Who Wants to Use an Augmented Reality Shopping Assistant Application?

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Abstract: Brick-and-mortar retailers need to stay competitive to the convenience provided by online channels. Technologies, such as personalized shopping assistants on smartphones can empower customers in-store towards a similar experience as in an online scenario. For instance, an augmented reality shopping assistance application with explainable recommendations (XARSAA) can mimic the behavior of recommender systems in personalizing offers to consumers in physical shops. However, before deploying such technologies, it is essential that retailers get to know the demographics of their customer base. Existing literature rarely addresses the influence of customers demographics towards XARSAA technologies. Therefore, we follow a design science approach, and develop an instantiation of a XARSAA artifact, which is artificially evaluated through a controlled online user experiment with 315 participants. Results illustrate multiple demographics which influence customers attitude towards an augmented reality shopping assistant application in brick-and-mortar stores. Additionally, we provide insights into the design of such technology to guide researchers in its implementation.

1 INTRODUCTION

Brick-and-mortar businesses are currently struggling. For example, emblematic companies such as J. Crew, GNC, and Brook Brothers, went bankrupt, leading some researchers to describe the situation as the "retail apocalypse". Still, physical stores certainly provide value to customers on their shopping journey, taking a crucial role in the product information search point (Pimenidis et al., 2019); To counter the "retail apocalypse," the sector and literature propose traditional retailers to transition into omnichannel retail. This retail model leverages technologies (e.g., recommender systems, explainable artificial intelligence, augmented reality, and smart devices) in order to create digital services around the customer experience (Lemon and Verhoef, 2016).

One manifestation of this is a personalized digital assistant that boosts the customer journey (Parise et al., 2016) as it allows retailers to suggest tailored options that can positively stimulate the customer. For instance, digital shopping assistants, levering explainable recommendations, are well regarded to enhance sales and profit online (Cirqueira et al., 2019a), as they provide customers with personalized offers and reasons, which clarify and improve their decision-making toward purchases (Zimmermann et al., 2019), leading to higher satisfaction and retention (Gao et al., 2019).

However, research exploring the impact of explainable recommendations in brick-and-mortar stores it is still scarce, which is why retail managers and practitioners lack guidance on how to implement such technology into their customers' customer journey in the most effective way.

An essential requirement for such technology would be to identify a typical user profile of cus-

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tomers who want to use explainable recommendations in brick-and-mortar stores (Peker et al., 2017). Additionally, retailers usually assess their customer groups based on demographics (Antony et al., 2018). Such analysis is essential as it influences the types of products, offers, and bundles which a retailer can plan (Wetzlinger et al., 2017). Furthermore, when implementing novel technologies in-store, it is fundamental to assess the potential acceptance of different customer profiles for such technologies (Ren et al., 2018).

Hence, this study investigates how customers' demographics influence the perception of an augmented reality shopping assistance application with explainable recommendations (XARSAA). Consequently, we address the following research question: I: Which customer demographic influences the customer perception of an XARSAA? II: Which demographics does the target audience of an XARSAA have?

We tackle the research questions following a design science approach, mainly focused on the stages of problem and objectives identification, development and artificial evaluation. We instantiate an XARSAA application and assess the feasibility of such an instantiation in increasing perceived usefulness, informativeness, irritation, purchase intention, and trust in the technology in-store, based on the model of (Hausman and Siekpe, 2009), and (Hoffman et al., 2018). The instantiation is evaluated following an artificial evaluation approach, through a controlled online user experiment with 315 participants.

The paper is structured as follows: Section 2 presents related work. Section 3 illustrates the research methodology and details on the study development. Section 4 provides the study results. Section 5 discusses results and main findings, followed by section 6 which focus on the current limitations of the study, as well as future work. Closing, the section 7 concludes the paper.

2 RELATED WORK

We review the state-of-the-art trends in the retail domain, as well as previous approaches in deploying recommender systems in physical stores as the underline mechanism to provide personalized shopping assistance. This allows us to identify limitations in the current corpus and draw motivation for our study, as the investigation of the feasibility of an XARSAA prototype in-store, also integrating Explainable Artificial Intelligence (XAI) methods.

2.1 Digital Retail

The concept of the digitization of retail has become quiet the trend starting with e-commerce and internet-based companies, such as Amazon.com, Otto.com, and many others. It expanded into different channels and customer touchpoints such as smartphones and social media.

Consequently, retailers rapidly began to target customers across different channels, giving birth to what is now known as the multi-channel retail approach. In turn, this is slowly morphing into omnichannel retail, which integrates all channels and touchpoints into a single seamless customer experience. In parallel, companies have started adopting customer experience at the center of the business model, and digital technologies are deployed to enhance that experience (Parise et al., 2016), (Rigby, 2011).

Accordingly, McKinsey's Consulting affirms that with omnichannel retailing, retailers can do personalized advertising and promotion via devices, such as the increasingly ubiquitous devices (MacKenzie et al., 2013); smartphones as the archetype of this devices (Pimenidis et al., 2019), which can also be enhanced by technologies that are prognostic to revolutionary the retail sector, such as, Augmented Reality (von Briel, 2018).

In (Parise et al., 2016), the authors acknowledge the problem of meeting customers' expectations in brick-and-mortar and evaluate how digital technologies can aid in the improvement of customer experience and in the transition to omnichannel retail. The authors consider in-store touchpoints essential, and identify digital shopping assistance as one of the key solutions to battle brick-and-mortar challenges to meet customers' expectations. The digital shopping assistant provides a more holistic experience for the customers in the physical stores, boosting utilitarian value through efficiency in information search and product comparison, as well as hedonic value creating a more immersive experience leveraging technologies such as augmented reality, thus, stimulating the customer perception of fun, pleasure, and enjoyability (Juaneda-Ayensa et al., 2016) – crucial factors influencing customers' shopping experience.

2.2 Explainable Recommendations

Recommender engines have helped online commerce in the past decades, providing customers with a more personalized experience, which has led to a high-impact on retails sales and customer retention (Amatriain and Basilico, 2015), (MacKenzie et al., 2013)

(Cirqueira et al., 2019b). The recommender systems work as a type of information filtering that leverage machine learning techniques, to determine users' preferences to generate a ranked list of products relevant for the users, based on their past behavior and similarities to other customers, as well as patters in items information (Mora et al., 2020). These engines allow enterprises to better understand how they can target customers or potential buyers, understanding customer experience throughout the customer journey (Lemon and Verhoef, 2016). Recommender systems provides utilitarian value for the users as it boosts efficiency on information searches, and product comparison (Pimenidis et al., 2019) – key stages on the path-to-purchase (Shankar et al., 2011), with the potential to enhance the digital sales conversion.

While AI empowers recommender systems, researchers have also considered the value of Explainable AI supporting in such application. Explainable AI research aims to enable understanding of AI predictions, while keeping good learning performance (Adadi and Berrada, 2018). Explainable AI has the potential to support decision-making of AI users, and enhance their experience and trust while dealing with automated partners (Cirqueira et al., 2020). In the context of recommender systems, explainable recommendations aim to enhance shopping experience, through high quality and intuitive recommendations, which are easy to consume (Wang et al., 2018). Indeed, it has been shown that such explanations increase purchase intention (Chen et al., 2019). In (Zhang and Chen, 2018), the authors classify explanations in the context of recommender systems within five types: 1) User or Item-Based; 2) Feature-Level; 3) Textual; 4) Visual; and 5) Social.

User or Item-Based explanations regard similar users and products to recommend items to a user. Feature-level refers to important features of a product, which a customer usually considers to make purchases. Textual explanations are presented as natural language sentences for a user to read. Visual explanations highlight features on the image of a product which are important for recommendations. Social explanations are connected to friends and social media activities to illustrate how a particular product is perceived to a user. Those have been explored in the scenarios of restaurants (He et al., 2015), E-commerce shopping (Cheng et al., 2019), movies recommendation (Huang et al., 2019).

However, it is lacking the assessment of explainable recommendations with augmented reality for retailers' assessment of such technologies when dealing with different customer profiles and demographics in-store.

3 RESEARCH METHODOLOGY

This research follows a Design Science Research methodology (Peffers et al., 2007). That methodology is suitable when taking and information systems perspective for a study, which considers the requirements of users for the development of a system fulfilling such requirements with an organization (Gregor, 2006; Creedon, 2016). Furthermore, it provides clear steps for identifying the problems within an organization, and for assuring rigor and relevance of a research outcome by analyzing the state of the art and practice, and to assure a problem is relevant for practitioners and industry. In addition, the methodology guides the development of an artefact to solve the problem, and the interaction with practitioners to guarantee it is fulfilling the research requirements.

In our study, we focus on investigating the impact of an application on customers attitude moderated by demographics, which might affect their willingness for shopping in-store. Given those aspects and connection to our research goals, we adopt this methodology to guide the development of this study, focused on the stages of problem and objectives identification, development, and artificial evaluation step.

We started by investigating the problem, based on the literature review described in section 2 and discussions with practitioners within the PERFORM Training Network (Perform, 2020), which is a Horizon 2020 project and consortium composed of retailers and universities. We perceived the problem as the lack of understanding how customer demographics influence customers acceptance of an XARSAA in-store. This is a barrier for retailers aiming to invest in innovative technologies in their physical shops. The research objective was then settled as to develop an XARSAA tool as an artifact, and assess the performance of its instantiation, moderated by demographics influencing the users attitude towards such a tool in-store.

Therefore, from the literature review and discussions with practitioners, the requirements for developing the XARSAA are to develop an XARSAA: R1) within a mobile user-interface; R2) based on past shopping data of customers; R3) enabling explainable recommendations for shopping in-store; R4) to evaluate the developed XARSAA artefact through its instantiation regarding the attitude of users moderated by their demographics.

Figure 1: Smartphone-based artifact illustration leveraring AR recommendations enhanced by XAI for the participants.

3.1 Mobile-based Augmented Reality Shopping Assistance Application

For development of the artifact and its instantiation, the proposed XARSAA, which customers can use throughout their shopping journey in brick-and-mortar stores, is developed as an application running on an android-based smartphone device. In our scenario, while the app is deployed by the retailer, the device is owned by the customer. Thus, the device has access to personal information, which is needed to provide tailored recommendations (e.g., social media, historical purchase data). We conceptualize the artifact instantiation to provide augmented content, anchored around the product of interest, and it displays recommendations, offers, and comparison of items on the smartphone as shown in Figure 1, besides to a buy option.

In this stage of the prototype development, the XARSAA leverages the smartphones camera to first detect the customers' object of interest (product-item), then the application can monitor the user's cameras field of view to determine which product is being examined by users at each point in time, as well to track the item in the physical space under the camera field of view overtime. The involved object recognition can be realized using SDKs such as Vuforia (Microsoft, 2019). Furthermore, the application displays multiple digital buttons (UI) anchored around the product to trigger and display relevant content using augmented reality.

3.2 Survey

Because of the early stage of our artifact, artificial artifact evaluation was conducted by using an online survey as this is the first evaluation and an online survey provides a fast and efficient way to get a sufficient number of participants. In the survey, participants were introduced to the concept of an XARSAA instantiation with the help of pictures and videos.

To measure participants attitude towards an XARSAA we adopted a questionnaire design proposed by Hausman and Siekpe (Hausman and Siekpe, 2009). Consequently, we measured the participants attitude towards the XARSAA with the constructs "Usefulness" (4 items), "Entertainment" (3 items), "Informativeness" (3 items), "Irritation" (3 items) and "Purchase Intention" (4 items). Additionally, we measured trust towards an XARSAA adopting a scale from Hoffman et al. (Hoffman et al., 2018) (6 items). Items were measured using a 5-point Likert-type scale ranging from "Completely Disagree" to "Completely Agree" and the sequence of questions was randomly shuffled to avoid order bias. Complementing, we asked participants open questions to get their general sentiment ("Yes, I agree" / "No, I disagree") about the presented XARSAA (5 items) as well as questions about their demographics ("Age","Gender","Income","Shopping Type", "Education"). The questionnaire was conducted using the software Surveygizmo (SurveyGizmo, 2020). An overview of all questions asked can be found in Table 3.

3.3 Participants

We recruited participants using a crowd-sourcing provider called Clickworker (Clickworker, 2020a) as this provider ensures a high level of qualification of their crowd workers by requiring the use of real personal data, testing of writing and language skills and a constant evaluation of their workers results (Clickworker, 2020b).

In total, we recruited 315 participants from the DACH region (Germany, Austria and Switzerland). To enrich the quality of our sample, we excluded participants who took less than seven minutes to complete our survey, used the same IP multiple times to answer the survey, or entered only one word or random letters in the open questions as the credibility of these participants is questionable. The resulting sam-

Table 1: Statistical Tests.

Construct	n	Age	Gender	Income	Shopping Type	Education
Usefulness	251	0.370^R	0.005^M	0.031^K	0.604^K	0.694^K
Entertainment	251	0.432^R	0.057^M	0.112^K	0.087^K	0.969^K
Information	251	0.338^R	0.173^M	0.007^K	0.040^K	0.851^K
Irritation	251	0.357^R	0.674^M	0.016^K	0.848^K	0.418^K
PI	251	0.160^R	0.002^M	0.082^K	0.006^K	0.505^K
Trust	251	0.631^R	0.002^M	0.445^K	0.192^K	0.528^K
Q1	240	$<0.001^T$	0.142^C	0.724^M	0.746^M	0.147^M
Q2	231	0.106^T	0.411^C	0.793^M	0.327^M	0.137^M
Q3	230	0.349^T	0.073^C	0.370^M	0.990^M	0.887^M
Q4	213	0.901^T	0.037^C	0.710^M	0.029^M	0.719^M
Q5	229	0.325^T	0.080^C	0.430^M	0.361^M	0.814^M

Note: R (Regression), T (T-Test), M (Mann-Whitney-U-Test), C (Chi Squared), K (Kruskal-Wallis-Test), PI (Purchase Intention)

Table 2: Bonferroni adjusted post-hoc tests and effect sizes.

D-C	Group Comparison	n1/n2	M1/ M2	T/Z/Chi	Sig.	d
Age - Q1	Yes-No	109/131	34.03/39.92	3.929	<0,001	0.509
Gender - Usefulness	Female-Male	131/118	3.18/3.55	-2.788	0.005	0.357
Gender - PI	Female-Male	131/118	2.92/3.31	-3.056	0.002	0.393
Gender - Trust	Female-Male	131/118	3.0/3.26	-3.066	0.002	0.395
Income - Information	<1000€- 1000€-1999€	63/84	3.41/3.90	-3.235	0.018*	0.554
Income - Irritation	1000€-1999€- 2000€-2999€	84/53	2.20/2.79	-3.194	0.021*	0.567
Shopping Type - PI	NAF-VF	25/42	2.6/3.42	-3.412	0.006*	0.917
Shopping Type - Q4	Yes-No	96/117	2.90/2.61	-2.189	0.029	0.303

Note: D - C (Demographic - Construct), M (Mean), Q (Question; see Appendix), d (Cohens's d), NAF (Not at All Frequently), VF (Very Frequently), PI (Purchase Intention), * (Bonferroni Adjusted)

ple included 251 participants between the age of 18 to 69 (mean age = 37.43, SD = 12.06) of which 131 (52.2%) were female, 118 (47%) were male, and 2 (0.8%) were divers. Looking at the participant's education, 16 (6.4%) had "Some secondary education (high school)", 69 (27.5%) "Completed secondary education (graduated high school)", 97 (38.6%) had "Some undergraduate education (college or university)", and 69 (27.5%) "Completed postgraduate education (masters or doctorate)". From the participants, 63 (25.1%) had a monthly net income of less than 1000 €, 84 (33.5%) earned between 1000 €and 2000 €, 53 (21.1%) earned between 2001 €and 3000 €, 29 (11.6%) earned between 3001 €and 4000 €, 15 (6%) earned between 4001 €and 5000 €and 7 (2.8%) earned more than 5000 €. Participants shopping frequency in the last 30 days was as follows, 25 (10%) "Not at all frequently", 63 (25.1%) "Slightly Frequently", 114 (45.4%) "Moderately Frequently", 42 (16.7%) "Very Frequently", and 7 (2.8%) "Extremely Frequently".

3.4 Statistics

To analyze for significant impacts of participants demographics on their attitude towards an XARSAA we performed the following statistical tests: We used a linear regression to check for a correlation between "Age" and attitudes, a Mann-Whitney-U-Test to check for single group differences in "Gender", and a Kruskall-Wallis-Test for multiple group differences in "Income", "Shopping Type", and "Education". When statistically significant differences were identified, we complemented the Kruskall-Wallis-Test with Bonferroni adjusted post-hoc tests to pinpoint the significant group differences. Despite having used Likert scales, we calculated this analyzes using the mean values of each construct as we regard the psychological difference of the items on the used Likert scales as equal and in such cases, Likert scales can be regarded as a continuous scales and their resulting data as interval data.

Additionally, we analyzed the influence of participant's demographics on their shown sentiment when answering the open questions using a T-Test (“Age”), Chi-Squared (“Gender”), and Mann-Whitney-U-Test (“Income”, “Shopping Type”, “Education”). We excluded participants who gave no answer or answered “I don’t know”. When analyzing “Gender” we excluded participants who answered “Diverse” as their small sample size (n = 2) does not allow for a robust statistical analyzes. We tested the effect size of all discovered differences using Cohen’s d’ (Cohen, 1992). The software SPSS (v. 26) (IBM, 2020) was used to analyze the survey data.

4 RESULTS

Looking at the results, participants “Age”, “Gender”, “Income”, and “Shopping Type” had a significant influence on participants attitude towards an XARSAA and participants sentiment when answering the open questions (see Table 1).

In detail (see Table 2), a lower “Age” has a significantly positive influence on participant’s desire for additional feature, showing a medium effect size (Yes: M = 34.03/ No: M = 39.92/ d = 0.509). “Gender”, has a significant impact on perceived usefulness (Female: M = 3.18/ Male: M = 3.55/ d = 0.357), “Purchase Intention” (Female: M = 2.92/ Male: M = 3.31/ d = 0.393), and “Trust” (Female: M = 3.00/ Male: M = 3.26/ d = 0.395) of an XARSAA, all showing small effect sizes and Male participants being more effected. “Income” has a significant influence on perceived “Information” (<1000€: M = 2.20/ 1000€-1999€: M = 3.90/ d = 0.554), with lower income participants perceiving the XARSAA less informative than higher income participants, and “Irritation” (1000€-1999€: M = 3.41/ 2000€-2999€: M = 2.97/ d = 0.567), with lower income participants perceiving the XARSAA more irritating than higher income participants, both showing medium effect sizes. “Shopping Type” has a significant influence on perceived “Purchase Intention”, with more frequent shoppers having a higher purchase intention than less frequent shoppers, showing a large effect size (Not at All Frequently: M = 2.60/ Very Frequently: = 3.42/ d = 0.917), and the possibility of an XARSAA to motivate people to go brick-and-mortar shopping, with more frequent shoppers being more motivated to go shopping than less frequent shoppers, showing a small effect size (Yes: M = 2.90/ No: M = 2.61/ d = 0.303). In contrast, participants ”Education” did not have a significant impact on participant’s attitude or sentiment towards an XARSAA.

5 DISCUSSION

Our study could detect multiple demographic influences on participant’s attitude and participant’s sentiment towards an XARSAA.

First, the age of a participant has a significant influence on the desire for additional features, with a younger participants requesting more features and older participants requesting no additional features. This demonstrates that when designing an XARSAA it should be taking into consideration to which age group the XARSAA should be targeted. Younger users prefer an application with a wide variety of features while older users might prefer a more streamlined and less complex experience.

Second, the gender of a participant has a significant influence on the perceived “Usefulness”, “Purchase Intention”, and “Trust” of an XARSAA, with women having a lower score then men in all these constructs. This indicates that an XARSAA should preferably be targeted to male target group. However, as the observed effect sizes only show a small effect this difference should not be overestimated.

Third, people with lower income showed a significantly lower value in perceived “Information” and a significantly higher value in perceived “Irritation” compared to people with higher income. This could indicate that differing income groups have differing requirements regarding the type and amount of presented information of an XARSAA. For example, people with lower income might value a feature to compare prices much higher compared to people with higher income and in turn, people with higher income could prefer information about the origin of a product. Indeed, price comparison has been perceived to empower consumers with low income previously (Hamilton, 2009). Although the observed differences show a medium effect size, it has to be noted that in each of the two constructs only a single group comparison showed a significant difference, which diminishes the overall strength of the observed effect.

Forth, ”Shopping Type” has a significant influence on users perceived “Purchase Intention” when using an XARSAA. In fact, “Very Frequent” shoppers have a much higher “Purchase Intention” when using an XARSAA than “Not at all Frequently” shoppers. This difference shows a high effect size further emphasizing that an XARSAA should be targeted to frequent shoppers to further increase their purchase intention instead of less frequent shoppers who might benefit less from using an XARSAA. Furthermore, although having a small effect, more frequent shoppers showed to be more motivated by the use of an XARSAA to shop in-store, then less frequent shoppers.

Fifth, participants education does not have an impact on participant's attitude or participant's sentiment towards an XARSAA, which is why it should not be taken into consideration when designing an XARSAA for a specific target group.

Summarizing, we argue that the optimal user of an XARSAA would be male, as they perceive an XARSAA as more useful and informative and trust explainable recommendations more. The user should not belong to the elderly group to still make use of a wide variety of features, which would be used to specifically tailor the information provided by the XARSAA to people with lower and higher income using in app personalization. Additionally, the XARSAA should be targeted to frequent shoppers as these would be motivated even more to shop in brick-and-mortar stores by using an XARSAA and when using an XARSAA would also have an increased purchase intention.

6 LIMITATIONS AND FUTURE WORK

In its current form, our study has some limitations that are mainly connected with the stage of research, as well as the design of the artifact and instantiation. First, we restricted our assessment to an artificial evaluation approach, following the design science research framework. Therefore, the study does not cover a whole design science project and steps, but it is particularly focused on the stages of identifying the problem, development of an artefact to solve the problem, and its artificial evaluation.

Thus, in the current form, the instantiation was not assessed in a real retail environment and as such misses important characteristics of real retail situations as for example an assessment of participants status of flow (Hausman and Siekpe, 2009). Additionally, our study did not test customers privacy concerns, which need to be further evaluated as usually customers express higher privacy concerns in personalized services than in non-personal ones (Wetzlinger et al., 2017).

Despite the mentioned issues, recommender systems and the shopping assistant artifact instantiation provide clear benefits to enhance user's experience on the path-to-purchase, as the system support customers and provide rich information for decision-making through the customer shopping journey, which has the potential to boost brick-and-mortar sales. However, as our study was focused on the influence of demographics on the the attitude towards an XARSAA, we did not measure how an XARSAA competes to a regular shopping scenario or an augmented reality shopping scenario without explainable AI features. Understanding the customer and working on their holistic experience are some of the major obstacles that retailers need to overcome. Some even go as far as to call them the most important constraints for the future of retail (Lemon and Verhoef, 2016).

Thus, we spotted different opportunities to complement the study. In addition, the design science methodology will be covered fully with iterations including practitioners, and the design practice and naturalistic evaluation of the instantiation. For instance, further investigation should be conducted to evaluate the artifact instantiation in comparison to other shopping scenarios. Moreover, it is aimed to provide retailers and developers with the design principles and practices for such an application, which fosters customer positive attitude towards shopping in-store. Additionally, the impact of an XARSAA on brick-and-mortar sales should be evaluated in a real-case scenario in order to include flow assessment and measure the impact of privacy concerns.

7 CONCLUSION

Looking at our first research question we conclude, that a customer's perception of an XARSAA is influenced by the demographics "Age", "Gender", "Income" and "Shopping Type". Regarding our second research question, we argue that the optimal user of an XARSAA would be a younger male who likes to shop at least frequently. Users with low income should receive different information then users with high income. The level of education is not relevant for designing an XARSAA. These results have various managerial implications. By understanding the impact of demographics on customers attitude towards an XARSAA, retailers can decide if such a tool is an appropriate tool to be used to engage with their main customer target group and as a consequence if it fits to the company in general.

As such, brick-and-mortar retailers need to understand that not all customers are alike. Gathering more information about individual customers than just their past purchases in the store may allow for more precise subsequent analyses and predictions. For example, adults could be differentiated from children in order to see whether and how their shopping habits differ.

Additionally, with XARSAA Brick-and-mortar stores have the opportunity to integrate innovative solutions, not by mimicking the e-commerce but by analyzing in-store customer desires and adapting technologies that have been proven to be key success factors in modern retail, like recommender systems (MacKenzie et al., 2013) and technologies that have the potential to enrich customer experience like AR (Papagiannidis et al., 2017).

To conclude, retailers needs to focus on solving the customers' problem, aiming to create a holistic experience along the shopping journey. As creating a shopping assistant which creates a more immersive experience, and by leveraging machine learning techniques can provide a more personalize in-store experience to the customers. These shopping assistant, such as an XARSAA, can enhance the digital transformation of brick-and-mortar stores and thus, help the shift in the physical environments in order to blur the perception of channels for customers toward omnichannel retail.

Therefore, as the retail sector moves forward, and most retailers face challenges to keep up the competition, this study can help traditional brick-and-mortar stores managers to create strategies, as well as it gives insights for the practitioners who are working on the transition toward the omnichannel model, in order to strengthen their market position and become more resilient to online competition.

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APPENDIX

In the following section, all questions of the used questionnaire in this study are shown in Table 3.

Table 3: Questions to the participants.

Constructs	Questions	
	Attitutes towards XARSAA	
Usefulness	Use1	This scenario can improve my shopping performance in-store
	Use2	This scenario can increase my shopping productivity in-store
	Use3	This scenario can increase my shopping effectiveness in-store
	Use4	This scenario seems useful in brick-and-mortar
Enjoyment	Enj1	The shown scenario is enjoyable
	Enj2	The shown scenario is pleasing
	Enj3	This scenario is entertaining
Informarion	Inf1	The shown scenario offers a good source of product information
	Inf2	This scenario supplies relevant information
	Inf3	This scenario is informative concerning the shown products
Irritation	Irr1	The shown scenario is annoying
	Irr2	The shown scenario is frustrating
	Irr3	This scenario is irritating
Purchase Intention	PI1	I would definitely buy products in this scenario
	PI2	I would intend to purchase products in this scenario in the near future
	PI3	If it would exist today, it is likely that I would purchase products in this scenario in the near future
	PI4	I would expect to purchase products in this scenario in the near future if it would exist today
	Sentiment of participants	
Sentiment	Q1	Looking at the presented application, are there features you are missing?
	Q2	Do you see any issues or room for improvement when using this app? If yes, could you give examples?
	Q3	Would this application help to make your shopping trip more secure during COVID-19? If yes, why and if no, why not?
	Q4	Would this application motivate you to shop in-store? If yes, why and if no, why not?
	Q5	Did you find the explanations given by the application helpful? If yes, why and if no, why not?