In-Store Augmented Reality-Enabled Product Comparison and Recommendation

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ABSTRACT

We present an approach combining the AR-based presentation of product attributes in a physical retail store with recommendations for items only available online. The system supports users' decision-making process by offering functions for comparing product features between items, both physical and online, and by providing recommendations based on selecting in-store products. The physical products may thus serve as anchors for forming the user's preferences, also offering a richer and more engaging experience when exploring the products hands-on. Both objective product attributes as well as the visual appearance of a physical product are employed for generating recommendations from the online space. In this way, the advantages of online and in-store shopping can be combined, creating novel multi-channel opportunities for businesses. An empirical evaluation showed that the comparison and recommendation functions were appreciated by users, and hinted some possible benefits of a hybrid physical-online shopping support system. Despite the limitations of the study, there is sufficient evidence to consider this a viable approach worth to be further explored.

CCS CONCEPTS

• **Human-centered computing** → *Human computer interaction (HCI)*; *Information visualization*; *Mixed / augmented reality*; • **Information systems** → *Recommender systems.*

KEYWORDS

augmented reality, recommender systems, preference construction, product comparison

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1 INTRODUCTION

Even though the idea of augmenting the physical world via the inclusion of digital elements is not a new concept at all [3], the technology that allows for it to be usable on a daily basis has only recently become available on a wider basis. It is in the working environment where augmented reality (AR) has shown its most notable benefits, especially when it comes to improving productivity and quality of production or to providing training and assistance for complex tasks [30]. Entertainment and marketing are also areas where AR has seen more use due to the attractiveness of the new technology and its potential to engage consumers [10], to such an extent that the investment in AR solutions is expected to grow exponentially as the technology matures [29]. In marketing and retail, AR has been applied in various forms at mobile and local customer touch-points [7]. However, in many cases, the engaging effect of AR may rely considerably on its novelty which tends to decrease rather quickly [18] in favour of more conventional methods of interaction.

Combining AR with recommender technologies appears to be an avenue that offers the potential for creating both an engaging customer experience and pragmatic benefits in terms of search and decision support [1, 31, 46]. This combination, however, has thus far only been exploited in specific contexts, such as providing recommendations for mobile users [40, 45]. The application of AR-based recommender techniques in the physical setting of a retail store, in contrast has hardly been investigated yet [9].

Applying AR in a physical store offers various opportunities for supporting users in their decision-making process. The most obvious advantage is that AR can give users the option to explore the properties of a product in situ without the need to switch attention between product and additional information sources, such as leaflets or product websites. A further promising, yet unexplored, function relates to comparing the properties between two and more physically present products since AR can virtually combine product attributes and display them in the vicinity or as overlay of a product the user is looking at . Providing such functions can relieve the burden on the user's memory [2, 39] which can be considerable when comparing a larger number of seemingly similar products in a store . Seeing the properties of a product in direct spatial relation to the product and its parts may enable the user to criticize a product feature and ask for products with different feature values, which can then be recommended from the set of products available.

The recommender function becomes much more powerful, however, if recommendations from the vendor's online offerings can be included in the AR presentation. In this case, the presence of a physical product can help the user to construct his/her preferences more effectively, in particular when certain product features are best understood when it is possible to examine a product in its physical form. A hybrid approach combining physical and virtual products in an AR interface allows to use a small selection of physical products as reference points or anchors[42] for a larger online collection thus reducing space requirements and costs.

The approach is also in line with the ideas of omni-channel retailing [19, 44] where different communication channels cooperate for a more rewarding shopping experience (e.g. use internet to obtain product information when in a physical store). It can also be particularly helpful when dealing with products that require technical knowledge or the assistance of experts to prevent a wrong buying choice. Avoiding inventory limitations, information accessibility and ease of comparison are some of the features for which online shopping is usually preferred over physical stores [47]. With the hybrid approach described in this paper, these benefits can be brought into the physical environment.

In this paper, we present an AR-based shopping support system that combines product comparison and recommending methods for both physical and online products, significantly extending the ideas described in [49]. The concept revolves around the idea of letting users browse the digital product space by exploring the physical one. Its main features include the ability to display relevant attributes of physical products, to allow direct product comparison and to provide product recommendations. Physical products can be compared against each other and against digital ones. Furthermore, recommendations can be influenced by critiquing attributes of physical products.

Our research goals in the matter of bringing virtual recommendations into the physical shopping scene can be summarized in the following research questions:

RQ1 How effective are product recommendations provided through AR?

RQ2 How can the development of user's preferences be supported by AR-enhanced product displays?

RQ3 Does the presence of a physical product serve as a cognitive anchor for selecting among online products?

In accordance with the described approach, a prototype for a shopping support system for Microsoft HoloLens has been implemented and tested in a user study, for the purpose of answering our research questions and evaluating the usefulness of the system when it comes to the alleviation of the limitations of physical retailing.

In the following, related work is discussed, while successive sections describe in deeper detail our approach, the functionality of the prototype developed and the design and results of its evaluation.

2 RELATED WORK

2.1 Recommendations in physical retailing

Online stores typically include features like product comparison tools [23, 32], price trackers, customer reviews and ratings [27], detailed descriptions or product recommendations [37], all of them oriented to providing useful information that supports clients in their purchase decision and overcome the limitations of not having direct access to physical goods. On the other hand, obtaining such amount of information in a physical context depends mainly on the interaction with sales staff [17], although it is not always possible to have access to reliable information sources. The inclusion of recommender systems could be a solution to the information demands of clients in retail stores. As an example of this approach, Kourouthanassis et al. [25] presents a system that automatically creates a shopping list that is updated in real time when the user picks something at the store, while also offering product information and recommending promotions based upon previous buying behaviour or cross-selling associations. Another example would be APriori [45], a system for mobile devices that lets consumers receive product data, recommendations and user ratings directly at the point of sale. There are a few instances in the research field where AR-based recommendations have been used for providing in-store support. In that regard, a system that recommends healthy products is presented in Ahn et al. [1], where the authors also assess, among other aspects, the benefits of using AR for product search in retail stores; in Gutiérrez et al. [15] an AR shopping assistant is described, PHARA, that delivers health-related information, focusing their research on visualization layouts and their convenience for different AR platforms.

2.2 User preference models

Consumers do not always have well-defined preferences, but often tend to build them on the spot when making a decision is required [33]. The lack of preferences becomes an issue especially with digital catalogues where there is a great number of choices that have to be evaluated, possibly leading to choice overload [6]. Recommender systems play a key role in reducing the amount of information that consumers need to evaluate, while they also have the capacity to influence the client's preference-construction process [16]. There are several recommending-related factors that may have an impact on the creation of preferences, from the influence of numerical attributes [26] to the mere presence of recommendations [24]. In our research, however, it is the presence of physical products what could have an effect on the client's final decision, a factor that has not yet been considered due to how rarely physical and digital products are presented together. In this particular scenario, psychological effects such as priming[41] and anchoring[12] should be considered, where physical objects may influence a client's judgement on a perceptual or cognitive level. It is through the usage of physical products that the exploration of a larger set of digital ones is performed, thus supporting a progressive discovery of the product catalogue and the development of consumer preferences.

2.3 AR in retail stores

After years of confrontation between online and physical retailers, traditional companies have begun to understand that the future is digital, to the extent that most of them now offer online retailing channels that may work in parallel or in combination to the already existent physical ones. Depending on the level of integration among the available channels, retailers can be classified as multi-channel, cross-channel or omni-channel [5, 20]. Omni-channel retailing stands for the greatest level of channel integration, where the boundaries between physical and virtual channels have disappeared to provide a seamless shopping experience to customers. The omni-channel approach is slowly taking the stage and replacing current multi-channel retailers [44] (for which each channel works independently), as demonstrated by the new functions that physical stores have gradually taken [13], such as pick-up points or showrooms.

AR in particular has gathered a lot of attention in the retailing context due to its capacity to increase consumer engagement and influence the purchase decision [31]. In-store AR applications have been made popular in the shape of virtual try-on (also called "magic-mirrors") that have gathered a lot of attention [4, 21, 22, 38]. An early example of AR being used in retail stores is The PromoPad [48] which is capable of providing context-aware information of products; Välkkynen et al. [43] developed an approach to visualize package contents before its opening; Rashid et al. [35] uses a combination of RFID with AR to browse physical product shelves; Acquia Labs created a demo [8] for an AR shopping assistant to showcase the possibilities of currently available technology, with features like the superimposition of useful information and customizable product search; Cruz et al. [11] created an AR mobile application for retail stores that detects where the user is located and provides guidance to the item that the user is looking for.

Despite the existence of previous research on AR-based in-store shopping assistants, their combination with product recommending features has rarely been explored so far. Additionally, psychological aspects that may play a role on user acceptance of the concept have been generally overlooked, as it could be the case of priming and anchoring effects.

3 AR-BASED RECOMMENDING AT THE POINT OF SALE

Most of the challenges related to the provision of recommendations can be summarized in three simple questions: what to show, when to show and how to show the information [36]. Rather than addressing these matters directly, we consider it necessary first to create a solid foundation on which recommendations can be built: in our case, it means to find basic activities that customers perform when buying in order to design solutions to support the recommendation aspect over them. That is, recommendations are built upon more elementary aspects that support the buying process in general, such as the access to external information, attribute explanations and comparison methods, which should be as integrated as possible within a normal buying behaviour.

Literature in the field of consumer behaviour point at the comparison of features of different buying options as one of the most common actions that clients of a physical store perform when making a purchase decision [28]. Comparing plays an important role in the client's decision-making process that precedes the selection of a product, which involves not only the comparison of the available items against each other but also against the customer's personal preferences. For this reason, we have taken the comparison of products as the foundation of our approach to AR-enabled shopping assistants. In it, clients can unveil the attributes of physical products, navigate them, learn about their meaning and compare them against the attributes of other products. On top of it, a recommender system has been designed to display products similar to the physical one at which the client is currently looking. These recommendations expand the limitations of the physical catalogue by enabling the selection of products that are not physically present at the store. The digital-product space is browsed by exploring the physical one, which opens room for interesting questions regarding the effects that real world items may have over the choice of digital ones when the former are used as a reference for the latter. Moreover, the recommender system allows user feedback by enabling attribute critiquing, which supports the creation of a mental preference model sustained over the examination of physically present products.

The outlined concept has been implemented into an application that runs under Microsoft's HoloLens and uses marker-based product detection (supported by the Vuforia Engine [1], which provides advanced computer vision functionality to recognize images and objects in AR applications). Although using a smartphone as AR enabler may be a more practical approach for present-day retailing, in this research a head mounted display (HMD) has been chosen instead, even if it means using a medium to which users are less accustomed and may be seen as adding complexity. The reasons behind this decision are: first, because HMD technology is becoming more relevant and it is likely to be more accessible in a near future; second, its nature makes it more interesting in retailing contexts, because it offers a more engaging experience (which is particularly relevant for advertising and promotion stands) and allows for a hands-free direct inspection of products without loosing sight of the augmentations; and third, research in this field is still immature and leaves more opportunities for future work.

The prototype here described is designed to work with physical vacuum cleaners (Fig. 1), but the concept itself could be applied to many different domains. More concrete aspects of the comparison and recommendation features and their implementation are explained over the following subsections.

3.1 Information access

In a normal set-up, clients of a physical store may only access product information by consulting flyers or asking a human sales person. In such scenario, consumers may face situations where the information provided is not sufficiently accurate or complete, or perhaps not enough personnel is available, or they do not have the required expertise to provide support. Human factor aside, even if a reliable source of information is at hand, clients would need to go back and forth from the real product to the place where its characteristics are presented, no matter whether they are written in a nearby sheet of paper or consulted in a smartphone. This process is less than optimal and can become tiresome after some repetitions. Besides, customers still need to interpret the meaning of the information and how it is linked to the product, a task that may happen to be too complicated for those that are not knowledgeable enough in the product space.

Our concept tackles these issues by using AR in a manner that consumers acquire relevant information just by looking at the products. The information is organized in attributes and categories as follows:

Attributes: an attribute is formed by a name and a value. Attributes of each product are put together in categories and displayed anchored to a side of the physical object they belong to. The selection of an attribute shows a brief description that helps to understand its importance and, for those that are linked to some part of the product, the related

[1] engine.vuforia.com/

Figure 1: Overview of the prototype. The attributes of a product are presented on the left side, while recommended items appear on the right side.

Figure 2: The selection of an attribute highlights it and shows a brief description of its meaning and where it is located in the product.

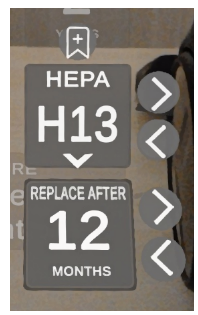

Figure 3: Attribute that contains sub-attributes. Bookmark (top) and Critique (right) buttons are shown as well.

physical part is highlighted to allow direct inspection (Fig. 2). Some attributes act as containers for others attributes (e.g. if a product is powered by a battery, the battery itself has attributes too); these "sub-attributes" are normally hidden, but they will appear if the attribute that contains them is selected (Fig. 3).

Categories: a category refers to a broader, significant aspect of the product (e.g. performance or required maintenance) and receives a score based on the values of the attributes that it encloses. The use of categories is specially significant for technical products, because they usually have many attributes that would overcrowd the display if no filtering means were provided. By accessing a category, the attributes of the product that have an effect on that specific aspect are revealed.

This design works towards making the information more accessible: the different categories help to create relationships between attributes, while the scoring system, attribute explanations and their linked physical parts give an insight of the product's qualities that is understandable even by clients who lack the required knowledge.

3.2 Product comparison

Comparing is regarded as a basic cognitive activity and holds great relevance in terms of understanding, exploring and evaluating our surroundings [14]. But comparing involves a mental effort and becomes harder the more information is required (e.g. when more than only two options are to be compared) as consequence of the limitations of short-term memory [2]. Once again, AR appears to tick all the right boxes: the mental workload of retaining information can be alleviated thanks to the utilization of spatial superimposition via AR, which eliminates short term memory demands[39].

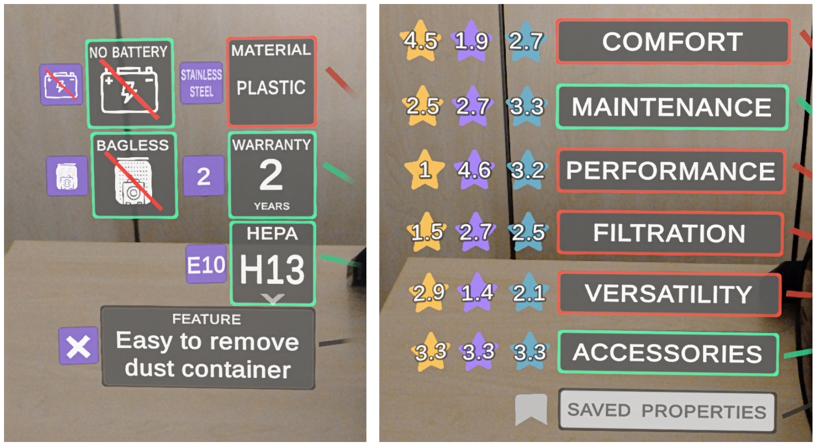

Figure 4: Attributes and categories during the comparison of 2 and 3 products respectively. Values belonging to different items are shown in the colour that has been assigned to them (yellow, purple and blue in the example; in this case, blue is the colour of the product the user is looking at when in the categories view). Selected products, and their assigned colours can be consulted on the right side of the UI (under the recommended items section), which is not shown here. Those attributes in the current product that are better than in the other compared items appear in green; otherwise, the are highlighted in red.

Considering how natural it is for consumers to compare different products before taking a decision, it only seems reasonable to at least explore the advantages that supporting the comparison of physical items may bring to the in-store context. Our approach aims to ease the comparison process and allow users to visualize differences between products regardless of the quantity of their attributes or their location within the shop.

Online stores already offer comparison tools that typically rely on the use of side-by-side tables of product attributes. This is a convenient method for online retailers where there is no physical item that the user can examine. However, as it has been mentioned in the previous section, using a similar solution in a physical store would add the extra effort of going back and forth from real products to the place where the comparison of their attributes is being displayed. Moreover, and in relation to our approach, showing a simple table of attributes on an AR display would not make much sense: in many cases the table would end occupying too much screen space, covering the real world (and products) behind it and giving an impression of disconnection between physical and digital elements. This leads to a waste of the potential of the technology and the rise of questions about why to use AR when more traditional means can achieve better results.

Keeping all the aforementioned points in mind, our approach makes use of the already explained categorization and positioning of product attributes for presenting the comparison. A product enters into comparison mode after being selected by using the "tap" gesture on it. The comparison takes place when two (or three) items are selected at the same time. The following elements are part of the comparison process:

Side by side values: attribute values of each one of the selected products are shown together, keeping the information attached to the product and organized in the same manner as when the comparison was not yet enabled. Values of different products are distinguished by highlighting them with a specific colour. Features not included in one of the products but appearing in the others are added to the former with a tag that indicates that they are "not included".

Visual aids to support the identification of differences: attributes are evaluated by using the same rules that are applied for scoring categories. Based on the results, it is possible to know whether the current product has the best value for a particular attribute among all the chosen ones (bordered in green) or not (bordered in red), but only when such distinction makes sense (Fig. 4). Besides, the comparison of product measurements is shown by superimposing them on a 1:1 3D scale representation that helps to better appreciate their relative dimensions.

Custom Category: an extra category called "Saved Properties" makes possible the combined comparison of multiple attributes that are scattered along different categories. It allows consumers to customize which attributes are shown within it and can be used to store only those that are relevant to their preferences.

Saved Products: up to seven products can be saved in digital form at any moment. They follow the client's movement and are placed slightly above the head in such a way that they can be selected and deselected even when the physical product that they represent is far away.

By combining these elements, it is possible to keep all the information required to make a comparison always within the client's reach, even if only one of the products to be compared is nearby. Customers can save the products that they like while exploring the shop, bring their attributes with them, and start the comparison as they please. It has to be noted that saving attributes and products are actions that are not exclusive of the comparison mode and can be performed at any moment. Also, the process here explained has made reference only to physical-to-physical product comparison, but physical-to-digital comparisons are also possible, as it is mentioned in the following section.

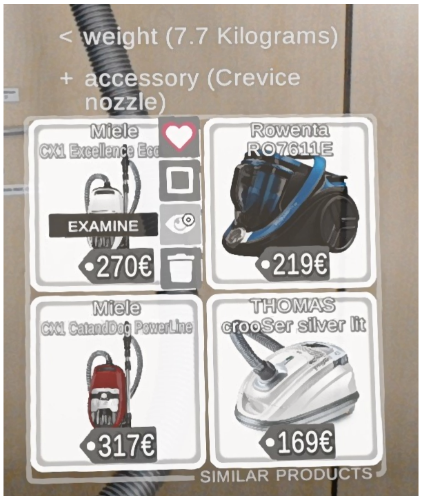

Figure 5: Recommended items. Critiqued attributes are listed above them.

3.3 In-store product recommendations

In our approach, recommendations are provided based on the physical product that is currently in the user's AR focus. Recommendations are calculated by using a content-based technique that takes the attributes of the product that has the attention of the client as an initial user preference model. Similar items are then retrieved from the database and four of them are displayed (Fig. 5). Two similarity scores are calculated: one based on functionality and another one on visual appearance. The functionality score only takes into account attributes that do not have an impact on the aspect of the product. On the other hand, the appearance score is obtained by mixing the similarity of visual-related attributes (e.g. colour, measures or material) and the outcome of comparing their product images against images of the base product. Image comparison is carried out by using DeepAI's API[2] which returns a value indicating how contextually similar they are (0 for identical images). When multiple images of a single product are available, only the lowest value is taken into account. This value is not calculated at runtime but stored in the database beforehand to avoid performance hiccups. The final set of recommendations is formed by the items with the highest scores, two of them based on functionality and two of them on appearance.

The initial set of recommendations can be further refined via critiquing (Fig. 5), which initiates a new recommendation process with a modified set of preferences that now includes the critiqued aspect. Categorical attributes are critiqued by telling the system whether it should be contained in the recommendations or not ("include this" or "exclude this") while for numerical ones it can be requested to consider higher or lower values. In any case, the critiqued properties do not act as a hard filter but as an added preference, thus recommendations are always retrieved. Critiqued properties are not universally shared among available physical products which means that they are set individually and create a unique preference model when joined to the base attributes of the product, thus obtaining distinctive recommendation sets.

[2]deepai.org/

Interaction-wise, other relevant aspects of the proposed concept are:

- Recommended items can be physical or digital, meaning that they may be accessible for inspection or not. This lets clients explore and choose items that are not in the shop, thus extending the catalogue and balancing the purchase options between online and physical retailing channels.
- Browsing the digital space is done by exploring the physical one. Recommended items change from product to product and are based on the specific item to which they are attached, thus users can find what they are looking for in the digital space by searching for similar products in the real world.
- Recommended items can be selected, saved, compared against physical ones or removed. The physical-to-digital comparison factor lets users experience their attributes by taking similar, real objects as a reference.
- Recommended items can be individually removed, which in turn brings forth new ones on their place.

These features provide a playground for clients to explore, learn and make decisions in a shopping situation. The whole buying process is supported: the system provides assistance from the information gathering phase to the point in which a final decision has to be made. Consumers with little knowledge about the product space can begin by exploring physical items in a natural manner; they learn about their attributes and other available purchase possibilities without any more hassle than looking at a product; product comparison is supported by the system, so that consumers do not need to remember attributes nor search for differences by themselves; clients can develop their own preference model that can be further elaborated by critiquing product attributes and obtain recommendations that adjust to it; finally, consumers are able to experience physical and digital products (to an extent) and take a more informed buying decision. The approach also provides a novel answer to open questions concerning the seamless integration of online and physical stores from a consumer's point of view.

4 EVALUATION

A study has been conducted to evaluate the validity of our approach and investigate the benefits of in-store recommending. The evaluation used only the system developed as no realistic baseline to compare against was available (a condition considering an online-only situation or a combined online-store scenario would have significant structural differences for it to be a comparable baseline).

4.1 Settings and experimental tasks

Three physical vacuum cleaner models were available (VC1, VC2, VC3), whose selection was done taking into account that they should cover different usage areas to let users explore a wide range of digital products through them, but remain similar enough to be compared. The database used to obtain the recommendations consisted of 100 vacuum cleaners.

During the study, a floating canvas shown via AR gave participants the information needed to complete the given tasks. Each participant had to solve two tasks concerning the search of an adequate product to match certain criteria. More specifically, each task asked to find products with the following characteristics:

Table 1: Short ResQue items

#	Question	mean	σ
1	The items recommended to me match my interests.	3.5	1.08
2	The recommender systems helped me discover new products.	4.1	0.99
3	The items recommended to me are diverse.	4.1	1.10
4	The layout and labels of the recommender interface are adequate.	4.0	1.05
5	The recommender explains why the products are recommended to me.	2.7	1.49
6	The information provided for the recommended items is sufficient for me to make a purchase decision.	3.9	0.87
7	I found it easy to tell the system what I like/dislike.	3.3	1.16
8	I became familiar with the recommender system very quickly.	4.1	0.87
9	I feel in control of modifying my taste profile.	3.7	1.49
10	I understood why the items were recommended to me.	3.5	1.17
11	The recommender helped me find the ideal item.	3.5	1.17
12	Overall, I am satisfied with the recommender.	3.9	1.19
13	The recommender can be trusted.	3.8	1.03
14	I will use this recommender again.	4.1	1.28
15	I would buy the items recommended, given the opportunity.	3.4	1.50

Task A High suction power and air flow values; moderate weight; attachments suitable for house and car cleaning; price under 200€.

Task B Small size and easy to store; good filtering system, appropriate for allergic persons; can handle pet hair; easy maintenance and handling.

It was taken into account that for each task at least one of the physical products could be a suitable choice.

4.2 Method

A total of 10 participants [3] (4 female, average age of 28.1, σ 4.06) took part in the experiment, 9 of whom had a strong technical background (3 Computer Science students, 5 PHD students and 1 telecommunications engineer in the industrial sector). Each participant was taught basic HoloLens usage and the main features of the prototype. After a brief time to let them get used to it and solve their questions, they were told to follow the instructions given by the application. Tasks were shown sequentially (but their order of appearance was counterbalanced between subjects), and after each of them a 3-item questionnaire was presented, treating aspects such as *purchase confidence* and *helpfulness of physical items*. After both tasks were completed they filled another questionnaire to assess the recommender systems' quality of user experience (*ResQue* [34]) and system-related items measuring the constructs *usefulness*, *decision-making* and *attractiveness*. In addition, task completion times and other empirical variables were measured.

4.3 Results

Items of the ResQue questionnaire are listed in Table 1. Most items show scores above 3.5, showing that users tended to rate positively the implemented recommender system in general, especially in those aspects concerning the novelty of the recommendations (items 2 and 3), perceived ease of use (8) and use intention (14). However, the system is lacking when it comes to the explanation of its results (5).

Table 2 shows the outcome of the system-related questions. They were also positively rated overall, but the highest scores were given to the preference of usage of the system over a traditional comparison tool (item 1) and participants' inclination to use the system if available (7). The two items concerning the helpfulness of physical products (2 and 3) were also rated favourably. However, participants seemed to encounter difficulties to find exactly what they wanted (item 4). Participants were also asked what they would choose if a salesperson and the system were both available. 2 of them would only use the system, 1 affirmed that he/she would prefer to only receive advice from the salesperson, and the remaining 7 would combine both asking for advice and using the system.

Items in Table 3 were answered by participants after each completed task (thus, twice per user of the system). They received high scores too, which suggests that the comparison function and the presence of physical products were perceived as helpful. Users also expressed confidence in their final choice.

Most participants said they felt able to use the system competently after having completed a first task fully. Despite completion times being shorter for the second task (Table 4), there were increments in the average number of critiqued, highlighted and bookmarked properties, as well as how often a category was changed and how many times a participant read the description of an attribute; user's attention moved from one product to another very consistently between tasks, and participants performed more interactions from a digital product to another digital product than from physical to physical or physical to digital ones.

Regarding the selection of a suitable product for each task, a digital one was chosen as the best fitting option in 18 occasions, while physical products were selected 2 times as the final choice (Table 5). For task A most final choices were either VC1 or an item recommended for VC1 or VC3, but never one of the recommendations based on VC2. Similarly, Task B was solved by choosing either VC2 or a recommended item based on VC1 or VC2, never for VC3.

[3] the number of participants needed to be limited because the study was conducted during the COVID-19 pandemic

Table 2: System-related items

#	Question	mean	σ
1	If I had the choice, I would prefer the proposed system instead of a traditional web-based product comparison tool.	4.10	1.97
2	I find that having physical products in front of me made it easier to make a decision.	3.90	1.10
3	I find it helpful/beneficial that I have the possibility to see/touch the products.	3.90	1.37
4	I found it easy to explore the product attributes and find what I was looking for.	2.80	1.03
5	I found it easy to compare the characteristics of different products.	3.70	1.05
6	I believe that I can make a faster buying decision by using the system than by using a more traditional mean (e.g. reading their attributes in a sheet of paper next to the physical products or consulting a salesperson).	3.50	1.17
7	If a store would offer this augmented reality application for a product I am interested in, I would use it.	4.4	0.69

Table 3: Within-subjects questionnaire

#	Question	mean	σ
1	I found it helpful to directly compare product features next to the physical product.	4.25	0.91
2	The physical product shown helped me to form an opinion about the products available online.	4.40	0.68
3	I am confident the product finally chosen would fulfil the requirements described in the task.	3.80	1.00

Table 4: Empirical data collected during the study

	first task		second task		overall	
	mean	σ	mean	σ	mean	σ
completion time (minutes)	14.8	6,20	8.28	1.8	11.54	5.56
frecuency of physical to physical product switches (switches/min)	2.46	2.48	2.59	1.79	2.52	2.10
frecuency of physical to digital product switches (switches/min)	6.85	3.69	8.21	4.91	7.53	4.27
frecuency of digital to digital product switches (switches/min)	11.57	4.81	11.33	5.99	11.45	5.27
products saved	3.00	1.32	2.00	1.00	2.50	1.24
properties critiqued per minute	0.56	0.34	0.72	0.45	0.64	0.39
properties highlighted per minute	1.99	1.01	2.65	1.48	2.32	1.25
properties bookmarked	2.00	1.14	2.22	3.07	2.11	2.32
property description readings per minute	0.60	0.40	0.75	1.5	0.67	1.06
category changes per minute	2.08	1.03	2.41	1.16	2.24	1.08

Table 5: Final choice by type (digital or physical) and item on which the recommendation was based. Task A/B refers to the description of the task, not their order.

	Based on VC1	Based on VC2	Based on VC3	Physical Product	Digital Product
Task A	7	0	3	1 (VC1)	9
Task B	3	7	0	1 (VC2)	9

Furthermore, 4 times out of 10 the same digital vacuum cleaner was selected among the 100 available as a solution for task A.

4.4 Discussion

The results suggest that participants considered the hybrid physical-online approach and the comparison and recommendation functions helpful. However, the system needed initial learning as can be seen in the more frequent use of some functions in the second task. Critiquing, for example, was used 28% more often in task 2.

Concerning the effectiveness of product recommendations via AR (RQ1), results of the ResQue items suggest a tendency towards a positive user perception of the implemented recommender system. Discovering new, diverse products has been relatively well rated, which may be the consequence of joining digital-product filtering through real-world exploration (selecting a physical product limits the digital space to only the similar ones) with critiquing techniques and the fact that recommendations where not only based on technical attributes but also on visual similarity (thus providing a more diverse set of recommendations). The intuitive process of discovering and filtering the digital space by exploring the real world could also be the reason behind participants generally finding easy to become familiar with the system, even with the added complexity that using a HMD may bring. Participants also seem to prefer the AR system over a traditional web-based one, which could be explained precisely by what makes both types of systems different, that is, the presence of real objects. This is supported by how highly regarded were the items of the questionnaire that deal with the helpfulness of having access to physical objects for both comparing and forming an opinion about products and their attributes as well as making a final purchase decision. Although the functions of the system were generally considered helpful, recommendation explanations and attribute exploration were scored lowest in the responses. Admittedly, recommendations have no more explanation than being linked to a physical product and being modified after a new critique is done, which is sufficient to understand the low scoring in that regard. However, the attribute exploration issue is not exclusive of the concept here presented nor recommender systems in general, and has more to do with the capabilities of AR technology when it comes to navigate through large attribute sets. Possibly, easier forms of presenting attributes and comparisons may become feasible when AR glasses will offer a larger viewing angle or if a different AR platform is used (e.g. smartphones, although they have their own challenges and limitations).

Regarding the possible implications of using AR product displays on the development of user preferences (RQ2), having access to physical products appears to be beneficial to some extent for understanding their properties and extrapolating them to the non-physically-present ones. Participants addressed this aspect directly in the survey, where the presence of physical products was judged mostly as helpful when making a decision in the digital sphere. Their perceptions in that regard are supported by how confident they were when assessing the suitability of the chosen products despite having selected digital ones for the most part.

Lastly, when it comes to possible anchoring or priming effects and the role that physical products play over the exploration of digital ones (RQ3), there appears to be a connection between what physical products are available and how users explore the digital space. The evaluation showed that users based their final choice on the physical item preferred for the task given and the recommendations that were provided for this physical item, mostly ignoring other online items. As has already been mentioned, selecting a physical product apparently acted as a filter for the online product space which suggest the existence of anchoring and priming effects.

4.4.1 Limitations. Participants of the study may not be representative of the population targeted by the concept due to their low number and strong technical background. For practical reasons there was only a limited number of physical products and not all product categories were properly represented , which would not have been the case in a real world scenario. This has an obvious impact in how often digital products were chosen over physical ones, which could have been very different if a larger variety of physical items were available. The usage of a HMD instead of a more conventional device may have had an impact on participants' perception of the system due to its novelty, thus possibly influencing the results. The interpretation of the results is also limited by the lack of a baseline against which to compare them and caution is required when interpreting an apparently positive finding. Lastly, the preferences implied by the task scenarios provided may have limited the users' need to engage more deeply in developing their own preferences. These aspects require a more careful exploration in further research.

5 CONCLUSIONS AND FURTHER RESEARCH

In this paper, an approach to in-store product recommendations provided via augmented reality is presented. It is built under the hypothesis that the creation of a mental preference model in a physical buying environment can be alleviated by having access to product information and recommendations, while at the same time the navigation of the digital space is improved by taking advantage of real world exploration. Furthermore, when the recommendations provide items that are not physically present in the store (taken from a digital catalogue), the inspection of other, similar items that are physically accessible could have an effect on how clients perceive the digital ones. In the implemented prototype for AR head mounted displays, clients can obtain product information of physical vacuum cleaners by just looking at them. The augmentations show product attributes and their meaning, as well as where the related parts are located in the product. Product comparison is supported by the inclusion of visual aids to directly perceive differences between them, which aims to mitigate the limitations of short-term memory. Recommendations of similar products (both real and digital) are provided for each physical one, whose outcome can be influenced by critiquing its attributes.

During the performed user study, the system was positively rated and perceived as useful and intuitive. The selection and exploration of products was influenced by the presence of physical items. The digital space was browsed based on the attributes of real objects, since participants focused on the recommendations given for specific vacuum cleaners (the ones that they considered more fitting for the given tasks). Physical products were predominantly regarded as helpful for forming an opinion of the ones available only in digital form. However, all these results should be taken with reservation due to the various limitations of the study in terms of the number of participants, the lab setting and the lack of a baseline. Altogether there is enough evidence to at least consider this to be a viable approach worth to be further explored. Future work will focus on consolidating the results presented here and on obtaining a deeper understanding of preference construction and the role of anchoring and priming effects in a hybrid physical-online setting. It is also in our scope to study new methods for combining appearance and function based recommendations and how different types of clients may react to them.

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