

Enhancing brick-and-mortar store shopping experience with an augmented reality shopping assistant application using personalized recommendations and explainable artificial intelligence

Enhancing
brick-and-
mortar shopping
experience

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Abstract

Purpose – The transition to omnichannel retail is the recognized future of retail, which uses digital technologies (e.g. augmented reality shopping assistants) to enhance the customer shopping experience. However, retailers struggle with the implementation of such technologies in brick-and-mortar stores. Against this background, the present study investigates the impact of a smartphone-based augmented reality shopping assistant application, which uses personalized recommendations and explainable artificial intelligence features on customer shopping experiences.

Design/methodology/approach – The authors follow a design science research approach to develop a shopping assistant application artifact, evaluated by means of an online experiment ($n = 252$), providing both qualitative and quantitative data.

Findings – Results indicate a positive impact of the augmented reality shopping assistant application on customers' perception of brick-and-mortar shopping experiences. Based on the empirical insights this study also identifies possible improvements of the artifact.

Research limitations/implications – This study's assessment is limited to an online evaluation approach. Therefore, future studies should test actual usage of the technology in brick-and-mortar stores. Contrary to the suggestions of established theories (i.e. technology acceptance model, uses and gratification theory), this study shows that an increase of shopping experience does not always convert into an increase in the intention to purchase or to visit a brick-and-mortar store. Additionally, this study provides novel design principles and ideas for crafting augmented reality shopping assistant applications that can be used by future researchers to create advanced versions of such applications.

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Data Availability: The qualitative and quantitative data used to support the findings of this study have been deposited in the Zenodo repository [DOI: 10.5281/zenodo.4723468].



Practical implications – This paper demonstrates that a shopping assistant artifact provides a good opportunity to enhance users' shopping experience on their path-to-purchase, as it can support customers by providing rich information (e.g. explainable recommendations) for decision-making along the customer shopping journey.

Originality/value – This paper shows that smartphone-based augmented reality shopping assistant applications have the potential to increase the competitive power of brick-and-mortar retailers.

Keywords Digital retail, Digital shopping assistant, Recommender systems, Explainable artificial intelligence, Retail sales

Paper type Research paper

1. Introduction

With department store revenue declining since 2001 (Bureau, 2018; ICSC, 2018; Wolf, 2018) and e-commerce revenue continually growing (Cirqueira *et al.*, 2020a; Statista, 2018), today's retailers face a significant challenge in staying competitive. In particular, traditional brick-and-mortar retail faces significant challenges (Berman, 2018). In the US alone, 9,879 stores declared bankruptcy in 2019 (Loeb, 2020). The COVID-19 pandemic has aggravated this problematic trend (Nicola *et al.*, 2020).

In these troublesome times, it is even more important for retailers to understand how they can enhance customers' offline shopping experiences (von Briel, 2018). As a response to these challenges, retailers are engaging in a new form of retail referred to as "digital retail", which uses information and communication technologies (e.g. smartphones) to engage customers, drive sales and offer unique shopping experiences that are superior to pure online shopping (Lemon and Verhoef, 2016). At the same time, customer expectations have been rising continuously (Parise *et al.*, 2016) including the preference for an omnichannel experience (Briedis *et al.*, 2020). In this regard, personalization and interactivity are key elements for creating a positive experience, leading to positive changes in customers' behaviors and intentions toward retail (Parise *et al.*, 2016). Therefore, traditional retailers need to develop new systems that can provide a more customized and immersive shopping experience for customers in brick-and-mortar stores. Particularly since such a shopping experience may positively affect purchase intention and actual sales (Arora *et al.*, 2021; Zimmermann *et al.*, 2019).

Contemporary marketing strategies integrate new technologies to create meaningful interactions with customers (Wang, 2021). It is argued that the use of smartphones can provide an augmented and personalized customer shopping experience, driving sales in brick-and-mortar stores (Eriksson *et al.*, 2018; Juaneda-Ayensa *et al.*, 2016; Parise *et al.*, 2016; Zimmermann and Auinger, 2020). A particular use case of such smartphone-based technology is an augmented reality shopping assistant application (hereafter ARSAA), which uses augmented reality (AR) to display content (e.g. tailor-made offers, product comparison and recommendations) by leveraging machine learning techniques (e.g. recommender systems) and explainable artificial intelligence (XAI). This technology enables a personalized and online-like shopping experience for customers in brick-and-mortar stores. Importantly, the usage of ARSAA in brick-and-mortar stores enables retailers to blur customers' perception of online and offline channels (Carroll and Guzman, 2013). Furthermore, it provides higher levels of interactivity, which is a primary area of future research in interactive marketing (Wang, 2021).

However, since the introduction of such technologies is expensive (Berman, 2018), retailers need to know if an ARSAA is a useful tool to deliver an augmented and personalized shopping experience. Unfortunately, current marketing literature does neither provide guidance on how to develop AR applications which provides personalized shopping experiences nor does it provide evaluation studies which empirically examined the impact of such applications on shopping experience.

Against the background of the presented research deficit and considering the need of corresponding research results for informed decision-making in practice (e.g. by retail managers and interactive marketing practitioners), the present study addresses the following research questions:

- RQ1.* How does a customer's shopping experience with an ARSAA differ from a shopping experience without an ARSAA in brick-and-mortar stores?
- RQ2.* How can the presented ARSAA prototype be improved to further enhance the shopping experience of brick-and-mortar store customers?

To answer these questions, we follow a design science research methodology. Here, an ARSAA is developed and evaluated by means of an online experiment. Thus, the present study addresses both phases of a design science research project: build and evaluate (Hevner *et al.*, 2004; March and Smith, 1995).

The paper is structured as follows: Section 2 presents the background of our study by providing a literature review, the conceptual background of our study and a conceptual framework. Section 3 outlines the research methodology. Section 4 provides the study results. Section 5 discusses the results and main findings and outlines the theoretical contributions, practical implications, limitations and future research opportunities. Section 6 presents our conclusion.

2. Literature review and conceptual background

2.1 Literature review

A systematic literature review was conducted to illuminate the state of research in the field of personalized recommendations provided by AR applications. In accordance with vom Brooke *et al.* (2009), our literature review is extensive as we reviewed all literature found on this topic. To cover an extensive field of literature we used the following search string in the Scopus database:

(TITLE-ABS-KEY ("brick and mortar" OR "brick-and-mortar") OR TITLE-ABS-KEY ("retail")) AND (TITLE-ABS-KEY ("augmented reality" OR "AR") AND TITLE-ABS-KEY ("personalization" OR "personalisation" OR "recommendations" OR "recommender system"))

The literature search resulted in 23 papers from the Scopus database that were screened for relevant information about recommender systems, which provide personalization in AR applications. A total of 16 papers did not contain such information and were excluded from the review. The remaining seven papers' contributions to literature in the field of personalized recommendations in AR are summarized in Table 1. Interestingly, no publication investigated the impact of personalized recommendations on shopping experience, although an explicit call for corresponding research exists (Lavoye *et al.*, 2021).

Thus, based on the previous approaches in deploying recommender systems in physical stores, we identify the use of a smartphone-based ARSAA as a particularly promising, yet under researched tool to provide personalized recommendations in brick-and-mortar stores.

2.2 Conceptual background

To conceptualize the impact of ARSAA on shopping experience we also reviewed the trends in retailing, providing details on the emerging field of digital retail and its potential influence on shopping experience in brick-and-mortar stores, the use of recommender systems in brick-and-mortar stores and their impact on purchase intention, and the potential to increase trust in recommender systems by using XAI.

Source	Type of study	Contribution to literature*
Löchtefeld <i>et al.</i> (2013)	Empirical – Experiment	Evaluated the effectiveness of personalized recommendations in augmented reality applications in the context of increasing paper leaflet views
Hiranandani <i>et al.</i> (2017), Tanmay and Ayush (2019) Cruz <i>et al.</i> (2019)	Empirical – Experiment Empirical – Experiment Empirical – Experiment	Improved visual representation of personalized recommendations in augmented reality applications Tested the general applicability of personalized recommendations in augmented reality applications
Márquez and Ziegler (2020)	Empirical – Experiment	Evaluated the acceptance of personalized recommendations in augmented reality applications when shopping for home appliances
Joerß <i>et al.</i> (2021)	Empirical – Experiment	Evaluated the effectiveness of personalized recommendations in augmented reality applications shifting customer product choice to sustainable products
Lavoye <i>et al.</i> (2021)	Conceptual – Literature Review	Highlighted lack of studies addressing personalized recommendations in augmented reality applications

Note(s): *Regarding personalized recommendations in augmented reality applications

Table 1.
Literature review
summary

2.2.1 Digital retail shopping experience in brick-and-mortar stores. Digital retail makes use of state-of-the-art technologies that allow retailers to use a variety of different customer touchpoints such as smartphones and social media to offer unique shopping experiences. Consequently, retailers have started targeting customers across different channels, giving birth to multi-channel retailing. This approach is morphing into omnichannel retailing today, which merges all channels and touchpoints into a single seamless shopping experience (Verhoef *et al.*, 2015).

Putting shopping experience at the center of their business model and deploying digital technologies to enhance this experience (Parise *et al.*, 2016; Rigby, 2011) retailers can make use of personalized advertising and promotion via increasingly ubiquitous devices (MacKenzie *et al.*, 2013). Smartphones represent the archetype of these devices (Pimenidis *et al.*, 2018) as they get continuously updated with technologies that are predicted to revolutionize the retail sector, such as AI and AR (von Briel, 2018).

Considering these developments, and in line with Lavoye *et al.* (2021), ARSAA is assumed to positively influence customers' perception of shopping experience in brick-and-mortar stores by boosting hedonic (e.g. enjoyment) and utilitarian value (e.g. usefulness, informativeness). However, it must be noted that the use of AR can create media irritation, potentially diminishing this effect (Yim and Park, 2019). Hence, for assessing the overall quality of shopping experiences, this research includes the concepts of "Usefulness", "Entertainment", "Informativeness" (Pantano *et al.*, 2017) and "Irritation" to capture the specifics of AR shopping experience.

"Perceived Usefulness" (PU) and "Perceived Ease of Use" (PEOU) are the key component of the technology acceptance model (TAM) (Davis, 1989). PU describes the degree to which a user believes that using a specific technology enhances the user's performance. PEOU describes how easy to use a system or application is. As PEOU was found to have a much weaker effect on behavioral intentions compared to PU (Venkatesh and Morris, 2000), this study focuses on PU only. In this regard, previous studies have shown (Chen and Wells, 1999; Song and Zinkhan, 2003) that, for websites, specific design features (e.g. menus, icons, colors and graphics) make websites fun, attractive and appealing thus increasing PU. As ARSAA uses similar design features to present information to users (e.g. interactive buttons, icons and graphics; see also Chapter 3.2), we hypothesize:

H1. ARSAA assisted brick-and-mortar shopping is perceived as more useful than unassisted brick-and-mortar shopping.

The perceptual constructs “Entertainment”, “Informativeness”, and “Irritation” are the most robust constructs in uses and gratifications theory (UGT) (Katz *et al.*, 1973; Luo, 2002). UGT has been shown to be a promising theory for explaining user behavior and perception of new media, especially in the area of interactive information and communication technologies (Baabdullah *et al.*, 2022; Lee *et al.*, 2020; McLean and Osei-Frimpong, 2019; Pelletier *et al.*, 2020; Qin, 2020).

“Entertainment” describes the extent to which a media is fun and entertaining for users by fulfilling the need for escapism, diversion, esthetic enjoyment or emotional release (Ducoffe, 1996; Luo, 2002). A higher entertainment value motivates users to use specific media more often than others. This, for example, stimulates their purchase intention and information seeking behavior in e-commerce (Huang, 2008). “Informativeness” describes the extent to which media provide resourceful and helpful information to users (Chen and Wells, 1999; Ducoffe, 1995). Gathering information for goods and services is one of the most prominent reasons for consumers to use the Internet (Capgemini, 2020; Central Statistics Office, 2020; Statistisches Bundesamt, 2020).

As the ARSAA designed for this study uses multiple design elements to increase “Entertainment” (e.g. live interaction with a physical product on the smartphone) and “Informativeness” (e.g. displaying product information, giving recommendations), we hypothesize:

H2. ARSAA assisted brick-and-mortar shopping is perceived as more entertaining than unassisted brick-and-mortar shopping.

H3. ARSAA assisted brick-and-mortar shopping is perceived as more informative than unassisted brick-and-mortar shopping.

“Irritation” describes the extent to which using media bothers users because of annoying, offensive, confusing, distracting or messy design choices (Chen and Wells, 1999; Ducoffe, 1996). Previous studies show that disorganized websites can generate negative advertising value and diminish the intention to return (Hausman and Siekpe, 2009). Additionally, Ducoffe (1996) notes that irritating banner ads may increase user anxiety, distract customers and thus dilute customer shopping experiences. Although ARSAA, as presented in this study, does not use banner ads, it still uses personalized recommendations to provide additional information to its users that might be perceived as similarly irritating. It is thus crucial to investigate the amount of irritation caused by ARSAA. Accordingly, we hypothesize:

H4. ARSAA assisted brick-and-mortar shopping is perceived as more irritating than unassisted brick-and-mortar shopping.

2.2.2 Recommender systems in brick-and-mortar stores. In the past decades, recommender systems have helped e-commerce to provide customers with more personalized experiences, creating a positive impact on sales and customer retention (Amatriain and Basilico, 2015; MacKenzie *et al.*, 2013). Modern recommender systems work as an information filter based on machine learning techniques to determine user preferences. These preferences are the foundation for the generation of a ranked list of relevant products, typically based on a customer’s past behavior, similarities to other customers and patterns in item information (Mora *et al.*, 2020a). These systems allow companies to understand how they can target customers throughout the customer journey (Mora *et al.*, 2020a). Recommender systems provide utilitarian value for users by improving their efficiency during information search and product comparison (Pimenidis *et al.*, 2018).

For in-store recommendations, applications on smartphones are currently the most popular approach (Mora *et al.*, 2020a; Piotrowicz and Cuthbertson, 2014). Their main advantages are

the access to data inputs, personal user information (e.g. historical transactions associated with an app account), and integrated sensors. An early example of this approach was a smartphone-based recommender system for shopping malls that implicitly captured customer's preferences for stores by tracking their positions (Fang *et al.*, 2012). Compared to conventional recommender systems, which do not consider a customer's context; this approach resulted in higher recommendation accuracy and customer satisfaction. Additionally, the system was perceived as more useful and easier to use. Recommender systems are also used in omnichannel contexts. Here, Carnein *et al.* (2019) developed a system that gathers and integrates data from different online channels, but without in-store context awareness—an important requirement in a brick-and-mortar application (Parise *et al.*, 2016).

Additionally, one should note that ubiquitous devices other than smartphones have been hardly used in brick-and-mortar retailing for enhancing shopping experience. This might be a result of the limited availability of the used devices (e.g. Microsoft HoloLens). In comparison, the smartphone is the ideal device for an ARSAA, which can use recommender systems to ease the customers' path-to purchase. In particular, recommender systems in ARSAA can stimulate multiple motivators of mobile shopping (Huang and Zhou, 2018). As such, it can increase convenience, lead to money saving and bargain hunting and can offer a greater product variety, by giving access to additional information based on interactive product recommendations acknowledging customer preferences. Additionally, ARSAA can display product reviews made by others, thus fostering social interaction, which has been shown to have a significant impact on customer behavior (Dennis *et al.*, 2009). Also, using ARSAA and exploring its product recommendations can motivate users to buy additional products (Ganesh *et al.*, 2010). We therefore hypothesize:

- H5. ARSAA assisted brick-and-mortar shopping leads to a higher purchase intention than unassisted brick-and-mortar shopping.

2.2.3 Explainable artificial intelligence in recommender systems. Recommender systems using AI and machine learning models are trained to understand shoppers' behavior for providing useful recommendations (Fernández-García *et al.*, 2019). However, with the ever-increasing amount of transaction data and complexity of AI, these recommender systems have often turned into black boxes for their users (Adadi and Berrada, 2018; Omar *et al.*, 2018). This affects users overall trust in services using recommender systems (Fu *et al.*, 2020). When shoppers receive recommendations, they typically do not know the reasons for these product suggestions, likely affecting consumers' reactions to such proposals. Therefore, XAI research now focuses on making AI predictions more understandable by developing transparent AI models and explanation methods (Adadi and Berrada, 2018). Indeed, explanations have the potential to support user decision-making, enhance customer shopping experience, increase trust, acceptance and adoption of AI-based technologies (Cirqueira *et al.*, 2020b).

Explanations in recommender systems aim to enhance shopping experience through high-quality, interactive and intuitive suggestions, while keeping the recommendations easy to understand for consumers (Wang *et al.*, 2018). In particular, explainable recommendations give the user reasons for the given recommendation (Wang and Benbasat, 2008). Here, evidence indicates that explanations can significantly impact customers' purchase intentions (Chen *et al.*, 2019). This corresponds to Gefen *et al.* (2003) who showed that trust (in the context of TAM) influences customers' purchase intention during online shopping. Based on a meta-analysis, Kim and Peterson (2017) also demonstrated that trust is a robust indicator for purchase intention. However, although existing literature provides valuable insights into recommender systems and corresponding use cases (e.g. Cheng *et al.*, 2019; He *et al.*, 2015; Huang *et al.*, 2019),

a combination of explainable recommendations with AR has not yet been explored in a physical retail context. This motivates this research to hypothesize:

- H6. ARSAA assisted shopping using explainable recommendations is perceived as more trustworthy compared to ARSAA assisted shopping not using explainable recommendations.
- H7. ARSAA assisted shopping using explainable recommendations is superior in terms of perceived shopping experience and purchase intention compared to ARSAA assisted shopping not using explainable recommendations.

2.3 Conceptual framework

In this research, we compare the effects of different brick-and-mortar shopping scenarios on perceived shopping experience, purchase intention and trust in technology of ARSAA users. Three shopping scenarios are investigated: a regular shopping scenario (RSS) that does not feature the use of an ARSAA in a brick-and-mortar store, an AR shopping scenario (ARSS), in which the user is supported by an ARSAA in a brick-and-mortar store, and an ARSS in which the user is supported by an ARSAA in a brick-and-mortar store, but that additionally uses explainable recommendations (XARSS).

Figure 1 summarizes the research hypotheses in a conceptual framework. In detail, Hypotheses 1-4 and 7 investigate the differences in user perception of shopping experience and Hypotheses 5 and 6 evaluate the differences in user intention and technology evaluation. In brief, Hypotheses 1-5 address the differences between all shopping scenarios, and Hypotheses 6 and 7 specifically assess the differences between ARSS and XARSS.

3. Methodology

This chapter describes how the study was guided by the design science methodology (3.1), how our ARSAA prototype is designed (3.2) and how it was evaluated (3.3).

3.1 Design science research

This research follows a design science methodology originating from information systems research (Gregor and Hevner, 2013). This approach focuses on the development of an artifact that “solves identified organizational problems” (Hevner et al., 2004, p. 77). This methodology

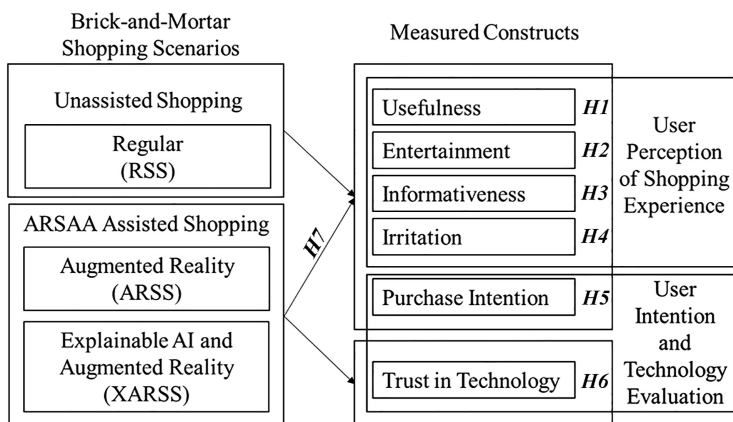


Figure 1.
Conceptual framework

allows us to analyze a problem space, extract requirements for a desired problem-solving artifact and match the requirements to design an instantiated prototype. The design science research framework (Hevner *et al.*, 2004; Prat *et al.*, 2014) involves six steps (see Figure 2).

3.1.1 Problem identification and motivation. We started by investigating the problem environment, based on the current state of research, and discussions with practitioners within the PERFORM network, which is a European project and a consortium composed of retailers and universities (Perform-Network.eu, 2022). We clarified the problem as the lack of understanding as to whether ARSAA, with recommender systems and explainable recommendations, can enhance customer shopping experience in brick-and-mortar stores. We found that this lack of understanding creates a barrier for retailers to invest in such technologies in their physical stores.

3.1.2 Definition of the objectives for a solution. The research objective was focused on developing an ARSAA as an artifact and assessing its influence on customer brick-and-mortar store shopping experience. The scope of the research centers on personalized recommendations that retailers can provide to their customers by deploying an in-store based recommender system leveraged by a smartphone-based application. These tailored suggestions build around a particular product with which the customer is interacting, in the form of product recommendations, comparisons and offers. From our literature review and discussions with practitioners, we extracted and categorized the requirements of the ARSAA (see Table 2).

3.1.3 Design and development. This research adopted the framework of Ge and Helfert (2014) to mitigate threats to the validity of the study regarding artifact development, experiment and data analysis. Therefore, to guarantee its validity, we first had to establish the kernel theory, which governs the development of the artifact. We investigated extant taxonomies of explanation methods to select explanation types for AI recommendations to customers (Arrieta *et al.*, 2020; Arya *et al.*, 2019; Mueller *et al.*, 2019; Sokol and Flach, 2020). Here, the focus was on local explanations to clarify the reasons for a particular recommendation.

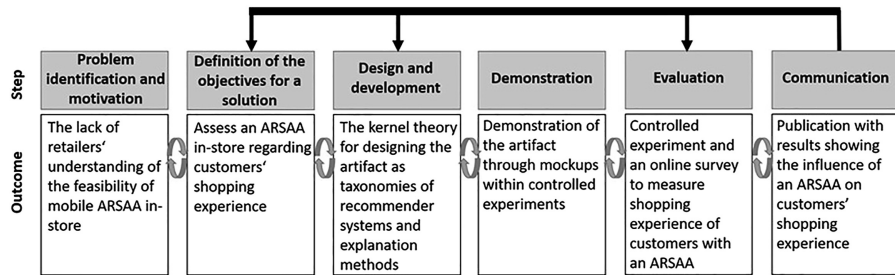


Figure 2. Design science research methodology in this study

Requirements	Description	Solution in section
R1 Device	The retailer needs to select the device to be used to enable the shopping assistant application	3.2
R2 Personalized experience	The app is required to provide recommendations of products to the users based on authorized personal information	3.2
R3 Brick-and-Mortar focus	The shopping assistant application should be context-aware to enable recommendations for shoppers in physical stores	3.2
R4 Explainable recommendations	The application should provide real-time explanations of the underlying decision-making for the items recommended	3.2
R5 Artifact evaluation	The shopping assistant application should be evaluated based on potential customers	5

Table 2. Identified requirements of the artifact (the ARSAA)

3.1.4 Demonstration. The ARSAA and recommendations were implemented by following the artifact design by [Mora et al. \(2020b\)](#), which represents a former iteration of this design science project. The authors developed a shopping assistant application and identified the user requirements for such an in-store assistant. The application also focused on the design of recommender systems as the underlying system to provide personalized recommendations and presents product comparisons based on items with which the customer is interacting. This research was inspired by the artifact design of [Mora et al. \(2020a\)](#) to develop the mobile-based ARSAA artifact and user interface mockups.

3.1.5 Evaluation. The evaluation of our artifact aimed at testing the formulated hypothesis and hence contributes to solving the identified problem. We followed the framework of [Prat et al. \(2014\)](#) to conduct the evaluation of the ARSAA artifact. Specifically, a user experiment within three scenarios and an online survey were conducted.

3.1.6 Communication. This study further clarified the evaluation design and results obtained. This demonstrated the varying impact of an ARSAA artifact on the shopping experience of customers in-store. We presented practical and theoretical implications of our study.

3.2 Augmented reality shopping assistant application

The proposed artifact was developed as an application running on an android-based smartphone (R1). In the scenarios, the app was deployed by the retailer and the device was owned by the customer. Hence, it had access to personal information that was required to provide tailored recommendations (e.g. social media, historical purchase data). We conceptualized the artifact to provide augmented content. Anchored around the product of interest, the application displayed recommendations, offers, a comparison of items and a buy button on the smartphone. The artifact provided support to the customer through the shopping journey. As an example, the shopping assistant application could identify the product with which the customer was interacting (see [Figure 3](#)) and provide tailored content (R2).

During this stage of the prototype development, the ARSAA used a smartphone camera to detect a customer's object of interest (product). By doing so, the application could monitor the camera's field of view, to determine which product the user was examining at each point in time and to track the item in the physical space while the customer interacts with the product (R3). The involved object recognition was performed using software development kits, e.g. Vuforia ([He et al., 2015](#)). When the application recognized the product, it displayed multiple digital buttons anchored around the product that can be triggered by the customer to display relevant content using AR.

The user interface provided support to the customer through the shopping journey by identifying the product with which the customer interacted to provide tailored suggestions. The user interface provided easy navigation and intuitive visualization (see [Figure 4](#)).

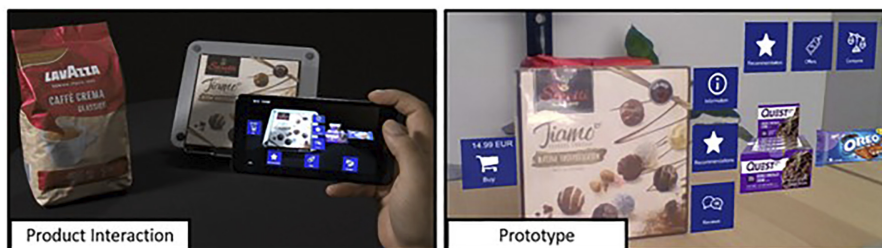


Figure 3. Demonstration of the application (left) and a prototype interface screenshot (right)

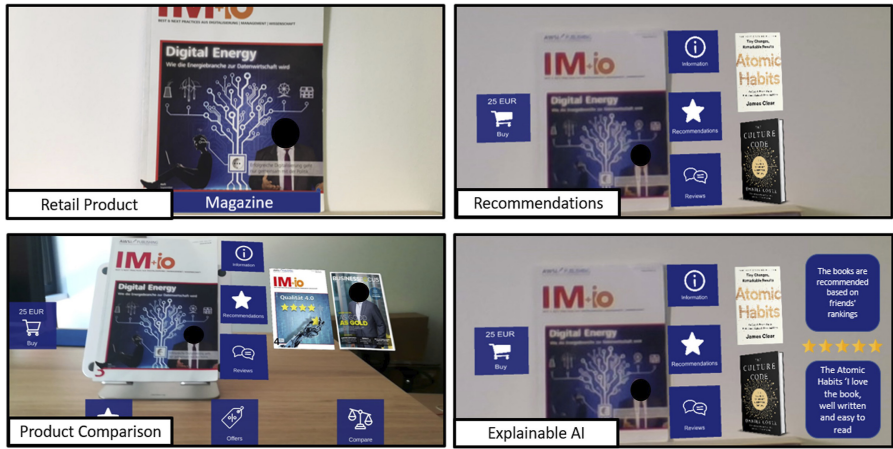


Figure 4. Screenshot of the interface of the functional prototype. In this example, book suggestions are provided with a *social* explanation based on friends' reviews

To provide explainable recommendations (R4), we adopted Zhang and Chen's (2020) classification of explanation methods in the context of recommender systems: (1) user or item-based; (2) feature-level; (3) textual; (4) visual; and (5) social. The impact of XAI types on the ARSAA interface is summarized in Table 3.

Following the taxonomy of Ge and Helfert (2014), we implemented the five explanation methods into our ARSAA as the kernel theory governing the design of the artifact. Each method provided users with an explanation type to support them during the brick-and-mortar shopping journey.

3.3 Evaluation design

The evaluation design of our study was based on an online experiment. In this phase of the project, the artifact has not been evaluated in the real context of the problem or environment (i.e. in-store) because of the early stage of the artifact. Therefore, study participants interacted with an online version and mockup of the ARSAA. This was followed by an evaluation which included an online survey with a quantitative and qualitative assessment of the shopping experience, purchase intention and trust (R5).

3.3.1 Participants. Participants of the within-subject experiment were recruited using the crowdsourcing provider Clickworkercom (2020a). This provider was chosen as it ensured a high level of qualification of the study participants by requiring the use of real personal data,

Table 3. Explanation methods for recommendations and their impact on the ARSAA interface

XAI types	Impact on ARSAA interface
User or Item-Based	Explains that other customers frequently buy certain products together or that a set of items are similar to each other
Feature-Level	Relevant features of an item are displayed, e.g. a nutritional table from a cookie
Textual	A box appears in the interface next to the recommendations with an explanation in text
Visual	The customer perceives important features on the representation of a product highlighted
Social	The explanations are visualized by a friend's or social media comment or by an aggregated rating

testing of writing and language qualifications and a constant evaluation of their members' response patterns (Clickworkercom, 2020b).

In total, 315 participants from the German-speaking area (Germany, Austria and Switzerland) were recruited. Participants who took less than seven minutes to complete the survey, used the same IP address to answer the survey multiple times, or entered only one word or random letters in the open questions were excluded to ensure data quality. Thus, the final sample size was 252 participants. A demographic overview of the participants is presented in Table 4. No abnormalities of our sample and resulting biases could be identified.

3.3.2 Survey. Our artifact evaluation was conducted by using an online survey, which took place in August 2020. In the survey, participants were introduced to the concept of ARSAA with the help of pictures and videos (the introductory videos provided in the survey can be accessed via the following links: <https://www.youtube.com/watch?v=YhJ9QHVN1rs>; <https://www.youtube.com/watch?v=LCj4Y18O9z4>).

Afterward, participants were presented with three different shopping scenarios. In each scenario, products on a shelf (e.g. groceries, luxury chocolate, shoes and books) were shown. The first experimental condition was a RSS, displaying no additional information (see upper-left image of Figure 4). The second condition was an ARSS, displaying augmented recommendations and product comparisons (see top-right and bottom-left image of Figure 4). The third condition was an ARSS with explainable AI features (XARSS), which additionally showed explanations why the recommendations and product comparisons were shown (see bottom-right of Figure 4). Following each condition, participants had to answer questions about how they perceived the shopping experience, how it influenced their overall purchase intention, and, for the second and third condition, how trustworthy they perceived the ARSAA.

For this assessment, the questionnaire included a series of validated constructs by Hausman and Siekpe (2009). Consequently, we measured the perception of the scenarios 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 ARSS and XARSS by adopting an established scale from Hoffman et al. (2018) (6 items). All items were measured using a 5-point Likert-type scale ranging from "Completely Disagree" to "Completely Agree". The sequence of the scenarios and the sequence of questions in each scenario were randomly shuffled to avoid order bias. We also asked participants six open-ended questions to get their general opinion about the presented ARSAA. The questionnaire also included standard demographics (six items). The questionnaire was implemented with the survey software SurveyGizmo.com (2020). The original survey is provided in the Supplementary Material S1.

	N	%		N	%
<i>Age ($M_{age} = 37.38$ years; $\sigma = 12.06$)</i>			<i>Country of Origin (GER 229; AUT 17; SUI 6)</i>		
<i>Gender</i>			<i>Education</i>		
Male	118	46.8%	High School	16	6.3%
Female	132	52.4%	Graduated High School	69	27.4%
Diverse	2	0.8%	College or University	97	38.5%
			Master or Doctorate	70	27.8%
<i>Net household income (per month in EUR)</i>			<i>Shopping frequency (last 30 days)</i>		
<1,000	63	25.0%	Not at all frequently	25	9.9%
1,000 and < 2,000	85	33.7%	Slightly frequently	63	25.0%
2,000 and < 3,000	53	21.0%	Moderately frequently	115	45.6%
3,000 and < 4,000	29	11.5%	Very Frequently	42	16.7%
4,000 and < 5,000	15	6.0%	Extremely Frequently	7	2.8%
5,000 and above	7	2.8%			
Total	252	100%		252	100%

Table 4.
Demographics

3.3.3 *Validity and reliability.* To assess validity and reliability of the constructs used, a confirmatory factor analysis was used to test the measurement models in each shopping scenario. It became apparent that in all scenarios one “Usefulness” item showed a misspecified error covariance, indicating a systematic measurement error for this item. Therefore, following [Byrne \(2010\)](#), we excluded the item. Additionally, in the ARSS and XARSS scenarios one trust item did not load on the “Trust” construct and two additional trust items were cross-loading on the factor “Usefulness”. Consequently, we also excluded these items from the measurement models ([Byrne, 2010](#)). All three final models showed an appropriate fit:

RSS: $X^2(94) = 174.833$, RMSEA = 0.059, CFI = 0.969, SRMR = 0.045; ARSS: $X^2(137) = 175.585$, RMSEA = 0.033, CFI = 0.990, SRMR = 0.028; XARSS: $X^2(137) = 168.461$, RMSEA = 0.030, CFI = 0.993, SRMR = 0.022.

All items displayed sufficient item to construct loadings ([Hair et al., 2008](#)) ranging from 0.609 to 0.926 (see [Table 5](#)). Establishing reliability, all constructs showed good Cronbach’s α coefficients in all scenarios ([Konting et al., 2009](#)), ranging from 0.773 to 0.934 (see [Table 6](#)). Verifying convergent validity, composite reliability (>0.7) and average variance extracted (>0.5) exceeded the desired thresholds ([Fornell and Larcker, 1981](#)) in all scenarios (see [Table 6](#)). As the square root of the average variance extracted for each construct was greater than its highest correlation with any other construct ([Hair et al., 2008](#)), discriminant validity was established in the RSS and ARSS scenario. In the XARSS scenario, a violation (difference = 0.06) of discriminant validity could be detected between the construct “Irritation” and “Entertainment”. However, because the violation is minimal, these constructs

Scale	Item	Factor loading		
		RSS	ARSS	XARSS
Usefulness	This scenario can improve my shopping performance	0.842	0.885	0.920
	This scenario can increase my shopping productivity	0.866	0.892	0.882
	This scenario can increase my shopping effectiveness	0.860	0.886	0.895
Entertainment	The shown scenario is enjoyable	0.839	0.885	0.897
	The shown scenario is pleasing	0.820	0.839	0.884
	This scenario is entertaining	0.762	0.817	0.756
Informativeness	The shown scenario offers a good source of product information	0.863	0.865	0.854
	This scenario supplies relevant information	0.786	0.888	0.862
	This scenario is informative concerning the shown products	0.880	0.817	0.834
Irritation	The shown scenario is annoying	0.650	0.776	0.759
	The shown scenario is frustrating	0.896	0.870	0.841
	This scenario is irritating	0.609	0.857	0.864
Purchase Intention	I would definitely buy products in this scenario	0.774	0.846	0.821
	I would intend to purchase products in this scenario in the near future	0.830	0.897	0.876
	If it would exist today, it is likely that I would purchase products in this scenario in the near future	0.899	0.913	0.926
Trust	I would expect to purchase products in this scenario in the near future if it would exist today	0.868	0.873	0.901
	I am confident in the application. I feel that it works well	N/A	0.807	0.855
	The application seems very reliable	N/A	0.788	0.840
	I feel safe that when I rely on the application, I get the right information	N/A	0.774	0.835

Table 5.
Item to construct loadings

Note(s): RSS (Regular Shopping Scenario), ARSS (Augmented Reality Shopping Scenario), XARSS (Augmented Reality Shopping Scenario with Explainable Artificial Intelligence)

Constructs	α	CR	AVE	1	2	3	4	5	6
<i>RSS</i>									
1. Purchase Intention	0.907	0.908	0.712	<i>0.844</i>					
2. Usefulness	0.891	0.892	0.733	0.623	<i>0.856</i>				
3. Entertainment	0.844	0.849	0.652	0.651	0.792	<i>0.808</i>			
4. Informativeness	0.881	0.881	0.712	0.574	0.745	0.679	<i>0.844</i>		
5. Irritation	0.773	0.768	0.532	-0.453	-0.434	-0.505	-0.449	<i>0.729</i>	
<i>ARSS</i>									
1. Purchase Intention	0.934	0.934	0.779	<i>0.883</i>					
2. Usefulness	0.917	0.918	0.788	0.768	<i>0.888</i>				
3. Entertainment	0.884	0.884	0.718	0.719	0.794	<i>0.847</i>			
4. Informativeness	0.891	0.892	0.735	0.640	0.743	0.695	<i>0.857</i>		
5. Irritation	0.873	0.874	0.698	-0.617	-0.681	-0.674	-0.588	<i>0.835</i>	
6. Trust	0.833	0.833	0.624	0.741	0.758	0.786	0.759	-0.670	<i>0.790</i>
<i>XARSS</i>									
1. Purchase Intention	0.933	0.933	0.778	<i>0.882</i>					
2. Usefulness	0.926	0.927	0.808	0.856	<i>0.899</i>				
3. Entertainment	0.883	0.884	0.719	0.811	0.837	<i>0.848</i>			
4. Informativeness	0.886	0.887	0.723	0.772	0.830	0.763	<i>0.850</i>		
5. Irritation	0.863	0.862	0.677	-0.697	-0.742	-0.829	-0.692	<i>0.823</i>	
6. Trust	0.881	0.881	0.711	0.778	0.793	0.793	0.771	-0.671	<i>0.843</i>

Note(s): α (Cronbach's alpha), CR (Composite reliability), AVE (Average Variance Extracted), RSS (Regular Shopping Scenario), ARSS (Augmented Reality Shopping Scenario), XARSS (Augmented Reality Shopping Scenario with Explainable Artificial Intelligence). Figures on the diagonal represent the square root of the average variance extracted of the corresponding factor

Table 6.
Construct reliability
and validity

have been validated by other researchers (e.g. Hausman and Siekpe, 2009; Hoffman *et al.*, 2018), and the RSS and ARSS scenarios did not indicate any violation, we consider discriminant validity as established.

3.3.4 Analysis. As the survey contained more than 30 participants, according to the central limit theorem (Bortz and Schuster, 2010; Kähler, 2004; Tavakoli, 2013), this was sufficient to assume normal distribution, allowing parametric testing. Therefore, we analyzed participants' perceptions of the conditions ("Usefulness", "Entertainment", "Informativeness", "Irritation") and their "Purchase Intention" using a repeated measurement analysis of variance analysis (rmANOVA). The differences in trust towards ARSS and XARSS were analyzed using a paired sample *t*-test. When statistically significant differences were identified, we used Bonferroni adjusted post-hoc tests to highlight the differences between the scenarios. Subsequently, we tested the effect size of the discovered differences using Cohen's *d*. The software SPSS 26 (IBM.com, 2020) was used to analyze the survey data except for the open questions, which were manually reviewed and coded.

4. Results

We present, the quantitative results based on rmANOVA and paired sample *t*-test (see Table 7) together with the Bonferroni-adjusted post-hoc analyzes and effect sizes (see Table 8). Also, we show the participants' qualitative responses by screening the open questions for observable patterns and general sentiments (see Table 9).

4.1 Quantitative results

Based on the rmANOVA, and the paired sample *t*-test (see Table 7), significant differences in the perceptions of the three shopping scenarios were identified: "Usefulness" ($p < 0.001$),

Construct	Scenario	Mean	Std. Dev.	df/error	F^*/t^{**}	Sig
Usefulness*	RSS	2.7977	0.85479	1.462/367.057	31.252	<0.001
	ARSS	3.2023	0.96053			
	XARSS	3.3292	1.04976			
Entertainment*	RSS	2.8172	0.81981	1.750/439.214	18.635	<0.001
	ARSS	3.0964	0.91896			
	XARSS	3.1678	0.94932			
Informativeness*	RSS	2.9206	0.91520	1.740/436.649	61.891	<0.001
	ARSS	3.3506	0.91306			
	XARSS	3.6655	0.84507			
Irritation*	RSS	2.2260	0.84444	1.671/419.324	8.824	<0.001
	ARSS	2.4826	1.00393			
	XARSS	2.4588	1.04002			
Purchase Intention*	RSS	3.1637	0.86789	1.448/363.442	1.431	0.240
	ARSS	3.0595	0.92332			
	XARSS	3.1200	0.98278			
Trust**	ARSS	3.1164	0.82783	251	-1.210	0.228
	XARSS	3.1627	0.88032			

Table 7. rmANOVA with Greenhouse-Geisser correction, significance level is 0.05; *(rmANOVA), ** (paired sample *t*-test), RSS (Regular Shopping Scenario), ARSS (Augmented Reality Shopping Scenario), XARSS (Augmented Reality Shopping Scenario with Explainable Artificial Intelligence)

Construct	Scenario	MD	SE	Sig	Cohen's d
Usefulness	RSS – ARSS	-0.405	0.077	<0.001	-0.445
	RSS – XARSS	-0.532	0.083	<0.001	-0.555
	ARSS – XARSS	-0.127	0.045	0.015	-0.126
Entertainment	RSS – ARSS	-0.279	0.063	<0.001	-0.321
	RSS – XARSS	-0.351	0.068	<0.001	-0.395
	ARSS – XARSS	-0.071	0.048	0.424	N/A
Informativeness	RSS – ARSS	-0.430	0.071	<0.001	-0.470
	RSS – XARSS	-0.745	0.075	<0.001	-0.389
	ARSS – XARSS	-0.315	0.053	<0.001	-0.358
Irritation	RSS – ARSS	-0.257	0.073	0.002	-0.277
	RSS – XARSS	-0.233	0.076	0.007	-0.246
	ARSS – XARSS	0.024	0.050	1.000	N/A

Table 8. Bonferroni-adjusted post-hoc tests and effect sizes **Note(s):** Significance level is 0.05, significance values adjusted for multiple comparisons (Bonferroni); MD (Mean Difference), SE (Standard Error) RSS (Regular Shopping Scenario), ARSS (Augmented Reality Shopping Scenario), XARSS (Augmented Reality Shopping Scenario with explainable Artificial Intelligence)

“Entertainment” ($p < 0.001$), “Informativeness” ($p < 0.001$), “Irritation” ($p < 0.001$). In contrast, no differences could be found with respect to “Purchase Intention” ($p = 0.240$), and “Trust” ($p = 0.228$).

The Bonferroni-adjusted post-hoc analyses (see Table 8) showed that participants rated “Usefulness”, “Entertainment”, “Informativeness” and “Irritation” significantly higher in ARSS and XARSS compared to RSS. Additionally, “Usefulness” and “Informativeness” were rated significantly higher in XARSS compared to ARSS. Concerning “Entertainment” and “Irritation” no statistically significant difference between ARSS and XARSS could be identified. Except for the construct “Usefulness”, the effect sizes for all significant differences ranged from $d = -0.277$ to $d = -0.470$, which, according to Cohen (1992), represents a small to medium effect. Regarding the construct “Usefulness” the significant difference between

Q	S	No.M	Code	No.M	Example statement
Q1	Yes	109	Product Information	50	<i>"Yes, like the detailed nutritional information, calories, etc. ..."</i>
			Price Comparison	32	<i>"Comparison with other stores for price"</i>
			Personalization	14	<i>"Customizability of the app, change appearance, sizes of the UI elements"</i>
	No	131	All fine	126	<i>"No, I don't miss any features"</i>
Q2	Yes	141	Overloaded	8	<i>"No, it's already quite overloaded with information."</i>
			App Design	63	<i>"The design of the tiles that pop up around the product could be improved"</i>
			Missing Features	31	<i>"Calculator for food waste reduction"</i>
			App Functionality	26	<i>"Internet connection in some malls is very bad"</i>
	No	90	N/A	N/A	N/A
Q3	Yes	124	Less need to touch	49	<i>"Yes, because you don't need to touch everything"</i>
			Less need to interact	37	<i>"Yes, because I do not need to talk to the shop assistant"</i>
			Effective Shopping	25	<i>"Yes, because then my shopping would be faster"</i>
	No	106	No Benefit	73	<i>"No, because I still have to go to the store"</i>
			Time Waste	16	<i>"No, even worse because I would stay in the shop for longer"</i>
Q4	Yes	95	Information	44	<i>"Yes, because I can get more Information easily"</i>
			Fun	19	<i>"Yes, fun to use"</i>
			Faster	8	<i>"Yes, it makes shopping faster"</i>
	No	117	Don't need this	34	<i>"No because in-store I get enough information"</i>
			Online Shopper	21	<i>"No, Online shopping would still be easier"</i>
			Time Waste	16	<i>"No, it would take too much time while using the application"</i>
Q5	Yes	191	Get Information	40	<i>"Yes, because it shows what I want to know about the product"</i>
			Ease of Use	29	<i>"Yes, they were clear and easy to understand"</i>
			Recommendations	10	<i>"I find the explanations helpful because they make the recommendations lucid for me"</i>
	No	38	Unnecessary	10	<i>"I do not really want to see what my friends think about a specific product"</i>
Q6	N/A		Overloaded	7	<i>"It's too much information"</i>
			Electronics	108	<i>"Probably electronics because it's not always easy to find the relevant information for these products"</i>
			Groceries	72	<i>"Grocery. I like to check the ingredients. Sometime I have to look up E-numbers ..."</i>
			Clothing	38	<i>"I guess I would most likely use that app for shopping clothing (shoes) in order to check for the sizes and measurements"</i>
			Would not use it	31	<i>"I would not use this application"</i>
			All Scenarios	18	<i>"In all retail shopping situations"</i>
			Luxury	13	<i>"I would use it for more expensive products and for products which I buy not very often"</i>
			Books	6	<i>"Books, seeing my friends and other peoples recommendations"</i>

Note(s): Q (Question), S (Sentiment), No. M (Number of Mentions); 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 COVID19? 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?; Q6. In which shopping scenario (grocery/electronics/luxury/clothing/etc.) would you most likely use such an application?

Table 9.
Qualitative results
(open question review)

RSS and ARSS signaled a small to medium effect ($d = -0.445$), the difference between RSS and XARSS showed a medium to large effect ($d = -0.555$) and the difference between ARSS and XARSS suggested a small effect ($d = -0.126$).

Regarding H1, H2 and H3, we conclude that ARSAA had a positive influence on perceived shopping experience, as the constructs “Usefulness”, “Entertainment” and “Informativeness” were all significantly higher in the ARSAA assisted shopping conditions (ARSS and XARSS) than in the unassisted condition (RSS). However, this positive effect might indeed be diminished as the ARSAA assisted shopping scenarios also showed a significantly higher level of consumer “Irritation” supporting H4.

H5 was not supported as no significant differences were found between participants’ “Purchase Intention” across the different scenarios. Similarly, H6 was not supported. Here the data did not reveal a significant difference in the “Trust”-level for the two ARSAA assisted shopping scenarios.

H7 was partially supported as “Usefulness” and “Informativeness” were rated significantly higher in ARSAA assisted shopping scenarios using explainable recommendations than in ARSAA assisted shopping scenarios not using explainable recommendations. However, for the constructs “Entertainment” and “Irritation” no significant influence of explainable recommendation could be observed.

4.2 Qualitative results

Answers from the qualitative questions were coded by patterns (i.e. recurring sentiments) given in the answers entered in the free text field. Results from qualitative data analysis are summarized in Table 9. It presents the general sentiment, most frequent patterns (defined as more than five text passages with a specific sentiment) and an example statement for each pattern.

5. Discussion

Our study revealed significant differences between the evaluated shopping scenarios (R5). In particular, participants evaluate RSS significantly lower in terms of “Usefulness”, “Entertainment”, “Information” and “Irritation” when compared to ARSS and XARSS. These results demonstrate that ARSAA is indeed able to positively influence the customer shopping experience. The observed effect sizes range from small to medium. This should be considered when interpreting the results. However, the difference between RSS and XARSS showed a large effect regarding “Usefulness”, which demonstrates that using ARSAA can indeed strongly support customers during shopping. Considering that PU is the key determinant of technology acceptance decisions (see the results of meta-analyses and reviews, e.g. King and He, 2006; Lee *et al.*, 2003), this finding is of paramount importance.

As a complement to the quantitative data, our qualitative data provide evidence for the positive effects of ARSAA on shopping experience. Drawing from the results of Q6, most participants could imagine using ARSAA during one of their shopping scenarios and only a minority had no interest at all. Additionally, we observed that nearly half the participants of our survey would be motivated by ARSAA to visit a brick-and-mortar store (Q4). The main reasons being the availability of additional information, the fun of using the interactive application and the increase in shopping speed. Furthermore, most participants stated that ARSAA could make their shopping trip more secure (Q3) as it would require touching fewer things, interacting with fewer people and possibly speeding up their shopping trip. Q1 and Q2 demonstrate that the presented ARSAA can be improved by design and functionality changes, and by including features like in-depth product information, price comparison and personalization options which could further increase effectiveness.

In contrast to previous research (Hilken *et al.*, 2017; Javornik, 2016; Poushneh and Vasquez-Parraga, 2017; Yim *et al.*, 2017), our study could not detect a statistically significant difference in “Purchase Intention” when comparing RSS, ARSS and XARSS. However, we argue that the cumulative effect of increased usefulness, entertainment and information, added to the positive sentiment expressed in the open questions Q3 and Q4 and the demonstrated confidence of using ARSAA in various shopping scenarios in Q6, provides notable evidence that ARSAA can be used to influence in-store shopping experience positively. Additionally, we argue that the strength of these effects could even be improved by future versions of ARSAA, if the participants’ feedback (see Q1 and Q2) is taken into consideration.

Analyzing the impact of explainable recommendations on “Trust”, in contrast to previous studies (Chen *et al.*, 2019; Cirqueira *et al.*, 2020b), no significant difference between XARSS and ARSS could be observed. However, partly in line with Cirqueira *et al.* (2020b), our study found further evidence that explainable recommendations can increase shopping experience as XARSS rated significantly higher in terms of “Usefulness” and “Entertainment”. This is also supported by the sentiment expressed in Q5, which shows that the explainable recommendations were perceived as helpful by the majority of participants.

Summarizing, in response to RQ1, it is evident that ARSAA can influence a customer’s shopping experience by significantly influencing perceived “Usefulness”, “Entertainment”, “Information” and “Irritation”. In response to RQ2, it became apparent that improving the design and functionality, while including features like in-depth product information, price comparison and personalization options, would improve the overall satisfaction with ARSAA and, therefore, enhance its influence on shopping experience.

5.1 Theoretical contributions

This study offers theoretical contributions to advance the state of research in the field of personalized recommendations provided by an AR application in brick-and-mortar stores. Our literature review shows that no previous studies have evaluated the impact of such an application on in-store shopping experience. Hence, our results widen this understanding by providing experimental results. Therefore, this study demonstrates that ARSAA assisted shopping is perceived as more useful, entertaining and informative than unassisted shopping. Contrary to TAM studies (e.g. Gefen *et al.*, 2003; Hausman and Siekpe, 2009) and UGT studies (e.g. E. Huang, 2008; Luo, 2002), our examination shows that this increase in customer shopping experience neither converted into an increase of purchase intention nor into intention to visit the store. Interestingly, although an increase of “Irritation” could be observed, its impact on shopping experience was not strong enough to cause an overall decrease in shopping experience, as suggested by previous studies (Chen and Wells, 1999; Ducoffe, 1996). Thus, this study provides evidence that, in the domain of “augmented reality applications used in digital retail”, classical theories such as TAM and UGT do not sufficiently account for the specific circumstances (e.g. connection of online and offline customer journey through smartphone applications) typical for digital retail to adequately describe the influence of the investigated perceptual constructs on customer shopping experience and purchase intention. This is line with recent research (for a recent review, see Sindermann *et al.*, 2020), which suggests that, e.g. user personality has a significant impact on technology acceptance particularly in the more modern retailing contexts such as online shopping and omnichannel shopping (Hermes *et al.*, 2022; Hermes and Riedl, 2021). Therefore, our study contributes to the further development of TAM and UGT by highlighting short comings of these theories, specifically concerning the interaction of customer experience, purchase intention and customer irritation in the omnichannel domain.

From a methodological perspective, the study illustrates the benefits of using design science methodology for solving real-world problems by designing an artifact with justified requirements that were extracted from an extensive literature review and discussions with retail experts. Hence, this research provides design principles and practices for developing an ARSAA. Scholars and practitioners, especially from the field of interactive marketing, can use this artifact to create advanced versions of ARSAA that can further increase shopping experience. Additionally, the study facilitates the need for user-centric experiments, which evaluate the impact of ARSAA artifacts in real world scenarios.

5.2 Practical implications

ARSAA provides an opportunity for retailers to enhance their customers' shopping experience, as it provides a more useful, entertaining and informative experience. Additionally, this study shows that ARSAA using explainable recommendations (XARSS) can increase the customers perceived "Usefulness" and "Informativeness" even further. Therefore, implementing explainable recommendations into AR applications is recommended.

Interestingly, explainable recommendations did not increase "Trust" in ARSAA. Consequently, we cannot advise retailers to implement explainable recommendations if their only goal is to increase trust in their AR application. Furthermore, in line with (Yim and Park, 2019), the results also show that an ARSAA can increase "Irritation", which must be considered by retailers who want to implement such technology. To decrease irritation, retailers should focus on their customers' needs, requirements and capabilities when developing ARSAA. Therefore, they should put emphasis on optimizing the features and functionalities of ARSAA to ensure the creation of a smooth and easy-to-use application (Apple, 2022; Google, 2022).

Additionally, our study could not detect a significant, direct impact of ARSAA on purchase intention. However, as ARSAA positively influences shopping experience, an important part of the path to purchase, we still recommend that retailers who seek to increase their sales implement this technology.

Strategically, we recommend digital retailers to provide ARSAA to their brick-and-mortar customers as it has the potential to increase competitive power against online pure players. In particular, digital retailers could use explainable recommendations to initiate cross-selling or up-selling directly at the point of sale by giving customers the chance to access the entire product portfolio in a useful, entertaining, informative and interactive way. In this regard, the marketing department of a company must deliver the right interactive experience by presenting the correct product recommendations on customers' smartphones.

5.3 Limitations and future research

As with all research, our study has limitations, which provide avenues for future research. We restricted our assessment to an online evaluation approach. Therefore, future studies should test actual usage of the technology in a real brick-and-mortar store thereby increasing external validity and allowing the evaluation of additional constructs that require participants to use the technology in a real-life setting (e.g. flow). Importantly, "flow" has shown to have a strong influence on purchase intention (Hausman and Siekpe, 2009; Huang and Liao, 2017; Javornik, 2016). Thus, we call for future studies assessing the impact on important outcome variables (e.g. purchase intention) eventually complemented by further downstream variables such as actual purchase behavior. Such a future endeavor should also incorporate the knowledge gained from this study. The insights from Q1 and Q2 in particular can be used to improve the design of the ARSAA. Additionally, the fact that XARSS is perceived as much more useful than RSS should inspire future research to investigate the

benefits of providing XARSS in brick-and-mortar stores. In this regard, it should also be noted that, according to the results of this study, theories like TAM and UGT might not give a complete picture of the impact of the investigated constructs on purchase intention or customer experience in the context of AR applications in the digital retail domain. Thus, future research might advance these theories to make them applicable in the emerging field of AR. In this regard, future research should especially consider personality as a direct determinant, or as moderator variable, in studies on ARSAA in brick-and-mortar stores as it has shown to have a significant influence technology acceptance (Hermes *et al.*, 2022; Hermes and Riedl, 2021).

Additionally, we did not measure the impact of privacy concerns on shopping experience or actual usage behavior. However, especially for European retailers who must comply with the General Data Protection Regulations, this is an important area to be investigated by future research.

6. Conclusion

In this study, we followed a design science research methodology and tested the influence of an ARSAA artifact on consumers' in-store shopping experience. The results illustrate that using an ARSAA that uses personalized recommendations and XAI features can indeed increase the shopping experience by providing higher levels of interactivity, making it an important avenue of future research in the field of interactive marketing.

To conclude, as the retail sector moves forward and most brick-and-mortar retailers face challenges to remain competitive, this study can serve as a foundation when assessing the influence of an ARSAA on shopping experience and the design of such an application. It will be rewarding to see what insights future design science initiatives will reveal.

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Supplementary Materials

The supplementary file is available online for this article.

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