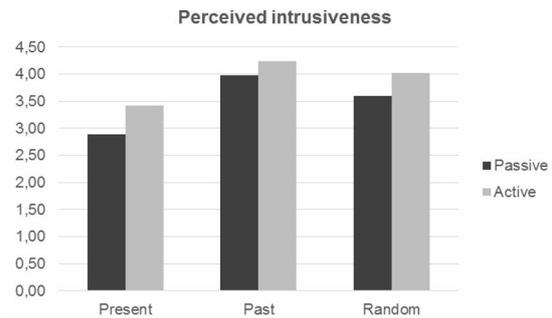


Figure 1. Perceived intrusiveness of personalized recommendations

Next, results of the analysis of the research data is presented.

4.3. Results

To analyze the effect of the research variables on consumers’ actual clicking behavior, we conducted chi-square tests and logistic regression analyses.

An analysis on the effect of active and passive message form on click-through rates was conducted. Of the total messages shown on front page, 4,521 were passive and 9,149 were active. 13.5% of the recommendations with active form on the front page were clicked while 14.9% of the recommendations with passive form were clicked. A chi-square test shows a statistically significant difference ($X^2 = 5,078, p < .05$). In addition, logistic regression further demonstrates that the results are statistically significant ($B = -.117, Wald = 5,074, p < .05$).

Of the messages shown after front page, 9,004 had a passive message form and 4,501 an active message form. 29.7% of the product recommendations with passive message form shown after the front page were clicked, while 21.9% of the product recommendations with active message form were clicked. The difference is statistically significant based on a chi-

Table 1. Recommendations

Recommendation	Company	Message form	Personalization base	Page	True displays	Click-through rate %
"A recommendation for you"	Outdoor apparel	Active	Past	Front page	4090	18,2
"Recommended for you"	Ticketagent	Active	Past	Front page	443	28,2
"We recommend also"	Consumer electronics	Active	Present	Purchase page	2233	16,7
"Buyalso"	Outdoor apparel	Active	Present	Purchase page	2268	26,9
"Buythis"	Children's wear	Active	Random	Front page	4616	7,9
"The most viewed"	Hypermarket	Passive	Past	Category page	2734	4,9
"The most viewed"	Outdoor apparel	Passive	Past	Category page	1769	34,8
"The most wanted right now"	Outdoor apparel	Passive	Random	Front page	2429	23
"Picks for February"	Hypermarket	Passive	Random	Front page	2092	5,6
"Others who viewed this, also viewed"	Hypermarket	Passive	Present	Productpage	4501	42,7

square difference test ($X^2 = 93,054, p < .000$). Logistic regression was conducted to further validate the results ($B = -.527, Wald = 297,036, p < .05$). The effect of message form on clicking behavior is shown in Figure 2. The results support hypotheses 1–3.

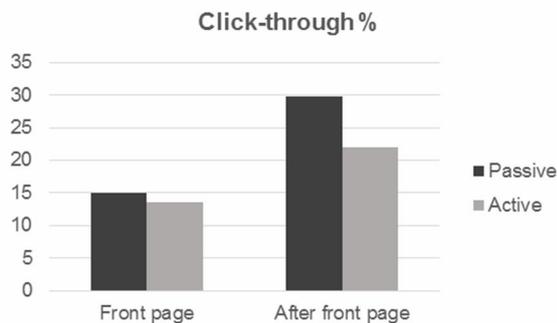


Figure 2. Effect of message form and page on click-through rate

Next, an analysis was conducted to investigate the effect base of personalization has on clicking behavior with regard to product recommendations shown on the front page. Past session-based recommendations on the front page were displayed 3,662 times, and 9.2% of the displays were clicked. Random-based recommendations on the front page were displayed 8,097 times, and 11.4% of them were clicked. A chi-square test shows that there was a statistically significant difference between past session and random recommendations on the front page ($X^2 = 154,565, p < .000$). Thus, it can be concluded that past session-based recommendations are more effective in generating clicks than random product recommendations. Logistic regression further demonstrated that the effect of personalization base on clicking intentions is statistically significant ($B = -0.616, Wald = 151,479, p < 0.05$). Thus, H4 is supported.

A similar analysis was conducted with product recommendations shown after the front page, including category, product and purchase pages. A total of 13,505 product recommendations on pages other than the front page were viewed by customers of the online stores. Of the recommendations based on present session ($N = 9,002$), 32.3% generated clicks while 16.7% of messages based on past session ($N = 4,503$) generated clicks. A chi-square test shows that there was also a statistically significant difference between present and past session-based recommendations on pages other than the front page ($X^2 = 371,693, p < .000$). The result indicates that present session-based product recommendations generate more clicks than past session-based recommendations on category, product and purchase pages. Logistic regression was conducted to further validate the findings ($B = -0.672, Wald = 1155,914, p < .05$). Thus, H5 is also supported.

5. Discussion

5.1. Theoretical implications

The results of the pre-test indicate that customers perceive product recommendations that are based on information about their past browsing session as more intrusive than recommendations that are based their current browsing activity. The result supports prior research on privacy and intrusiveness of online advertising [e.g., 12, 27, 28] – using customer information that could not have been known based on the present session’s browsing activity, is thought to violate ones privacy. The results also support prior research that has shown that customers react negatively to explicit use of data [4, 29]. In addition, the results illustrate that customers are more interested in product recommendations that are based on their present shopping process. The explanation for this is, most probably, that product recommendations that are based on the current shopping activity of a customer have a higher fit with the customer’s current need. This supports the notion of White and colleagues [30] that the better justified a personalized message is, the more likely consumers are to respond positively to it.

The results of also highlight that a high degree of personalization does not necessarily result in increased click-through rates. The research of White and colleagues [30] and Van Doorn and Hoekstra [28] argue that intrusiveness results in lower purchase intentions. The results of the present study indicate that recommendations with a passive form generate more clicks than recommendations with an active message form. This applies to all stages of a customer’s buying process. The explanation could be that customers perceive product recommendations with an active message form as more intrusive and forced, resulting in reactance due to perceived loss of freedom. Moreover, product recommendations with passive message form may be perceived as unintentionally personalized to customers. The argument of Sela and colleagues [24], which points out that customers react positively to recommendations that are unintentionally valuable to them, may be applied here. Thus, customers may feel that passive messages are not forced, and find them more interesting, particularly if they fit their needs and preferences.

The analysis of message form and message base was divided into two categories based on the page the product recommendation was placed at. The result shows that product recommendations on the front page generated less clicks than product recommendations on further pages, probably because consumers are more open to seller’s recommendations after they have fulfilled their first immediate need to visit the particular store.

The distinction of page categories enables the possibility to compare the effectiveness of product recommendations with different kinds of

personalization bases. According to the analysis, past session-based product recommendations generate more clicks on the front page than randomly chosen product recommendations. However, on pages after the front page, product recommendations based on the present session generate more clicks and purchases than recommendations based on a user's previous visits. It can be concluded that present session-based information is more relevant than past session-based information. The findings of van Doorn and Hoekstra [28] state that a high degree of personalization increases purchase intentions even though it also increases intrusiveness. However, the results of this study imply that a high degree of personalization increases intrusiveness *and* lowers the effectiveness of the recommendation. Thus, the most recent customer behavior data and passive message form are most positively responded by customers.

5.2. Managerial implications

The results provide tools for companies to use when designing their online personalization strategies. E-commerce companies using recommender systems should take into consideration the degree of personalization they are applying in their advertisements and other content. More specifically, managers should consider the message form and personalization base of product recommendations. They should also remember that the page and stage of the buying process may affect the type of product recommendation that should be used. In general, product recommendations in the later phases of the shopping process generate more clicks than recommendations on the front page.

This research implies that product recommendations with a passive message form are more effective than recommendations with active message form in all phases of the buying process. Thus, online stores should implement product recommendations that do not imply the amount of information known about customers. Generalized lines such as "the most popular" are effective forms for targeting customers with personalization without creating reactance – even if the recommendation would be based on known customer information.

E-commerce companies should also consider the message base they use in making the recommendations. Based on this study, companies should use the most recent information they have on their customers. Thus, information that has been acquired during past visits should be used on the front page in order to increase click-through rates. However, after the front page, such as category, product and purchase pages, it is the most effective to use information that is based on the current shopping session of the customer. Thus, product recommendations on further pages should reflect the choices and preferences the customer has implied on

the current visit instead of past visits. This kind of personalization is also appreciated by the customers.

5.3. Limitations

The data was acquired from a company that provides a personalization software to its clients. Thus, the data is limited to certain types of online stores and to certain types of product recommendations – there are many other kinds of recommendations that could have different kind of effect. Moreover, customers' clicking and buying behavior may differ between the stores as the sold products and the designs of the stores are different. Additionally, the products sold vary in terms of price, which might affect the effectiveness of the recommendation. However, the variance in products, stores and prices can also be considered a strength as the results provide better generalizability. In regards to the research design, future research should control the exposure of recommendations based on present and past behavior and thereby rule out the self-selection bias that affects the results of this study.

A scenario-based pre-test was conducted with participants that were shown screenshots of possible product recommendations. Under ideal circumstances, the same questions would have been posed to real customers during their shopping experience, and all the different recommendation types would have been considered. However, as the researchers had no control over the decisions of the companies or had any contact information or other touchpoint to the customers, such procedure was not possible. In addition, no online store that would have used all the different types of product recommendations could not be included in the study. Therefore, the compared recommendations are subject to a number of uncontrolled variables. This limitation was alleviated by categorizing the analyzed recommendations as objectively as possible.

6. Conclusion

Online personalization has become a vital marketing and sales tool for e-commerce companies. Product recommender systems, which apply consumer data in making recommendations, are a common tool for e-commerce companies. The effects of privacy issues and perceived intrusiveness have been studied in the advertising literature but research on the effect of online personalization on actual clicking behavior is limited. Thus, the aim of this study was to fill this research gap by utilizing clickstream data from five different online stores. The results suggest that personalized product recommendations that are based on customer's previous browsing session increase perceived intrusiveness and decrease click-through rate. The analysis implies that product recommendations generate the most clicks when they are based on the

most recent information acquired of the customer. In addition, the results suggest that product recommendations with passive message form generate higher click-through rates than active message form, which suggest the need to mitigate the perception of intrusiveness.

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