Smartphone Effect on Shoppers: How Mobile Information Storage Influences Price Knowledge

Short Paper

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Abstract

Researchers have recently raised concerns about the harmful effects of external information storage on memory. At the same time, new and emerging mobile technologies have led to the increasing capacity and convenience of external memory aids. Our research investigates the effects of mobile information storage on consumers' price knowledge. Results from our two studies suggest that consumers who think that the price information will be available on their smartphones show lower price recall scores than a control group without available price information. In addition, we find that the level of general mobile information storage influences consumers' explicit price knowledge negatively, while implicit price knowledge remains unaffected. Finally, we show that less price-conscious consumers are more strongly affected by the smartphone effect than are price-conscious customers. Implications for consumers, companies, information systems design and further research as well as limitations of the study are discussed.

Keywords: Smartphone, price knowledge, information storage, shopping

Introduction

Information systems (IS) research in the field of new technology acceptance has been a familiar topic since the 1990's (e.g., Venkatesh et al. 2003). It was followed by investigations of the characteristics of online consumers (e.g., Gefen et al. 2008), as well as studies on multichannel and technological features and their influence on consumer response (e.g., Kim and Krishnan 2019; Sahoo et al. 2018). Due to the latest technological developments, new factors influencing consumer response arise: this year, the number of smartphone users in the world is forecast to grow to around 4 billion (Newzoo 2021). Smartphones have become a commonplace, powerful, and multifunctional tool—an all-in-one information and communication technology (ICT), a sort of electronic Swiss Army knife (Barkhuus and Polichar 2011). They enable constant connection to information and entertainment. As such, smartphones act as technological aids. Think of humans' imperfect memory, which requires different techniques to improve chances of remembering information. We might, for example depend on calendars and shopping lists, or rely on other people to remember information for us. By doing this, we can "offload" our memories onto external aids in the environment, and new and emerging ICT such as smartphones can support the ability to remember through these methods (Mercer 2016). With the help of databases and search engines such as Google, we can find the answers to most of our urgent questions almost immediately. Sparrow, Liu and Wegner (2011) even claim that these databases and search engines have become an external memory source where personal data is stored outside of the brain. Therefore, people tend to memorize where they can access the information rather than memorizing the information itself.

In this context, the negative effects of smartphone use have been subject to psychological and IS research in recent years (for an overview from an IS perspective and a comprehensive qualitative study, see Salo et al. 2021). Current studies have uncovered negative emotional consequences of extensive smartphone use, such as increased stress and anxiety levels (e.g., Salo et al. 2021), and lower levels of analytic thinking (e.g., Barr et al. 2015). However, research on how smartphone use influences *consumers* in their everyday life are quite rare. We therefore connect IS literature on the influence of smartphones on human behavior with marketing literature on consumer behavior, in order to analyze how smartphones influence today's shoppers. Marketing theory highlights a specific form of memory as being especially important for explaining shopping decisions: price memory (also referred to as price knowledge; e.g., Jensen and Grunert 2014). Consumers make price-based decisions by comparing and observing prices. Within this process, some level of price knowledge should help them to distinguish between low and high prices for products they intend to buy. Taking this prevalence of consumer-price interactions as a basis, it might be intuitively expected that price knowledge of customers can be explained fairly well by now. However, the question of why customers are able or unable to remember prices is still not fully resolved (e.g., Linzmajer et al. 2021). Against this background, most of the articles in marketing research implicitly concede that price knowledge should not just depend on category, macro-economic, product-related, or socio-demographic factors but should also consider the ability of consumers to memorize product prices.

To date, and to the best of our knowledge, there is no study on price knowledge, that explicitly integrates the way in which consumers store and retrieve price information in an environment of new ICT that changes the way we remember information. The question at the intersection of IS, psychological, and marketing research, therefore, is whether and how consumers' price knowledge might be affected by increasing the amount of external information storage. To close the research gap, this publication seeks to analyze the possible effects of external information storage (via smartphone use) on consumers' price knowledge.

Conceptual Background and Hypotheses

Depending on how prices are processed – intentionally, incidentally or unconsciously – the prices perceived by consumers are stored in different memory systems (Jensen and Grunert 2014). Price knowledge is thus distributed throughout various areas of the long-term memory system, which consist of two sub-systems: explicit memory and implicit memory (Squire 1992). When testing for price knowledge, therefore, one measurement is not sufficient to uncover all price information stored in a consumer's brain (Jensen and Grunert 2014). Three measurements have been developed in response: price recall, price recognition and deal spotting (Jensen and Grunert 2014). Depending on the test, specific price cues are given to the participants to facilitate the retrieval of even the weakest traces of price information (Jensen and Grunert 2014).

Researchers across disciplines have shown that today's consumers increasingly rely on mobile devices for offloading information from their internal memory system (e.g., Barr et al. 2015; Grinschgl et al. 2020; Sparrow et al. 2011; Spitzer 2016). By doing so, they also rely on that same external device to retrieve that specific information (Sparrow et al. 2011). Thus, recall of the "offloaded" information without the external device is impaired (Sparrow et al. 2011). In line with these findings and with the trend toward more and increasingly accessible external information storage devices (smartphones), the way consumers store and retrieve price-related information is expected to have changed as well. We therefore hypothesize the following:

> ***H1:*** Consumers who expect that price information will be available to them in the future on an external information storage device (such as a smartphone) will show lower price recall values than consumers who expect that the price information will not be saved on their smartphone.

Furthermore, relying on external memory aids on a regular basis may even lower the consumers' general cognitive ability to store new information (Spitzer 2016). This expectation leads us to hypothesize that people who frequently use their smartphones as an external information storage device will show lower price recall values. In contrast to H1, this effect is hypothesized to occur regardless of the storage of specific price information, but dependent on the smartphone use to store general information. Throughout this article, we will call this hypothesized phenomenon the "smartphone effect on shoppers". As a condition, extensive research has shown that a consumer's price perception, and therefore the processing of the price information, strongly depends on the individual level of price consciousness (e.g., Kukar-Kinney et al. 2007). Less price-conscious customers will, therefore, have shallower processing of price information, whereas price-conscious shoppers will process the information on a deeper level (Kukar-Kinney et al. 2007). As a consequence, less price-conscious consumers are more likely to be affected by the negative effect of frequent smartphone use to store general information on price recall.

> ***H2:*** The general use of mobile devices to externally store information negatively influences price recall values. This effect is moderated by the consumer's level of price consciousness.

As the three price knowledge dimensions touch distinct parts of the long-term memory (Jensen and Grunert 2014), the smartphone effect is expected to affect the dimensions differently as well. The three dimensions of price knowledge are hierarchically related (Jensen and Grunert 2014). This means that the ability to answer all three price knowledge questions depends solely on the strength of the price information's memory trace in the consumer's mind, and on the cues given (Jensen and Grunert 2014). Accordingly, a consumer who successfully recalls a price would also recognize a price and spot deals while a weak memory trace would not be enough to recall the correct price.

We therefore hypothesize for H3 that the strength of the effect of external storage on mobile devices will decrease according to the price knowledge dimension's hierarchy. Additionally, it may be more difficult to offload implicit price knowledge because a consumer might not even be aware of its traces in his/her memory. On this basis, we expect that mobile information storage will lead to a greater decrease in price recall than in price recognition and deal spotting.

> ***H3:*** The smartphone effect is expected to affect explicit price knowledge dimensions (price recall) significantly more strongly than implicit price knowledge dimensions (price recognition and deal spotting).

Study 1: First evidence of the smartphone effect

Methodology

For our first study we recruited 401 North American adults (175 females, median age = 34 years) on Amazon's crowdsourcing internet marketplace "Mechanical Turk", in exchange for a payment of $0.40. The aim of this study is to address Hypothesis 1 in an experimental grocery shopping setting. Before the first task, we randomly assigned the participants to one of the two experimental conditions (smartphone and control conditions). There was no statistical difference between those experimental groups in mean age ($M_{Smartphone}$ = 37.28 years, $N_{Smartphone\ group}$ = 203, $M_{Control}$ = 37.34 years, $N_{Control\ group}$ = 198, $t(399) = -.0.53$, $p > 0.1$) or in gender distribution ($Male_{Smartphone}$ = 58.6%, $Male_{Control}$ = 53.5%, $Chi^2(2) = 2.152$, $p > 0.1$). In both conditions, we welcomed participants with a short scenario description: "It is Friday afternoon and you still have some grocery shopping to do. However, before you go, you first compile a shopping list." Directly under this description we placed a picture of a grocery store aisle and a shopping cart taken from an ego perspective to make the scenario feel more realistic. For the smartphone condition, we added to the same picture a hand with a smartphone displaying a blurred shopping list, with the text remaining unchanged.

On the next page, participants in both conditions saw ten grocery products. The products were the same for all conditions. We randomly selected grocery products from different sub-categories on Walmart's website. In order to avoid a previous familiarity with the products and their prices, we exclusively selected products marked as "new". We instructed both groups to use those ten items as the products they were to buy on their shopping trip, and asked both groups to drag and drop the products into a box on the other side of the screen, sorting them by descending price. The only difference between the two conditions was that in the smartphone condition we told participants that by dragging and dropping the products into the box, the product and price information would be saved on their shopping app. Directly after the sorting task, we asked participants to recall the prices of the products as accurately as possible. Finally we asked them to indicate their age and gender.

Results and Discussion

Price Knowledge Calculation

We calculated the price recall scores as the number of participant's correct estimates within a certain price range, divided by the total number of products. As pointed out by Hooman and Lehmann (2001), it is common practice in price research to report the price recall values as correct answers if the values are "within 5%", "within 10%" or "within 20%" ranges from the correct price. Table 1 gives an example for the calculation of the four price recall values, using one participant's price estimates for the ten products. All participants in Study 1 saw the same products with the same prices. Therefore, none of the products was affected by cross-season or cross-store variation and the same calculation was applied to all ten products. We calculated four different recall scores for every participant: (1) the percentage of correctly recalled prices, (2) the percentage of prices ± 2.5% of the correct price (within 5% range), (3) the percentage ± 5% of the correct price, and finally (4) the percentage ± 10% of the correct price.

Product	***Price***	***Estimate***	***Deviation***	***Number of correct answers***			
				Correct	+-2.5%	+-5.0%	+-10%
Beef Snack Sticks	$4.18	$5.79	38.5%	0	0	0	0
Mexican Menudo	$13.98	$13.30	-4.9%	0	0	1	1
Peach Preserves	$2.98	$4.19	40.6%	0	0	0	0
Energy Granola	$4.48	$4.48	0.0%	1	1	1	1
Twists	$1.34	$1.78	32.8%	0	0	0	0
Olive Oil	$8.64	$5.98	-30.8%	0	0	0	0
Hazelnut Milk	$5.99	$6.33	5.7%	0	0	0	1
Cocktail Mix	$4.98	$5.99	20.3%	0	0	0	0
Curry Powder	$5.98	$4.17	-30.3%	0	0	0	0
Fitness Bread	$2.94	$1.99	-32.3%	0	0	0	0
Total number of points scored				***1***	***1***	***2***	***3***
Price recall scores				***10%***	***10%***	***20%***	***30%***
Reading example: For her answer '$5.79' to the first price recall question, this participant received no points. The deviation of 38.5% from the correct price was too high to be counted in any of the price recall score categories. For the second product, however, the participant's price recall was low by only 4.9%. Thus, she received a point within the range of +-5% and +-10% from the correct price. The scores were then calculated by the sum of points within one price recall score category, divided by number of products (ten). For scoring three points, she received price recall scores of 30% within the +-10% category.							

Table 1. Recall score calculation example

Mean Comparison

On average, participants showed lower price recall values in the smartphone condition (correct recall) (M = .09, SE = .01) than in the control condition (M = .13, SE = .01). This difference was statistically significant (Mann-Whitney U = 16786.5, $p < .05$). and, as shown in Table 2, the difference holds at all accuracy levels. Across both experimental conditions and all accuracy levels, there is a significant difference between the observed distribution of recall values and a normal distribution (Kolmogorov-Smirnov test, $p < 0.05$,). Accordingly, a normal distribution cannot be assumed. We therefore used non-parametric Mann-Whitney U tests to analyze group differences. Analyses with t-tests lead to statistically significant differences across all accuracy levels as well. To rule out an alternative explanation for the higher recall scores of the control group, we controlled for the average time participants spent on the product list page and did not see a significant difference (Mann-Whitney U = 18438, $p > .1$) between the smartphone condition (M = 117.07s, SE = 7.99) and control condition (M = 114.19s, SE = 5.65). This indicates that the lower price recall scores of the smartphone group are not a result of a shorter memorization time, but rather are evidence for the existence of the smartphone effect.

Accuracy Level	**Recall Values of Respondents**				**Mann-Whitney U Test**	
	Smartphone Condition		Control Condition		*Mann Whitney U*	*p-value*
	Mean	*SE*	*Mean*	*SE*		
Correct	9.41%	.011	12.93%	.012	16786.5	.00
Within 5%	17.09%	.014	23.79%	.016	16013	.00
Within 10%	21.13%	.014	29.39%	.017	15538	.00
Within 20%	26.26%	.015	34.85%	.018	15783.5	.00
N = 401						
Reading example: In the smartphone condition, on average, participants recalled 9.41% of the product prices correctly and 26.26% were within a 20% range from the correct price. Alternatively, participants in the control group recalled 12.93% of prices correctly, and 34.85% were within a 20% range from the correct price, on average. These differences between the two experimental groups are statistically significant ($p < .05$).						

Table 2. Independent Sample T-Test per Accuracy Level

The results of Study 1 support Hypothesis 1, as the consumers in the control condition displayed higher recall levels than the ones who thought that the price information would be available to them on their smartphone. These findings are consistent with Sparrow et al. (2011), who show that offloading information leads to lower recall scores of trivia statements.

Study 2: Disentangling the smartphone effect for price knowledge dimensions

Methodology

With Study 2, we address Hypotheses 2 and 3 by analyzing the general effect of frequent external information storage on explicit and implicit price knowledge dimensions. Using a web questionnaire, we recruited 252 participants (149 females, median age = 25 years) from the population of a Swiss state university. At the beginning of the survey, the participants had to indicate whether or not they owned and used a smartphone. Only smartphone users were then directed to a set of additional questions containing seven items on a five-point Likert scale that measured the level of external information storage on their smartphones. The items were developed for this research and included four everyday and three retail-specific applications of external information storage. We used this procedure to minimize inconsistencies between self-reported and objective measurements of smartphone use (Ellis et al. 2019). Specifically, we asked participants to respond to statements related to everyday applications: “I take notes on my smartphone in order to avoid forgetting something important”, “I save appointments on my smartphone, so I don’t miss them”, “I prefer to search for an answer online (on Google, for example) rather than spend a long time trying to figure it out.”, “I use my smartphone as a kind of knowledge database to look up anything I need to know.” We also asked them to respond to statements in the retail context: “I compare prices of products online during my store visit”, “I look up recipes online during my store visit to decide what to buy.”, “I keep track of my expenses on my smartphone”.

The second part of the questionnaire focused on measuring each participant’s price knowledge. First, we showed a list of products to the participants. The products on the list were chosen and grouped using the

Swiss Federal Statistical Office's (BFS) groceries selection for the calculation of the Swiss consumer price index (BFS 2018). In the survey, we asked participants to choose at least four products they had bought at least once during the last six months from one of the two major supermarket chains. Based on their product selections, the questionnaire tested the participants' price recall ability by asking them to recall the correct price as accurately as possible (answering in open-ended format). Furthermore, we included two additional price knowledge tests in order to uncover the smartphone effect on consumer's implicit price knowledge dimensions: price recognition and deal spotting. We used reliable and well-known testing procedures (e.g., Jensen and Grunert 2014) for each of the three price knowledge dimensions. During the price recognition task, participants were presented three incorrect prices and one correct price per product. They then had to select the correct one (single choice with four options). For the deal spotting task, participants were shown one price per product—an incorrect price—and had to indicate whether this price was higher or lower than the correct price (single choice with two options). In the third and final part of the questionnaire, we measured participants' individual levels of price consciousness (four items, 5-point Likert scale, Lichtenstein et al. 1993). Further measures from past price knowledge research were included as control variables: Store (four items, 5-point Likert scale) and brand loyalty (five items, 5-point Likert scale, Jensen and Grunert 2014), value consciousness (three items, 5-point Likert scale, Lichtenstein et al. 1993), shopping frequency ((1) less than 1x a week, (2) 1x a week, (3) 2-3x a week, (4) 4-5x a week and (5) more than 5x a week), days since the last shopping trip (open-ended format), age and gender.

Results and Discussion

Price Knowledge Calculation

Again, participants' price recall score was calculated by the percentage of correctly answered questions within a certain range. However, in contrast to Study 1, some of the products' prices varied between seasons and across supermarkets. Therefore, before judging the participants' price recall, we divided the products into three groups based on their price variability: (1) Fixed prices across supermarkets and/or seasons (e.g. branded products), (2) minimal variations across supermarkets and/or seasons (e.g. butter) and (3) small variations across supermarkets and/or seasons (e.g. vegetables and meat). Depending on the group, a specified range of deviation from the sample price was accepted and still counted as a correct answer: (1) ± 2.5% deviation from sample price, (2) the percentage ± 5% and (3) the percentage ± 10%. For the calculation of the price recall index with values from 0 - 1, the number of correct answers was then divided by the number of products chosen. In order to calculate the price recognition and deal spotting values, the number of correctly answered price/deal spotting questions was divided by the number of products chosen. Values for price recognition and deal spotting range from 0 – 1.

Moderation Analysis

To validate the hypothesis that frequent mobile information storage (Cronbach`s $\alpha = .68$) moderated by price consciousness (Cronbach`s $\alpha = .76$) leads to lower price knowledge, we conducted a moderation analysis using the PROCESS macro for SPSS by Hayes (2017). According to H2, we predicted that participants with high levels of mobile information storage would show lower levels of price recall. Price consciousness was examined as a moderator of the relationship between mobile information storage and price recall. In a first step of the regression analysis, we entered price consciousness and mobile information storage. The interaction term between mobile information storage and price consciousness was entered in a second step of the analysis, which explained a significant increase in variance in price recall, $R^2 = .03$, $F(3, 248) = 2.67$, $p < .05$. Hence, price consciousness ($b = -.23$, $p > .10$) was a statistically significant moderator (interaction term: $b = .10$, $p < .05$) of the relationship between mobile information storage ($b = -.06$, $p < .05$) and price recall. Simple slopes for the association between mobile information storage and price recall were tested for low (-1 SD below the mean), moderate (mean), and high (+1 SD above the mean) levels of price consciousness. Only the simple slope test for low values revealed a significant negative association between mobile information storage and price recall ($b = -.05$, $SEb = .02$, $t = -2.61$, $p < .05$). Figure 1 plots the simple slopes for the interaction.

We used the same procedure to test the effect of mobile information storage on the implicit price knowledge dimensions of price recognition and deal spotting. However, the calculated regression models (recognition: $R^2 = .01$, $F(3, 248) = .98$, $p > .10$; deal spotting: $R^2 = .00$, $F(3, 248) = .00$, $p > .10$) and interaction effects (price recognition: $b = .08$, $p > .10$; deal spotting: $b = .01$, $p > .10$) were not statistically significant.

We can therefore conclude that mobile information storage has a significant effect on consumers' price recall when consumers show low levels of price consciousness. This finding supports H2. On the other hand, mobile information storage and price consciousness showed no significant effects on either price recognition or deal spotting. Even though it is hard to draw any conclusions from non-significant results, we could argue that, since the effect on price recall is significant and the implicit price knowledge dimensions are not affected, the effect of mobile device use for externally storing price knowledge information is higher for price recall than for price recognition and deal spotting. Even after including all control variables adapted from previous studies into the moderation model with mobile information storage as independent variable, price recall as dependent variable and price consciousness as moderator, the negative effect of mobile information storage on price recall was still statistically significant ($b = -.06$, $p < .05$) and the interaction term with price consciousness was still marginally significant ($b = .10$, $p < .10$). Price ($b = -.24$) and value consciousness ($b = .05$), brand ($b = .02$) and store loyalty ($b = .02$), age ($b = .00$) and gender (coded as female = 1 and male = 0, $b = -.00$) were not significant ($p > .10$). Only shopping frequency ($b = -.03$, $p < .10$) and days since the last shopping trip ($b = .01$, $p < .10$) had a marginal effect on price recall. We repeated the same calculation for price recognition and deal spotting separately. The regression model with price recognition as dependent variable showed no significant effects of the independent variable, the moderator, the interaction term or any covariate on price recognition ($p > .10$). In the deal spotting model, only store loyalty had a significant effect ($b = .26$, $p < .05$).

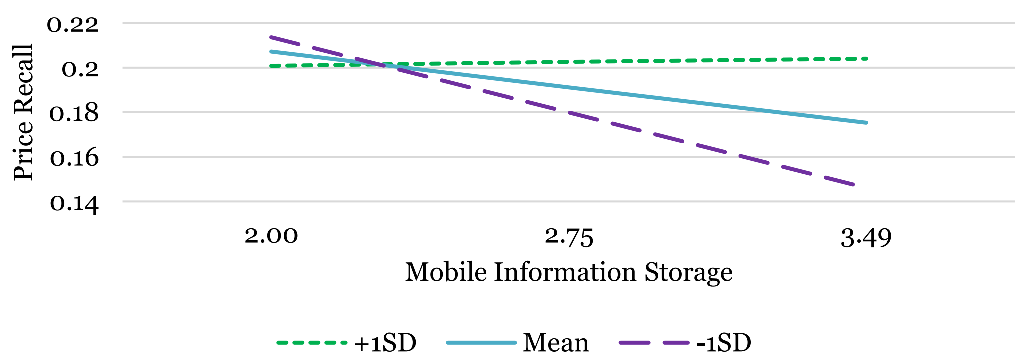

Figure 1. Simple slope analysis.
Simple slopes of mobile information storage predicting price recall for 1 SD below the mean of price consciousness, the mean of price consciousness, and 1 SD above the mean of price consciousness.

General Discussion, Implications and Preliminary Conclusion

According to Spitzer (2016), the external information storage of mobile devices leads to a decrease in users' general cognitive ability. Furthermore, Sparrow et al. (2011) proves that offloading information leads to a decrease in explicit memory. It is therefore not far-fetched to conclude that in our study the level of mobile information storage has had a significant effect on the participants' ability and/or willingness to store price information during their store visits. Hence, their ability to retrieve the price information while answering the online questionnaire in Study 2 was possibly impaired as well. Independent of the individual tendency to store information on smartphones, Study 1 reveals that price information can be offloaded to an external device. We have shown that consumers offload explicit price information to a smartphone when given the opportunity. The knowledge that needed information can be readily found on their smartphones appears to cause people to be less attentive and to register less information in the memory. Although this is most likely an unconscious process, the result is a lessened ability to recall prices in the future. Another important finding was the moderating role of price consciousness in Study 2, noting that price conscious customers have a lower risk of falling victim to the smartphone effect. Nevertheless, implicit price knowledge scores (price recognition and deal spotting) of the shoppers participating in Study 2 were unaffected by the level of mobile information storage.

From a consumer perspective, the smartphone effect is a double-edged sword. On the one hand, a lower ability to recall prices in the future is likely to affect internal reference prices negatively. When consumers carry price knowledge in their pockets, they are less able to make correct price judgments, and their buying decisions are impeded by a false feeling of having good price memory. On the other hand, implicit price knowledge, which is not affected by the smartphone effect, acts as a gatekeeper to prevent consumers from completely falling victim to false price judgments (Linzmajer et al. 2021). In an age when there is an expectation that everything that can be digitized will be digitized, knowing about the effect of offloading price information via smartphones is an important step toward being an informed consumer.

From a business perspective companies should not overestimate consumers' ability to store price information perfectly, and should take best advantage of consumers' price recognition or deal spotting abilities. Today, most B2C companies either follow an everyday low price (EDLP) strategy, or a Hi-Lo strategy (Gauri et al. 2021). Taking into account the results from our research, companies should focus on a Hi-Lo strategy, as the consumers who participated in this study revealed themselves to be much more likely to react to price promotions than to smaller price differences. Therefore, the general price difference of regularly priced items between EDLP companies and Hi-Lo companies could go unnoticed by consumers. Considering the negative effects of mobile information storage on explicit price knowledge, the focus on Hi-Lo pricing could possibly have even greater relevance for companies.

From an IS design perspective, for developers of mobile apps that support consumers' abilities our findings are useful for implementing interventions that mitigate negative effects of the smartphone effect on shoppers. Design principles in assistance systems gain momentum in IS research (Voss et al. 2021). When a consumer frequently stores price information on a smartphone, a pop-up message might remind them that their price knowledge has been lowered, so they should pay close attention to product price before purchasing. As the information-carrying capacity of mobiles is more constrained as screen sizes are smaller than on other devices (Choi et al. 2020), data presentation approaches for pop-up messages should facilitate the use of information in consumer choice. This said, the price knowledge of consumers offers a new mobile targeting variable that can be used for IS design, especially to better manage online impulsive buying tendencies (Zhao et al. 2021).

Limitations and Further Research

Against the background of the "short paper" format, our study does present limitations and unanswered questions that suggest avenues for further research. We conducted both studies with a non-representative and rather young online sample. Our results, thus, exclude some relevant target groups of retailers and ICT technology in general—such as "Baby Boomers" or "Generation X". In Study 2, the self-developed mobile information storage scale needs further development, as suggested by the rather low (but still acceptable; Nunnally 1978) reliability scores. Additionally, participants' self-selection of products before answering the price knowledge questions might have influenced the responses, as the participants only chose products from the list of products they had remembered buying. Furthermore, the participants had to complete all three price knowledge tasks (recall, recognition and deal spotting) for the same self-selected products every time. By randomly assigning pre-selected products to the different price knowledge tasks, a learning effect from previous tasks could be minimized. We were able to show the smartphone effect on shoppers with this research. A proof of its existence in the field is still missing. Therefore, we are currently collaborating with a leading European grocery retailer in an effort to uncover this effect in real shopping situations.

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