Investigating the impact of Internet of Things services from a smartphone app on grocery shopping

Article *in* Journal of Retailing and Consumer Services · September 2019

DOI: 10.1016/j.jretconser.2019.101927

3 authors, including:

Asle Fagerstrøm
Kristiania University College

Valdimar Sigurdsson
Reykjavik University

Investigating the Impact of Internet of Things Services from a Smartphone App on Grocery Shopping

Asle Fagerstrøm[a,b,*], Niklas Eriksson[b], and Valdimar Sigurdsson[c]

[a]Kristiania University College, Christian Krohgs gate 32, 0186 Oslo, Norway

[b]Arcada University of Applied Sciences, Jan-Magnus Janssonin aukio 1, 00560 Helsinki, Finland

[c]Reykjavik University, Menntavegur 1, 101 Reykjavik, Iceland

*Corresponding author. Kristiania University College, Department of Technology, Christian Krohgs gate 32, 0186 Oslo, Norway (asle.fagerstrom@kristiania.no)

Abstract

This study investigates the impact of Internet of Things (IoT) services from a smartphone app in a retail grocery shopping situation. It examines four variables, namely price, expiry date, quality indicators and offers. All four variables were examined in relation to two levels; traditional information and IoT services. A scenario was arranged whereby 226 participants were to purchase, among other products, fresh salmon in a grocery store using the store's smartphone app. Findings from a conjoint study show that the following IoT services; "updated expiry date", "aggregated national customer experience index", and "personalized offer based on product in the basket" evoked the approach and abated avoidance tendencies to explore the smartphone app, while simultaneously increasing the likelihood of buying based on information from the app. The IoT service "Real-time price" had a varied impact on participant approach-avoidance tendencies to interact with the app. Scenario simulation analysis shows that some IoT services can be a deal-breaker in a competitive grocery market. Consequently, analyzing the impact of IoT services through the lenses of approach-avoidance distinction and choice indication can help retail grocery managers develop more effective marketing strategies that deliver convenience to the consumers.

Keywords: Retail grocery, shopper-facing technology, Internet of Things services, approach and avoidance, conjoint study.

1. Introduction

According to Nielsen [1], consumers demand more convenience when shopping for groceries, and today there are a variety of technological opportunities to deliver convenience to the consumers [2]. In addition, there is a high probability that hybrid technological models that bring the best of personalized online shopping through smartphones will be used in the future [2]. The Internet of Things (IoT) is a representative technological innovation towards a digitally enriched environment. IoT technologies and services differ from other innovations in that they are ubiquitous and aim to deliver intelligent and autonomous solutions [3, 4]. For example, location-based beacon technology allows retailers to interact directly with customers as they enter the store, and IoT-connected digital signage can push personalized content such as offers in real time. In addition, data collected through IoT devices can provide the store with valuable insights through analytics, which can potentially support the enrichment of consumer shopping experiences. However, it seems that retail grocery stores are not as up to the increasing consumer trend toward smart retailing as would be expected [5, 6]. Thus, understanding consumer interaction with IoT services in the retail grocery shopping environment, and how it can support consumers' convenience when shopping for groceries, would therefore be of great interest to both researchers and practitioners.

According to Gubbi, Buyya [7], IoT consists of three technological components; hardware, middleware and presentations. While hard- and middleware are part of the background components, presentation is the visible part which allows the consumer to interact with the smart environment [8]. Technologies such as touchscreens in the grocery store, smart shopping carts, websites installed on smart devices, and mobile apps enable the consumer to connect to various IoT services. This type of shopper-facing technology might be the only part of the IoT technology with which consumers interact [9]. An example of a shopper-facing technology would be a smartphone app which allows grocery retailers to support the consumer's choices through IoT services [e.g., 10, 11, 12]. Such applications would provide IoT-enabled information such as real-time price based on demand and other trends, personalized customer offers based on selected products in the shopping chart, or suggested products based on desired calorie intake levels tracked by wearable fitness devices. To the best of our knowledge, no research has formed a connection between IoT services from smartphone apps with consumer motivation and empirically tested its impact in a grocery choice situation. Thus, this study extends the current literature by investigating consumers' motivation to interact with IoT services from smartphone apps in the grocery retail setting and its impact on choice. A better understanding of the impact of IoT services in this context can help grocery retailers improve the retail ecosystem so that it allows for real-time, personalized, or, bidirectional interactions with customers.

To investigate consumers' motivation to interact with IoT services from smartphone apps, we use the approach-avoidance distinction from Mehrabian and Russell [13], who conceptualized a model which relates qualities of physical environments to people's approach-avoidance behaviors. Based on the stimuli-organism-response paradigm, their model has been used extensively to measure approach-avoidance responses to physical atmospheric variables in a variety of contexts, especially retail choice situations [14-16]. Investigating the impact of IoT services from the lens of approach-avoidance contributes to the understanding, predicting, and influencing of choice behavior in this context.

The paper consists of four parts. The first part provides a review of literature related to IoT services. This is followed by descriptions of the conjoint method and procedure used in the study. The results of our conjoint analysis are then discussed. Finally, managerial and practical implications as well as limitations of this analysis, and directions for future research are presented.

2. IoT Services

Grewal, Roggeveen [12] highlights that, ‘technology and tools which facilitate consumer choices’ are one of the key areas that that will form the future of retailing. IoT technology has the potential to deliver ubiquitous, intelligent, autonomous, and personalized services to aid consumers when shopping for groceries [3, 4]. For example, IoT technologies have the capability to offer consumers real-time prices on their smartphones when shopping for groceries [17], and aid in providing in-store, location-based, and contextual personalized discounts and offers, which might not be possible through traditional devices. Therefore, we want to investigate the motivational impact of IoT services relative to traditional information on consumer interaction with the grocery store’s smartphone app, and its relative impact on choice. Therefore, we arranged a scenario whereby participants were going to buy fresh salmon, amongst other products. The independent variables defined for this study are price, expiry date, quality indicators, and offers.

We chose to focus on price, expiry date, quality indicators, and offers since the literature shows that these variables are relevant for purchasing salmon (fresh fish), which is the product used in this study. A conjoint study on the importance of different seafood attributes by Mueller Loose, Peschel [18], revealed that customers consider price, information about how the product was prepared (not relevant to our study as fillets are always prepared the same way) and country of origin (which can be interchangeable with expiry date in our study) as the most important factors when purchasing seafood. Both freshness (expiry date in our case) and price were shown to be the most important factors when purchasing salmon [19]. Customers’ willingness-to-pay also increases when quality indicators as eco-labels are included [20]. Present technology users suffer from information overload, which triggers difficulties in making decisions. However, personalizing services has been found to increase user satisfaction in this hectic environment [21]. Customers have positive attitudes and high levels of satisfaction after purchasing personalized products [22]. Therefore, we added personalized offers on top of standard offers as one of our variables. The dependent variables are defined as approach and avoidance tendencies to interact with a smartphone app in the retail grocery environment, and likelihood to buy based on IoT services from the smartphone app.

2.1 Price

Retail customers want to know if the product they are intending to buy is not only the best in terms of quality, but also in terms of price [23]. Price also plays an informational role. It can, for instance, represent quality in a product substitution setting, and can have different effects on demand [24]. In addition, consumer perceptions of a(n) (un)fair price has been investigated. A study by Haws and Bearden [25] demonstrated that consumers perceived price change within very short time periods as being more unfair than changes over a more extended time period, especially when the prices are low. However, according to Bolton, Warlop [26], consumers use different reference points in their price judgments, such as competitor prices, past prices for the same product and cost of goods sold, but they usually underestimate inflation, vendor costs and reasons for price differences. A real-time, or a near real-time, price that is based on a national price index (reference point) and other volatile variables ought to enhance consumer perceptions of fair price. IoT technology has the possibility to improve the communication of such rapid price changes in grocery retail stores [17]. A study on consumers' acceptance and perception of electronic shelf labels by Garaus, Wolfsteiner [27] demonstrated that electronic shelf labels did not affect price fairness perception compared to traditional price tags. Furthermore, real-time price as opposed to fixed price fluctuates. Therefore, it is expected to trigger the feeling of time scarcity [28] for customers by implicitly informing them that the price might go up at any time. Studies confirm that limited time offers increase purchase intentions [29].

Thus, our first assumption is that real-time information about price evokes approach and abates an avoidance tendency to interact with a smartphone app in a grocery shopping situation to a higher degree than traditional price information, and, simultaneously, increases the likelihood to buy.

2.2 Expiry Date

For consumers, fresh food such as fish may appear relatively similar, and thus consumers often rely on information provided on the package or labels to evaluate the attributes of competing products [30]. Nowadays, consumers demand high-quality and safe food products, which generates a need for more product information [31]. However, Verbeke [31] argues that the provision of large quantities of highly detailed information may involve a risk of information overload. In addition, Leykin and Burke [32] highlight that the complexity of modern retail stores and personal time constraints force consumers to be selective regarding information. Against this backdrop, IoT applications can provide new types of information regarding the conservation status of products during transportation, storage, etc. [33]. According to Rautiainen, Parkkinen [34], information traceability of product origin, transport, and storage conditions is important for the distribution of fresh food. In that particular IoT research project, consumers were asked for their opinion on relevant fish information. The results showed that the catch day of the fish, shelf time and storage temperature across the entire distribution chain were the most important information attributes [34].

Our second assumption is that updated information about the expiry date evokes approach and abates an avoidance tendency to interact with a smartphone app in a grocery shopping situation to a higher degree than traditional expiry date information, and, simultaneously, increases the likelihood to buy.

2.3 Quality Indicators

Consumer choice is influenced by quality indicators such as presentation of the product itself, brand, and country of origin. Social proof plays a major role in influencing individuals' everyday choices. It implies a strong correlation between people relying on the perceptions of others, arguments, and actions to directly influence their own behavior and decisions, especially under uncertain circumstances [35]. Thus, aspects such as product reviews and ratings help consumers evaluate grocery quality based on peer reviews and thereby influence their choices. According to Sen and Lerman [36], online word-of-mouth publicity differs from traditional word-of-mouth publicity in that consumers only need to interact with devices while reviewing or rating a product online. Dellarocas [37], for instance, states that online customer review systems are one of the most powerful channels to generate online word-of-mouth publicity. Not only can organizations reach audiences of exceptional scale at a low cost, but also individuals can make their personal thoughts, reactions, and opinions easily accessible to the global community [37].

Our third assumption is that aggregated information related to customer experience with product quality evokes approach and abates an avoidance tendency to interact with a smartphone app in a grocery shopping situation to a higher degree than traditional information about the quality, and simultaneously increases the likelihood to buy.

2.4 Offers

The effectiveness of targeted sales promotions with in-store digital signage technology on consumer shopping behavior should be studied [38]. Online retailers can tailor their offers based on historical and real-time data into their promotional campaigns [38]. In offline stores, personalized offers have principally been printed coupons based on loyalty programs [39]. However, with IoT, it is possible for retailers to provide personalized offers based on the items picked in the consumers' shopping cart. Hence, personalized offers can be set up based on actual in-store behavior rather than promoting the daily deal that is available to most consumers.

Our fourth assumption is that a personalized offer evokes approach and abates an avoidance tendency to interact with a smartphone app in a grocery shopping situation to a higher degree than a traditional offer, and simultaneously, increases the likelihood to buy.

3. Method

3.1 Participants

Yip, Chan [40] conducted interviews with youths aged 15-21 in Hong Kong and found that most attractive attributes when choosing their favorite store are product and service quality and price. Interestingly, their findings also indicate, among other aspects, that the environment in the store is also important for these youths [40]. For example, superior interior design or a comfortable shopping environment can reinforce shopping experience. This indicates that IoT has the potential to assist this age group when making choices in the grocery store. Based on the preferences of young consumers, a group of undergraduate students was invited to participate in a study relating to using a smartphone app while buying groceries. A Nordic student population was chosen as Nordic young adult consumers are one of the key target markets for the product (salmon) used in the study. Hence, the sample for the study comprised 120 undergraduate students at Kristiania University College (Oslo, Norway) and 106 at Arcada University of

Applied Sciences (Helsinki, Finland). The sample comprised 107 men and 119 women, across the age range of 19 to 41 years, with an average age of 23. All participants had a smartphone. Among the participants, 23% had bought groceries online at some point in time, and 26% had used a smartphone app while buying groceries from a physical store. The participants were informed that the study would last up to 15 minutes. They were not offered any payment or incentive to participate in the study.

3.2 Apparatus

As suggested by Holbrook and Moore [41], participants were presented with verbal representations of a scenario, together with visuals. The stimulus cards that were used in the study were created using Microsoft PowerPoint™ and Microsoft Paint™. The evaluation scenario together with an example of the stimulus cards and questions are presented in the Appendix A. The study was administrated by presenting the stimulus cards using a PowerPoint presentation for the participants conducted within a classroom. The participants' response was recorded with a pencil and paper questionnaire.

3.3 Procedure

When the participants had voluntarily accepted to engage in the study, they were presented with the following scenario, in which they were to assume that they were going to purchase fresh salmon in the grocery store:

> "Assume that you are going to have a barbecue party with your friends. Everybody should contribute, and you have been given the task to do some of the grocery shopping. In your shopping list, you have charcoal, new potatoes, crème fraîche, dill, barbecue spices, and fresh salmon. You are now in the grocery store and you are using the store's smartphone app. On your smartphone screen, you can see the products that you already

have in your shopping chart. You are now in the process of selecting fresh salmon and the app gives you information on your purchase."

Based on the information above, the participants were presented with 12 different situations that they were asked to evaluate. To establish a common frame of reference [42], all evaluations were elicited in terms of the same shopping scenarios. Participants were presented with one of the 12 stimulus cards each, and were then asked to evaluate each picture in relation to the tendency to interact with the smartphone app, and the likelihood to buy based on information from the smartphone app.

3.4 Design

Conjoint analysis is a multivariate technique to understand how people value different attributes of objects such as products and services [43]. This method was chosen due to the exploratory nature of our study. No studies have been performed on IoT services in the context of in-store preferences towards salmon or other seafood products. We do not add to a robust stream of research. On the contrary, our study is rather supposed to show the applicability of IoT services in the aforementioned context. Conjoint analysis is an excellent technique when it comes to delivering preliminary results regarding consumers' preferences towards new products and services [44]. Indeed, our research falls into this category.

The technique starts with the participant's overall evaluation of a set of complex variables (for example, real-time price, standard expiry date, quality indicators given by a national customer experience index, and offers based on the product in the basket). It then performs the job of deconstructing the participant's original evaluation into separate and compatible impact scales by which the original overall evaluation can be reconstituted [45]. A main-effects model was chosen, as it measures the direct impact of each stimulus. A full-profile method was chosen to collect the data. In this method, each profile card was described separately. This method was chosen because of its perceived realism and its ability to perform a fractional factorial design and because the number of factors in this study is below six [43]. All four variables were operationalized at two levels, as presented in Table 1; the traditional information and IoT services. Price was operationalized as: Fixed price represented by "Fixed price: EUR 25 per. kg." and real-time price represented by "Real-time price: EUR 25 per. kg. Price was based on a national index that is updated every second hour." Expiry date was operationalized as: Standard expiry date was represented by "Expiry: 5 days – Find out more" and real-time expiry date was represented by "Real-time expiry: 5 days – Find out more Keep-it™ technology gives a real-time expiry based on catch day and storage conditions." The quality indicator was operationalized as: Standard quality statement was represented by "This is a quality product – Find out more" and aggregated national customer experience index was represented by "A national customer experience index shows that users give this product 4.7/5 stars related to quality – Find out more". The offer was operationalized as: Standard offer represented by "Today's offer: Toothpaste 30% off – Find out more" and offer based on product in the basket represented by "Your offer: Based on selected products in your shopping cart we give you 30% off on all "Barbecue Spices" – Find out more".

When using a factorial design, the number of combinations can be reduced. Using IBM SPSS Statistics 24, the fractional factorial design resulted in 12 stimulus cards (including four hold-out cards), summarized in Appendix B. Sample sizes of more than 200 participants in conjoint analysis have been found to provide an acceptable margin of error [43]. In this study our total sample size is 226.

Table 1

Variables and levels considered in the study

Variables	Levels
Price	1. Fixed price 2. Real-time price
Expiry date	1. Standard expiry date 2. Updated expiry date
Quality indicator	1. Standard quality statement 2. Aggregated national customer experience index
Offer	1. Standard offer 2. Personalized offer based on product in the basket

The tendency to interact with the smartphone app in the retail situation was measured by participants' response to approach and avoidance items adapted from [46]. The approach was measured by asking the participants, "How much would you like to explore this app?" Avoidance was measured by asking, "How much would you like to leave and get away from this app?" The scale for the approach and avoidance variables ranged from "Not at all" (coded 0) to "Extremely so" (coded 7). The likelihood to buy based on information from the smartphone app was measured by asking the participants, "Based on the information the app gives, what is the likelihood that you would buy this salmon?" The "likelihood to buy" variable scale ranged from "Not at all likely to buy" (coded 0) to "Certainly would like to buy" (coded 7). An example of a stimulus card and questionnaire was presented to the participants before starting their evaluation. When the evaluation of the 12 stimulus cards was performed, participants were asked to provide demographic information.

4. Analysis and Results

While analyzing the data, a linear effect was assumed for all four variables in the study, which indicates that the data are expected to be linearly related to levels (e.g., preference is lower for standard offer than for personalized offer based on the product in the basket). The model for the response r_i for the i th card from a subject is

$$r_i = \beta_0 + \sum_{p=1}^{t} u_{pk_{pi}} \qquad (1)$$

where $u_{pk_{pi}}$ is the utility (part-worth) associated with the k_{pi} th level of the pth attribute on the ith card. Consumer preferences were modeled using part-worth utility function model (Green & Srinivasan, 1978). The model posits that

$$s_k = \sum_{p=1}^{t} f_p\left(y_{kp}\right) \qquad (2)$$

where s_k denotes the preference for a stimulus object at kth level, f_p denotes the part-worth function of each of the k different levels of the stimulus object y_{kp} for the pth attribute. In practice, $f_p(y_{kp})$ is usually estimated only for three or four levels for y_{kp} with the part worth for intermediate y_{kp} obtained by linear interpolation [47]. The relative importance of a product attribute compared to others can be calculated based on the utility attached to that particular attribute's single performance level, using the equation below

$$O_p = \frac{(\max u_p - \min u_p)}{\sum_{p=1}^{t} (\max u_p - \min u_p)} \qquad (3)$$

where O_p is the relative importance of the product attribute, max u_p is the utility of the attribute's most preferred level and min u_p is the utility of the attribute's least preferred level.

A total of 13 cases for approach, 20 cases for avoidance, and seven cases for likelihood to buy based on information from the smartphone app were removed due to equal values in RANK or SCORE. The analysis shows correlations between the observed and estimated preferences for approach (Pearson's r = 0.923, p = 0.001), avoidance (Pearson's r = 0.881, p = 0.002), and the likelihood to buy based on information from the smartphone app (Pearson's r = 0.948, p = 0.000). Table 2 shows the values for price, expiry date, quality indicators, and offers. As can be seen in Table 2, a fixed price has a positive approach tendency (0.088) and a positive avoidance tendency (0.036) to interact with the smartphone app. A real-time price has a positive approach tendency (0.176) and positive avoidance tendency (0.073). Fixed price and a real-time price have positive impacts on the likelihood to buy based on information from the smartphone app, with an impact estimate score of 0.029 and 0.057, respectively.

Table 2 shows that a standard expiry date has a positive approach tendency (0.086) and a negative avoidance tendency (–0.063) to interact with the smartphone app. An updated expiry date has a positive approach tendency (0.171) and a negative avoidance tendency (–0.126) to interact with the app. Standard expiry date and an updated expiry date have positive impacts on the likelihood to buy, with an impact estimate score of 0.207 and 0.413, respectively.

As can be seen in Table 2, a standard quality statement has a positive approach tendency (0.396) and a negative avoidance tendency (–0.308) to interact with the smartphone app. An aggregated national customer experience index has a positive approach tendency (0.791) and a negative avoidance tendency (–0.617) to interact with the app. Standard quality statement and an aggregated national customer experience index have a positive impact on the likelihood to buy, with impact estimate scores of 0.647 and 1.295, respectively.

Table 2 shows that a standard offer has a positive approach tendency (0.283) and a negative avoidance tendency (–0.223) to interact with the smartphone app. A personalized offer based on the product in the basket has a positive approach tendency (0.566) and a negative avoidance tendency (–0.447) to interact with the app. A standard offer and a personalized offer based on the product in the basket have positive impacts on the likelihood to buy, with an impact estimate score of 0.353 and 0.705, respectively.

Table 2:

Test of the impact of variables on approach-avoidance behavior to interact with the smartphone app and likelihood to buy.

	Tendency to interact with the smartphone app						Likelihood to buy based on information from the smartphone app (n=219)		
	Approach (n=213)			Avoidance (n=206)					
Variables and levels	Impact estimate	Standard error	Importance values	Impact estimate	Standard error	Importance values	Impact estimate	Standard error	Importance values
Price			24.487			22.843			19.148
Fixed price	0.088	0.120		0.036	0.120		0.029	0.148	
Real-time price	0.176	0.241		0.073	0.241		0.057	0.296	
Expiry date			24.290			25.279			24.415
Standard expiry date	0.086	0.120		–0.063	0.120		0.207	0.148	
Updated expiry date	0.171	0.241		–0.126	0.241		0.413	0.296	
Quality indicator			29.566			28.689			32.822
Standard quality statement	0.396	0.120		–0.308	0.120		0.647	0.148	
Aggregated national customer experience index	0.791	0.241		–0.617	0.241		1.295	0.296	
Offer			21.188			23.189			23.123
Standard offer	0.283	0.120		–0.223	0.120		0.353	0.148	
Personalized offer based on product in the basket	0.566	0.241		–0.447	0.241		0.705	0.296	
(Constant)	2.553	0.366		3.967	0.366		2.243	0.450	

Table 3:

Outcomes of the scenario simulation analysis related to likelihood to buy based on information from the smartphone app.

		Variables and levels				Outcomes			
Scenarios	Cases	Price	Expiry date	Quality indicator	Offer	Preference scores	Maximum utility[a]	Bradley-Terry-Luce[b]	Logit[b]
IoT service levels	A	Real-time price	Updated expiry date	Aggregated national customer experience index	Personalized offer based on product in the basket	4.713	59.0%	21.1%	38.0%
Mixed variable levels	B	Fixed price	Updated expiry date	Standard quality statement	Standard offer	3.684	5.7%	15.6%	11.1%
	C	Real-time price	Standard expiry date	Standard quality statement	Standard offer	3.506	2.2%	14.8%	9.4%
	D	Fixed price	Standard expiry date	Standard quality statement	Personalized offer based on product in the basket	3.830	13.0%	16.3%	14.0%
	E	Fixed price	Standard expiry date	Aggregated national customer experience index	Standard offer	4.125	12.8%	17.8%	16.6%
Traditional variable levels	F	Fixed price	Standard expiry date	Standard quality statement	Standard offer	3.478	7.3%	14.5%	11.0%

a. Including tied simulations
b. A total of 216 out of 219 subjects are used in the Bradley-Terry-Luce and logit methods because these subjects all have non-negative scores.

A scenario simulation related to “likelihood to buy” based on information from the smartphone app was devised, whereby all variables were on the IoT service level (Case A), variables varied between traditional level and IoT service level (Case B to E), and all variables were on the standard static level (Case F). All cases were analyzed in relation to each other. Table 3 shows the variables and levels for cases A to F. The output for each case is shown according to the preference score along with three preference probability scores: maximum utility, Bradley-Terry-Luce, and logit. According to Hair, Black [43], the Bradley-Terry-Luce probability and logit probability are the primary methods to analyze the results, as buying groceries is a routine choice rather than a sporadic one for grocery shoppers. Maximum utility is an optimal measurement for situations involving sporadic choices. We chose to use the logit probability for analyzing the defined scenarios.

According to logit probability, Table 3 shows that Scenario A is the most preferred option, where 38.0% of the participants favor a situation with a real-time price, updated expiry date, aggregated national customer experience index, and, personalized offers based on the product in the basket. Scenario E is second in order of preference, where 16.6% of the participants prefer a situation with a fixed price, standard expiry date, aggregated national customer experience index, and standard offers. The third scenario is D, where 14.0% of the participants prefer fixed price, standard expiry date, standard quality statement, and personalized offers based on the product in the basket. The least preferred scenarios are B, F, and C, with logit probability scores of 11.1%, 11.0%, and 9.4%, respectively.

5. Discussion

5.1 Research Implications

The aim of this study was to extend the current literature by investigating consumers' motivation to interact with IoT services from smartphone apps in the grocery retail setting and its impact on choice. A conjoint study was performed to investigate the impact of the following IoT services “real-time price,” “updated expiry date,” “aggregated national customer experience index,” and, “personalized offer based on the product in the basket” relative to standard static information given on a smartphone app in the grocery choice situation. The findings show that “updated expiry date,” “aggregated national customer experience index,” and a “personalized offer based on product in the basket” evoke approach and abate avoidance tendencies to explore the smartphone app and simultaneously increase the likelihood to buy. The impact was greater for the IoT service levels than for the traditional information levels for these three variables. Assumptions for the IoT services expiry date, quality indicators, and offers were supported in that they evoke approach and abate an avoidance tendency to interact with IoT services from a smartphone app in a grocery retail situation, at a higher degree than traditional information. It also simultaneously increased the likelihood to buy more than traditional information. The IoT service level “real-time price” had a varied impact on the participant's approach-avoidance tendency to interact with the smartphone app. However, the likelihood to buy based on “real-time price” was greater than for “fixed price.” The assumption for this IoT service was, therefore, partly supported.

Previous studies on IoT and consumer impact have focused on the perceived value of IoT technology in general [48] and consumers' purchase intention related to specific IoT-related technology such as RFID [10, 49]. The present study extends the current literature by investigating the impact of specific IoT services in the retail grocery choice situation. This is the first study that investigates the motivating impact of real IoT services in a grocery shopping situation by the use of the approach-avoidance distinction from the Mehrabian and Russell [13] model, together with the likelihood to buy. Tooby and Cosmides [50] state that the decision to approach or avoid is a fundamentally adaptive decision that organisms have had to make in the evolutionary past. Using the Mehrabian and Russell [13] model, similar studies have been conducted in order to determine the factors that influence a user's tendency to approach or avoid websites [51], as they can also influence the behavior of users in a manner similar to their behavior in a physical setting [52]. As such, the present study has gone a step further, using the Mehrabian and Russell [13] framework to determine IoT services that influence the consumer's tendency to approach or avoid with smartphone apps in a grocery choice situation. Moreover, approach-avoidance reveals the underlying motivation in this specific situation, and, together with measuring the likelihood to buy, based on information from a smartphone app, it strengthens the validity of the study. To make valid inferences about the actual behaviors of the consumers in a similar situation, it is beneficial to measure approach, avoidance, and likelihood to buy.

Our study broadens the generalizability of the Mehrabian and Russell [13] model and finds it applicable to research on IoT services. This conceptual framework inspired numerous studies focusing on physical aspects of the in-store environment such as lighting, music, scents, friendliness of employees or even fulfillment of organization's internal goals [14-16, 53-55]. This has only been sparsely studied in online environments like online retailing [see i.e., 52]. Nonetheless, all these studies focus on static rather than dynamic aspects of retail. Factors like store dominant colors in in-store environments or lighting do not change over time as rapidly as IoT services, which provide instant feedback and unlimited access to information. Therefore, the nature of these services is different from the traditional in-store environment. Nevertheless, we proved the applicability of approach-avoidance model [13] even to such dynamic environmental variables.

Since Mehrabian and Russell's model [13] focuses exclusively on emotional responses [53] and is a somewhat broad concept that we apply for specified and definite conditions in an IoT services context, namely to predict the likelihood to buy products depending upon the level of given price, expiry date, quality indicators and types of offer, we found that it can be useful for reaching more specific retail goals than gross evaluation of environment. In particular, we found it suitable for research on salmon promotion and, perhaps, can be extrapolated to the entire seafood category.

Ultimately, our research transgressed temporal boundaries of Mehrabian and Russell's [13] model developed almost half a century ago by fitting it into the upcoming era of IoT services. In addition, the approach-avoidance distinction used is a fundamental determinant of behavior that encompasses several automatic and non-automatic processes [see 56 for a review]. Therefore, as used in this study, we demonstrate that approach-avoidance tendencies related to environmental stimuli can be measured without the exclusive reliance on emotional responses. We supported studies on IoT services by delivering a new predictor of tendencies to interact with digital technologies, namely smartphone apps.

5.2 Managerial Implications

The findings from the scenario simulation in this study demonstrate that IoT services such as "updated expiry date," "aggregated national customer experience index," and "personalized offers based on product in the basket" substantially increase the consumers' likelihood to buy relative to traditional point of purchase stimulus on groceries smartphone apps. In addition, Inman and Nikolova [9] argue that product quality information, personalized promotions and just-in-time promotions ought to drive benefits to the consumer. From a retailer's point of view, this is interesting as it helps them decide the kind of variables they should include in their IoT solutions. The scenario simulation analysis can be useful for managers for the purposes of inventory control. Additionally, IoT-enabled services can help manipulate products on display to keep their inventory at optimal levels. At the same time, Grewal, Ailawadi [38] discuss that there appears to be a mixture of evidence of the effectiveness of one-to-one offers when compared to offers targeted at higher segmentation levels. The present study shows that different variable mixes (IoT service and/or standard variable) do also increase the likelihood to buy. Hence, retailers may well benefit from providing technological solutions to customers that combine IoT services with traditional point of purchase stimulus.

The IoT service "real-time price" had a varied impact on a participant's approach-avoidance tendency to interact with the smartphone app and a relatively low impact on the likelihood to buy. We argue that this finding indicates that a real-time price, a dynamic price that is updated frequently based on a national price index, does not necessarily increase the perceived price fairness from a consumer's point of view. According to Campbell [57], price fairness is "a consumer's subjective sense of a price as right, just, or legitimate versus wrong, unjust, or illegitimate." In fact, price fluctuations may increase the sense of uncertainty a consumer may have as regards the best price [25], which may hinder a purchase rather than stimulate it. Real-time price is related to the monetary sacrifices in the grocery retail choice situation [9]. Hence, grocery retailers need to bear in mind consumer aspects of price fairness and price uncertainty while using real-time pricing.

The present study shows that IoT services updated expiry date, aggregated national customer experience index, and personalized offer based on product in the basket creates convenience when shopping for groceries. However, the grocery retailer should consciously evaluate to what degree the investment in IoT technology contributes to their competitiveness by continuously testing and learning from rapid, small-scale trails and following these data [2].

5.3 Limitations and Further Research

This study is not without limitations. One limitation is the order effect that occurs when a list of variables is presented sequentially [58]. Order effects therefore occurred in the present study because it is not reasonable to expect that participants encounter variables in the real world in the same order as they did in this conjoint survey. A follow-up study could be conducted to arrange the conjoint study in a computer lab, instead of in a lecture room with projectors. The order effect could be controlled for a randomized presentation of the stimulus cards. Secondly, experimental design may lack external validity due to the artificial situation. Conjoint analysis as a technique and method is, nevertheless, regarded as a realistic way to capture consumer decisions. However, it should be viewed as primarily explorative in the sense that in its design and execution, assumptions and limitations need to be made by the researcher [43]. Moreover, reviews of studies on economic choice with real outcomes and hypothetical outcomes have shown that methods involving hypothetical choices and those involving real consequences usually show similar results qualitatively [59]. However, a future study could aim to develop a prototype smartphone app, and conduct an experiment in a physical grocery store.

Lastly, the external validity of our research would benefit greatly by extending it to other product categories. We focused on salmon and we suggest future studies on other food categories like fruits and vegetables or non-perishables to see if the obtained results correspond to ours. Furthermore, we also recommend future research focus on different samples. We conducted our research on students. Peterson and Merunka [60] suggest that such samples might not even generalize to other student populations. Moreover, even though in-store behavior seems relatively homogenous between countries like USA and China, comparisons between developed and developing countries are rather scarce in this context and are worth future investigation [61].

6. Conclusion

This is the first study that has examined the impact of real IoT services in a retail grocery choice situation. The results suggest that the IoT services related to expiry date, quality indicators and offers had a positive impact on tendencies to explore the smartphone app, and simultaneously increase the likelihood to buy the product based on the information from the smartphone app. Hence, retailers may well benefit from providing shopper-facing technology to customers that combine IoT services with standard points of purchase variable. IoT service price had, however, a varied impact on the tendency to interact with the smartphone app. From this, we conclude that managers should be aware of the consumer's perspective of price fairness and price uncertainty when using IoT service real-time pricing. Further analysis shows that IoT services, such as an aggregated national customer experience index and personalized offer based on a product in the basket, can be a deal-breaker in a competitive grocery market. The present study on shopper-facing technology, IoT service, approach and avoidance, combined with a conjoint study, resulted in relevant implications for researchers as well as for practitioners and managers. Future research should replicate the methods used in this study and develop them accordingly by taking into account and improving the limitations discussed here.

Acknowledgments:

The authors thank Lindstedt Fund (Helsinki, FI) and The Icelandic Centre for Research (RANNIS, grant no. 216011) for partially funding the study.

References

1. Nielsen, *The Nielsen total audience report Q3*, T.N. Company, Editor. 2018: https://www.nielsen.com/no/no/insights/reports/2019/q3-2018-total-audience-report.html#.
2. Walker, H., *Shoppers have an appetite for retail tech – but they're picky* in *The Grocer*. 2018: Online.
3. Miorandi, D., et al., *Internet of things: Vision, applications and research challenges.* Ad Hoc Networks, 2012. **10**(7): p. 1497-1516.
4. Gigli, M. and S. Koo, *Internet of Things: Services and Applications Categorization.* Advances in Internet of Things, 2011. **1**: p. 27-31.
5. Gao, L. and X. Bai, *A unified perspective on the factors influencing consumer acceptance of internet of things technology.* Asia Pacific Journal of Marketing and Logistics, 2014. **26**(2): p. 211-231.
6. Madhani, P.M., *Enhancing customer lifetime value in fast fashion retailing with RFID initiatives.* International Journal of Business and Globalisation, 2015. **15**(2): p. 205-237.
7. Gubbi, J., et al., *Internet of Things (IoT): A vision, architectural elements, and future directions.* Future generation computer systems, 2013. **29**(7): p. 1645-1660.
8. Jayavardhana, G., et al., *Internet of Things (IoT): A vision, architectural elements, and future directions.* Future Generation Computer Systems, 2013. **29**(7): p. 1645-1660.
9. Inman, J.J. and H. Nikolova, *Shopper-Facing Retail Technology: A Retailer Adoption Decision Framework Incorporating Shopper Attitudes and Privacy Concerns.* Journal of Retailing, 2017. **93**(1): p. 7-28.
10. Chen, C.-C., *RFID-based intelligent shopping environment: a comprehensive evaluation framework with neural computing approach.* Neural Computing and Applications, 2014. **25**(7): p. 1685-1697.
11. Gregory, J., *The Internet of Things: Revolutionizing the Retail Industry*. 2015, Accenture.
12. Grewal, D., A.L. Roggeveen, and J. Nordfält, *The Future of Retailing.* Journal of Retailing, 2017. **93**(1): p. 1-6.
13. Mehrabian, A. and J.A. Russell, *An Approach to Environmental Psychology*. 1974, Cambridge: MA:MIT Press.
14. Baker, J., M. Levy, and D. Grewal, *An experimental approach to making retail store environmental decisions.* Journal of Retailing, 1992. **68**(4): p. 445-460.
15. Donovan, R.J. and J.R. Rossiter, *Store Atmosphere: An Environmental Psychology Approach*. Vol. 58. 1982.
16. Donovan, R.J., et al., *Store atmosphere and purchasing behavior.* Journal of Retailing, 1994. **70**(3): p. 283-294.
17. Prater, E., G.V. Frazier, and P.M. Reyes, *Future impacts of RFID on e-supply chains in grocery retailing.* Supply Chain Management: An International Journal, 2005. **10**(2): p. 134-142.
18. Mueller Loose, S., A. Peschel, and C. Grebitus, *Quantifying effects of convenience and product packaging on consumer preferences and market share of seafood products: The case of oysters.* Food Quality and Preference, 2013. **28**(2): p. 492-504.

19. Halbrendt, C., et al., *Marketing Problems and Opportunities in Mid-Atlantic Seafood Retailing.* American Journal of Agricultural Economics, 1995. **77**(5): p. 1313-1318.
20. Uchida, H., et al., *Demand for ecolabeled seafood in the Japanese market: A conjoint analysis of the impact of information and interaction with other labels.* Food Policy, 2014. **44**: p. 68-76.
21. Lai, H.-J. and Y.-C. Ku, *Personalized Content Recommendation and User Satisfaction: Theoretical Synthesis and Empirical Findings AU - Liang, Ting-Peng.* Journal of Management Information Systems, 2006. **23**(3): p. 45-70.
22. Freiden, J.B. and R.E. Goldsmith, *Have it your way: consumer attitudes toward personalized marketing.* Marketing Intelligence & Planning, 2004. **22**(2): p. 228-239.
23. Kiran, V., M. Majumdar, and K. Kishore, *Innovation in In-Store Promotions: Effects on Consumer Purchase Decision.* European Journal of Business and Management, 2012. **4**(9).
24. Gaur, V. and M.L. Fisher, *In-Store Experiments to Determine the Impact of Price on Sales.* Production and Operations Management, 2005. **14**(4): p. 377-387.
25. Haws, K.L. and W.O. Bearden, *Dynamic Pricing and Consumer Fairness Perceptions.* Journal of Consumer Research, 2006. **33**(3): p. 304-311.
26. Bolton, L.E., L. Warlop, and J.W. Alba, *Consumer Perceptions of Price (Un)Fairness.* Journal of Consumer Research, 2003. **29**(4): p. 474-491.
27. Garaus, M., E. Wolfsteiner, and U. Wagner, *Shoppers' acceptance and perceptions of electronic shelf labels.* Journal of Business Research, 2016. **69**(9): p. 3687-3692.
28. Cialdini, R.B., *Influence: the psychology of persuasion*. 2007, New York: Harper Collins.
29. Jun, S.Y. and J.H. Huh, *Scarcity Messages AU - Aggarwal, Praveen.* Journal of Advertising, 2011. **40**(3): p. 19-30.
30. Holland, D. and C.R. Wessells, *Predicting Consumer Preferences for Fresh Salmon: The Influence of Safety Inspection and Production Method Attributes.* Agricultural and Resource Economics Review, 2016. **27**(1): p. 1-14.
31. Verbeke, W., *Agriculture and the food industry in the information age.* European Review of Agricultural Economics, 2005. **32**(3): p. 347-368.
32. Leykin, A. and R.R. Burke, *Identifying the Drivers of Shopper Attention, Engagement, and Purchase*, in *Shopper Marketing and the Role of In-Store Marketing*, D. Grewal, A.L. Roggeveen, and J. NordfÄlt, Editors. 2014, Emerald Group Publishing Limited. p. 147-187.
33. Lee, I. and K. Lee, *The Internet of Things (IoT): Applications, investments, and challenges for enterprises.* Business Horizons, 2015. **58**(4): p. 431-440.
34. Rautiainen, T., et al., *Järvikalan saatavuuden, laadun-hallinnan ja jäljitettävyyden kehittäminen RFID –teknologiaa hyödyntäen, Loppuraportti*. 2014, MAMK University of Applied Sciences.
35. Sherif, M., *A study of some social factors in perception.* Archives of Psychology (Columbia University), 1935. **187**: p. 60-60.
36. Sen, S. and D. Lerman, *Why are you telling me this? An examination into negative consumer reviews on the web.* Journal of Interactive marketing, 2007. **21**(4): p. 76-94.
37. Dellarocas, C., *The digitization of word of mouth: Promise and challenges of online feedback mechanisms.* Management Science, 2003. **49**(10): p. 1407–1424.
38. Grewal, D., et al., *Innovations in Retail Pricing and Promotions.* Journal of Retailing, 2011. **87, Supplement 1**: p. S43-S52.

39. Zhang, J. and M. Wedel, *The Effectiveness of Customized Promotions in Online and Offline Stores.* Journal of Marketing Research, 2009. **46**(2): p. 190-206.
40. Yip, T.C., K. Chan, and E. Poon, *Attributes of young consumers' favorite retail shops: A qualitative study.* Journal of Consumer Marketing, 2012. **29**(7): p. 545-552.
41. Holbrook, M.B. and W.L. Moore, *Feature Interactions in Consumer Judgments of Verbal versus Pictorial Presentations.* Journal of Consumer Research, 1981. **8**(1): p. 103-113.
42. Wright, P. and M.A. Kriewall, *State-of-mind effects on the accuracy with which utility functions predict marketplace choice.* Journal of Marketing Research, 1980. **27**(3): p. 277-293.
43. Hair, J.F., et al., *Multivariate data analysis*. 7 ed. 2014, Upper Saddle River New Jersey: Pearson Prentice Hall.
44. Galli, B.J., et al., *Application of Conjoint Analysis in Improving the Value of New Product Development: A Hotel Case Study Analysis.* International Journal of Strategic Decision Sciences (IJSDS), 2017. **8**(2): p. 11-30.
45. Green, P.E. and Y. Wind, *New way to measure consumer´s judgments.* Harvard Business Review, 1975. **53**: p. 107-117.
46. Russell, J.A. and A. Mehrabian, *Approach-Avoidance and Affiliation as Functions of the Emotion-Eliciting Quality of an Environment.* Environment and Behavior, 1978. **10**(3): p. 355-387.
47. Green, P.E. and V. Srinivasan, *Conjoint analysis in consumer research: Issues and outlook.* Journal of Consumer Research, 1978. **5**(2): p. 103-123.
48. Balaji, M.S. and S.K. Roy, *Value co-creation with Internet of things technology in the retail industry.* Journal of Marketing Management, 2016. **33**(1-2): p. 7-31.
49. Müller-Seitz, G., et al., *Customer acceptance of RFID technology: Evidence from the German electronic retail sector.* Journal of Retailing and Consumer Services, 2009. **16**(1): p. 31-39.
50. Tooby, J. and L. Cosmides, *The past explains the present: Emotional adaptations and the structure of ancestral environments.* Ethology and Sociobiology, 1990. **11**(4): p. 375-424.
51. Clark, W.R., et al., *Stay or leave: Applying Approach–Avoidance Theory to virtual environments.* Journal of Database Marketing & Customer Strategy Management, 2009. **16**(4): p. 231-240.
52. Eroglu, S.A., K.A. Machleit, and L.M. Davis, *Atmospheric qualities of online retailing: A conceptual model and implications.* Journal of Business Research, 2001. **54**(2): p. 177-184.
53. Bitner, M.J., *Servicescapes: The Impact of Physical Surroundings on Customers and Employees.* Journal of Marketing, 1992. **56**(2): p. 57-71.
54. Milliman, R.E., *Using Background Music to Affect the Behavior of Supermarket Shoppers.* Journal of Marketing, 1982. **46**(3): p. 86-91.
55. Spangenberg, E.R., A.E. Crowley, and P.W. Henderson, *Improving the Store Environment: Do Olfactory Cues Affect Evaluations and Behaviors?* Journal of Marketing, 1996. **60**(2): p. 67-80.
56. Elliot, A.J. and M.V. Covington, *Approach and Avoidance Motivation.* Educational Psychology Review, 2001. **13**(2): p. 73-92.
57. Campbell, M.C., *Perceptions of Price Unfairness: Antecedents and Consequences.* Journal of Marketing Research, 1999. **36**(2): p. 187-199.

58. Chrzan, K., *Three Kinds of Order Effects in Choice-Based Conjoint Analysis.* Marketing Letters, 1994. **5**(2): p. 165-172.
59. Camerer, C.F. and R.M. Hogarth, *The effects of financial incentives in experiments: A review and capital-labor production framework.* Journal of Risk and Uncertainty, 1999. **19**(1-3): p. 7–42.
60. Peterson, R.A. and D.R. Merunka, *Convenience samples of college students and research reproducibility.* Journal of Business Research, 2014. **67**(5): p. 1035-1041.
61. Sorensen, H., et al., *Fundamental patterns of in-store shopper behavior.* Journal of Retailing and Consumer Services, 2017. **37**: p. 182-194.

Appendix A

Assume that you are going to have a barbecue with your friends. Everybody should contribute, and you have been given the task to do some of the grocery shopping. In your shopping list you have charcoal, new potatoes, crème fraîche, dill, barbecue spices, and fresh salmon. You are now in the grocery store and you are using the store´s smartphone app. On your smartphone screen, you can see the products you already have in your shopping chart. You are now in the selection process of fresh salmon and the app gives you information regarding your purchase. The first purchase situation is an example.

Stimulus card 3: (All pictures in the study were original, but the sample picture in this Appendix has been blurred due to copyright issues. The hyperlink “Find out more” indicated that it was possible to obtain more information by interacting with the smartphone app. However, since the stimuli cards was presented by using a PowerPoint presentation, it was not possible for the participants to interact.)

1. How much would you like to explore this app?

Not at all Extremely so

0	1	2	3	4	5	6	7
❑	❑	❑	❑	❑	❑	❑	❑

2. How much would you like to leave and get away from this app?

Not at all Extremely so

0	1	2	3	4	5	6	7
❑	❑	❑	❑	❑	❑	❑	❑

3. Based on the information the app gives, what would be the likelihood that you would buy this salmon?

Not at all likely to buy Certainly would like to buy

0	1	2	3	4	5	6	7
❑	❑	❑	❑	❑	❑	❑	❑

Appendix B

Factorial design used to synthesize stimulus cards. Stimulus cards 9-12 are hold-out cards.

	Variables and levels			
Stimulus card	Price	Expiry date	Quality indicator	Offer
1	1	2	2	2
2	2	2	1	1
3	1	1	2	1
4	2	1	2	2
5	2	1	1	2
6	1	1	1	1
7	1	2	1	2
8	2	2	2	1
9	2	1	1	1
10	2	1	2	1
11	1	2	2	1
12	1	2	1	1

Note. Antecedent variables and their levels correspond to Table 1.