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ABSTRACT

Digital technologies are having a profound effect on the grocery retail environment worldwide. Marketers have been intrigued by potential for digital technologies to influence consumers at the point of purchase, yet little is known about how digital technologies impact consumer purchasing decisions. An exploratory PLS-SEM model is used to analyze U. S. panel data and the effect of in-store digital use, consumer innovativeness and engagement on unplanned grocery shopping behavior and spending. This study finds that consumer engagement, rather than in-store digital use, is found to be the key variable when it comes to predicting unplanned shopping and spending. Findings identify an ancillary role for in-store digital use as it directly affects engagement and indirectly affects unplanned shopping and spending. Finally, this study finds that gender moderates the relationship of innovativeness and digital use, digital use and engagement, and digital use and total spending. As a result, the effects of consumer engagement and in-store digital use on unplanned purchase behavior have been clarified.

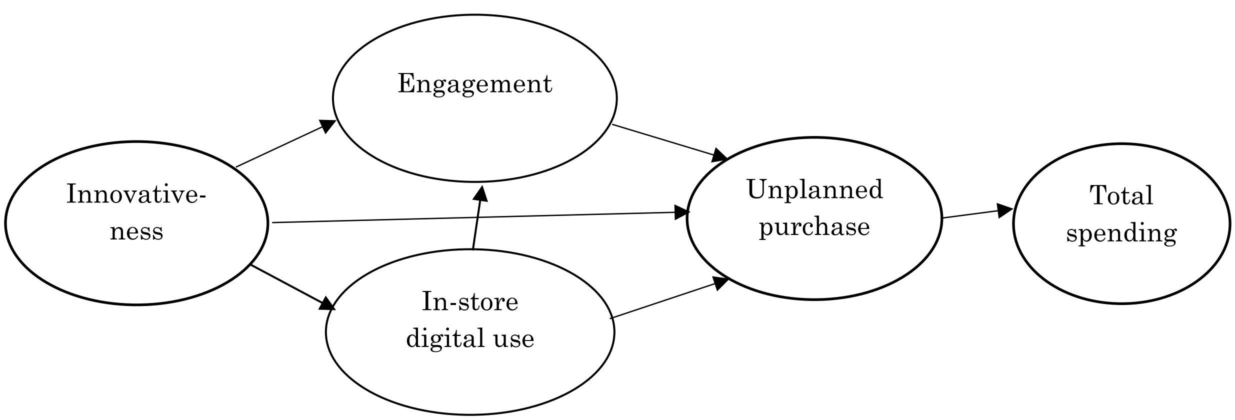
INTRODUCTION

Shopping patterns are changing as consumers gain experience with the increasing volumes of product information available through digital technologies (Labrecque et al., 2013). Looking up product information or reviews, downloading a coupon, looking at emails or texts from retailers, friends or family, checking out recipes, or making a shopping list etc. are becoming routine consumer behaviors while engaged in shopping. As a result, marketers must understand how to promote and engage consumers, how to manage "big data" and how to interpret it to maximize results (Kunz et al., 2017).

According to Pew Research (2015), over two thirds of people have smart phones with over 84% of smartphone owners report using their device in stores (Google, 2013). This new digital technology may be influencing the path to purchase and in particular, in-store purchase and unplanned shopping behavior (Baik et al., 2014; Dennis et al., 2014). While many shoppers may have a preferred brand or set of brands mentally embedded when starting to shop, according to Powers et al. (2012), one quarter of consumers decisions are influenced by information gathered in an active shopping mode. Bell, Corsten, and Knox (2009) found that unplanned shopping behavior was very frequent, with up to 70% of all product decisions made in the store. Unplanned shopping behavior may be even more frequent if a consumer is more innovative- that is, having more of a propensity to try something new, having a greater stimulation level, or being more of risk taker (Roehrich, 2004; Steenkamp et al.,1999). In store digital technology may cause consumers to become more engaged with their favorite or acceptable brands, products or categories. Consumer engagement, whose multiple dimensions include cognitive, affective and behavioral aspects, is still being refined by key scholars as a measurable construct (Hollebeek et al., 2014; Vivek et al., 2014). Some have suggested that consumer engagement may be the next, best way to understand what further motivates purchase behavior and leads to long term loyalty (Bowden, 2009; Kumar et al., 2010; Tripathi, 2014). The effect of in store stimuli on unplanned purchase behavior has been studied for some time (e.g., Beatty and Ferrell, 1998, Bell et al., 2009, Chandon et al., 2009, and Inman et al., 2009). Recent research suggests that the digital use is affecting in-store purchase and unplanned purchase behavior (Hui et al., 2013; Johnson and Pontes, 2015; Sciandra and Inman, 2015). Other research suggests that engaged consumers may be more impulsive, seek more excitement, or may have a more innovative personality (Goldsmith et al., 2015). Such factors may contribute to the incidence of unplanned purchases and associated spending. Research on the effects of in store stimuli, unplanned shopping and the effect on the total shopping purchases is mixed and may be contingent on environmental, situational, behavioral or other factors (Bellini and Aiolfi, 2017; Roggeveen et al., 2016; Stilley et al., 2010).

Thus, this research will be a first step toward understanding the relationship of digital stimuli, consumer engagement and innovativeness and resulting unplanned purchase and spending behavior. Since in-store digital use is still a burgeoning research area, this research fills a vital gap by examining these variables and their effect on unplanned shopping and spending, a topic of great importance to academics, manufacturers, and retailers. The proposed model is shown in Figure 1 below.

Figure 1
Proposed Model



What follows is a literature review, methodology, analysis and discussion of data and implications for academic theory, plus retail and manufacturing management of grocery products. Secondary data from a shopping habit study of over 700 shoppers conducted by a marketing and services research company was utilized to help answer these research questions and to formulate hypotheses and models for future research testing. PLS-SEM modeling was used to analyze the factor loadings on all constructs measured and relationships of innovativeness, in store digital use, engagement, unplanned shopping and spending. Various demographic characteristics were further examined as moderators of these relationships.

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LITERATURE REVIEW

Despite the potential for increasing consumer spending at the point of purchase, little research has been done on the effect of digital stimuli, consumer engagement and innovativeness on subsequent unplanned grocery purchases and overall spending, as both digital stimuli and customer engagement are relatively new academic research topics.

Unplanned Shopping Behaviour

Marketers have long been intrigued by the potential to influence consumers at the point of purchase and prompt unplanned purchases (e.g. Bucklin and Lattin, 1990, Powers et al., 2012). Powers et al. (2012) discovered that while many shoppers have a preferred brand or brands embedded mentally when starting to shop, one quarter of shoppers changed their minds once more engaged from exposure to stimuli when in active shopping mode. In fact, Bell et al. (2009) found the incidence of unplanned shopping behaviour to be very high, with up to 70% of all product decisions made in the store.

Unplanned purchases have been defined as those that "are not specifically planned before the shopping event or as an unplanned purchase in a category (deciding at the point of purchase) where the consumer may process in-store information and be strongly influenced by promotions" (Bucklin and Lattin, 1990). Shopping lists, often prepared by consumers prior to shopping, are clearly associated with their future planned shopping activity (Spiggle, 1987). Those who buy "off" their list are conducting unplanned buying activity. Block and Morwitz (1999) reported that shopping lists are useful tools for helping consumers make planned purchases, but do not help them to totally avoid unplanned purchases. This could mean that without a shopping list, more unplanned purchases could take place. Although in 2004, Thomas and Garland found that people with shopping lists bought fewer items and spent less than those without.

Unplanned purchases are distinguished from impulse purchases or intentionally buying items without prior planning to satisfy an excited, hedonic state of behaviour (Gültekin and Özer, 2012; Wood, 1998; Wood, 2005). In 1998, Beatty and Farrell operationalized impulse buying as part of unplanned purchases. They found that time and money availability, shopping enjoyment and an urge to browse do lead to more unplanned buying (Beatty and Farrell, 1998).

In-store stimuli, increased engagement and other distractions may divert consumers from their planned purchasing path, possibly adding time to their shopping experience and resulting in unplanned purchases (Abratt and Goodey, 1990; Donovan et al., 1994). In-store stimuli such as store atmosphere, displays, pricing, and signage have at times increased shopping time, positively affected unplanned shopping and potentially basket size (Abratt and Goodey, 1990; Donovan et al., 1994). People who enjoy shopping more, find it more pleasurable and are aroused, may spend more time in the store and thus spend more versus if only cognitive related stimuli, such as variety, quality or price/value are exhibited (Donovan et al. 1994). However, little research has been done on in-store digital stimuli, unplanned purchases and effect on spending.

Research suggests that mobile promotional strategies may affect in-store purchase behaviour, time spent in-store, and unplanned purchases (Johnson and Pontes, 2015). In 2016, Roggeveen et al. determined that digital displays increased spending in hypermarkets when associated with price. In addition to displays, many in-store shoppers are using their mobile phones for shopping related tasks such as to send text messages, look up product or promotional information, scan QR codes, download coupons, or gather and evaluate other information, and other non-related shopping tasks (Belinni and Aiolfi, 2017). In 2013, Hui et al. found that a digital promotional stimulus increased a consumer's shopping distance travelled and unplanned purchases by as much as 16%. They concluded that the shopping experience would take more time because of the stimulus, thus confirming that more time shopping meant potentially more unplanned purchases.

Further, Sciandra and Inman (2015) discovered that when consumers got "off task" because of mobile technology (unfocused on buying planned items) and spent more time shopping, unplanned purchases increased, while purchases that were planned decreased. Yet, Bellini and Aiolfi (2017) found that mobile use in store decreased unplanned purchases and did not affect the total spending. They theorized that digital may help with planning a list more often, while also keeping track of a budget that some consumers may not want to go over. Nevertheless, digital stimuli are affecting purchasing patterns in one way or another and most likely it is affecting unplanned purchases.

H1*:* In store digital use will have a positive direct effect on unplanned purchase behaviour.
H2: In store digital use will have a positive direct effect on consumer engagement with brands.
H3: Unplanned shopping will have a positive direct effect on total in store spending.

Consumer Engagement

There have been numerous attempted definitions of the consumer engagement construct over the past ten years. Recently, Masalowska et al. (2016) viewed it as an "ecosystem encompassing brand actions and experiences, shopping behaviors, brand consumption and dialogue." Others have looked at it as a multi-dimensional psychological state and behavioral process or self-concept (Bowden, 2009; Hollebeek, 2011; Mollen and Wilson, 2010; Sprott et al., 2009; Vivek et al., 2012). Engagement, unlike involvement, which includes personal stimulus and situational characteristics (Zaichkowsky, 1985), requires experiential and instrumental value satisfaction (Mollen and Wilson, 2010). Higgins and Scholer (2009) describe engagement as "a state of being involved, occupied, fully absorbed, or engrossed in something."

In 2009, Vivek identified and defined five conceptual consumer engagement dimensions- awareness, enthusiasm, interaction, activity, and extraordinary experience, perhaps creating high levels of interest and caring about a brand. Three basic multi-dimensions (cognitive, affective and behavioral) now are thought to play a key role in the relationship exchange of engagement (Hollebeek, 2011; Mollen and Wilson, 2010; Vivek et al., 2010). Vivek et al. (2012) explained consumer engagement as cognitive or the focus and interest in a brand (thinking); affective or the feelings (emotion) of inspiration or pride caused by the brand; and behavioral or the effort and energy necessary for interaction with the brand or object. Hollebeek (2011) defined brand engagement as "the level of an individual customer's motivational, brand-related and context-dependent state of mind characterized by specific levels of cognitive, emotional and behavioral activity in direct brand interactions." It encompasses a proactive, interactive customer relationship with a specific engagement object (the brand or a company), "putting the brand into action" (Kumar et al., 2010). Brodie et al. (2011) went on to say that it was "a psychological state that occurs by virtue of interactive, co-creative customer experiences with a focal agent/object (e.g. brand)." This appears to follow Fishbein's and Azjen's (1975) original behavioral intention model that postulated that attitudes, both positive and negative, influence the amount of affect or feeling for performing an action towards an object or brand. Sprott et al. (2009) proposed that engagement is based on how people use a brand as an extension of themselves. Brands become part of their self-concept and life, taking on a whole new meaning and importance, while creating a potential long-term relationship. If consumers are engaged with brands they may be more motivated to buy them if aroused by stimuli, even if they are not planning on buying them.

H4: Consumer engagement will positively directly affect unplanned shopping and purchases.

Innovativeness

Using engagement theory, research by Goldsmith et al. (2015) suggested that there may be a strong positive relationship between brand engagement and a consumer's "innovativeness" or willing to try new products.

Tellis et al. (2009) and others have concluded that there is a relationship between innovativeness and new product trial and adoption (Foxall, 1988; Hirschman, 1980; Im et al., 2003; Manning et al., 1995; Venkatraman, 1991). Consumer innovativeness is a predisposition to buy new products in a specific category, toward the market and across product categories or to purchase new products and brands rather than to remain with previous choices and consumption patterns (Steenkamp et al., 1999). Innovative consumers may have a greater, optimum stimulation level, a more open personality, are more risk taking and venturesome, and have a higher ambiguity tolerance (Foxall, 1988; Raju, 1980; Roehrich, 2004; Steenkamp et al., 1999). Innovators may also be very involved or engaged with a particular category of products and have great knowledge about brands in that category. Goldsmith et al. (2015) showed that there is a strong relationship between brand engagement and innovativeness. They discovered that those shoppers who described themselves as "impulsive" and "wandering" (unplanned buyers) appeared to be very engaged. This willingness to buy or try new products may lead to unplanned buying among those more engaged. A consumer's willingness to try new ideas/other products and have brand engagement may be affected by in store digital stimuli (Johnson and Pontes, 2015).

H5: Higher levels of innovativeness will have a positive direct effect on engagement.
H6: Innovativeness will have a positive direct effect on in store digital use.
H7: Higher levels of innovativeness will have a positive effect on unplanned shopping.

RESEARCH METHOD AND DATA ANALYSIS/TESTING

Sampling and Measurements

Secondary data from a 2017 national, demographically representative sample of 1851 adult shoppers was gathered via a 35 minute online survey. The panel study was specifically done to understand and track overall shopping patterns and behavioral trends in the consumer products grocery marketing industry. As such, the data was not collected to meet the research needs of the researchers per se but is being used in an exploratory context.

Specific data for the unplanned shopping, innovativeness, and engagement constructs studied was gathered using a 5 point Likert scale with 1 – Agree Strongly, 2 – Agree, 3 – Neither Agree nor Disagree, 4 – Disagree and 5 – Disagree Strongly as the points on the scales. Questions for the innovativeness scale were derived by applying the Goldsmith and Hofacker (1991) consumer innovativeness scale developed in 1991. The engagement variables were adapted from the consumer engagement construct and scale developed by Vivek et al. in 2014. Unplanned purchase was a single item scale based on whether a person "often bought items that weren't planned on". Literature suggests that single item measures should be generally avoided (Hair et al., 2017). However, since the data was collected by a third party, researchers had little control over the design of construct. Spending was based on the question: "in an average month, about how much does your household spend on groceries excluding restaurant meals, take-out and delivery."

In-store digital use data was gathered using a 6-point Likert Scale- 1 – Extremely imp, 2 – Very imp, 3 – Somewhat imp, 4 – Not very imp, 5 – not at all imp, and 6 – Don't do this. While screening the data, all cases with option 6 were eliminated from the analysis as they were not representative of the population who uses digital devices in-store. This reduced the usable number of observations from 1851 to 778, which is still big enough to perform the PLS-SEM analysis. The study sample size

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exceeded the minimum recommended level of 103 for this research, assuming a statistical power of 0.80, a significance level of 5% and minimum anticipated R-square value of 0.10 (Hair et al., 2017).

Data Analysis and Testing

Several tests were conducted to test the validity and reliability of the data set and resulting constructs. In order understand whether the variance was attributed to the method of measurement rather than to the constructs represented by the measures (which can be a potential problem per Podsakoff et al. 2003), a common method bias (CMB) test was conducted to ensure the validity of conclusions drawn about the relationships between constructs (Bagozzi et al.,1991). The test results show that all VIFs were well below the threshold value of 3.3, thus indicating the absence of common method (Kock, 2015).

Two structural model approaches were considered in estimating the relationships of multiple constructs at once a: covariance-based SEM (CB-SEM) and component-based PLS-SEM (Chin et al., 2008; Hair et al., 2017). PLS-SEM path modeling was chosen as its research objective is prediction (in this case unplanned shopping and total spending), there were formatively measured constructs in the model, the model was relatively complex with many manifest and latent variables, the sample size was small, and/or the data were non-normally distributed, and latent variables scores may be used in future analyses. CB-SEM is usually recommended when the goal is testing, confirming, or comparing theories, error terms require additional specification, the model has circular relationships, and the research requires a goodness-of-fit measure (Hair et al., 2011; Hair et al., 2017; Hair et al., 2018).

All first order constructs were developed and modeled as reflective based on guidelines of Hair et al. (2017) and MacKenzie et al. (2005). The indicators of these constructs were expected to covary, and there was a common theme for indicators within each reflective construct. The model was tested using SmartPLS 3 (Ringle et al., 2015).

The initial model included three measures for the innovativeness construct, six for engagement, 18 for in-store digital use, one for unplanned purchase and one for spending. Based on initial indicator loadings (<0.7), two measures from the engagement construct and two measures from the in-store digital use construct had been removed. For further model parsimony, measures lower than 0.8 for in-store digital use were also removed, leaving a total of 10 measures in it. In all 10 indicator variables across three latent constructs were dropped. Assessment of the outer model was determined by examining the relationship between the constructs and their indicators.

Internal consistency reliability, convergent validity, and discriminant validity were tested for all reflective constructs. Internal consistency reliability was evaluated by using composite reliability. As seen in Table 1, the three reflective constructs (innovativeness, engagement, and in-store digital use) ranged from .81 to .96, exceeding the minimum requirement of 0.70 for composite reliability (Hair et al., 2010). The .96 composite reliability for in-store digital may indicate that this scale needs further testing due to semantically redundant items (Hair et al., 2017).

Convergent validity was confirmed by assessing the standardized indicator loadings. The loadings ranged from 0.71 to 0.85, exceeding the minimum recommended requirement of 0.708 (Hair et al., 2017). The average variance extracted (AVE) for the constructs ranged from 0.53 to 0.69, exceeding the minimum requirement of 0.50 (Hair et al. 2017).

Discriminant validity was confirmed based on the recommended guidelines by Hair et al. (2017) through Fornell and Larcker (1981) criterion. All the square roots of the AVEs for the three constructs were higher than the inter-construct correlations, thus demonstrating initial discriminant validity. Additionally, discriminant validity was confirmed through Heterotrait-Monotrait (HTMT) criterion (Henseler et al., 2015) as all constructs exhibited ratios of less than 0.857, below the 0.90 threshold (Hair et al., 2017). In addition, the bootstrap confidence interval bias corrected results (for 5000 subsamples) do not include the value of one.

Table 1
Reliability, Convergent, and Discriminant Validity Results

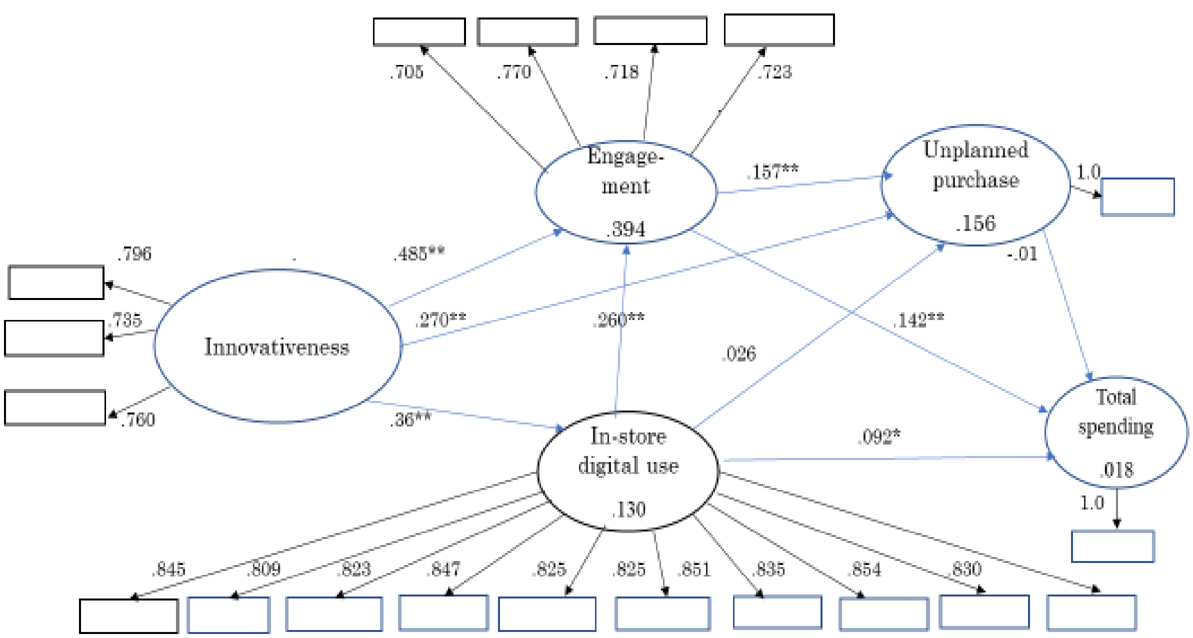
Latent variable	Internal consistency reliability composite reliability range: .60 - .90	Convergent validity AVE > .50	Discriminant validity HTMT confidence interval does not include 1
Innovativeness	.808	.584	yes
Engagement	.820	.532	yes
In-store digital use	.958	.696	yes

The next step was to ensure that the model did not have collinearity issues since the path coefficients were based on OLS regression and may be biased if multicollinearity was present. Analysis indicated that all VIFs were well below the threshold value of 5.0, resulting in no collinearity issues (Hair et al., 2017).

RESULTS

Once the theoretical model was constructed in PLS-SEM, two new relationships or paths were developed and hypothesized. The structural model results were then assessed to examine the relationship between constructs as well as the model's predictive capabilities (Hair et al., 2017). The final model including the measurement and structural model results with R-square, path coefficients

Figure 2
Final Model Factor Loadings, Standardized Path Coefficients, Construct R-Squareds



* * significant path at .05 * Significant path at .10

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and outer loadings as shown in Figure 2.

To evaluate the underlying theory of the model, hypothesis tests, R-square values, and predictive relevance were examined. To obtain the significance levels, the bootstrapping option was run using 5000 subsamples (Hair et al., 2017). Table 2 below provides the standardized path coefficients and significance levels, as well as summarizes the results of the hypotheses tests.

Table 2
Hypotheses Results

Hypothesis	Standard Path Coefficient	t statistic	p value
H1: In-store digital use -> Unplanned Shopping	.026	.684	.494
H2: In-store digital use -> Engagement	.260	8.054	0**
H3: Unplanned Shopping -> In-store spending	-.010	.356	.722
H4: Engagement -> Unplanned purchase	.157	3.347	.001**
H5: Innovativeness -> Engagement	.485	16.143	0**
H6: Innovativeness -> In-store digital use	.360	10.605	0**
H7: Innovativeness -> Unplanned Shopping	.270	6.200	0**
New: In-store digital use -> In-store spending	.092	2.42	.015*
New: Engagement -> In-store spending	-.142	3.327	.001**

* sig. at .05 level ** sig. at .01 level

As you can see in Table 2, seven hypotheses were accepted, and two were rejected. Surprisingly, the positive relationship between in-store digital use and unplanned shopping (H1) and the positive effect of unplanned shopping and in-store spending (H3) were both rejected at p=.494 and .722 respectively.

However, the positive relationship between in-store digital use and engagement (H2) at p=0.000 level was accepted. Engagement also had a positive influence on unplanned purchase (H4) and is supported at p=0.001. Hypothesis 5 predicted a positive relationship between innovativeness and engagement and was accepted at the p=0.000 level. There was a positive relationship between innovativeness and in-store digital use at p=0.000 level (H6). The positive effect of innovativeness on unplanned shopping (H7) was also accepted.

In terms of the new hypothesized paths, there was a negative, but significant (p=.015) relationship between in-store digital use and in-store spending. The standardized path coefficient was positive. Lastly, there was a negative significant (p=0.001), but positive relationship between engagement and in-store spending as the standardized coefficient was -.142. Please note the scale for engagement ranged from 1- being extremely important to 5- being not at all important, while the spending scale is from a low to high spending amount. Therefore, a negative engagement coefficient depicts that as engagement level goes up for the consumers, in-store spending goes up as well.

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Table 3
Total Effect

Path	Standardized coefficient	p-values
Engagement -> Spending	-0.144	0.001*
Engagement -> Unplanned Shopping	0.157	0.001*
Innovativeness -> Engagement	0.579	0.000*
Innovativeness -> Instore Digital	0.360	0.000*
Innovativeness -> Spending	-0.053	0.029*
Innovativeness -> Unplanned Shopping	0.370	0.000*
Instore Digital -> Engagement	0.260	0.000*
Instore Digital -> Spending	0.054	0.144
Instore Digital -> Unplanned Shopping	0.067	0.073**
Unplanned Shopping -> Spending	-0.010	0.723

* sig. at .05 level ** sig. at .10 level

The total effect of each variable on unplanned shopping and spending was also analyzed. As you can see from Table 3, innovativeness best predicted unplanned shopping with a coefficient of .37 versus .16 for engagement, while the total effect of engagement on spending was highest with a -.144 standardized coefficient.

Innovativeness had a strong total effect on engagement at .579, while in-store digital had a moderate total effect at .27. In-store digital had a significant total effect on unplanned shopping at the .10 significant level.

Of the three demographics tested for moderation (age, income and gender), only gender had a significant moderating effect on several of the variable paths. As in Table 4, gender significantly moderated the relationship between innovativeness and instore digital (p=.011, male higher than female), while gender significantly moderated in store digital (p=.05, male higher than female) and engagement (p=.10, female higher than male).

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Table 4
Path Between Group Gender Differences

Path	Between group difference	p-value	Gender
Engagement -> Spending	0.065	0.755	
Engagement -> Unplanned Shopping	0.094	0.159	
Innovativeness -> Engagement	0.06	0.159	
Innovativeness -> Instore Digital	0.152	0.011*	M
Innovativeness -> Unplanned Shopping	0.015	0.568	
Instore Digital -> Engagement	0.106	0.947*	M
Instore Digital -> Spending	0.106	0.896**	F
Instore Digital -> Unplanned Shopping	0.013	0.566	
Unplanned Shopping -> Spending	0.039	0.746	

* sig. difference at .05 level ** sig. difference at .10 level

R-Squared values were also analyzed as one of PLS-SEM's objectives is to maximize the R-squared of endogenous latent variables. R-square values of an endogenous construct at 0.75, 0.5, or 0.25 can be described as substantial, moderate, and weak respectively (Hair et al., 2017). Based on these standards, the prediction of engagement was slightly below moderate (R2 = 0.394), prediction of in-store digital use (R2=0.13) and unplanned shopping (R2=0.156) were weak, while prediction of in-store spending, while significant was very low (R2 = 0.018).

The predictive relevance of the endogenous constructs of innovativeness, engagement, in-store digital use, unplanned purchase and in-store spending was tested. As can be seen in Table 5, all Q^2 values were greater than zero, thus indicating predictive relevance for the endogenous constructs (Hair et al., 2017).

Table 5
Construct Predictive Relevance Using Q2 values

Latent variable	SSO	SSE	Q^2 (=1-SSE/SSO)
Engagement	3,112.00	2,498.82	0.197
Innovativeness	2,334.00	2,334.00	0.089
In-store digital	7,780.00	7,128.46	0.084
Spending	778	771.517	0.008
Unplanned shopping	778	663.568	0.147

DISCUSSION

Unplanned shopping (buying items that were not planned on either from a list or by memory) and spending has been studied extensively for years, however, with the advent of various new digital technologies, a new “engagement” construct and other variables, it needs further study. This study has explored the relationships of variables through data that captured total spending, unplanned shopping behavior, in-store digital technology use, consumer engagement and innovativeness within an in-store grocery shopping environment. With PLS-SEM modeling many direct and indirect relationships were simultaneously assessed.

The results indicate some expected, yet surprising findings for both academic theory and practical application. Innovativeness and engagement both play a key role in unplanned shopping behavior and total spend when buying groceries, while surprisingly, new digital technologies play a lesser direct role, but a more indirect effect. Contrary to previous study on the effects of in-store digital (Hui et al., 2013), in store use of digital technology did not increase unplanned shopping behavior directly. Nor did it increase spending as had been suggested as a result of other in-store stimuli in the past (Heilman et al., 2002; Gilbride et al., 2015; Roggeveen et al., 2016). As theorized by Belinni and Aiolfi (2017) and Bellini et al. (2017), this may be true because with pre-store and/or in-store digital use, many consumers may be planning more by looking at specials, recipe needs, coupons, product information, price comparisons, or making lists etc. Thus, this may be helping them plan better, to engage with brands they have in their preferred evoked set, or just to stay on track with budgets while in the store. In addition, they found that if consumers got distracted by mobile activity unrelated to shopping (off task), they made fewer unplanned purchases compared to those that did not have mobile or used mobile to stay on task.

Consumer engagement is the key variable which influences unplanned shopping and total spending. Those consumers who are more engaged or become more engaged while shopping are more likely to have unplanned shopping and additional total spending behavior. The research confirmed that engagement means consumers enjoy shopping and looking for their favorite brands and are passionate about their favorites, however may be more likely to try other brands if with more innovative personalities and if digital stimuli are present.. This adds to the 2015 Goldsmith et al. study, where innovativeness was a strong influencer of engagement.

One would expect those who are more willing to try new products or more open to other items (more innovative) would have more of a propensity for unplanned purchases than others. Consumers who have a more innovative personality may have the need for additional stimulation, more arousal and may be more sensation seeking than others. Therefore, they may be more motivated to seek items to buy that were not planned on, especially if aroused by stimuli or if more engaged. Consumers who are very engaged may be engaged with an entire category, while still having a particular brand that they may prefer. This may lead to a change in a planned purchase or a pure unplanned purchase, particularly if some stimuli affects them, or they are more innovative to start with. As was shown in the analysis, there is a strong relationship between innovativeness and engagement.

Some gender differences do exist. Compared to women, men who are more innovative may have a higher propensity for in-store digital and subsequent engagement as a result of that digital use, while women’s use of digital may lead more often to higher spending then men.

IMPLICATIONS FOR MARKETING PRACTITIONERS

Managements of both grocery manufacturers and grocery retailers are both very concerned about consumer behavior, the effect of new digital technology on that behavior in a retail setting and new competition. They know that the path to final purchase is very important to understand and that understanding how to leverage the massive amount of Big Data to provide value to consumers is very important. This deep understanding of what motivates the consumer to come to a retail establishment, to select particular brands, while maximizing his/her shopping basket dollars is paramount to their survival. The use of in-store digital and understanding its effect just adds to the multitude of "Big Data" that already exists for interpretation and use.

From a marketing point of view, engaging consumers who are more innovative and use digital for their shopping assistance, while at the same time meeting their needs, should be a key loyalty or switching tactic. Engaging existing users to deepen emotional ties to the brand or engaging non or light brand users is key. Understanding that a consumer's innovativeness and digital use affect consumer engagement with a brand or set of brands in a category, consequently affecting purchase behavior and choice will help the manufacturer and retailer plan and to strategize better. The research dictates that retail and manufacturing marketing management should test various digital strategies and target those who are more innovative and/or by other segmentation definitions to understand what drives consumer engagement. This will lead to a better understanding of how to add value to the consumer to initially and maintain engagement through these stimuli or other means and how that specifically leads to additional unplanned purchases and growth in the grocery basket or revenue. Knowing the path of decision-making will help retailers and manufacturers understand how to motivate specific groups of consumers best to induce switching or trial or to maintain their loyalty. Key digital promotional strategies to attract customers and once in store, to capture their trial and/or loyalty to their brands or store will be necessary.

LIMITATIONS

This research was conducted using secondary data. While a large sample was done, and the data was robust, because the data was not gathered for our specific purpose, a better data set may have been possible if we had conducted our own proprietary research. In addition, the data, while possibly projectable to other retail segments, was only collected from the grocery segment.
Future research could be conducted with specific research questions in mind within a grocery store setting or in a more controlled setting where variables can be manipulated and asked within the framework of accepted academic constructs. This could be expanded to other store segments of trade as well as cross culturally.

Research that will determine which digital strategies are most influential and optimally increase a shopping basket is limited at best and should be done. Research on task related and non-task related digital use could be deepened. Inman and Nikolova (2017) suggested additional research using quasi-experiments and control test methodologies to determine acceptance and effect on revenue from different technologies and strategies. Most likely, changing technologies will continue to affect unplanned purchases and basket size. Given the amount of information and stimuli that consumers are exposed to at retail, research to understand the effect of information overload on engagement and unplanned shopping and spending could be undertaken.

In the future, these authors will do additional proprietary research and analyzation that looks at the moderation of demographic and specific shopping situational variables, as well as personality, behavioural, and differing digital stimuli characteristics within a grocery store and/or online setting.

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