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Consequences of personalized product recommendations and price promotions in online grocery shopping

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ABSTRACT

Shopping convenience can be turned into a competitive advantage for online grocery retailers. Consequently, we study how personalized product recommendations (recommendation agents) and price promotions (algorithmic pricing) compensate for the negative impact that consumer's perceived cognitive effort causes on loyalty. By default, the relationship from perceived cognitive efforts to attitudinal and behavioral loyalty is negative, yet these results demonstrate that personalized price promotions lessen the negative impact, while personalized product recommendations do not have such an influence. The findings contribute to a better understanding of personalized marketing activities in today's data-driven online grocery retailing.

1. Introduction

Grocery retailing changes fast, and boosted by the COVID-19 pandemic, consumers increasingly buy groceries online (Statista, 2021). During the COVID-19 pandemic, the biggest growth in online sales occurred in two categories – groceries and pharmacy (Lone et al., 2021) – when consumers began avoiding physical shops, opting instead to buy groceries online. Traditional brick-and-mortar grocery retailers have struggled in this transformation, and faced challenges with retaining their existing customers (Singh and Rosengren, 2020), as along with home deliveries gaining in popularity, consumers suddenly were confronted by a vast number of new online grocery shopping options in addition to brick-and-mortar grocery shopping. Consequently, retailer's efforts in building customer loyalty have become more fundamental than ever, and we contribute to the recent discussion on customer loyalty (Liu-Thompkins et al., 2022; Nesset et al., 2021; Molinillo et al., 2021; Agarwal et al., 2022) in online retailing by examining: *how retailer-to-consumer personalization of product recommendations and price promotions can assist retailers in their efforts in building and strengthening customer loyalty*. This understanding is salient for grocery retailing, as recent research evinces that customer loyalty can lead to increased purchase enjoyment and happiness (Agarwal et al., 2022), thus improving the entire customer experience in the digital realm.

Indeed, grocery retailing has recently undergone an impactful transformation. Consumers who used to make daily visits to the nearest brick-and-mortar grocery store, now make online their weekly grocery orders through a food delivery service (Colaço and e Silva, 2021) and a click-and-collect option (Milioti et al., 2020; Gielens et al., 2021). While grocery retailers used to compete mainly with other stores located in close proximity, online shopping has intensified the competition between different providers, and the digital realm enables consumers to switch and become customers of not only other brick-and-mortar stores, but also other evolving food delivery concepts (Ray et al., 2019; Tandon et al., 2021). Consequently, it is fundamental for a grocery retailer to respond to this development and value-adding services, including personalization of the customer experience, provides a fruitful avenue to enhance a consumer's shopping experience in the digital realm (Tyrväinen et al., 2020), thus contributing to customer loyalty (Liu-Thompkins et al., 2022). Indeed, online grocery stores can develop the ease of shopping into a competitive advantage, yet most retailers mainly scratch the surface when it comes to the provision of a personalized shopping experience (Silverstein, 2021; Lambillotte et al., 2022). Online personalization encompasses the provision of product recommendations, as well as individualizing other aspects of the information content and interaction a retailer exchanges with its customers (Zanker et al., 2019), yet retailers have been cautious regarding personalized pricing,

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particularly because early results indicated that differentiated pricing might be perceived unfair (Unglesbee, 2019).

From this backdrop, we focus on the use of two contemporary online marketing techniques – recommendation agents (Behera et al., 2020a,b) and algorithmic pricing (Chen et al., 2021) – which enable well-targeted retailer-to-consumer product recommendations and price promotions for individual consumers. We contribute to the retailing literature with an empirical study demonstrating that such online marketing tactics can ease the consumer's cognitive effort in online grocery shopping. From a theoretical point of view, this research provides a better understanding of the 1) interrelationship between cognitive effort and customer loyalty and 2) extends it to the context of online grocery shopping, wherein purchase frequencies are high and purchase volumes are large. This sets new opportunities but also challenges for online grocery retailing, in order to better understand how personalized marketing can assist and ease consumer decision-making. In examining the impact of cognitive effort on customer loyalty while consumers shop groceries online, this research 3) emphasizes the presence of two concomitant dimensions of customer loyalty: attitudinal and behavioral loyalty. While the relationship between perceived cognitive effort and customer loyalty is negative by default, we 4) explore how data-driven personalization built on the detailed customer loyalty program data that the retailers possess, can be built into a strategic asset, in compensating the negative effect of cognitive effort. While the existing research (Appendix A) has strongly focused on personalized product recommendations, we extend to this research and cover the differentiated impact of personalized product recommendations (recommendation agents) and price promotions (algorithmic pricing) in moderating the cognitive effort – customer loyalty relationship. From a methodological point of view, we use 5) a methodologically adept marginal effects approach in visually demonstrating these findings.

Overall, we suggest online grocery retailers to pursue on these findings because due to the large amount of detailed customer loyalty program data generated both from physical and online shopping, the opportunities for personalization are vast for grocery retailers and enables personalization at a level not yet seen before. Furthermore, malleability of the environment, e.g., through personalization, drives customer loyalty in different ways (Liu-Thompkins et al., 2022), and consequently retailer-to-consumer personalization can be built into an effective tool for grocery retailers in reducing the cognitive effort associated when consumers buy groceries online. Indeed, online grocery retailers can promote online sales not only through recommendations that assist and ease consumers in choosing the right product, but also through personalized discounts that enhance the value of those products (Venkatesh et al., 2021).

2. Research framework and hypotheses

2.1. Customer loyalty

We follow Oliver (1999, p. 34) in defining customer loyalty as a "*deeply held commitment to rebuy or repatronize a preferred product or service consistently*." Academics and practitioners widely acknowledge that retaining and maintaining existing customers is more beneficial in the long term than attracting new customers. Yet it is a challenge for online retailers to retain their existing customers when the digital realm provides a growing variety of shopping options which are not tied to a physical and temporal location. Also, switching costs are relatively low in online shopping, and consumers who otherwise tend to be loyal to a specific retailer may be tempted to choose an alternative in the digital realm. Information technology can therefore play a key role in enhancing customer loyalty and building enduring customer relationships (Liu-Thompkins et al., 2022; Lin and Wang, 2006; Luarn and Lin, 2003) through value-adding services, including well-targeted retailer-to-consumer personalization which is matched to consumer's purchase history and preferences (Zhang et al., 2011). In defining loyalty, we follow the previous literature, which distinguishes between attitudinal and behavioral dimensions in loyalty (Liu-Thompkins et al., 2022; Dick and Basu, 1994; Watson et al., 2015). Attitudinal loyalty reflects attitudes that favor a particular entity (Chaudhuri and Holbrook, 2001; Oliver, 1999), and behavioral loyalty, also known as habit, indicates a behavioral disposition which consumers exercise frequently (Liu-Thompkins and Tam, 2013). In practice, repurchasing, repurchase intentions, customer retention, and customer return operate as proxies for behavioral loyalty (Watson et al., 2015).

2.2. Perceived cognitive effort

Perceived cognitive effort reflects the effort that is associated when consumers complete a specific action (Mosteller et al., 2014). Cognitive effort includes the right place and timing for an action, deciding what type of action is necessary, and interpreting the results of that action. Perceived cognitive effort refers most commonly to an assessment of the costs that are associated with choosing and evaluating products (Xiao and Benbasat, 2018). However, today's online shopping requires cognitive effort in many other respects too, as groceries may need a specific treatment and temperature while being delivered. The allocation of home delivery times also requires cognitive effort, as delivery of groceries typically poses a need to be physically present. Perceived cognitive effort resembles what Shugan (1980) refers to as the "cost of thinking." According to Shugan (1980), decision making requires an effort from the consumer and this effort, and hence the cost of thinking, depends on the availability of information, a variety of alternatives, the pressure of time, and the consumer's limited information-processing capabilities. The valence of cognitive effort is negative by default (Yoo et al., 2017) and perceived cognitive effort negatively influences customer loyalty (Zhang et al., 2018) because customer loyalty is determined by the efficiency of the shopping process (Zhang et al., 2011), which is distracted by the efforts required in screening the prices and in evaluating a alternative options. Building on previous research, we expect a negative association between perceived cognitive effort and customer loyalty (Zhang et al., 2018). To account for potentially confounding factors, we control for gender, age, and purchase volume.

H1. Perceived cognitive effort is negatively associated with a) attitudinal and b) behavioral loyalty when controlling for gender, age, and purchase volume.

2.3. Personalization

Personalization is defined as "*the tailoring of products and purchase experience to the tastes of individual consumers based upon their personal and preference information*" (Chellappa and Sin, 2005, p. 181). Personalization refers to adaptation based on information that has been derived from consumers' previous transactions and behavior (Montgomery and Smith, 2009) and Zanker et al. (2019, p. 160) describe online personalization system as "*a system that (1) makes assumptions on an individual's goals, interests and preferences, (2) in order to tailor interaction and content (3) so as to provide the most relevant user experience*". In the literature, *perceived personalization* refers to the extent to which a consumer perceives that personalization represents personal preferences (Komiak and Benbasat, 2006; Xiao and Benbasat, 2018). While the existing research has almost entirely focused on personalized product recommendations through decision support systems, we distinguish between personalized product recommendations (i.e. recommendation agents) and price promotions (i.e. algorithmic pricing) because online retailers can promote online sales not only through recommendations that assist and ease consumers in choosing the right product, but also through personalized discounts that enhance the value of those products (Venkatesh et al., 2021).

2.3.1. Personalized product recommendations through recommendation agents

Recommendation agent is an interactive decision aid which helps consumers in screening and evaluating different options that are available in an online store (Häubl and Trifts, 2000). The use of such systems is tempting for online retailers: online recommendation systems are known to be effective in engaging consumers (Senecal and Nantel, 2004; Xiao and Benbasat, 2007; Ampadu et al., 2022), as well as in cross-selling, up-selling and increasing customer loyalty (Srivastava et al., 2020). According to Zhang et al. (2011), the efficiency of the shopping process drives online customer loyalty—that is, consumers are more loyal to online stores that can offer greater efficiency to consumers in their online shopping. Consequently a potential approach for online retailers to distinguish themselves from other players in the marketplace is to utilize value-adding services, such as product recommendations, to make online shopping more convenient for a consumer. Altogether, personalized product recommendations enable better targeted retailer-to-consumer product recommendations, reducing the associated product-screening and product evaluation costs (Zhang et al., 2011). Indeed, by improving the quality of decision-making and reducing product-screening and evaluation costs (Zhang et al., 2018), online recommendation systems—decision aids that analyze previous customer behavior and introduce products that fit to customer's preferences (Jiang et al., 2010)—can significantly improve consumers' shopping experience. Thus, efficient data analytics can operate as a strategic tool for online retailers in offering the products that interest individual consumers. Following Zhang et al. (2011), we consider personalized product recommendations as a means for online retailers to reduce the influence of the perceived cognitive effort on customer loyalty:

H2. Personalized product recommendations reduce the negative impact of perceived cognitive effort on a) attitudinal and b) behavioral loyalty when controlling for gender, age, and purchase volume.

2.3.2. Personalized price promotions through algorithmic pricing

Kamishima and Akaho (2011) describe a personalized pricing recommender system as a system that enables personalized pricing and promotions based on consumers' previous purchase history and preferential data, enabling discounted pricing for individual customers. The existing literature uses several parallel terms for such systems and mechanisms, including algorithmic, dynamic, personalized, and customized pricing (Seele et al., 2021). Following Seele et al. (2021), we consider algorithmic pricing as an umbrella term for different approaches of price personalization and customization, defining it as a mechanism that uses data mining and analytics to automatically generate customer-specific and/or dynamic pricing in real time. This study therefore considers the provision of personalized price promotions a specific subcategory of algorithmic pricing.

In retailing, algorithms take into account various factors in determining pricing, including product demand data analyzed with consumers' purchase history and characteristics, and combined with information about competing prices, market characteristics, and knowledge of temporal and spatial variation. Advanced versions of algorithmic pricing may even be able to estimate consumers' willingness to pay for a specific product (Greenstein-Messica and Rokach, 2018), thus enhancing the algorithm's effectiveness. Overall, the previous research reports both the advantages and disadvantages of algorithmic pricing (Haws and Bearden, 2006; Weisstein et al., 2013; Xia et al., 2004; Lii and Sy, 2009). The use of pricing algorithms may result in lower prices and cost savings, while algorithmic pricing may also have a negative effect in discriminating between consumers (Garbarino and Lee, 2003; Hinz et al., 2011). It should not be overlooked that when the customer becomes aware of price discrimination, they may be outraged by unfair pricing (Hinz et al., 2011). Grocery retailers commonly reward customers based on their level of loyalty and through loyalty-rewarding pricing schemes. The development of algorithmic pricing enables retailers to use differentiated pricing for individual customers, and a study by Martin et al. (2009) report a positive interrelationship between perceptions of price fairness and customer loyalty. We therefore expect personalized promotions to reduce the negative association of the perceived cognitive effort with customer loyalty. Fig. 1 presents the research model.

H3. Personalized price promotions reduce the negative impact of perceived cognitive effort on a) attitudinal and b) behavioral loyalty when controlling for gender, age, and purchase volume.

3. Methodology

3.1. Sample selection and data collection

We test our research model through an empirical study, which we conducted among customers of a large Finnish grocery retailer. This specific grocery retailer can be credited with being a pioneer in exploiting online marketing and highly customer centric retailer-to-consumer personalization: the retailer provides highly targeted product recommendations and personalized price promotions based on each customer's unique purchase history and habits in a mobile app for members of its loyalty card program (Molinillo et al., 2021). The grocery retailer is one of the largest grocery chains in Finland with an overall 36.5 percent market share of Finland's grocery trade (Finnish Grocery Trade Association, 2020), and a loyalty card program that covers approximately 65 percent of Finnish households. We cooperated with the grocery retailers in collecting the data for this study, and the retailer sent an invitation to members its online customer community to participate in our survey. The online community is open to everyone, and it is free to join—even when there is no relationship with the retail chain, however, the online community requires registration and the disclosure of personal background information.

In collecting the data, 3,910 customers were invited to participate and the data collection resulted in 2,061 responses with a response rate of 52.7 percent. We targeted consumers with an experience of shopping groceries online, and we received altogether 356 valid responses from consumers with an experience of shopping online groceries, which forms the sample we use in this study (Table 1).

3.2. Measures

The survey questionnaire consists of responses to 13 questions related to the constructs of perceived personalization (Xiao and Benbasat, 2018; Zhang et al., 2018), perceived cognitive effort (Xiao and Benbasat, 2018; Zhang et al., 2018), attitudinal loyalty (Watson et al., 2015; Zhang et al., 2018), and behavioral loyalty (Watson et al., 2015; Liao et al., 2017) (Appendix B). For this study's purposes, we adapted the scales and measurement items to the context of online grocery shopping, and at the same time, the scale of perceived personalization was applied to capture its two distinct aspects: personalized product recommendations; and personalized price promotions. Appendix C describes the modifications in detail by comparing original survey

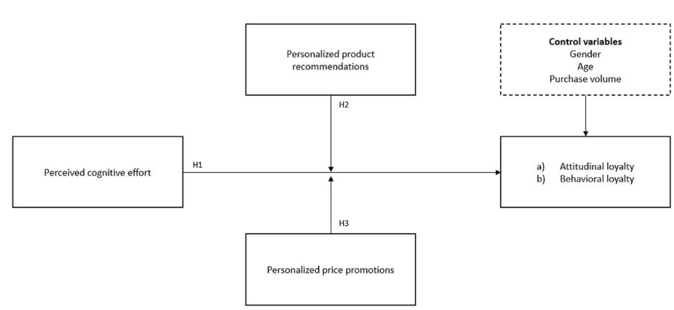

Fig. 1. Research model.

Table 1
Descriptive statistics and frequency of the control variables.

	Frequency	Percent
Gender		
Female	264	74.2
Male	92	25.8
Age		
18–34	101	28.4
35–44	124	34.8
45–54	79	22.2
55–	52	14.6
Purchase volume, monthly grocery purchases in €		
€0–300	86	24.2
€301–500	123	34.5
€501–800	99	27.8
More than €801	48	13.5

questionnaire items with the items used in this study. The adaptation of the scales included translation and adaptation to the local language due to linguistic differences. We used a five-point Likert scale ranging from *1 = Strongly disagree* to *5 = Strongly agree* for all the constructs. In addition, the questionnaire asked respondents to provide information about their background characteristics, including gender, age, and volume of monthly grocery purchases, which we use as the model's control variables.

4. Analysis and results

4.1. Validity and reliability of constructs

We performed a confirmatory factor analysis (CFA) with χ^2 = 288.251 (53), $p < 0.001$, CFI = 0.912. Given that the model fit indices were mainly satisfactory (Hu and Bentler, 1999; Hair et al., 2019), we carefully inspected the model to detect potential concerns regarding the data. We evaluated the construct reliability using composite reliability (CR) and Cronbach's alpha (α) and Table 2 illustrates that both indices met the threshold of 0.7, which indicates appropriate reliability (Fornell and Larcker, 1981). The factor loadings were all significant ($p < 0.001$). The average variance extracted (AVE) for all constructs exceeded 0.60, supporting convergent validity (Fornell and Larcker, 1981). The focal constructs all possessed discriminant validity, given that the AVE exceeded the squared correlation between the constructs (Fornell and Larcker, 1981) (Table 2). A closer analysis revealed that the constructs of attitudinal and behavioral loyalty were highly correlated, which was reflected in the goodness-of-fit indices. We created an alternative model in which the items of attitudinal and behavioral loyalty were forced to load onto a single factor. However, this model resulted in a decreased model fit and also theoretically, attitudinal and behavioral loyalty are considered two distinct aspects of customer loyalty, and the recent literature suggests that they be separately operationalized (Watson et al., 2015). We therefore retained the theorized model, because it prompted no concerns of convergent or discriminant validity.

Given the study's cross-sectional nature, we followed statistical procedures to account for common method bias in the data, referring to variance attributable to the measurement method (Chang et al., 2010; Podsakoff et al., 2003). Following the CFA marker technique approach (Lindell and Whitney, 2001; Williams et al., 2010) we used "the use of retail chain's mobile app" measured with the options "yes" and "no" as a marker variable, because it was theoretically unrelated to the model variables. The results showed low correlations with the marker variable (Table 2).

4.2. Hypothesis testing

We used linear regression in Stata 15 to test the hypotheses and run the analysis step by step separately with attitudinal (Table 3) and behavioral (Table 4) loyalty as the dependent variable. First, with attitudinal loyalty as the dependent variable, we tested several alternative models, which allowed us to compare models and assess the explanatory power of the included variables.

4.2.1. Attitudinal loyalty

Model 1 included only the control variables (gender, age, and purchase volume), which were all non-significant (Table 3). The control variables explained only 1.3 percent of the variance of attitudinal loyalty (R^2 = 0.013). Model 2 added the perceived cognitive effort to the model, and this model operated as the baseline model in the comparisons that followed. Adding perceived cognitive effort remarkably improved the model's explanatory power (R^2 = 0.227). Perceived cognitive effort had a highly significant negative association with attitudinal loyalty (β = −0.431, $p < 0.001$), supporting H1a. Models 3 and 4 added the interactions. Model 3 included the interaction between perceived cognitive effort and personalized product recommendations,

Table 3
Results for attitudinal loyalty.

Variables	Model 1	Model 2	Model 3	Model 4
	β (p)	β (p)	β (p)	β (p)
Dependent variable				
Attitudinal loyalty				
Independent variable				
Perceived cognitive effort (cognitive effort)		−0.431 (<0.001)	−0.370 (0.022)	−0.808 (<0.001)
Moderator variables				
Personalized product recommendations			−0.314 (0.007)	
Personalized price promotions				0.055 (0.606)
Interaction terms				
Cognitive effort x personalized product recommendations			0.004 (0.932)	
Cognitive effort x personalized price promotions				0.133 (0.003)
Control variables				
Gender	0.149 (0.168)	0.051 (0.597)	−0.009 (0.925)	0.036 (0.691)
Age	−0.054 (0.245)	−0.030 (0.474)	−0.029 (0.464)	−0.152 (0.691)
Purchase volume	−0.034 (0.266)	0.007 (0.806)	−0.012 (0.654)	−0.067 (0.796)
Explained variance				
R^2	0.013	0.227	0.304	0.342
Δ R^2 (vs. Model 2)			0.077	0.115

Table 2
Discriminant validity.

	α	CR	AVE	1	2	3	4	5
1. Personalized product recommendations	0.838	0.841	0.726	**0.852**				
2. Personalized price promotions	0.778	0.780	0.639	0.629	**0.800**			
3. Perceived cognitive effort	0.869	0.870	0.691	−0.294	−0.303	**0.831**		
4. Attitudinal loyalty	0.799	0.818	0.602	0.456	0.527	−0.602	**0.776**	
5. Behavioral loyalty	0.815	0.873	0.699	0.215	0.316	−0.258	0.643	**0.800**
6. Marker variable				−0.107	−0.128	0.093	−0.054	−0.104

Table 4
Results for behavioral loyalty.

Variables	Model 5	Model 6	Model 7	Model 8
	β (p)	β (p)	β (p)	β (p)
Dependent variable				
Behavioral loyalty				
Independent variable				
Perceived cognitive effort (cognitive effort)		−0.306 (<0.001)	−0.262 (<0.001)	−0.222 (0.001)
Moderator variables				
Personalized product recommendations			0.212 (0.006)	
Personalized price promotions				0.319 (<0.001)
Interaction terms				
Cognitive effort x personalized product recommendations			−0.047 (0.501)	
Cognitive effort x personalized price promotions				0.088 (0.179)
Control variables				
Gender	0.211 (0.133)	0.141 (0.301)	0.096 (0.479)	0.124 (0.352)
Age	0.121 (0.045)	0.139 (0.018)	0.137 (0.018)	0.150 (0.009)
Purchase volume	0.059 (0.139)	0.089 (0.024)	0.078 (0.048)	0.077 (0.045)
Explained variance				
R^2	0.024	0.087	0.108	0.141
ΔR^2 (vs. Model 2)			0.021	0.054

and the R^2 increased to 0.304 ($\Delta R^2 = 0.077$). However, the interaction term was statistically non-significant ($\beta = 0.004$, $p = 0.932$), which lent no support to H2a. Model 4 included the interaction term between perceived cognitive effort and personalized price promotions, and the R^2 increased to 0.342 ($\Delta R^2 = 0.115$). Hypothesis H3a is supported as the interaction term was significant and positive ($\beta = 0.133$, $p = 0.003$).

4.2.2. *Behavioral loyalty*

We followed similar analysis procedures, with behavioral loyalty as the dependent variable (Table 4), and compared the results based on four stepwise models. Model 5 included only the control variables (gender, age, and purchase volume) suggesting that age had a significant association with behavioral loyalty ($\beta = 0.121$, $p = 0.045$). However, the combined control variables explained only 2.4 percent of the variance in behavioral loyalty ($R^2 = 0.024$). Model 6 added perceived cognitive effort to the model—this model operated as the baseline in the comparisons that followed. Adding perceived cognitive effort increased the explanatory power (R^2) of the model to 0.087. Our results supported H1b, which posits that perceived cognitive effort has a negative association with behavioral loyalty ($\beta = -0.306$, $p < 0.001$). Models 7 and 8 added the interactions. Model 7 included the interaction between perceived cognitive effort and personalized product recommendations, and the R^2 increased to 0.108 ($\Delta R^2 = 0.021$), but the interaction term was non-significant ($\beta = -0.047$, $p = 0.501$), giving no support to H2b. Model 8 included the interaction term between perceived cognitive effort and personalized price promotions, and the R^2 increased to 0.141 ($\Delta R^2 = 0.054$). The interaction term was non-significant ($\beta = 0.088$, $p = 0.179$), suggesting that the result did not support H3b.

4.3. *Marginal effects*

Recent studies and editorials (e.g., Brambor et al., 2006; Meyer et al., 2017) highlight that p-values seldom reflect the whole truth. Researchers are therefore recommended to report confidence intervals when testing interactions. To examine the interactions in greater detail, we plotted the marginal effect line and its confidence boundaries, taking into consideration the range of the moderating variables and using example codes provided by Golder (2021). Figs. 2 and 3 show the marginal effect of perceived cognitive effort on attitudinal and behavioral loyalty (solid line and y-axis) respectively, and the two dashed lines show a confidence range of 95 percent for the interaction, enabling to detect the conditions under which the interaction was statistically significant over different values of the moderating variables (x-axis). On the left, the vertical y-axis shows the magnitude of the marginal effect, and on the right, the vertical axis depicts histogram, which illustrates the distribution of observations (%) in the sample on the variable depicted on the horizontal x-axis.

Fig. 2a and b shows the interaction of personalized product recommendations and personalized price promotions respectively on the relationship between perceived cognitive effort and attitudinal loyalty. Fig. 2a shows a nearly flat line, indicating no interaction of personalized product recommendations. Fig. 2b shows that the interaction was significant and positive for the values of personalized price promotions ranging from 1 to 4.8 (to the left of the marked point).

Fig. 3a and b repeat a similar analysis, with behavioral loyalty as the dependent variable. Fig. 3a yields a contrasting finding with the hypothesis, showing that the interaction was negative and significant on the values of personalized product recommendations ranging from 2.3 to 5 (to the right of the marked point). The interaction plotted in Fig. 3a indicates that high levels of personalized product recommendations strengthened the negative association of perceived cognitive effort with behavioral loyalty.

In contrast, Fig. 3b shows that the interaction was significant and positive and significant over the values of personalized price promotions ranging from 1 to 4.2 (to the left of the marked point). The interaction plotted in Fig. 3b contrasts with the results reported in Table 4 (Model 8), because the interaction term was indeed positive, but the p-value of 0.179 suggested is statistically a non-significant. Fig. 3a and b exemplify an understatement of interaction coefficients, which occurs "when the interaction term coefficient is not statistically significant, but the marginal effect is statistically different from zero for some value(s) of the moderating variable" (Kingsley et al., 2017, p. 286).

5. Conclusion

5.1. *Implications*

Recent research has increasingly focused on multichannel (Kondo and Okubo, 2022; Harris et al., 2021) and omni-channel retailing (Barann et al., 2020; Hajdas et al., 2020) as well as how digital technology shapes the valuescape in physical retail spaces (Nöjd et al., 2020). Indeed, recent retailing literature has emphasized the importance of different touchpoints (Hallikainen et al., 2019) in cross-channel buying behavior (Shankar and Jain, 2021) through the integration of physical and online channels (Jebarajakirthy et al., 2021). We contribute to this discussion by focusing on the consequences of well-targeted retailer-to-consumer personalization in online grocery retailing and how it lessens the negative association of cognitive effort with customer loyalty. In fact, in today's attention economy, retailers compete to attract consumer attention while at the same time consumers need to cope with an information overload which requires an increasing cognitive effort for them to process (Mosteller et al., 2014). Digitalization thus represents not only the cause for this development but also offers a remedy through personalized marketing in which retailer-to-consumer marketing can be individually tailored to better match consumer needs and preferences in order to deliver the right message to the right shopper at the right time (Villanova et al., 2021). The key theoretical and practical implications of this study are as follows:

First, this study advances the current understanding on the consequences of cognitive effort on customer loyalty, and, consistent to literature (Zhang et al., 2011, 2018), we find that the association of perceived cognitive effort is negative by default. Of the few previous

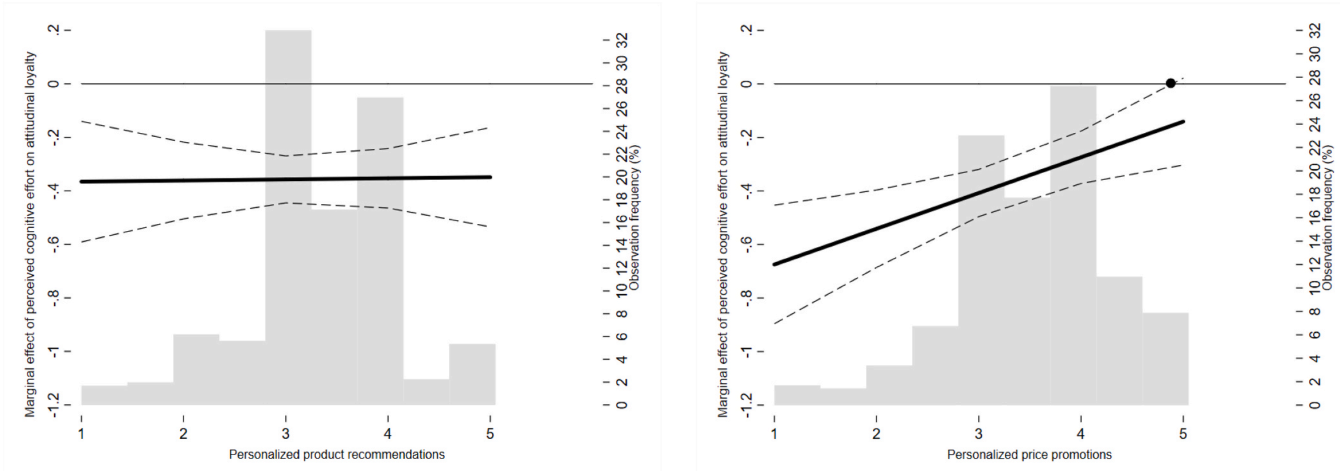

Fig. 2. a. Marginal effect of perceived cognitive effort on attitudinal loyalty, moderated by personalized product recommendations (based on Model 3 in Table 3). Fig. 2b. Marginal effect of perceived cognitive effort on attitudinal loyalty, moderated by personalized price promotions (based on Model 4 in Table 3).

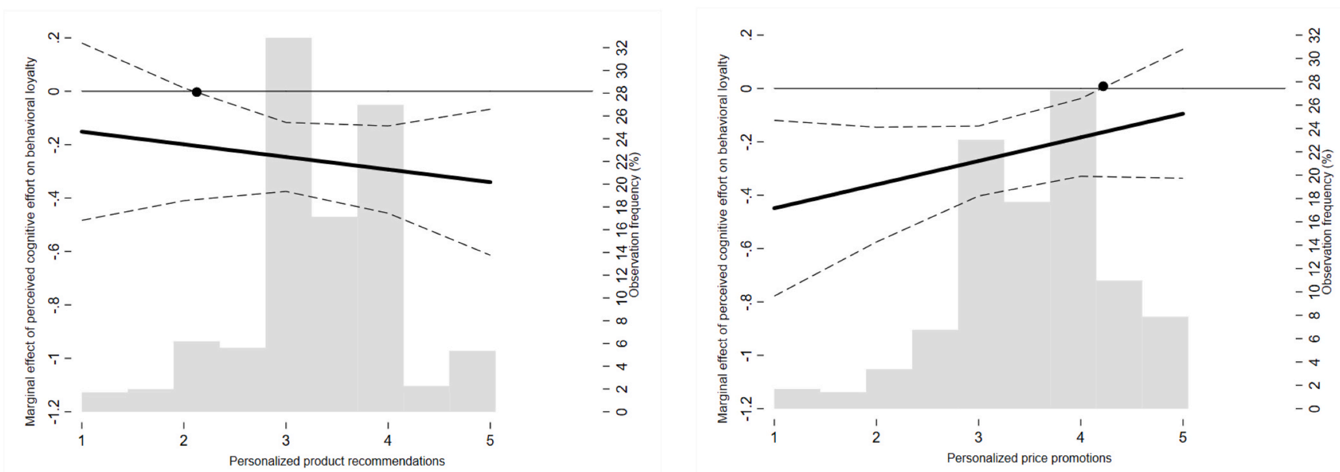

Fig. 3. a. Marginal effect of perceived cognitive effort on behavioral loyalty, moderated by personalized product recommendations (based on Model 7 in Table 4). Fig. 3b. Marginal effect of perceived cognitive effort on behavioral loyalty, moderated by personalized price promotions (based on Model 8 in Table 4).

studies that exist, Zhang et al. (2011) focused only on behavioral loyalty which they measured through repurchase intentions. In their study, they reported a highly significant effect of screening costs on repurchase intention, while the effect of evaluation costs was not supported (Zhang et al., 2011). Furthermore, Zhang et al. (2018) reported a weakly significant effect of product screening costs and a non-significant effect of product evaluation costs on customer loyalty. Consequently, we call future research to delve deeper into the effect of cognitive effort on customer loyalty, taking into consideration different aspects of both as we consider that the conflicting findings may relate to differences in operationalizing customer loyalty.

We extend the findings of existing research (Yoon et al., 2013) to cover both the attitudinal and behavioral dimensions of customer loyalty (Liu-Thompkins et al., 2022; Watson et al., 2015). We find that the explanatory power of perceived cognitive effort is remarkably better at explaining attitudinal loyalty than behavioral loyalty. This finding is consistent to the existing loyalty research, since customer satisfaction, as an example, is shown to explain a remarkably higher portion of the variance in attitudinal loyalty compared to behavioral loyalty (Kumar et al., 2013). This finding is also supported by classic psychological theories such as the theory of reasoned actions, the theory of planned behavior and the elaboration likelihood model which shows that attitudes profoundly drive human behavior (Fishbein and Ajzen, 1975; Ajzen, 1991). Thus, the extent of cognitive processing inherent in making a decision determines attitude strengths, which influences behavior (Petty and Cacioppo, 1986). The results of this study indicate that similarly perceived cognitive effort operates mainly through attitudinal loyalty rather than behavioral loyalty.

Second, with the focus of existing research being heavily in product recommendation systems, studies conducted so far suggest that product recommendations operate as the key in driving personalization in online commerce. This study extends to previous findings (Zhang et al., 2011; Thirumalai and Sinha, 2013) by showing that personalized price promotions implemented through algorithmic pricing, rather than product recommendation, are effective in reducing the negative association of perceived cognitive effort with customer loyalty. Therefore, the product recommendations separately may not be the most optimal strategy for online grocery retailers. Consequently, we extend the previous work by focusing more than on personalized product recommendations alone, because pricing is a crucial element of the online marketing mix, and in this light, surprisingly few studies have examined the consequences of personalized pricing. Future studies are encouraged to take a more holistic view of how personalization can benefit different components of the personalization marketing mix, including not only the product but also the price, place, and promotional elements of the marketing mix.

Indeed, we have shown that personalized price promotions operate as an effective online marketing tool for online grocery retailers to ease consumer decision making and flatten the negative relationship of cognitive effort when consumers shop online. This finding is highly insightful as retailers have been cautious in exercising personalized pricing due to related concerns of price discrimination (Unglesbee, 2019). Yet, our results demonstrate that personalized price promotions, rather than personalized product recommendations, operate to lessen the negative effort of cognitive effort on customer loyalty when it comes to online grocery shopping. Competing with the pricing strategy is a special characteristic of grocery retail (Gauri et al., 2008), and we call future research to elaborate on this finding in order to better understand whether this finding is pertinent to online grocery shopping, or to online shopping at broad.

Third, from a methodological viewpoint and going beyond our main findings, we contribute to recent editorials and discussions according to which researchers should take a look beyond p-values in reassessing best practices for conducting and reporting hypothesis-testing research (Kingsley et al., 2017; Meyer et al., 2017). By plotting the marginal effects of perceived cognitive effort on attitudinal and behavioral loyalty, moderated by personalized product recommendations and price promotions, we provide more fine-grained results in comparison to sole reporting of p-values.

Finally, managerial implications of this study highlight that personalized price promotions rather than personalized product recommendations operate as the focal mechanism in easing the effort of online grocery shopping. Furthermore, it also reduces the impact of perceived cognitive effort on customer loyalty in online grocery shopping. Personalized pricing opens an entirely new avenue for grocery retailers, and we encourage grocery retailers to pursue this, particularly because grocery retailers typically build upon large-scale loyalty card programs that provide detailed insights into consumer preferences. In this respect, grocery chains have an advantage in the considerably more detailed data that operates as the basis for their personalized marketing strategies, which can be build into a competitive advantage. It is of high relevance for grocery retailers that consumers are satisfied with the loyalty card programs including personalized marketing because such efforts not only induce loyalty toward loyalty programs, but also loyalty toward stores (Suh and Yi, 2012).

5.2. Limitations and future research

One of the study's strengths lies in the data we collected from the customers of a large grocery chain operating in Finland, representing true customers buying groceries online. However, the data was collected at a single point of time and in a single country. Also, the data consists of the respondents of an online community and therefore respondents may be more positively predisposed compared to customers who do not belong to the online community. We measured attitudinal and behavioral loyalty using established measures (Watson et al., 2015), yet it must be noted that measuring customer loyalty is challenging as repurchase behavior and patronage can also result as an outcome of additional processes, such as learning to use a specific system and building its use into a habit. In general, recent editorials recommend a combination of subjective and objective measures of focal constructs (Hulland et al., 2018), and such data would have been desirable. Consequently, we encourage future studies to seek objective measures in examining consumer decision-making online, including marketing analytics data (Guha et al., 2021) on revisits to an online store reflecting behavioral loyalty, together with cognitive measured obtained, e.g., using eye-tracking (Otterbring et al., 2014, 2016). We measured personalization using the construct of perceived personalization, which according to Li (2016) is the underlying psychological mechanism for the effectiveness of personalized marketing communications, in contrast to actual personalization. We used the measurement items of personalization adapted from the existing literature (Xiao and Benbasat, 2018; Zhang et al., 2018), and applied them to capture two different aspects of online personalization: personalized product recommendations and personalized price promotions. This forms a limitation to this study, as the adaptation process may pose risks to construct validity. However, our thorough measurement and construct validation shows that the used constructs and measurement items are adept and they do not show concerns regarding convergent nor discriminant validity. The use of a readily available scale would have been desirable. However, personalization literature seems to lack a measurement scale for measuring different aspects of personalized price promotions. This opens a fruitful avenue for a scale development study in the future.

The present study included the marketing mix's product- and price-related elements, and future studies might elaborate on this topic, including the locational and promotional aspects of personalization. Age and purchase volume had a statistically significant relationship when controlling for behavioral loyalty. This opens up avenues for future research that might examine in more detail how different types of consumers, representing diverse households, differ in terms of the effectiveness of personalization on attitudinal and behavioral loyalty. This present study finds that cognitive effort explains attitudinal loyalty better than behavioral loyalty, which opens an avenue for future research to explore in greater detail how different aspects of cognitive effort, such as timing and place, and the chosen action, interrelates with attitudinal and behavioral loyalty. Today's consumers buy groceries through different interfaces, including websites and mobile apps, and future studies might also explore whether the experience of personalization and its impact on customer loyalty is congruent across various devices and channels.

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Declaration of competing interest

None.

APPENDIX A. Related studies

Search in Scopus with keywords "product" + "recommendation" + "personalization" + "loyalty".

Study	Empirical study	Key difference with the present study
1. Behera, R. K., Bala, P. K., & Jain, R. (2020).	Yes	Uses a rule-based automated machine learning approach to find a best fitting recommendation engine algorithm. The focus of this paper is in exploring which machine learning algorithm is the most optimal for recommendation agents.
2. Srivastava, A., Bala, P. K., & Kumar, B. (2020).	Yes	Focuses on psychographic models-based approaches for gray sheep user identification with improved performance. Customer loyalty, whis os our focal variable, is not part of the empirical study.

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(*continued*)

Study	Empirical study	Key difference with the present study
3. Lewis and Loker, (2017).	No	Focus is on apparel store's employees' while our sample is representative of online grocery store customers. Additionally, loyalty is not a focal construct in this paper.
4. Zhang T., Agarwal, R., & Lucas Jr, H. C. (2011).	Yes	Explores the interrelationship between personalized product recommendation and store loyalty, with repurchase intentions as the dependent variable. The study focuses on product recommendations only. We deepen the findings as we operationalize customer loyalty through the two dimensions of it: attitudinal and behavioral loyalty.
5. Schafer et al (2001).	No	A conceptual study which discusses the outcomes of recommendation systems conceptually. The paper states that recommendation systems enhances sales in 3 ways: converting browsers into buyers, increasing cross-selling and building loyalty but this is not tested empirically.

Search in Scopus with keywords "price" + "personalization" + "loyalty".

Study	Empirical study	Key difference with the present study
1. Rahman et al (2022).	Yes	Develops a measurement instrument for perceived omnichannel customer experience while our focus is on the consequences of personalized product recommendations and price promotions in online grocery shopping.
2. Smirnov (2020).	No	Explores the influence of non-price factors of banks' activities on their financial results. Focus is on banking, not retailing, and this study is a conceptual paper with no empirical results.
3. Nastasoiu and Vandenbosch (2019).	No	Focuses on loyalty reward programs and how such programs can be successfully developed.The study is a conceptual paper with a focus on how to develop successful loyalty reward programs.
4. Aichner and Coletti (2013).	Yes	Explores how useful the respondents find the Internet as a channel for personalizing mass-customable end-products. Focus is on mass customization of physical products, and not in customer loyalty nor personalization in the digital realm.
5. Thirumalai and Sinha (2013).	Yes	Explores personalization strategies from a retailer's perspective while we focus on online grocery store customers. The paper covers transaction personalization and decision personalization while our study covers personalized product recommendations (recommendation agents) and price promotions (algorithmic pricing).
6. Zhang (2011).	Yes	Explores behavior-based personalization of physical products. Focus is on physical products, while our focus is on personalization in the digital realm.
7. Changchien et al (2004).	No	Develops a prototype to illustrate how personalized promotion decision support system works in electronic commerce. The paper develops a prototype while our study is an empirical study.

APPENDIX B. Measurement items

Personalized product recommendations (Xiao and Benbasat, 2018; Zhang et al., 2018)	
1. The online grocery store presented products that were personalized to best represent my preferences.	0.783
2. I perceived that the product recommendations matched my preferences well.	0.920
Personalized price promotions (Zhang et al., 2018)	
1. I perceived that there were personalized price promotions for me based on my past purchase history.	0.798
2. I perceived that the personalized price promotions fit my tastes very well.	0.800
Perceived cognitive effort (Xiao and Benbasat, 2018)	
1. The task of shopping groceries online took too much time.	0.803
2. The task of shopping groceries online was very frustrating.	0.829
3. The task of ordering groceries online was too complex.	0.859
Attitudinal loyalty (Watson et al., 2015; Zhang et al., 2018)	
1. I like buying from this online grocery store.	0.743
2. I would consider this website the first choice in buying groceries online.	0.708
3. I would recommend this online grocery store to my friends and relatives.	0.844
Behavioral loyalty (Watson et al., 2015; Liao et al., 2017)	
1. I often buy products from this online grocery store.	0.654
2. I buy most of my groceries from this online grocery store.	0.536
3. I intend to repurchase from this online grocery store.	0.789

APPENDIX C. A comparison of survey questionnaire items between this study and the original source

Questionnaire items used in this study	Original item	Source
Personalized product recommendations		
1. The online grocery store presented products that were personalized to best represent <u>my</u> preferences.	The website presented products that were personalized to best represent <u>my friend's</u> preferences	Xiao and Benbasat (2018)
2. I perceived that the product recommendations matched my preferences well.	I perceived that the product recommendations on this website matched my preferences very well.	Zhang et al. (2018)
Personalized price promotions		
1. I perceived that there were <u>personalized price promotions</u> for me <u>based on my past purchase history</u>.	I perceived that there were product offers for me from this website.	Zhang et al. (2018)
2. I perceived that the <u>personalized price promotions</u> fit my tastes very well	I perceived that the product recommendations on this website fit my tastes very well	Zhang et al. (2018)

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