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How Do Customers Alter Their Basket Composition When They Perceive the Retail Store to Be Crowded? An Empirical Study

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Abstract

Using data from a large-scale field study, we show that (perceptions of) crowding change(s) the composition of a consumer's shopping basket. Specifically, as shoppers experience more crowding, their shopping basket contains (a) relatively more affect-rich (“hedonic”) products, and (b) relatively more national brands. We offer a plausible dual-process explanation for this phenomenon: Crowding induced distraction limits cognitive capacity, increasing the relative impact of affective responses in purchase decisions. As we are the first to show that level of crowding relates to what shoppers buy (at both product and brand level), the implications of these effects for retailers are discussed.

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Keywords: Crowding; Retailing; Shopping behavior; Basket composition; Large-scale field study

Introduction

Crowding is an ubiquitous ambient factor in retail settings. In-store crowding forms a dilemma for store managers. Overall, in the current highly competitive multichannel retail environment, brick and mortar stores are looking for ways to attract customers to their stores (Kumar, Anand, and Song 2017) in order to maintain (and grow) profitability. Thus, they aim to maximize store traffic. At the same time, crowding can be a stressor in a retail environment (Aylott and Mitchell 1998). Therefore, retailers strive to reduce shoppers' perceptions of crowding by, for example, the layout design of the retail space, its personnel, or the number of check-out counters (Mehta 2013). Some retailers go even further, by offering discounts to shoppers in off-peak times to mitigate heavy traffic in their stores (e.g., Colruyt in Belgium, HLN 2015). It appears to be unclear for store managers whether they should fuel or temper crowding, and how crowding influences in-store shopping behavior.

Previous research addressing this question has mainly studied aggregate retailing outcomes of crowding. In particular, crowded retail environments reduce consumers' shopping time and store

satisfaction (Hui and Bateson 1991; Harrell, Hutt, and Anderson 1980; Machleit, Eroglu, and Mantel 2000), and affect product valuations, (O'Guinn, Tanner, and Maeng 2015), shopping intentions (Pan and Siemens 2011), and shopping basket value (Knoeferle, Paus, and Vossen 2017). However, to the best of our knowledge, there are no studies investigating the effect of retail crowding on shopping basket composition which is critical in understanding the dynamics of a consumer's shopping trip. The purpose of this paper is to help inform retailers' decisions by refining our understanding of how perceived crowding influences the composition of a consumer's shopping basket, particularly in terms of product and brand choice.

Building on research on in-store crowding and consumer decision making, we suggest that consumers will alter the contents of their shopping basket as they shop in a crowded store. Specifically, consumers in crowded a environment—whose cognitive capacities are constrained by the crowded environment (Epstein 1981; Milgram 1970; Saegert 1973; Schmidt and Keating 1979) — rely more on affective processing (Hock and Bagchi 2018; Shiv and Fedorikhin 1999). Consequently, crowding may shift consumer preferences toward products and brands that elicit greater affective responses. This reasoning leads us to predict that consumers tend to purchase relatively more affect-rich (hedonic) products and national brands when they perceive the retail store to be crowded.

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We test this proposition in a large field study using a unique dataset covering four weeks of grocery shopping by approximately 3,600 households for 15,000+ shopping trips across all major traditional grocery chains in the Netherlands. During these four weeks, we conducted a survey to measure consumers' perceptions of crowding while shopping, which allowed us to investigate its relationship with consumer's shopping behavior. The results show that if a store is perceived as crowded, consumers' shopping baskets contain relatively more affect-rich (hedonic) products, and relatively more national brands.

In the remainder of this article we first briefly review prior research on the effect of crowding on shopping behavior and formalize our predictions regarding how perceived crowding might influence shoppers' actual choices. We then report the empirical work carried out in the field to test our predictions. We conclude with a discussion of our results, elaborate on a plausible theoretical explanation and identify practical implications for retailing.

Conceptual Background

Crowding and Shopping Behavior

Crowding is a subjective experience of social density – defined as the number of people per unit area (Rapoport 1975; Stokols 1972). Overall, the presence of a high density of individuals in a specific location induces crowding perceptions. When the retail environment is judged to be dysfunctionally dense, shoppers are likely to experience crowding (Eroglu and Harrell 1986). This conceptualization has two elements. First, it suggests that crowding can be regarded as both a physical state of high social density and as an experiential state of the individual (Harrell, Hutt, and Anderson 1980). As such, recent research on crowding in retail settings treats social density and crowding synonymously (Huang, Huang, and Wyer 2017; O'Guinn, Tanner, and Maeng 2015; Maeng, Tanner, and Soman 2013).

Second, crowding is generally associated with a negative experience of having too many people in the same environment (Hui and Bateson 1991). In line with this view, prior research has mainly focused on negative outcomes of crowding. In particular, crowding can trigger stress and anxiety (Collette and Webb 1976; Maeng, Tanner, and Soman 2013), reduce perceptions of control (Hui and Bateson 1991), decrease motivation to engage in social interaction (Sommer 2009), and prompt a need for avoidance (Maeng, Tanner, and Soman 2013). In response to these undesirable states, consumers in a shopping setting can adjust their behaviors in a number of ways. For example, in-store crowding has been shown to reduce consumer satisfaction (Eroglu and Machleit 1990; Machleit, Eroglu, and Mantel 2000), shorten times spent in the store (Harrell, Hutt, and Anderson 1980), negatively affect shopping intentions (Baker and Wakefield, 2012) and decrease willingness to pay for stores' products (O'Guinn, Tanner, and Maeng 2015). As crowding increases, consumers can also adapt by becoming more responsive to mobile advertisements (Andrews et al. 2015) and more attached to brands that they frequently use (Huang et al. 2017). However, the effect of crowding on consumer decision making

may be neither simple nor linear (Uhrich and Luck 2012). As such, some researchers have shown an inverted-u-shape effect of crowding on self-reported store patronage and purchase intentions (Pan and Siemens 2011) as well as actual shopping basket value (Knoeferle, Paus, and Vossen 2017).

The majority of the aforementioned prior work studying the effect of crowding on shopping behavior has looked at self-reported outcomes. However, it is not obvious to what extent these shopper self-reports translate into actual purchases which is presumably of greatest interest to retailers. The only two studies that have focused on actual purchases (Andrews et al. 2015; Knoeferle, Paus, and Vossen 2017) investigate *how much* people spend in response to crowding. The focus of our empirical study is *what* they spend on – precisely, the composition of the shopping basket that a consumer assembles during a shopping trip. That is, do shoppers buy different products and brands as they shop in crowded stores? To the best of our knowledge, our paper is first to document the impact of perceived crowding on actual product and brand choice through a unique field study which allows us to link actual purchase behavior to perceived crowding. We present our predictions in the following subsection.

The Impact of Crowding on Shoppers' Preferences

Early research within and outside of marketing suggests that crowding is experienced when a person is unable to cope with the amount and rate of environmental stimuli (Eroglu and Machleit 1990; Desor 1972; Milgram 1970). In other words, under high-density conditions, consumers are faced with too many informational cues from the environment that they are unable to process. This crowding-induced cognitive load lowers availability of processing resources, which in turn disrupts cognitive processing (Schmidt and Keating 1979). In fact, researchers have demonstrated that consumers in a crowded store recalled fewer details about the merchandise in the store (Saegert 1973), and performed worse in a complex cognitive task (Langer and Saegert 1977) than consumers in an uncrowded store.

We argue that to the extent that crowding reduces consumers' cognitive processing capabilities, it should increase the relative impact of affective responses on in-store decision making. This is evident from the robust finding that constraints on processing resources, such as distraction or cognitive load, inhibit deliberate cognitive processing, but have no impact on automatic affective processes, thereby increasing the reliance on affective responses in decisions (Albarracín and Wyer 2001; Nowlis and Shiv 2005; Shiv and Fedorikhin 1999). Consistent with this view, recent work has shown that crowding-induced distraction in a restaurant leads to more affect-based eating decisions (Hock and Bagchi 2018). Similarly, we propose that the shift in processing style triggered by crowding influences shopping behavior and this has consequences for the consumer's actual in-store choices. In the present study, we focus on product and brand choice and formalize our predictions based on the notion that product categories and brands differ in the level of affective response they generate.

Prior research has shown that relying on affect during decision making increases the appeal of stimuli that are rich in affect (Pham et al., 2001; Shiv and Fedorikhin 1999). Affect-rich (hedonic) products (e.g., ice cream, cookies, soft drinks, tobacco) are products whose choice is made spontaneously based on the liking or disliking that they evoke. In contrast, the choice of affect-poor (utilitarian) products (e.g., vinegar, eggs, and oral care products) is likely to be made deliberately based on cognitive assessments of the product specifics (Aydinli, Bertini, and Lambrecht 2014; Rottenstreich, Sood, and Brenner 2007; Shiv and Fedorikhin 1999). In a seminal paper, Shiv and Fedorikhin (1999) have shown that when processing resources are limited, spontaneously evoked affective responses rather than cognitive assessments have a greater impact in choice, swaying preferences toward an affectively superior option over a functionally superior option. In our context, we predict that as consumers experience more crowding in the store, their shopping baskets will be more affect-rich—that is, contain relatively more affect-rich products.

Not only products, but also brands differ in terms of their potential to elicit affective responses (Chaudhuri and Holbrook 2001). Here, we rely on the distinction between national brands and private label brands (Ailawadi, Lehmann, and Neslin 2003). Prior research suggests that compared with private labels, national brands offer greater hedonic benefits (Chandon, Wansink, and Laurent 2000) and greater experiential utility through brand imagery and brand associations that are formed via brand communications (Sethuraman 2003). More specifically, national brands provide comfort, security and emotional value, whereas private labels are bought primarily for functional reasons (Hankuk and Aggarwal 2003). For example, in one study, researchers found that a national brand had a higher hedonic (vs. functional) value than a generic store brand (Romero and Craig 2017). In addition to differences in purchase motivation, recent research has shown that national brands are marked by stronger affective feelings compared with private labels (Ravaja, Somervuori, and Salminen 2013; Somervuori and Ravaja 2013). As a result, affective responses play a greater role in determining the purchase decision for national brands versus private labels. If this is the case, crowding should increase the share of national brands in the shopping basket.

In sum, we propose that when consumers perceive the retail store to be crowded, they tend to purchase relatively more affect-rich (hedonic) products compared to affect-poor (utilitarian) products and national brands relative to private labels. We test our predictions in a large field study of the Dutch grocery market. Next, we describe our dataset and measures, present our methodology, and discuss our results.

Empirical Analysis

Description of Data and Measures

To obtain field data on crowding and how it influences grocery shopping behavior, we collaborated with AiMark and GfK. GfK, the market leader with respect to household panel data in The Netherlands, gave us access to the home-scan panel data

Table 1
Perceived Crowding Across the Different Chains.

	Market share ^a	Number of trips in our sample		Avg perceived crowding
		Total	%	
Albert Heijn	24.82%	6,002	40%	4.91
C1000	6.17%	779	5%	4.69
Dirk	3.30%	1,126	7%	5.06
Emté	3.06%	813	5%	5.03
Hoogvliet	3.05%	981	7%	4.99
Jumbo	13.35%	3,911	26%	4.68
Plus	5.56%	1,447	10%	4.76
Total	59.31%	15,059	100%	4.85

^a National value market share based on GfK purchase data for 2014.

from January 2014 to March 2015, and collaborated with us to collect the necessary crowding data during four consecutive weeks (corresponding with trips between February 9 and March 14, 2015) by surveying their home-scan panel.¹ The GfK panel consists of more than 5,500 panel members, representing a stratified national sample of Dutch households and is frequently used by researchers (e.g., Ailawadi, Pauwels, and Steenkamp 2008; van Lin and Gijbrenchts 2014). First, their home-scan panel members provided after each shopping trip the info they always provide, namely information about which chain they shopped at, the volume of each product that was bought, and the price paid. Second, panelists were asked to report how crowded it was. *Perceived crowding* was measured using 1 item on a 10-point scale. Specifically, panelists were asked “How uncrowded or crowded did you think it was in the store?” (0 = very uncrowded, 9 = very crowded) (Mean = 4.85; Median = 5; SD = 2.18). In 16.06% of the observed shopping trips, consumers perceive the store as not crowded (i.e., crowding = 0, 1 or 2), and in 25.73% of the trips, consumers perceive the store as very crowded (i.e., crowding = 7, 8 or 9). Table 1 shows the average perceived crowding across the different chains. Table 2 displays the average perceived crowding across different times. While it may be more crowded during certain periods of time, such as the weekend (t -test -17.49 ; $p < .01$), there is still considerable variation in crowding across all those times (please see the third column of Table 2) and, hence, crowding and certain shopping times are certainly not confounded.

Our sample encompasses trips to the 7 traditional retail chains with a national market share of at least 3%, covering 60% of the Dutch grocery market, and includes panelists that shopped at least twelve times in the year 2014 as to initialize certain control variables.² From these panelists we include all the shopping trips for which they (voluntarily) shared perceived crowding in the GfK survey and bought at least one item within the 72 categories as listed in Table 3. This leaves 15,059 shopping trips made by 3,599 panelists. On average, we observe 4.18 shopping trips per

¹ During the first week we surveyed panelists for the first shopping trip only irrespective of the retail chain. During the following three weeks, we surveyed panelists for each shopping trip to one of the seven traditional retail chains.

² We therefore remove 192 panelists.

Table 2
Perceived Crowding Across the Different Times.

Time	Mean Crowding	Standard Deviation	Test
Weekend vs. Week	5.42/4.68	2.20/2.14	$t = -17.49, p < .01$
Morning vs. Midday vs. Evening	4.61/5.11/4.04	2.30/2.03/2.24	$F = 164.20, p < .01$
Holiday vs. Regular Day	4.12/4.88	2.33/2.17	$t = 7.98, p < .01$

Table 3
Variable Operationalization.

Variable	Description
ShoppingBasket Outcomes _{hct}	The shopping basket outcome measures of shopping trip t by household h at chain c are: 1. Affect-richness score: Summated weighted affect-richness score of the different categories bought, weighted by the relative category's purchase volume within the shopping basket. 2. National brand share (%): Purchase volume bought from national brands/total trip volume (logit-transformed) To aggregate purchase volumes across categories and different volume units (e.g., kilogram and liters) at the trip level we use an average overall category price per equivalent unit volume computed across 2014 (cf. Ma et al. 2011).
Crowding _{hct} TripNeed _{hct}	"How uncrowded or crowded did you think it was in the store?" (0 = very uncrowded, 9 = very crowded) Ratio of the no. of days since household h 's last trip to chain c to the average no. of days between trips of household h in chain c in 2014 multiplied by the ratio of the number of categories last bought by household h in chain c to the average number of categories bought during a trip by household h in chain c in 2014. Before multiplying the two ratio's, the second ratio is reverse coded so that large values imply a relatively low number of categories bought and small values imply a relatively large number of categories bought. Specifically, for reverse coding we take the sum of the minimum and maximum value for the second ratio across all trips of household h , and subtract the respective value. ^a
PromoIntensity _{ct}	Ratio of the number of categories in chain c where at least one product is on price promotion during the week where shopping trip t was made to the total number of categories offered by chain c .
Initial AvgShopping _{mhc}	Average value of the respective shopping basket outcome m for all trips during the initialization period 2014 to chain c by household h ^b
Chain _c	Chain dummy variables which equal 1 if shopping trip t is at that chain and -1 if otherwise (Albert Heijn (reference category), C1000, Dirk, Emté, Hoogvliet, Jumbo, Plus)
Time _f	Time fixed effects, corresponding with weekend (0/1)*holiday (0/1)*time of day (morning, midday, evening) (a holiday evening trip during a weekend is the reference category).
Household _h	Household fixed effects

^a For 3% (i.e., 455) of the trips in our final sample, we cannot compute trip need for a household for that specific chain, as (i) h did not shop at that chain, or (ii) h only shopped at that chain once in 2014. For those cases we impute h 's trip need computed across chains.

^b One hundred and sixty-four households do not shop at chain c of the trip of interest in the initialization period and we then assign a value of 0. We do this for 1.68% (i.e., 254) of the trips in our final sample.

household during the four weeks, which accounts for 72% of all of the household's trips during the four weeks of data collection.³

Based on the GfK panel data for those four weeks, we derive the shopping basket outcomes that could be affected by crowding: *product choice* in terms of (i) the (weighted-average) affect-richness score of the shopping basket, and *brand choice* in terms of (ii) the volume share of national brands. First, to compute the *affect-richness score of a basket*, we collected affect-richness scores per product category on Amazon.com's Mechanical Turk (our survey ran from March 30 to April 1, 2018). The survey included 72 product categories that cover 97% of household grocery spending in the Dutch market.⁴ 286 respondents from the United States (46.50%

female; Mean_{age} = 38.11; Min_{age} = 19; Max_{age} = 81) judged a random set of 13 out of the 72 categories on the extent to which each category provides (i) pleasure and fun (from 1 = "very little pleasure and fun" to 7 = "a lot of pleasure and fun") and (ii) practical benefits (from 1 = "very little practical benefits" to 7 = "a lot of practical benefits"). Each category is rated, on average, by 48 respondents. Next, we derive a category's affect-richness score, by subtracting the mean of its "practical benefits" ratings from the mean of its "pleasure and fun" ratings (cf. Aydinli, Bertini, and Lambrecht 2014; Huyghe et al. 2017; Milkman, Rogers, and Bazerman 2010). For the 72 categories, we find an average affect-richness score of -0.87 , but there is great variation across categories, with Ice Cream at the top (a score of 3.47) and Household Cleaners at the bottom (a score of -4.19) of the range. Table A1 in Web Appendix gives an overview of the 72 categories and their respective affect-richness scores. Finally, we calculate the weighted-average affect-richness score of a shopping basket, using the relative volume of the products within the

³ This does not amount to 100% as we only surveyed respondents for their first trip during the first week (see also footnote 1) and for some trips, respondents did not participate in the GfK survey.

⁴ The product categories used in the survey are based on GfK's 69 category names out of which we co-classified 10 as 5 categories (e.g. "Pet supplies" and "Pet supplies other" were surveyed together) and we have separately surveyed 8 subcategories that we expected to differ in affect score from their overall GfK category (e.g. "Natural, organic, and healthy snacks" as separate from "Cookies", and "Chocolate milk" separate from "Milk and dairy beverages").

The survey did not include several non-CPG categories (e.g. flowers, plants, car parts, electrical appliances, and books) which together represent only 2.94% of household grocery spending (based on GfK purchase data for 2014).

shopping basket. If a product accounts for 10% of the volume of the shopping basket, the affect-richness score for that product takes a weight of .10.

Second, we take national brand purchase volume relative to the total shopping basket volume as *the volume share of national brands*.⁵ On average, 60% of consumer’s basket volume corresponds with a national brand.

Note that, for all shopping basket outcomes, we focus on purchases within the 72 product categories that cover 97% of household spending. We use an average overall category price per equivalent unit volume (computed across 2014) to aggregate purchase volumes across categories and different volume units (e.g., kilogram and liters) at the trip-level (cf. Ma et al. 2011). The resultant purchase volume, which we use as weights, and variation herein are only driven by volume changes and not by price differences over time and across chains. To correct for a potentially skewed distribution of our shopping basket measures, we adopt a logit transformation to the share of national brands to account for the fact that they are bounded between 0 and 1.⁶

Details on the operationalization of all variables are provided in Table 3; the overview of the descriptive statistics and correlations is provided in Web Appendix Table A2. As Table 3 shows, we operationalize several additional control variables that are expected to influence basket composition. To control for the likelihood that a trip is a major or a fill-in trip, we include a chain-specific household’s trip needs. The household’s trip needs at the start of a given shopping trip is based on the number of days since the household’s last shopping trip at the chain and the number of categories bought then and there. We further include the chain’s price promotion intensity per week, and the average of the dependent variables as measured in the initialization period 2014.

Method

We model a consumer’s basket product choice in terms of its (i) affect-richness score (AffectScore_{hct}), and brand choice in terms of (ii) national brand share (NBShare_{hct}),

$$\text{ShoppingBasketOutcomes}_{hct} = \frac{\text{Affectscore}_{hct}}{\text{logit}(\text{NBShare}_{hct})} \quad (1)$$

The model specification for these outcomes is in the following equation. For notational ease, we denote the m-th dependent

variable for household *h* during shopping trip *t* at chain *c* as ShoppingBasketOutcomes_{mhct}.

$$\begin{aligned} \text{ShoppingBasketOutcomes}_{mhct} &= \beta_0^m + \beta_1^m \text{Crowding}_{jct} + \beta_2^m \text{Crowding}_{hct}^2 + \beta_3^m \text{TripNeed}_{hct} \\ &+ \beta_4^m \text{PromoIntensity}_{ct} + \beta_5^m \text{InitialAvgShopping}_{mhct} \\ &+ \sum_{i=1}^6 \alpha_i^m \text{Chain}_{i,c} + \sum_{i=1}^{11} \delta_i^m \text{Time}_{i,f} + \sum_{i=1}^{3,599} \mu_h^m \text{Household}_{i,h} + \epsilon_{hct}^m \end{aligned} \quad (2)$$

Each shopping basket outcome is modeled as a function of the variable of central interest, perceived crowding (Crowding_{hct}). Following Knoeferle, Paus, and Vossen (2017), we also include the squared term of crowding (Crowding_{hct}²) to capture a potential nonlinear pattern. We control for the trip needs of household *h* at the start of shopping trip *t* at chain *c* (TripNeed_{hct}) and the intensity of price promotions present in chain *c* during shopping trip *t* (PromoIntensity_{ct}). We further control for heterogeneity in the chain-specific shopping preferences of households, by including the average shopping behavior within chain *c* by household *h* (InitialAvgShopping_{mhc}), computed from the initialization period 2014 and appropriately log-transformed. Eq. (2) also includes dummy variables indicating in which chain (Chain_c: Albert Heijn is the reference category) the shopping trip took place to capture chain-related differences. We include time fixed effects (Time_f) that correspond with whether a trip took place in the weekend, at which time of day (morning, midday, or evening), and during a holiday (i.e., Valentine’s day (Febr. 14) and Carnival (Febr. 15–17)). This entails the inclusion of 11 dummy variables (weekend vs. no weekend * morning, midday, or evening * holiday or not) (with a holiday evening trip during a weekend as the reference category). Finally, we include household-specific fixed effects: μ_h^m to account for time-invariant household differences. For ease of interpretation, we mean-center all of the continuous explanatory variables.

Endogeneity. It might be true that certain shopping trips (e.g., trips with a certain basket composition) are only made during certain shopping occasions (i.e., while shopping at a certain chain, at a certain time or with a certain shopping need), and that at those occasions it might also be more or less crowded. Moreover, shoppers may a priori have certain expectations about the level of crowding, and act accordingly. As a result, consumer’s perceived crowding may not be exogenously determined. In line with current recommendations to deal with endogeneity, we first exploit the panel structure of our data (Papies, Ebbes, and Van Heerde 2017). By estimating Eq. (2) with household- and chain-fixed effects (i.e., by including one dummy per household and chain), all time-invariant household and chain characteristics are controlled for. In addition, following Germann, Ebbes, and Grewal (2015), we include time fixed effects to capture time-varying unobserved components of crowding that are common across chains and households, which influence the content of a consumer’s shopping basket as well.⁸ As such, we control for

⁵ GfK flags whether a product is a national brand or a private label.
⁶ Because of negative values in the weighted-average affect-richness score, we do not take the log-transformation. However, if we re-scale the affect-richness scores to positive values and then take the log-transformation of the re-calculated weighted-average affect-richness scores, results remain the same.
⁷ Before the logit transformation, values equal to one (zero) are decreased (increased) with 0.0001. Using a different number, e.g. .00001 (cf. Melis et al., 2016) or .01 (cf. Cleeren, van Heerde, & Dekimpe 2013) does not change our results.

⁸ Our results are stable when we additionally interact our time fixed effects and chain-specific fixed effects to control for possible time unobserved effects at the chain level.

the fact that the timing of (high or low levels of) crowding may not be random. As the source of endogeneity is not likely to stem from a certain date itself (i.e., e. there is no reason why a trip on Monday February 9 should be different from Tuesday February 10 or Monday February 16), we have identified the likely time-varying sources of endogeneity as stemming from whether the date corresponds with a weekend trip, whether the trip was made during a specific time of day, or during a holiday and, as such include 11 time-related fixed effects (and a reference category).

To address any remaining endogeneity of crowding, we follow recent studies in marketing (e.g., Lim, Tuli, and Dekimpe 2018), and include a Gaussian copula (γ) to deal with this (cf. Park and Gupta 2012). Note that to be allowed to include a copula, we first have to confirm non-normality of crowding using a Shapiro–Wilk test. This is indeed the case (z -value = 12.36; $p < .01$). We add a copula term that represents the correlation between crowding and the error term, to our focal model in Eq. (2). Similar to the control function approach, a significant copula term is indicative of endogeneity, in which case, its inclusion simultaneously controls for it (Wooldridge 2015). Including just the one correction term will be sufficient to address the regressor's endogeneity as well as the endogeneity in the squared term (Papies, Ebbes, and Van Heerde 2017). We also include a Gaussian copula to account for the potential endogeneity of promotional intensity within the chain. Again, results from the Shapiro–Wilk test indicate that this variable is not normally distributed (z -value = 15.72; $p < .01$), confirming the suitability of this method.

We first estimate a model in which we include a copula for both potentially endogenous variables (crowding and promotional intensity). Following Mathys, Burmester, and Clement (2016) and Gielens et al. (2018), we retain the copula terms that are statistically significant ($p < .10$ two-sided) and then re-estimate the model. We estimate all models with bootstrapping to correct the standard errors since the copula correction terms are an estimated quantity (Park and Gupta 2012).

Results

Bivariate Association Between Crowding and Shopping Basket Outcomes. We first provide some model-free insights into the relation between crowding and the shopping basket outcomes. The average affect-richness score of the shopping basket is significantly ($p < .05$) higher for trips with high levels of crowding (based on median split; $M = -.29$) than for low levels of crowding ($M = -.33$). For the share of national brands, we find in line with our expectations, a negative difference (i.e., low crowding: $M = 59.98\%$ vs. high crowding, $M = 60.43\%$; $p = 0.36$).

Model Estimates. As shown in Web Appendix Table A2, none of the correlations between our explanatory variables are high enough to cause concerns with multicollinearity (Hair et al. 2010, p. 204). Table 4 shows the parameter estimates. Our model fits the data well as the model R -square values are 33.94% for product choice (i.e., affect-richness score) and 36.73% for brand choice (i.e., national brand share). In both equations, crowding seems not be endogenous (both p 's $> .10$).

We expect that (perceived) crowding triggers a reliance on affect and thereby increases the appeal of products and brands that are rich in affect. Consistent with our expectations, we find that perceived crowding increases the purchasing of affect-rich products when we look at the affect-richness score of their total shopping basket ($\beta_1 = .014$; $p < .05$). In addition, we find that perceived crowding increases the purchasing of affect-rich brands. In fact, a heightened reliance on affect, positively affects the share of national brands ($\beta_1 = .060$; $p < .05$). Following Knoeferle, Paus, and Vossen (2017), we included the squared term of crowding to test whether there is a nonlinear pattern. We do not find evidence for a nonlinear effect of crowding on affective buying (both p 's $> .10$).

Robustness Check. Prior research has used terminologies somewhat interchangeably to infer the affect-richness of products (e.g., Wertenbroch 1998: vices and virtues; Dhar and Wertenbroch 2000: hedonic and utilitarian). While we use a composite measure that takes into account the level of affect-richness of a category (Aydinli, Bertini, and Lambrecht 2014; Dhar and Wertenbroch 2000; Milkman, Rogers, and Bazerman 2010), others have used a binary classification (Hui, Bradlow, and Faber 2009). Indeed, in our data, there is a high correlation between the share of hedonic products within a consumers shopping basket and a basket's affect-richness score ($\rho = .79$). To see if our results hold if we use this alternative binary classification, we have used the categorization made by Hui et al. (2009, Table 1), and then take the purchase volume of hedonic (utilitarian) items relative to the total purchase volume. The average share of hedonic products equals 26%, while 47% of the shopping basket consists of products from a utilitarian category.

We adopt a logit transformation to the volume share of hedonic and utilitarian products to account for the fact that they are bounded between 0 and 1. Consistent with our expectations, we find that perceived crowding increases the purchasing of affect-rich products when we look at the share of hedonic products ($\beta_1 = .072$; $p < .01$). In addition, a heightened reliance on affect does not have an effect on the share of utilitarian products bought ($\beta_1 = -.021$; $p > .10$), while the parameter is in the expected negative direction.

General Discussion

The primary goal of our paper is to improve the understanding of how retail crowding influences shopping behavior. While previous studies on the topic focused on aggregate retail outcomes (such as store satisfaction, purchase intentions, and overall basket size), the present work, to the best of our knowledge, is the first study to examine the effect of retail crowding on a consumer's shopping basket composition. The results of our large-scale field study across seven retail chains in the Dutch grocery market show that when faced with crowded retail stores, consumers change their shopping basket composition, namely the type of products and brands that they purchase. Specifically, consumers, who experience crowding during shopping, purchase relatively more affect-rich (hedonic) products, and relatively more national brands.

Table 4
The Effect of Crowding on Product and Brand Choice ($N = 15,059$).

	Affect-Richness Score		National Brand Share	
	Coeff.	Z-value	Coeff.	Z-value
Crowding (β_1)	.014**	2.48	.060**	2.75
Crowding ² (β_2)	.003	1.00	-.009	-1.49
Control variables				
Household Trip Needs (β_3)	-.001	-.32	.031***	3.58
Store Promotion Intensity (β_4)	-1.967**	-2.32	4.614	1.61
Initial Avg Shopping Beh. (β_5)	.463***	8.13	.999***	3.33
Chain Fixed Effects (α_i)				
Time Fixed Effects (δ_i)				
Household Fixed Effects (μ_i)				
Copula Crowding (γ_1)	n.i.	-	n.i.	-
Copula Promotion Intensity (γ_2)	.045	1.51	-.164*	-1.86
Intercept	.160	.22	7.189***	4.08
R-Square	33.94%		36.73%	

* $p < .10$, ** $p < .05$, *** $p < .01$ two-sided. Significant effects are indicated in bold. Chain, Time, and Household fixed effects are included in all equations but not reported here. Full results are available from the authors upon request.

n.i. = not included due to insignificance ($p > .10$ two-sided) (cf. [Gielens et al. 2018](#)).

While our field study is unable to reveal the underlying process due to its correlational nature, the observed results are consistent with a dual-process account of preference construction. The starting point of this account is the familiar notion in marketing research that people make purchase decisions by integrating two qualitatively distinct types of processing: one, automatic and *affect-based*; the other, deliberate and *cognition-based* ([Dhar and Gorlin 2013](#); [Shiv and Fedorikhin 1999](#)). One property that separates cognitive processes from affective processes is their relative demand on mental processing resources ([Dhar and Gorlin 2013](#)). Affective responses are automatic and effortless, therefore primed by default when a behavioral opportunity presents itself. In contrast, cognitive processes are deliberate and consume scarce processing resources. This distinction suggests that any influence limiting the availability of processing resources (e.g., distraction or cognitive load) inhibits cognitive processing but has no impact on affective processes, thereby increasing the likelihood that behaviors are based primarily on the latter ([Avnet and Pham 2004](#); [Nowlis and Shiv 2005](#); [Shiv and Fedorikhin 1999](#)). We argue that crowding is one such influence. Crowding discourages deliberation (i.e., reduces availability of processing resources) because it creates distraction for people who are unable to cope with the amount and rate of environmental stimuli ([Eroglu and Machleit 1990](#); [Desor 1972](#); [Milgram 1970](#); [Hock and Bagchi 2018](#)). If this is the case, in-store crowding should increase the relative impact of affective responses on purchase decisions.

In order to test this proposition, we conducted a controlled experiment in which participants ($N = 200$) were randomly assigned to crowded and uncrowded grocery store shopping scenarios. They were asked to report the level of distraction they would experience and the decision process they would follow when making purchases in the given scenario. The results show that a crowded (vs. uncrowded) retail store increases reliance on affect for in-store purchase decisions which is driven by heightened distraction while shopping (see Web Appendix for Study Stimuli, Procedure and Results).

Still, retail crowding probably not only increases reliance on affect but can also trigger specific negative emotions such as stress and anxiety ([Collette and Webb 1976](#); [Maeng, Tanner, and Soman 2013](#)), decrease motivation to engage in social interaction ([Sommer 2009](#)), and prompt a need for avoidance ([Maeng, Tanner, and Soman 2013](#)). However, none of these accounts are likely to explain our observed pattern of results with regards to consumers' product and brand preferences. Therefore, we propose that a distraction-based reliance-on-affect account is the most plausible theoretical explanation for our findings. This account is consistent with the notion that the effect of retail atmospherics elements on shopping behavior is the product of cognitive and affective responses ([Roggeveen, Grewal, and Schweiger 2020](#)).

Managerial Implications

A retail environment should create an atmosphere that attracts shoppers. Some of the atmospheric cues that retailers can use to affect shopping behavior are music, lighting, scent, layout and design, to name a few. Crowding is also considered an important ambient factor that can influence retail outcomes (e.g., [Eroglu and Machleit, 1990](#); [Harrell, Hutt, and Anderson 1980](#); [Hui and Bateson, 1991](#); [Roggeveen, Grewal, and Schweiger 2020](#)). As retailers try to increase their customer base and, as such, store traffic, this increases the likelihood of crowding. At the same time, crowding can be a stressor in a retail environment ([Aylott and Mitchell 1998](#)). Therefore, consumers most of the time try to avoid crowded environments as evidenced by the success of the Popular Times feature introduced by Google in 2016 displaying (real-time) crowding within a store, and Facebook's Popular Hours which also shows consumers when a retail store is most crowded. While consumers try to avoid crowded environments and retailers try to manage (perceptions of) crowding, the phenomenon itself is inevitable given that retailers also want to increase store traffic (i.e., the number of customers in the store) to improve retail sales ([Lam, Vandenbosch, and Pearce](#)

1998). Hence, knowing the impact of crowding on consumers' shopping behavior is highly relevant for the retailer.

Basket Composition Implications. First, our results suggest that brick-and-mortar retailers can use crowding to their advantage. Increased perceptions of crowding have especially positive effect on the sales of affect-rich products and national brands. This suggests that, especially in aisles where affect-rich (hedonic) products (e.g., ice cream, cookies – see Web Appendix Table A1 for a ranking of categories' affect-richness score) are stocked, retailers could consider increasing crowding perceptions. One way to increase perceived crowding is by using store design aspects such as the free-flow layout (rather than grid layout), lower ceiling height, and the use of aisle tables in the store to highlight products (Lee, Kim, and Li 2011). Retailers that worry about losing market share for their private labels (e.g., because of the higher margins they offer), could consider making them more affective through brand image building. Some retailers (in particular when launching premium private labels), already emphasized their objective to “democratize luxury” (SPAR Austria, Press release of October 7, 2010) by offering premium quality at affordable prices, allowing their customers to “indulge in something special” and thereby making private labels more affective. Second, in stores that are always more crowded (e.g., due to location or limited store size), a retailer could consider stocking more affect-rich (hedonic) products and national brands, or draw more attention to these products through in-store (point-of-purchase) displays or shelf placement at eye level.

Basket Size Implications. From a retailer's perspective, it is also important to know whether crowding affects the basket size in addition to changing the composition of the basket. In order to explore this question, we re-estimated Eq. (2) with two additional shopping basket outcome measures, namely the number of items bought during the shopping trip and the total spending amount (in euros), reflecting the size of the basket (see Table A3 in the Web Appendix).⁹ Consistent with previous research (Knoeferle, Paus, and Vossen 2017), we find that crowding increases the basket size. Interestingly, we observe a slight concave upward curve, implying that the number of items and the total spending amount increases with higher levels of crowding. Hence, heightened store traffic not only results in more customers in store but the shopping basket per customer also expands, both improving retail sales.

Limitations and Ideas for Future Research

While our results demonstrate a strong relation between (perceived) retail store crowding and shopping basket composition, our field data measured at the shopping trip level prevents us to draw causal inferences and to reveal the underlying mech-

anism. Therefore, researchers should replicate our results in a controlled experimental setting and extend it by investigating the proposed underlying mechanism of our results.

Albeit we provided evidence for a positive effect of crowding on the purchase of affective products and brands, it remains possible that consumers may decide not to enter a crowded store (Mehta, Sharma, and Swami, 2013). Although this is probably less likely in our grocery context, the data at our disposal are not able to track whether such deferral occurred. Further research could investigate the optimal level of crowding so that retailers reap the benefits of increased buying and spending while not scaring potential customers away.

While we focus on affective buying in terms of product and brand choice, there might be other interesting outcomes from a retailer perspective that could be studied. For example, consumers might respond differently to certain types of promotions when it is crowded. One could argue that in-store displays or certain freebies with a product purchase could serve as affective product cues. Linked to that, there could be other affective in-store cues that become more effective at crowded times. Similarly, while we look at affect-richness at the category-level, certain products within those categories might be considered more affective than others (e.g., chocolate cereal vs. plain cereal). This could be tested.

Our results showed a concave upward curve of the effect of crowding on basket size whereas Knoeferle, Paus, and Vossen (2017) reported an inverted u-shaped curve. Future research could investigate what could possibly be driving the difference between our and prior findings.

Our study is conducted in the Dutch grocery market, which is a utilitarian retail context. Prior research shows that consumers respond differently to crowding in utilitarian as opposed to hedonic settings (for a recent review, see Mehta 2013). Therefore, one may wonder whether our findings would also hold in a hedonic retail context where the main motive of consumers would be to shop for fun and enjoyment rather than to purchase the needed products (Babin, Darden, and Griffin 1994). While this question warrants proper empirical testing, our proposed explanation for the effect of crowding on consumer choice relies on the availability of cognitive resources triggering affect- versus cognition-based decision making and thus would make similar predictions regardless of the shopping environment. Nonetheless, we leave it for future research to test whether our findings would generalize to different retail contexts across different cultures and societies.

In the current work our focus is on crowding rather than uncrowding. However, with the social distancing rules and restrictions in place due to the COVID-19 outbreak, retail stores limited the number of shoppers that can be in a store at the same time. While it is still unclear how the post-COVID-19 era will look like, it is possible that there will be a temporary “new-normal” in which capacity will be limited in stores to avoid crowding. As shoppers will be able to keep a safe distance from each other in the stores, they may no longer experience ‘crowding stress’. Therefore, based on our results, private labels and utilitarian products may become relatively more attractive compared to national brands and hedonic products, respectively. As

⁹ To correct for a potentially skewed distribution of our shopping basket size measures, we adopt a log transformation.

¹⁰ On an average shopping trip, 17.93 (SD = 17.96) items are bought, resulting in an average trip spending of 20.22 Euro (SD = 19.48) (see also Table A2 in Web Appendix).

such, one potential avenue for further research is how changes in in-store crowding in the post-COVID-19 era impacts shopping basket compositions.

Given the current COVID-19 crisis, it may be worthwhile to investigate how shopping basket compositions look like during this crisis as well. For instance, one could argue that social distancing is beneficial for private labels and utilitarian products, given that it leads to lower levels of in-store crowding. On the other hand, one could hypothesize that consumers who experience COVID-19 stress in a shopping environment given the risk of infection are likely to be cognitively constrained. As a result, reduced deliberation may increase the relative impact of affective responses on in-store purchase decisions. Accordingly, Nielsen indeed reported a decrease in private label share in the first four weeks of the COVID-19 lockdown in Belgium (Nielsen 2020). At the same time, this effect may invert when COVID-19 stress is alleviated and merely social distancing may increase cognitive processing later on in the crisis. Therefore, it may be interesting to study how, when and why the COVID-19 outbreak may influence the consumers' product and brand preferences.

Finally, the urbanization trend, where consumers move toward area clusters, is predicted to have enormous effects on store traffic. Consequentially, crowded areas may become even more crowded (Retail Trends 2018). As such, the relevance of the topic is high and opportunities for future research are plentiful. For now, we can at least conclude that when shoppers experience more crowding their shopping basket contains relatively more affect-rich (hedonic) products and relatively more national brands.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at <https://doi.org/10.1016/j.jretai.2020.05.004>.

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