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Evaluating the impact of personalized recommendations: Application in the mass-retailing sector

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Summary

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In our experiment, participants received folder with either personalized recommendations or non-personalized recommendations. These recommendations are defined on what other shoppers, who act similarly in terms of shopping basket, buy.

Results show that personalized recommendations have significant effects on customers’ perceptions on mass-retailer personality, on the flyer, on the recommendation system, and also on the intention to visit the store, on word-of-mouth and intention to purchase recommended products.

Keywords: Recommendation, Personalized communication, Offline mass-retail sector.

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Abstract

This research aims at experimentally examining the impact of personalized recommendations – specific products recommended to a customer based on his purchase history – on the customer’s decision-making process, in the offline mass-retailing sector. In our experiment, participants received folder with either personalized recommendations or non-personalized recommendations. These recommendations are defined on what other shoppers, who act similarly in terms of shopping basket, buy. Results show that personalized recommendations have significant effects on customers’ perceptions on mass-retailer personality, on the flyer, on the recommendation system, and also on the intention to visit the store, on word-of-mouth and intention to purchase recommended products.

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1. Introduction

A recommender system is “an information filtering system that predicts the preference that users would give to an item they had not yet considered” (Tourwé, 2012). In other words, customer preferences are assessed and recommendations are derived. The output thus consists of a list of recommended items that the customer could be interested in, even though he has not bought them. Recommendations can take various forms though however. A recommender system for selling books, for example, could either provide an individual-level list of readings for a specific customer (called “personalized recommendations” in this paper) or operate at an aggregate level and generate a list of products for a cluster of customers. The latter system does not provide recommendations for one unique person. Thus, we call them “non-personalized recommendations” in this paper.

Our goal is to investigate customer evaluation of personalized versus non-personalized recommendations. Of particular interest are: attitudes and perceptions (a) towards the mass-retailer, (b) of the mass-retailer’s personality, (c) of the variety of the assortment, (d) of the interest in the flyer, and (e) towards the recommender system itself. We also focus on behavioral variables such as (f) intention to visit the store, (g) intention to make purchase there, (h) word-of-mouth, and (i) intention of purchase the recommended products (see Fig. 1).

First, we develop our main hypotheses in line with personalization and collaborative systems. Second, we present our experimental method research design. Then, we expose our analysis and main findings. Finally, we discuss the results while highlighting relevant implications for retail managers.

2. Literature Review and Hypotheses Development

2.1. Impact of personalized recommendations on customers’ attitudes and perceptions

The attitude, defined by Loudon and Della Bitta (1993), is “how for or against, positively or negatively, favorably or unfavorably, a person regards a particular object”. According to Petty et al. (1991), attitudes are “global and relatively durable evaluations of objects, problems or persons”. Support through personalized recommendations allows mass-retailers “to meet customer needs [and to] boost the success of a company”, and thus influences customers’ attitude towards the company (Liang and Lai, 2002). A personalization strategy where customers are directly targeted and at the heart of the retailer’s objectives (Kotler et al., 2009; Claeyssen et al., 2011; Stenger et al., 2011) may lead to a more favorable attitude towards the mass-retailer.

**H1**: The attitude, towards the mass-retailer, of customers who receive personalized recommendations is more positive than the attitude of those who receive non-personalized recommendations.

Customers receive various information on products in terms of commercialized brands, categories, characteristics, content, quantity, etc. Customers today face an incredibly large assortment of products. In this context of information overload, personalized recommendations can play a key role in providing precise information that can help the customer (Weng and Liu, 2004). Receiving relevant and targeted information compiled just for him (Jannach et al., 2011)
can be decisive for the purchasing process. Alba et al. (1997) showed that the assistance of automated recommendation agents significantly reduces the complexity of the retail environments (i.e., a large number of products available) and decrease customers’ search costs.

**H2: Customers develop more positive perceptions towards the products that are recommended in the folder if these recommendations were personalized (compared to non-personalized recommendations)**

Also of interest is to measure the impact of personalized recommendations on other dependent variables (DV), such as the customer’s perception towards the mass-retailer’s personality features, towards the variety of the assortment, and towards the flyers. These dependent variables are not subject to hypotheses, but they will be measured in our empirical application.

**2.2. Impact of personalized recommendations on customers’ intentions and behaviors**

We hypothesize that personalized recommendations influence customers’ behavioral intentions such as the intention to visit and make purchases at this store. Advice provided by personalized recommendations “enables [them] to find the products they want, [so] the customer loyalty and desires of purchasing may be increased” (Weng and Liu, 2004). In line with our research, but in an online environment, Weng and Liu (2004) showed the importance of information filtering, in order to deliver recommendations that lead to customers’ revisiting or repurchasing in the store.

**H3a: Customers who receive personalized recommendations have a higher intention to visit the mass-retailer’s store than customers who receive non-personalized recommendations.**

**H3b: Customers who receive personalized recommendations have a higher intention to make their purchases at the mass-retailer’s store than customers who receive non-personalized recommendations.**

A personalized recommendation is a piece of advice, a proposition for a product that the customer could be interested in. If these recommendations are coherent to customers’ preferences, they can increase selling opportunities (Weng and Liu, 2004). Moreover, recommendations can increase non-planned purchases (Hostler et al., 2011) or have a positive effect on customers’ behavior (Smith et al., 2005). Consequently, personalized advice seems to promote purchases (Chevalier et Mayzlin, 2006) and result in more recommended products bought.

**H4a, H4b, H4c: Customers who receive personalized recommendations buy a higher percentage of recommended products than those who receive non-personalized recommendations.**

We also measured the impact of personalized recommendations on other behavioral dependent variables (DV), such as word-of-mouth, even though the corresponding hypotheses are not presented here.

**2.3. Recommendations in an offline mass-retailing context**

Collaborative filtering is generally used as an online tool to predict preferences or propose recommendations on websites with evaluation, scores, and ratings. These recommendations are defined on what other shoppers, who act similarly in terms of shopping basket, buy. To test our hypotheses, we implement personalized collaborative recommendations in the context of an offline mass-retailer folder and adapt collaborative filtering to the specific characteristics of a mass-retailer. (a) We use an implicit recommendation system based on shopping basket (purchase history) observation. This observational method is particularly adapted to mass-retailers, as they are usually equipped with scanner systems or loyalty systems that track customers’ purchase history. (b) We adopted a trans-category view wherein “neighbors” (see below) were designated based on purchases in various categories. This is particularly adapted to mass-retailing, since mass-retailing customers (i) usually buy items from multiple categories during one shopping trip (ii) and are permanently involved in multi-category decision-making (Mild and Reutterer, 2003).
3. Method

3.1. Design

Our experiment consists of three steps (see Fig. 2): (a) the manipulation-free questionnaire in T₁ provides the 112 respondents’ purchase intentions; it allows us to create two equivalent groups. (b) From the data on purchase intentions obtained in the step (a), we mathematically compute, in T₂, personalized recommendations, which are used in step (c). In step (c) in T₃, the key manipulated variable – personalized versus non-personalized recommendations – is introduced. The remaining 80 respondents received a folder of a fictitious mass-retailer. The folder consists of 4 pages identical for all respondents and a 5th page – an insert – containing recommendations. Group 1 received personalized recommendations, customized for each member of group 1, while group 2 received non-personalized recommendations, that is, the top 4 of the most-bought products (identical for all members of group 2).

Participants and procedure.
The experiment used a random sample of 112 students from a Belgian university, who answered the first questionnaire. Then, 80 out of the 112 students answered the second questionnaire.

Sample description. In the first questionnaire, questions on socio-demographic characteristics were asked, such as age (AGE), sex (SEX), if they are their household’s main buyer (BUYER), how regularly they shop (FREQ), if they live at home with their parents, in a student room or elsewhere (RESID), and how much they spend per week for shopping at the mass-retailer (in Euros) (MONEY).

3.2. First Step – Questionnaire 1 (T₁)

To avoid any order effect, two versions of the questionnaire with different product order were developed. The questionnaire started with a mini scenario explaining that “a new mass-retailer would like to open in Belgium and specifically targets a public aged 14-29 years”. The participants were presented a list of 30 products and were asked to choose a maximum of 10 products (out of the 30 products available in the list) that they could buy in one week.

3.3. Second Step – Algorithm and recommendation method (T₂)

We determined each product’s nearest neighbors items, in order to mathematically compute a list of recommended products for each customer. Then, we used these neighborhoods and the shopping basket of the customers to compute recommendations. We apply the “commute-time kernel” algorithm (see Fouss et al., 2007).

3.4. Third Step – Questionnaire 2 (T₃)

One week later, 80 students took part in the second step of the experiment. The participants were distributed half into the manipulated group and the other half into the control group.
Equivalence of groups. We formed two equivalent experimental groups of participants in order to manipulate the key manipulated variable. Splitting the participants and attaining equivalence was done using a stratified sample. We used socio-demographic characteristics like sex, age, main buyer, housing, and the purchase (or not) of four random products.

Questionnaire 2. In addition to the 2nd questionnaire, participants received a four-page, 30-product brochure, including an extra insert with recommended products. The insert of the manipulated group (GR1) contained 4 products specifically personalized for each respondent (determined by the algorithm presented in the section 3.3). The control group (GR2) received an insert containing the 4 most-bought products as recommendations.

Dependent variables. First, variables related to attitudes and perceptions were measured, in the following way. The attitude towards the mass-retailer (ATTITUDE) was measured through a 3-item validated scale (Miniard et al., 1990), while the scale developed by Linquist (1974) was used to measure the retailer’s personality features (PERSONALITY). The scales of Chaabane et al. (2010) are used to measure respondents’ perception on the store variety of assortment (3-item scale) (VARIETY) and on the flyer itself (2-item scale) (FLYER). Respondents’ attitudes towards the recommendations made were also measured through 3 items (REC).

Second, variables related to behavioral intentions were measured in the following way. We collected information on the intention to visit the store and the intention to make purchases at the store (BEHAVINT), and the intention to do positive word-of-mouth about the store (WOM), via mono-item Likert scales.

Lastly, the intention to purchase the recommended (with or without personalization) products is measured through three proportions. POURC_PR is the proportion of recommended products fictively bought by the respondent in T3, compared to the total number of recommended products: since 4 products were recommended to each respondent, POURC_PR can take 5 values (0%, 25%, 50%, 75% or 100%). POURC_TOT is the proportion of recommended products fictively bought by the respondent in T3 compared to the total number of his purchases, and POURC_PRICE is the ratio between the money spent for recommended purchased products for a given customer divided by his total price of purchased products. Note that the variable POURC_PR represents the so-called recall and POURC_TOT the so-called precision in the data mining field (Olson and Delen, 2008).

4. Results

Cronbach alpha. The Cronbach alpha, computed for the six multi-item scales of our model, showed that four of them (ATTITUDE, PERSONALITY, REC, BEHAVINT) represent the same construct (α>0.7 - cf. Table 1), while this conclusion cannot be drawn for the other two (FLYER, VARIETY). The other variables are mono-item and thus not concerned by this test.

Homogeneity test. An ANOVA analysis was conducted, in order to test differences between the two groups. As a preliminary condition of ANOVA, Levene’s test of homogeneity of variances leads to the acceptance of the null hypotheses (at a 5% level) for all the variables except REC, which is close to 5% though (Sig. 0.042). We thus consider that variances are homogenous.

ANOVA analysis. Regarding variables related to attitudes and perceptions, the ANOVA results (Table 1) show that the enrichment of the brochure with personalized recommendations (GR1) leads to significantly better perception of the mass-retailer’s personality (p-value=0.025) and higher interest for the flyer (p-value=0.000). Personalized recommendations (GR1) also bring more positive attitude towards recommendations (p-value=0.000) compared to non-personalized recommendations.

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1 An average score for each construct is obtained for each respondent from the set of items used to measure said construct. For example, the “attitude towards the store” construct (ATT) is computed by averaging the scores obtained on each of the 3 items measuring this construct, and aggregating for all respondents.

2 Please note that the Cronbach alpha was borderline for this construct, which requires to cautiously interpret this result.
recommendations (GR2), which supports H2. The attitude towards the mass-retailer turns out to be more positive in GR1 (personalized recommendations), but only at a 10% level, which allows us to cautiously accept H1. The perception of the variety of the assortment is not significant. As far as behavioral intentions are concerned, personalized recommendations (GR1) lead to significantly higher intention to visit and purchase the store (p-value=0.010), supporting H3. Personalized recommendations provides higher intentions to purchase the recommended products (p-values=0.000, 0.002, 0.014), respectively supporting H4a, H4b, H4c. Finally, The intention to do positive word-of-mouth is also significantly higher in the group that received personalized recommendations (p-value=0.036).

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Variables</th>
<th>mean GR1 – perso</th>
<th>mean GR2 – non perso</th>
<th>Fisher’s F</th>
<th>SIG. (α=0.05)</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>ATTITUDE</td>
<td>3.1417</td>
<td>2.800</td>
<td>3.295</td>
<td>0.073³</td>
<td>Sig. at a 10% level - H1 supported</td>
</tr>
<tr>
<td>Extra test</td>
<td>PERSONNALITY</td>
<td>3.2330</td>
<td>2.8924</td>
<td>5.199</td>
<td>0.025</td>
<td>Sig.</td>
</tr>
<tr>
<td>Extra test</td>
<td>FLYER</td>
<td>3.125</td>
<td>2.325</td>
<td>14.132</td>
<td>0.000</td>
<td>Sig. but Cronbach=0.64</td>
</tr>
<tr>
<td>H2</td>
<td>REC</td>
<td>3.5</td>
<td>2.51</td>
<td>24.710</td>
<td>0.000</td>
<td>Sig. – H2 supported</td>
</tr>
<tr>
<td>Extra test</td>
<td>VARIETY</td>
<td>2.7583</td>
<td>2.5833</td>
<td>0.844</td>
<td>0.361</td>
<td>Non Sig.</td>
</tr>
<tr>
<td>H3</td>
<td>BEHAVINT</td>
<td>3.0625</td>
<td>2.4744</td>
<td>6.96</td>
<td>0.010</td>
<td>Sig. – H3 supported</td>
</tr>
<tr>
<td>H4a</td>
<td>POURC_PR</td>
<td>0.2677</td>
<td>0.1774</td>
<td>15.597</td>
<td>0.000</td>
<td>Sig.- H4 a,b,c supported</td>
</tr>
<tr>
<td>H4b</td>
<td>POURC_TOT</td>
<td>0.2666</td>
<td>0.1609</td>
<td>10.581</td>
<td>0.002</td>
<td>Sig.- H4 a,b,c supported</td>
</tr>
<tr>
<td>H4c</td>
<td>POURC_PRICE</td>
<td>0.4938</td>
<td>0.2750</td>
<td>6.260</td>
<td>0.014</td>
<td>Sig.- H4 a,b,c supported</td>
</tr>
<tr>
<td>Extra test</td>
<td>WOM</td>
<td>3.5</td>
<td>2.5167</td>
<td>3.019</td>
<td>0.036</td>
<td>Sig.</td>
</tr>
</tbody>
</table>

Table 1: ANOVA and Fisher Test – Variables summary

5. Discussion and Conclusion

Recommendations and personalization techniques are often used online. They are easy and fast to use. Online users often receive recommendations during their purchase process and it may provide many advantages for the company (higher revenue, better corporate image, etc.) (Adomavicius & Tuzhilin, 2005). On the other hand, the customer also benefits from it (time saving, reduced search costs, help, etc. – see Oufaida and Nouali, 2008). However, personalization in the offline environment is not trivial, and giving personalized information to customers during their shopping process is a challenge for the offline retail sector. Implementing personalization has such high costs, such as training staff and managers, or integrating them to communication materials. Furthermore, in this kind of study, privacy issues are at play, as many customers dislike the intrusion of personalization systems into their private life (Acquisti et al., 2005; Stenger et al., 2011).

In spite of these difficulties, our results show the promising nature of research on personalized recommendations. Our experiment tests if personalized recommendations can provide added value in an offline environment, and more specifically in the mass-retailing sector. In particular, our experimental study looks at the effect of personalized recommendations – provided in a promotional brochure –, compared to non-personalized recommendations, in the setting of the offline mass-retail sector. Results show that personalized recommendations have a significant and positive impact on several measures of the customer’s perceptions and attitudes towards the store and the recommendations, and on the customer’s behavioral intentions.

These promising results can lead to relevant managerial implications. Development of new marketing strategies in the offline retail sector could be considered, following the results of our research. For example, one possible application would lie in the area of targeted promotional material, such as advertising brochures or leaflets adapted for each customer. The objective there

³ At a 10% level, ATTITUDE is significant.
is to convey appropriate information to the appropriate offline retail customer using personalized offline communication. As such, it could lead to increased customer loyalty.

Another idea would be using additional knowledge on which items are frequently purchased together (Lin et al., 2003). This information could increase “cross- or up-selling by helping retailers conduct selective marketing and plan their shelf arrangement” (Lin et al., 2003).

Bibliography