RECOMMENDATIONS IN AUGMENTED REALITY APPLICATIONS – THE EFFECT OF CUSTOMER REVIEWS AND SELLER RECOMMENDATIONS ON PURCHASE INTENTION AND PRODUCT SELECTION

Research paper

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Abstract

Not only since the launch of Pokémon Go in July 2016, augmented reality (AR) has received a big boost in awareness and popularity. AR-based start-ups have entered the market, and established companies start to offer AR functionalities in their smartphone applications. A new distribution channel in form of augmented commerce has been emerging, although only little is known about optimized design of AR environments due to the limited number of user studies researching the effects of AR usage. This paper's research objective is to tackle this gap by analysing AR technology in combination with online recommendations, a well-established, ubiquitous design element in today's e-commerce. We conducted a controlled online experiment with 208 subjects to examine the effects of customer recommendations (CR) and increasingly emerging seller recommendations (SR) in AR applications. Our results demonstrate that CRs in AR applications positively influence the intention to purchase and the selection of products by decreasing a customer's product fit uncertainty, whereas SRs displayed no significant influence. These insights are the first steps to further understand how AR and online recommendations can be used and have to be implemented to provide customers with novel and accepted sources of value.

Keywords: augmented reality, recommender systems, digital nudging, product uncertainty

1 Introduction

Augmented reality (AR) is a direct or indirect view of a physical, real-world environment that allows to add virtual, computer-generated elements that ‘augment’ the perception of the user. Since the invention of the first prototype ‘The Sword of Damocles’ built in the 1960s (Sutherland, 1968), technology has advanced tremendously. With 2.3 billion smartphones (Statista, 2017a) and 1.23 billion tablet users (Statista, 2017b) worldwide, the possibility of using AR is available for more people than ever before. Under these circumstances, AR is on the verge to become the next defining technology in the mobile channel. Hence, AR commerce is on the rise and according to estimates, AR and virtual reality has the potential to generate $150 billion in revenue by 2020 (Gaudiosi, 2015).

Despite the steady growth of AR commerce and the economic forecasts, AR has received only little attention from IS researchers yet. Recently, Harborth (2017) showed that AR user studies are underrepresented in the IS domain. So far, the majority of AR research is about the development and presentation of new AR technologies. Hence, as of today, little is known about how AR environments can be enhanced through informational design features. The need for more corresponding AR research was already exclaimed over 10 years ago by Swan II and Gabbard (2005, p. 1-2) and still persists today: ”What these approaches do not tell us, and what, to date has not been researched, is how information should be presented to users,” and ”for AR devices to reach their full potential, what is now required are new paradigms which support heads-up information presentation and interaction”.

Digital nudges refer to the use of user-interface elements to improve the outcome of the decision making process of individuals online and are one of the most important technologies in today’s e-commerce. There is manifold IS research that has investigated digital nudges in various contexts, such as user assessment of website value (Benlian, 2015), scarcity and personalization cues in seed stage referrals (Koch and Benlian, 2015), the impact of free sampling strategies in freemium conversion rates (Koch and Benlian, 2017), and how software updates influence user attitude (Fleischmann et al., 2016). In fact, the most widespread digital nudges are online recommender systems (ORS), which are algorithms that use historical, demographic or heuristic data to make recommendation vicarious for the seller (Xiao and Benbasat, 2007). Previous research about ORSs has primarily focused on exploring the effects in traditional online marketplaces, such as the trust in and adoption of such systems (Wang and Benbasat, 2005), the influence on consumer’s choice (Senecal and Nantel, 2004) or satisfaction (Jiang et al., 2010), but lack investigations in connection with non-traditional technologies like AR. However, AR-enabled technologies might be able to revolutionise the use of ORSs. The obligatory AR peripherals, like cameras and sensors combined with analysation algorithms and techniques lead to easy data collection of users and their surroundings. The usage of AR commerce applications, automatically provides more precise, current and relevant information for sellers than all other used forms of e-commerce, utterly effortless for both sides of the transaction. Hence, this can enhance the ORS endorsements, letting them surpass today’s value by making them more personalised, suitable and fitting. Thereby, SRs in conjunction with AR possibly have a greater influence on customers’ perceived product fit uncertainty than without AR, leading to a mediation effect on product selection that might be greater than similar effects of CRs. Consequently, if CRs are less valuable or even completely obsolete in AR commerce applications, sellers can go without them, avoid their disadvantages entirely and use ORSs instead to regain complete control over the product recommendations process, without any drawbacks. To investigate the possible divergent effects of SRs and CRs in AR commerce, research crucially needs to examine them in AR environments.

The paper sheds light on the effect of seller and customer recommendations in AR on customer’s product fit uncertainty, based on data collected in an online experiment with 206 participants. The objective is to extend the manifold online product recommendation research by adding AR as a new context and observe the effects separately for SRs and CRs. Moreover, we seek to examine the influence of SRs and CRs on product selection in AR commerce applications by investigating the related user’s product fit uncertainty and its mediating effect. Lastly, this work gives practical implications for practitioners on how online recommendations should be used as of today to improve the effectiveness in AR commerce applications.

This paper is divided into three parts. First, we present our theoretical foundations on AR, online recommendation and product fit uncertainty as well as our hypotheses. Second, we provide a detailed description of the conducted online experiment. Third, we elaborate on the results of the study, discuss the findings and give an outlook for future research.

2 Theoretical foundation and hypotheses development

2.1 Augmented reality (AR)

Milgram and Kishino (1994) describe AR as a mixed reality, a subset of virtual reality technology that merges the real and the virtual world. AR displays an otherwise real environment with added virtual objects to enhance the view of the user. While AR is often connected to the use of head-mounted displays, most definitions agree that AR is not restricted to a particular technology.

Today's AR applications are manifold, whereby the biggest ones are commerce, education and entertainment (Carmigniani and Furht, 2011). Commercial AR applications aim to simplify the user's life. For example, IKEA provides an AR application that allows users to see how new furniture looks in their homes and check whether it fits without measuring or moving in the actual environment. Education applications are mostly about cultural or sightseeing experiences. For instance, a museum can give additional information through AR about their exhibits or can offer interactive tours. Entertainment applications include pure AR-based presentations, such as AR games or more traditional applications with AR features. The biggest broad market AR phenomenon so far was the launch of Pokémon Go in 2016, a cross-platform mobile device game with AR features. In 2017, the game still has 65 million monthly users and has generated about 1 billion in revenue since it was released (Forbes, 2017).

Early research by Swan II and Gabbard (2005) reviewing AR technology-related papers found that although the majority of the extant work focussed on human perception and cognition on low-level tasks in AR and the impact of AR technology on user task performance: Only two papers focussed on design decisions and user interaction in AR environments (Azuma and Furmanski (2003); Lehikoinen and Suomela (2002). Recent research from Harborth (2017) examined in a systematic literature review the current state of AR studies in the IS domain and highlighted that most AR-related IS research focusses on either reviewing or developing new AR technologies. He confirmed that user studies represent a minority accounting only 21.92% of all AR related papers in the IS domain. Most of these studies focus on the effects and benefits of AR on different domains, such as education or status quo technologies (e.g. Djamasbi et al., 2014; Krishna et al., 2015; Phil et al., 2015). Others are about the acceptance, potential and adaption of AR by firms and the broad market (e.g. Gautier et al., 2016; Kumar et al., 2016; Ross and Harrison, 2016). The two papers that are closest to the topic of AR environment designs are by Huang and Liu (2014), investigating the importance of a narrative storyline in AR applications, and by Nguyen et al. (2012), observing the effectiveness and advantages of mobile devices as smart shopping assistant in retail stores.

However, none of these studies dealt with concrete design decisions of AR environments and their corresponding effects on the user, leading to a considerable research gap. As a result, informational design features like online recommender systems in AR commerce applications are practically used by many online marketplace websites, but are understudied in the context of AR research. Especially emerging AR-enabled techniques, such as simultaneous localization and mapping (Reitmayr et al., 2010), make it easy to collect and process information about the user and their surroundings by analysing the customer provided live picture.

2.2 Online recommendations

According to estimates, an amount of 10% to 30% of online retailers' sales are coming directly from recommendations (Mulpuru et al., 2007). Previous studies indicated that subjects, who consulted product recommendations, selected the recommended products twice as often as subjects who did not (Senecal and Nantel, 2004). Online recommendations are predominantly impersonal information sources as they usually consist of online word-of-mouth (OWM) (e.g., user reviews and ratings), on the one hand, and of ORSs, on the other hand.

OWM uses data provided by former customers to generate subjective experience-driven recommendations. Other peoples' opinions can be considered even more valuable than private information (Banerjee, 1992; Banerjee, 1993) and, eventually, influence the user's decision-making (McFadden and Train, 1996). However, CRs have their disadvantages and need certain circumstances to be effective. Since, the conformity effect is one of the reasons CRs work (Lascu and Zinkhan, 1999; Lee et al., 2008) there is an idle time before a critical number of votes or reviews is reached. Additionally, like bad reviews, a large number of too good reviews can also have a negative effect (Maslowska et al., 2016). Further, the ideal product for the majority of people, may not be the right choice for every individual customer. Moreover, CRs, as an additional source of information, reduce the seller's influence over the customer. If AR applications are able to give personalised and fitting product recommendations, CRs are possibly obsolete in AR commerce, leaving the influence over the customer to the seller. Therefore, the individual contribution of SRs and CRs need to be separately examined in AR contexts.

In comparison to CRs, recommendations made by sellers in online marketplaces are usually made by ORSs, using algorithms that work like "a salesperson who is highly knowledgeable about both the alternatives and the consumer's tastes" (Ariely et al., 2004, p. 81-82). These systems use variations of historical data (e.g., search and purchase history) and current data (e.g., consumer behaviour) to generate recommendations. Although recommendations can have great influence on product choice (Xiao and Benbasat, 2007) and are usually more influential than other sources (Senecal and Nantel, 2004), online transactions are typically between people or firms that have little information about each other. This makes them vulnerable to opportunistic behaviour (Ba and Pavlou, 2002). The competitive customer-seller-relationship (Evans and Beltramini, 1987) causes customers to assume that the sellers act mainly for their own good, making recommendations by their systems less trustworthy.

Despite the negative perception of SRs, ORSs are an important feature for the shopping experience in online markets because "a wealth of information creates a poverty of attention" (Simon, 1971, p.40). Although online marketplaces lower the search costs for product information and quality information (Stiglitz, 1989), the myriad of easily presentable product alternatives rises the search costs to identify the ideal product (Chen et al., 2004). The huge amount of possible alternatives creates heavy cognitive loads for customers, making it more difficult to choose (Chen et al., 2004). ORSs help customers to process the overwhelming amounts of information and alternatives by presenting a small selection of only relevant, fitting options to them (Häubl and Trifts, 2000; Senecal and Nantel, 2004). They reduce search costs and improve the quality of customer decisions, resulting in increased customer satisfaction (Hanani et al., 2003; Komiak and Benbasat, 2006; Xiao and Benbasat, 2007). In fact, customers who interacted with ORSs reported a more positive shopping experience than customers who did not (Felfernig and Gula, 2006).

2.3 Product fit uncertainty

Uncertainty is defined as a situation in which not all information is available, clearly defined or reliable (Merriam-Webster Dictionary, 2017). The uncertainty in online market places is distinguishable into seller uncertainty, the incapability of predicating the seller's behavior that arises from the information asymmetry, and product uncertainty, the lack of information that prevents a buyer to assess all characteristics of a product (Pavlou et al., 2007). Following Hong and Pavlou (2010) product uncertainty can be split into three distinct dimensions: description uncertainty (i.e., inability to identify product characteristics), performance uncertainty (i.e., uncertainty about product's future performance), and fit uncertainty (i.e., doubt if product's characteristics and buyer's needs match), with only product fit uncertainty yielding a significant effect on price premiums, satisfaction, product returns, and repurchase intentions.

The effectiveness of a recommendation depends on the type of product (Bearden and Etzel, 1982; Childers and Rao, 1992; King and Balasubramanian, 1994). In general, two categories of products exist: search goods and experience goods. In contrary to search goods, whose characteristics are easily observable before the purchase, the value of experience goods can only be truly determined by consuming or experiencing them (Nelson, 1970; Collier, 2012). Since it is impossible to completely evaluate their attributes, a purchase involves an amount of risk that has a direct negative effect on transaction behaviour (Jarvenpaa et al., 2000; Featherman and Pavlou, 2003). Pre-purchase information scarcity refers to the effect that customers can't evaluate all quality attributes before the purchase (Wells et al., 2011). Unlike consumers in retail who can examine products with their hands and eyes to assess the product's physical information, the disadvantageous circumstances of e-commerce lead to an even bigger information asymmetry which amplifies uncertainty (Chen et al., 2004; Wells et al., 2011).

2.4 Hypotheses and research framework

Although online marketplaces lower the search costs for product and quality information (Stiglitz, 1989), the myriad of easily presentable product alternatives automatically rises the search costs to identify the ideal product (Chen et al., 2004). The huge amount of possible alternatives creates heavy cognitive loads for customers, making it more difficult to choose (Chen et al., 2004). Studies have shown that ORSs help customers to process and handle the overwhelming amounts of information (Häubl and Trifts, 2000; Senecal and Nantel, 2004). In fact, subjects, who consulted product recommendations, selected the recommended product twice as often as subjects who did not (Senecal and Nantel, 2004).

Therefore, we hypothesise that customers take the evaluations of other customers and of the seller as an informational source that helps them determining whether they want to buy a product and if so, which item they will select (Ardnt, 1967; Olshavsky and Granbois, 1979; Duhan et al., 1997). Specifically, we expect that even in the new environment of AR, recommendations are accepted information cues and, therefore, increase the likelihood of the customer to buy a product.

H1a*: Customers will be more likely to buy a product if the presented products have been recommended by other customers in comparison to the situation without any CR*

H1b*: Customers will be more likely to select a product that has been recommended by other customers in comparison to a product without any CR*

H2a*: Customers will be more likely to buy a product if the presented products have been recommended by the seller in comparison to the situation without any SR*

H2b*: Customers will be more likely to select a product that has been recommended by the seller in comparison to a product without any SR*

Since uncertainties are caused by incomplete information availability, recommendations are able to compensate the drawbacks that arise from product uncertainty partially. In the current state, particularly OWM has proven to be more influential for experience goods than ORSs (Dellarocas, 2003; Godes and Mayzlin, 2004). By knowing other consumers' experiences, the uncertainty and perceived risk of buying is lowered (Lee et al., 2008) due to the conformity effect, influencing the customer's decision making and quality (Chen et al., 2004; Senecal and Nantel, 2004; Xiao and Benbasat, 2007).

Therefore, we hypothesise that recommendations are not only informational cues to indicate demand or reduce effort, but also sources to decrease the uncertainty related to product fit. The recommendation by other customers signals that the product has been bought and, thus, tested before and that the perceived likelihood that the product will work and fit in general is increased. With regards to SR, easy and detailed personal data collection through AR has two theoretical effects: First, when using the information extracted from customer's video stream it automatically provides an explanation on how and with which data the seller's system derives its recommendations, strengthening the users' trusting beliefs in the competence and benevolence of the system and resulting in an increased users' trust and satisfaction (Wang and Benbasat, 2004). Second, sellers can mitigate the customer's product fit uncertainty by giving highly personalised recommendations, derived from the characteristics of the customer's direct surroundings that fit in size, colour, and style. Thus, we expect that CRs and SRs, individually, will reduce product fit uncertainty and, thus, partly mediate the main effect on intention to purchase and selection of the offered products.

***H3a**: Product fit uncertainty will mediate the effect of CR on customer's intention to purchase*

***H3b**: Product fit uncertainty will mediate the effect of CR on product selection*

***H4a**: Product fit uncertainty will mediate the effect of SR on customer's intention to purchase*

***H4b**: Product fit uncertainty will mediate the effect of SR on product selection*

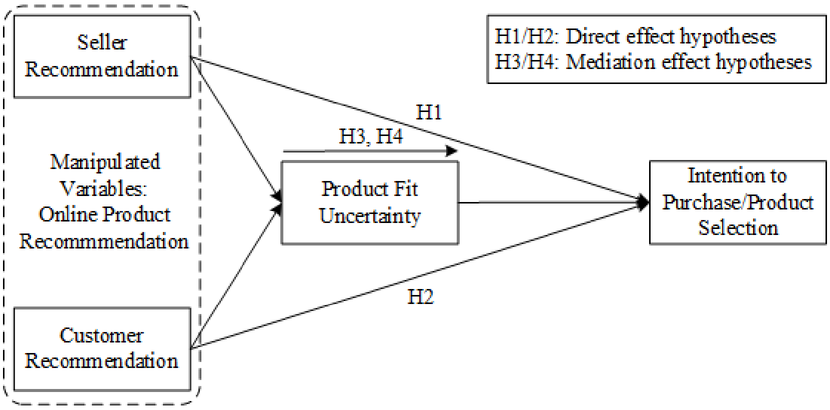


Figure 1. Research framework.

3 Research methodology

3.1 Experimental design

To test our hypotheses and the effectiveness of recommender systems in AR environments, a 2 (CR: absence vs presence) x 2 (SR: absence vs presence) full factorial design online experiments on computers was conducted. 208 Participants were recruited through Amazon Mechanical Turk (AMT), a business marketplace for on-demand workforce, and received a monetary compensation for their survey participation. Based on the recommendation by Goodman and Paolacci (2017), we only accepted AMT participants with an approval rate higher than 95%. The participants were set in a shopping scenario in which they were instructed to use an AR shopping application to buy furniture. We segmented the experiment into three parts. The first part started with a short introduction of the experiment's rule set and a simple definition and example of AR and AR commerce. In the second part, we told the attendees that they want to buy a new bookshelf for their living room. Afterwards the fictional company 'Augmented Furniture' was introduced through an ad and the participants were told that they decided to use Augmented Furniture's AR shopping application for their purchase. The next page showed a smartphone with a picture of a living room as a starting situation for the AR application. Scenarios with SR got two extra screens with manipulations that underline the SR calculation process. Then, the participants were presented a choice scenario with two different shelves, similar in most features: design, size, prize and colour. The participants then had to choose a shelf. At this point the buying process stopped. The final part of the experiment was a survey about the participants' shopping experience over multiple pages ending in a short debriefing.

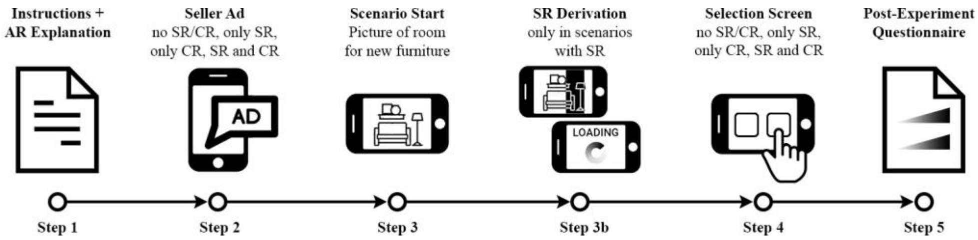


Figure 2. Experimental procedure.

3.2 Manipulation of independent variables

For the manipulations in the experiment, we used a SR and a CR to represent two different forms of online recommendation. The participants were randomly assigned to one of four groups that included either no recommendation, only a SR, only a star rating as established form of CR, or SR in conjunction with star rating. Figure 3 shows the ad of the fictional firm ‘Augmented Furniture’, including an extra text description for every type of recommendation used in a scenario, as a short introduction.

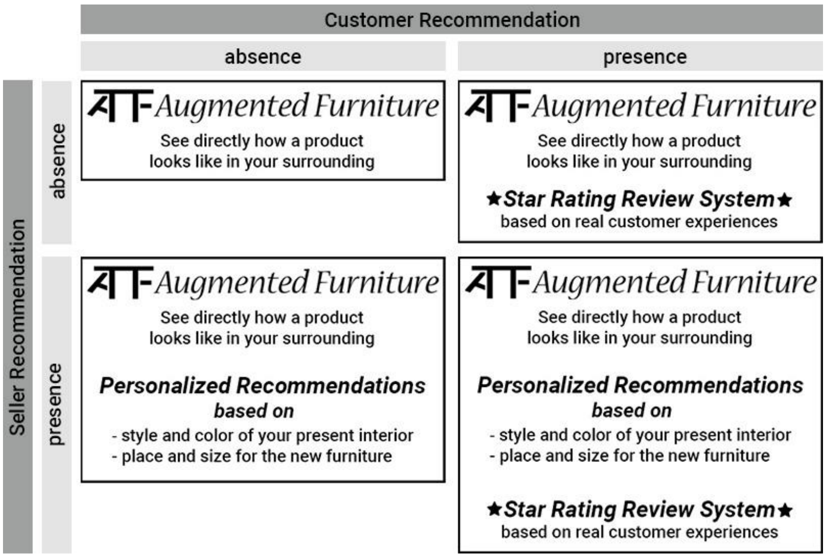


Figure 3. Ad configuration for different scenarios (2x2 full factorial design).

In the scenarios with the SR, participants received two extra screens prior to the selection screen to indicate and simulate that a personalised recommendation is calculated with a waiting time based on the individual properties of the room pictured in the live video feed (Moon, 1999). First, they saw an animation of the application scanning the whole room. Afterwards they were presented a loading animation, with a text ‘Please wait. We are looking for a product that is best for you’, in which the recommender system took the scanned properties into account and calculated the individual best fit product. After a certain while the calculations finished and the animation changed, displaying the recommended item with a text above saying ‘We have a recommendation for you’.

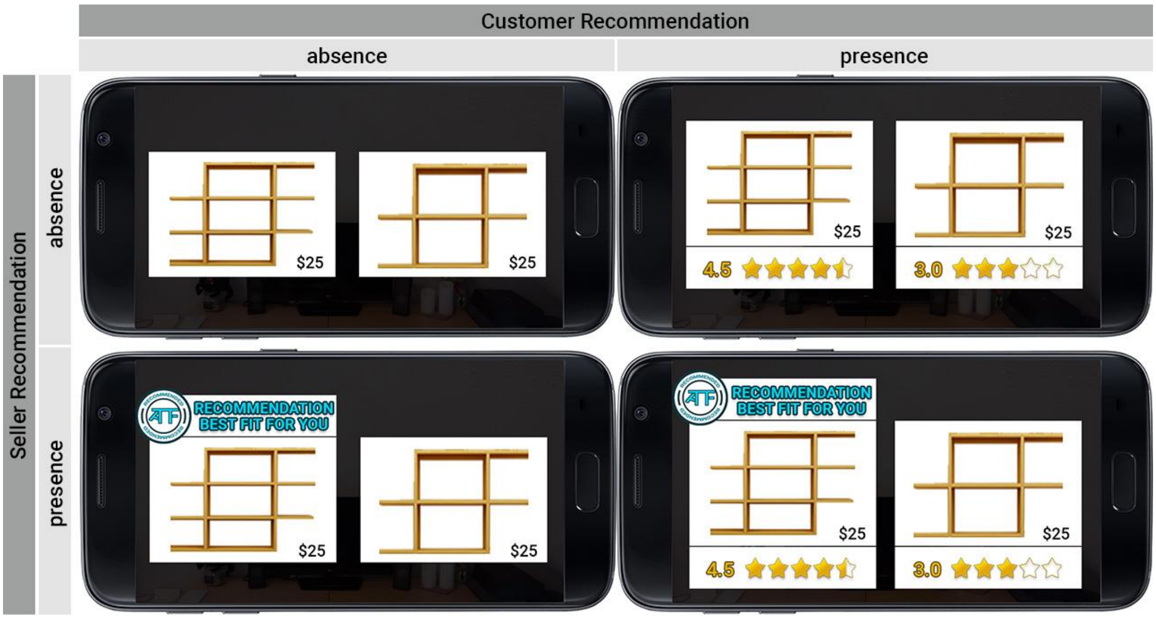


Figure 4. Selection screen for different scenarios (2x2 full factorial design).

The selection screen of all scenarios displayed the same two products. However, the left product, as the recommended option, was highlighted correspondingly to the used types of recommendation in each scenario. For SR, a text along with a logo that emphasized the connection between the recommendation and the firm ‘Augmented Furniture’ was added above the product. Further, Maslowska et al. (2016) found out that sales were higher for products with ratings between 4.2-4.5 stars and decreased for even higher ratings of 4.5-5.0 stars. To avoid cross-effects for the CR, the recommended left shelf got a rating inside the optimal rating range of 4.5 stars and the right shelf got a rating of 3 stars to be less preferable but still a valid alternative. SR and CR were positioned in their ‘usual positions’ where customer expect them to be, based on the practice of today’s top e-commerce websites (e.g. Amazon and Walmart). Star ratings are usually placed below, while seller recommendation (e.g. ‘Bestseller’) are usually placed above the product picture on the selection screen.

3.3 Dependent variables, control variables and manipulation checks

The dependent variables are the intention to buy any of the presented shelves as well as the proportion of the chosen shelves in the different conditions. While the intention to buy serves as an approximation for the likelihood to purchase in real life, the proportion of the chosen shelves indicates any shift in preferences between the available products. Whereas the intention to purchase was measured by an adapted single item (Meyers-Levy and Peracchio, 1996) on a 7-point Likert-type scale, we measured the proportion of shelves by a binary variable, which equals 0 when a participant selected the left (recommended) shelf and 1 when the right shelf was selected, divided by the total number of participants in the respective subgroups. The predictive validity of single items is comparable to multi-item measures (e.g. Bergkvist and Rossiter, 2007; Sarstedt and Wilczynski, 2009). Moreover, in addition to our mediator variable product fit uncertainty, we also tested for age, gender and various control variables that have been identified as the most influential drivers in extant literature: The items for product fit uncertainty (PFU) were adapted from Hong and Pavlou (2014), seller uncertainty (SU) and product quality uncertainty (PQU) from Dimoka et al. (2012), product involvement (PI) from Zaichkowsky (1985), familiarity with product class with regards to previous knowledge (PK) and usage experience (PE) with shelves and augmented reality applications from Johnson and Russo (1984). Moreover, we used several items from the scale about risk propensity (RP) from Meertens and Lion (2008) and need for conformity (NFC) from Bearden and Rose (1990). All aforementioned items were measured on a 7-Point Likert-type scale with anchors majorly ranging from strongly disagree (1) to strongly agree (7). All scales exhibited satisfying levels of reliability ($\alpha > .7$). A confirmatory factor analysis also showed that all analysed scales exhibited satisfying convergent validity. Furthermore, the results revealed that all discriminant validity requirements (Fornell and Larcker, 1981) were met, since each scale’s average variance extracted exceeded multiple squared correlations. Since the scales demonstrated sufficient internal consistency, we used the averages of all latent variables to form composite scores for subsequent statistical analysis. Online shopping experience and internet usage were measured based on respondents’ statements in years and hours per week, respectively. Lastly, one attention and two manipulation check questions were included in the experiment. We used the checks to ascertain that participants comprehended and followed the instructions and that our manipulations were successful and noticeable. Moreover, we used one item to measure perceived popularity of the left shelf (Van Herpen et al., 2009) to check the manipulation of our CR directly. Additionally, we assessed participants’ perceived degree of realism and overall comprehension of the instructions and presented information with two items on a 7-point Likert-type scale.

4 Analysis and results

4.1 Sample description, controls and manipulation checks

208 participants were included in the final dataset. 291 respondents filled out the survey without missing a question or failing our attention check. Out of these 291, 83 were removed because they failed our manipulation checks and could not properly recall either whether and how many stars the present-

ed products had or whether the application explicitly recommended a shelf. The average age of the respondents was 37 years, ranging from 18 to 72. Table 1 summarizes the descriptive statistics of the data.

	Mean	StD
Demographics		
Age	36.93	11.55
Gender (Females)	56%	
Controls and Mediator		
Seller Uncertainty (SU)	3.09	1.03
Perceived Quality Uncertainty (PQU)	3.48	1.17
Product Involvement (PI)	4.23	1.70
Risk Propensity (RP)	5.09	1.06
Need for Conformity (NFC)	4.00	1.21
Online Time (hours/week)	28.50	18.38
Online Shopping Experience (years)	10.89	4.95
Product Knowledge: Shelves (PK_S)	4.34	1.61
Product Experience: Shelves (PE_E)	4.90	1.64
Product Knowledge: AR (PK_AR)	3.09	1.80
Product Experience: AR (PE_AR)	2.64	1.66
Product Fit Uncertainty (PFU)	3.91	1.54

	Mean	StD
Dependent Variable		
Intention to Purchase		
SR absent _ CR absent	3.76	1.73
SR present _ CR absent	4.33	1.86
SR absent _ CR present	4.44	1.72
SR present _ CR present	4.93	1.65
Selection (Left Shelf)		
SR absent _ CR absent	59%	
SR present _ CR absent	67%	
SR absent _ CR present	89%	
SR present _ CR present	89%	

Table 1. Descriptive statistics of demographics, controls, mediators and dependent variables. (means, standard deviations, N = 208)

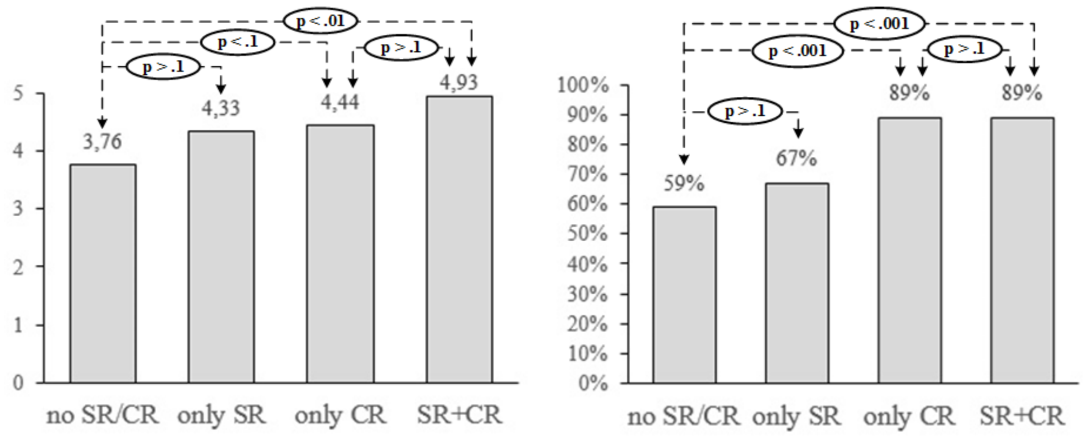


Figure 5. Results and comparisons for the dependent variables intention to purchase (left) and product selection of shelf A (right) for the various conditions.

We conducted several one-way ANOVAs to determine whether the random assignment of participants to the different experimental outcomes was successful. The results confirm the success since no significant difference (p>.1) was found between the experimental groups. Consequently, respondents' demographics and controls were homogenously present across our four conditions and do not confound the effects of our manipulations. Moreover, we checked whether our manipulation by CR also impacted perceived popularity. Results demonstrate that perceived popularity of the left shelf was significantly higher among the two groups with the CR than in the two without (F=61, df=1, p<.001). To check for external validity, we assessed the participants' answers regarding their perceived degree of realism of the experiment. Degree of realism reached high levels ($\bar{x}$ = 4.99, σ=1.52), thus we can assume that the manipulations worked as intended and the experiment was considered realistic.

4.2 Main effect analysis

To test the main effect hypotheses, we first performed a three stage hierarchical linear regression on the dependent variable intention to purchase (see Table 2), following other researchers (e.g., Hayes, 2017, p. 71) who consider OLS regression an acceptable analysis for examining our dependent variable. We first entered all controls (Block 1), then added the manipulations SR and CR (Block 2) and lastly inserted the mediator product fit uncertainty (Block 3). Although CR (p<.05) demonstrated a statistically significant direct effect for intention to purchase, SR surprisingly did not (p>.05). After adding our mediator, product fit uncertainty showed a statistically significant effect (p<.001), while CR was still significant, indicating partial mediation. Therefore, our findings show that participants confronted with a CR have significantly higher intentions to purchase than those who are not confronted with CR, regardless whether the application presented a SR or not. This indicates that presenting customers CRs in augmented reality applications increases the likelihood of them to purchase a product.

	Block 1		**Block 2**		**Block 3**	
	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Intercept	.326	0.949	.105	0.978	3.175**	0.978
Manipulation						
SR			0.334	0.182	0.224	0.166
CR			0.524**	0.184	0.355*	0.170
Mediator and Controls						
PFU					-.465***	.074
SU	.073	.138	.089	.135	.028	.123
PQU	-.250	.132	-.275*	.129	-.096	.121
Gender	.453	.213	.380	.209	.296	.192
Age	.004	.009	.001	.009	-.001	.008
PI	.606***	.062	.585***	.061	.399***	.063
RP	-.083	.094	-.071	.092	-.046	.086
NFC	.230**	.078	.245**	.077	.146*	.072
OTime	-.006	.005	-.007	.005	-.005	.005
OShopping	.003	.021	.010	.020	.023	.019
PK_S	-.012	.098	-.005	.096	.011	.087
PE_S	.026	.090	.040	.088	.053	.081
PK_AR	.030	.102	.060	.100	.106	.091
PE_AR	-.033	.108	-.070	.106	-.081	.097
Adjusted R^2	0.448		0.473		0.561	

*Note: * p<.05; ** p<.01; *** p<.001, N = 208.*

Table 2. OLS linear regression on intention to purchase.

Moreover, we also investigated the effect of SR and CR on the proportion of the chosen shelves. Therefore, we performed a three stage hierarchical binary logistic regression on the dependent variable selection (Table 3). Just as before, we first entered all controls (Block 1), then added the manipulations SR and CR (Block 2) and lastly inserted the mediator product fit uncertainty (Block 3). Again, we inspected Nagelkerke's R^2 and computed χ^2-Statistics to examine the model's significance for all stages. Similar to the effect on intention to purchase, our SR did not display a significant effect on the selection of the products but CR did (b=-1.740, Wald statistic (1) = 12.745, p<.001). If customers see a CR that clearly favours a product, they are more than five times as likely to choose the recommended product (coded as 0) in contrast to the other presented product (coded as 1). When we added the mediator, perceived fit uncertainty exhibited a significant influence on selection as well (p<.001) while CR was still significant, indicating partial mediation. Thus, the higher the perceived fit uncertainty of the left shelf, the less likely people will choose that product.

	Block 1			**Block 2**			**Block 3**		
Intercept	Coeffi-cient	S.E.	Exp(B)	Coefficient	S.E.	Exp(B)	Coefficient	S.E.	Exp(B)
Constant	3.171	1.860	23.841	3.867*	1.969	47.816	-5.297	2.902	.005
Manipulation									
SR				-.008	.384	.992	.404	.460	1.498
CR				-1.693***	.416	.184	-1.740***	.487	.176
Mediator and Controls									
PFU							1.263***	.254	3.536
SU	-.395	.265	.674	-.469	.283	.625	-.137	.321	.872
PQU	.108	.252	1.114	.153	.268	1.166	-.270	.317	.764
Gender	-.131	.415	.878	-.161	.458	.851	.248	.533	1.281
Age	-.015	.019	.986	-.012	.021	.988	-.010	.025	.990
PI	-.447***	.121	.640	-.440***	.127	.644	.023	.170	1.023
RP	-.255	.183	.775	-.166	.198	.847	.029	.238	1.029
NFC	-.180	.151	.835	-.274	.165	.760	.013	.214	1.013
OTime	-.019	.011	.981	-.019	.011	.982	-.029*	.014	.971
OShopping	.056	.039	1.057	.046	.042	1.047	.045	.052	1.046
PK_S	.126	.205	1.135	.174	.218	1.190	.289	.262	1.335
PE_S	-.022	.188	.978	-.079	.201	.924	-.273	.235	.761
PK_AR	.349	.196	1.417	.384	.213	1.468	.270	.255	1.310
PE_AR	-.262	.208	.770	-.266	.221	.766	-.148	.272	.862
-2 (Log Likelihood)	193.823			174.701			135.419		
Nagelkerke's R^2	0.209			0.324			0.528		
Omnibus Model $\chi 2$	30.902**			50.024***			89.305***		

Note: * p<.05; ** p<.01; *** p<.001, N = 208.

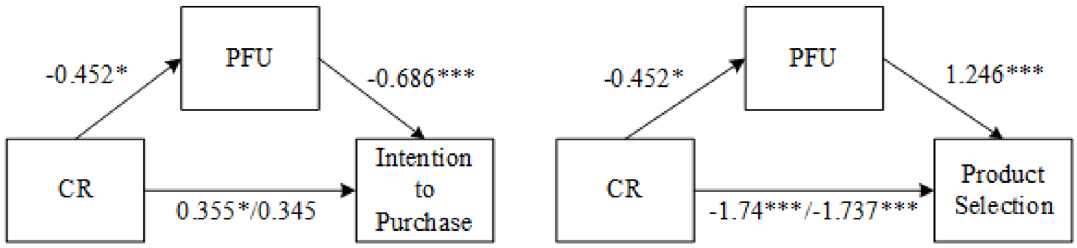
Table 3. Binary logistic regression on product selection.

4.3 Mediation effect analysis

For our mediation hypotheses we argued that the CR would affect the intention to purchase as well as the selection of the bookshelf through the perceived product fit uncertainty. Thus, we hypothesized that in the presence of a CR the product uncertainty decreases and, hence, the intention to purchase increases and selection of the recommended product is more likely. Therefore, in a mediation model using bootstrapping with 1,000 sampled and 95% bias-corrected confidence interval, we analysed the indirect effect of our CR on intention to purchase and selection through product fit uncertainty. We conducted the mediation test applying the bootstrap mediation technique (Hayes, 2013).

To analyse the process driving the effect of our CR on intention to purchase (product selection), we inserted product fit uncertainty as our potential mediator between CR and intention to purchase (product selection). For our dependent variable intention to purchase, the indirect effect of CR was statistically significant, thus perceived fit uncertainty mediated the relationship between CR and intention to purchase: indirect effect = 0.31, standard error = 0.135, 95% bias-corrected confidence interval (CI) = [0.072, 0.621]. Moreover, CR was negatively related with product fit uncertainty (b= -0.452, p<.05), and higher perceived product fit uncertainty was associated with lower level of intentions to purchase (b=-0.686, p<.001; see Figure 6), whereas the direct effect of our CR became insignificant (b=0.345, p>.05) after adding our mediator product fit uncertainty to the model.

Therefore, our results demonstrate that product fit uncertainty significantly mediated the impact of CR on intention to purchase: Our CR reduced the product fit uncertainty and, thus, increased the intention to purchase. Similar results could be found when inserting product selection as our dependent variable: indirect effect=-0.564, standard error = 0.334, 95% bias-corrected confidence interval (CI) = [-1.116, -0.002]. However, product fit uncertainty only partially mediated the effect of CR on selection (Figure 6). The reason for this mismatch is that other aspects that may also influence product selection were not considered. For example, the bandwagon effect (Van Herpen et al., 2009) states that if people have to select a product they tend to follow the crowd but it does not increase the intention to purchase the product. We conducted the same mediation analyses with SR as our independent variable on intention to purchase and product selection as dependent variables, yet no significant direct or indirect effect could be observed.



Note: Coefficients were computed based on mediation analysis using bootstrapping with 1,000 samples and a 95% bias-corrected confidence interval (Hayes, 2013); we included both manipulations and all control variables in the analysis; the first coefficient on a given path presents the direct effect without the mediator in the model. The second coefficient presents the direct effect when the mediator is inserted in the model. * p<.05, ** p<.01, *** p<.001.

Figure 6. Mediation analysis.

5 Discussion, implications and future research

In the past, IS AR research has majorly focused on topics regarding the development of new AR technologies and has neglected user behavior. This imbalance implies the risk that users are omitted while technology advances. The objective of our paper was to shed light on some of the effects on users of the relatively new, but steadily growing broad market AR technology. Therefore, two forms of online recommendations, seller and customer recommendation, were tested in an AR commerce environment. Our results strongly support our hypotheses that customers can be nudged in their product selection and purchase behaviour by online recommendations. However, not all online recommendations are significantly influential as demonstrated. Our findings show that CR is an influential information source, whereas SR is not. Moreover, the effect of CR was mediated by product fit uncertainty, reflecting the influence of other customers' recommendations on the parts of perceived risk associated with buying the product. However, no effect was found for the SR manipulation.

This paper contributes to AR IS literature by merging the research on a rising technology that is on the verge to sustainably change the way customers shop with human-centered investigations of the effects of SRs and CRs on users in the early stages of AR commerce. The study's main theoretical implication relates to the impact of online recommendations on customer's online purchase intention and product selection. The results extend existing online product recommendation research by showing that the effects of SRs and CRs in AR environments are similar to the effect in traditional online market places. As the Internet emerged and online commerce started to bloom, customers have gained access to new sources of information that can provide non-personalised recommendations, such as customer reviews in form of star ratings, as well as personalised recommendations, such as seller recommendations. Even though past results showed that personalised recommendations influence more than non-personalised ones (Brown and Reingen, 1987; Senecal and Nantel, 2004), that is not true for seller recommendations. Particularly, the collected data does not reflect the expected theoretical advantages that an AR-based commerce system may have for customers and sellers with personalised recommendations that are directly derived from real-world data. Consequently, AR's full potential it not usable at the moment, so in relation to SRs AR commerce cannot exceed the other more established e-commerce platforms, yet. Although, the existing algorithms in AR can create individualized value for customers, there are two possible reasons preventing SRs from having a significant impact on the intention to purchase or product selection. First, especially in e-commerce scenarios in which all contact points are impersonal, the competitive customer-seller-relationship (Evans and Beltramini, 1987) creates suspicion that prevents customers from trusting the recommendation. Second, emerging technologies usually miss user acceptance (Davis et al., 1989) and therefore fail to utilise their full potential. Thus, users underestimate the true value and usefulness of the AR SR in the beginning. The results could change in the next few years if AR is used more frequent and becomes accessible for a broader market. More and more people will get familiar with AR technology, and user acceptance may rise. Consequently, our study contributes to AR IS literature and consumer research by analysing the influences of emerging recommender systems and influences on customer decision processes as AR and technology in general advance.

Our paper carries practical implications for marketers as well. First, we demonstrated that CRs are also influential and worthwhile in AR applications. Precisely, customers were more than five times as likely to choose a customer recommended product. The tested star rating is by far the most established form of online-word of mouth and is, therefore, known by almost every customer that has ever bought something online. The outcomes of our study extend the manifold research and applications by validating its effectiveness in a new technological environment. Second, the results showed that CRs decreased the perceived uncertainty of users and thereby mediated the impact of the manipulation. For practitioners this leads to the conclusion that star ratings are accepted and work as intended in AR environments and can directly be used as usual in AR commerce applications. However, these observations were only significant when taking customers as a source of information. When the seller functioned as the source and provided a recommendation with regards to personalised product fit, no significant effect was found. Even though an AR application enables advanced technologies that might be able to give individual and highly fitted recommendations, as for our experiment these endorsements had no effect on the outcome at all. Consequently, practitioners who want to use automatically generated recommendation in AR commerce at that moment have to address the acceptance and trust of the customer, for example, potentially by communicating the advantages more strongly and explaining how exactly the system derives the recommendations. The value for the customer seems to exist but is not yet accepted.

Moreover, since research on AR, online product recommendations and product uncertainty has just begun, our study provides several more avenues to explore. This paper is a basis for future research focusing on the phenomenon of SRs in AR environments and finding determining reasons for their ineffectiveness. Since the study was conducted in an experimental setting with a simplified version of an AR application and with people from the crowdsourcing platform AMT, future research needs to confirm and refine the results in a more realistic setting, such as a field study with a real AR application and gear. Further, a longitudinal design approach can be used to measure the influence when people get more and more used to AR over time. Furthermore, other established and emerging recommendations need to be examined in AR. With our study we investigated the effects on product fit uncertainty and controlled for seller uncertainty and product quality uncertainty, but other forms of effects of ORSs, such as perceived enjoyment, perceived decision quality, perceived product diagnosticity and perceived decision effort (Xu et al., 2014), need to be researched as new technologies and, thus, new forms of value creation will evolve. Lastly, our study does not experimentally and statistically explain why SR was not significant in contrast to CR. Comprehending the current state of the acceptance of the AR technology as well as the SR is a worthwhile endeavour for future research to help AR technology and SRs keep developing and finding more acceptance regarding use and value creation for customers.

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