ShoppingCoach: Using Diminished Reality to Prevent Unhealthy Food Choices in an Offline Supermarket Scenario

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Figure 1: ShoppingCoach helps users to choose healthier grocery products by visually diminishing unhealthy products. (a) A user reading the nutrition label of a packaged product without assistance. (b) A user wearing a head-mounted display with ShoppingCoach installed which visually diminishes the perception of unhealthy products as depicted in (c).

ABSTRACT

Non-communicable diseases, such as obesity and diabetes, have a significant global impact on health outcomes. While governments worldwide focus on promoting healthy eating, individuals still struggle to follow dietary recommendations. Augmented Reality (AR) might be a useful tool to emphasize specific food products at the point of purchase. However, AR may also add visual clutter to an already complex supermarket environment. Instead, reducing the visual prevalence of unhealthy food products through Diminished Reality (DR) could be a viable alternative: We present ShoppingCoach, a DR prototype that identifies supermarket food products and visually diminishes them dependent on the deviation of the target product's composition from dietary recommendations. In a study with 12 participants, we found that ShoppingCoach increased compliance with dietary recommendations from 75% to 100% and reduced decision time by 41%. These results demonstrate the promising potential of DR in promoting healthier food choices and thus enhancing public health.

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CCS CONCEPTS

• **Human-centered computing** → **Mixed / augmented reality**; **Ubiquitous and mobile computing systems and tools**; • **Applied computing** → *Consumer health*; *Health informatics*.

KEYWORDS

diminished reality, extended reality, food choices, nutrition and health, health informatics

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1 INTRODUCTION

Unhealthy diets are a major risk factor of non-communicable diseases (NCD) around the globe [41, 43]. Modifying them is an applicable solution to reduce NCDs [43]. In 2019, 7.9 million deaths and 187.8 million disability-adjusted life-years were attributable to dietary risk factors [45]. To promote health, help reduce the risk of diet-related NCDs, and meet nutrient needs, many regions provide food-based dietary guidelines (FBDG) about what to eat and drink [26, 50]. During diet counseling processes, these FBDGs are frequently referenced by dietitians to support their clients to

modify their food choices, while considering individual health status and personal preferences [27]. Existing research shows that diet counseling is indeed effective for the management of diet-related NCDs [4, 20].

However, individuals frequently exhibit suboptimal compliance and adherence to proposed dietary strategies [16, 47], which undermines the effectiveness of diet counseling. Implementing interventions during meals, whether at home or in a restaurant, is challenging due to the social, cultural and emotional significance of food, which can create resistance to interruptions. In addition, the complexity and variety of food recipes hinder accurate estimation of the food composition, essential for further interventions. Conversely, when people purchase packaged food products from a supermarket, there is less social tension, and nutrition labels enable them to make more informed food choices. At the food product level, front-of-package (FOP) labels such as the Nutri-Score [14] have been introduced to help customers make healthy food choices. These FOP labels are viewed more frequently than nutrition facts on the back of product packaging [21]; however, they are only mandated in few countries. For online supermarkets, interventions such as browser plug-ins that display food labels [19, 34] or recommend healthier alternatives, have been implemented and proven to be effective [11, 31]. In offline supermarkets, in addition to FOP labels, Augmented Reality (AR) has been used to display virtual labels on top of or next to physical products [2, 24, 44]. This influences individuals' food choices at the point of purchase and enables personalized interventions in various languages or based on user context. On the other hand, research has documented adverse effects of cluttering, finding that "attention to [nutrition] labels decreases with an increasing number of additional design elements appearing on the front of the packaging" [7].

An alternative to emphasizing the nutritional composition of a product via an additional label is to *de-emphasize products that are not healthy* for a given customer; this is also motivated by a recently documented finding that "interventions are more effective at reducing unhealthy eating than increasing healthy eating" [10, p.1]. One approach to achieve such a de-emphasis is the usage of Diminished Reality (DR), which describes the controlled reduction of the perceptual salience of objects in a user's environment [15]. The usage of DR might thus be especially beneficial in environments that already have a high degree of visual clutter, where additional information might cause information overload and distraction; it might be a particularly ecologically viable approach to providing shopping suggestions.

In this work, we thus investigated whether de-emphasizing unhealthy products via DR can provide effective support for making healthy food choices. To this end, we have designed and implemented a prototype DR application called *ShoppingCoach*. ShoppingCoach diminishes the perception of physical grocery products that it deems unhealthy based on product nutrition information and user-specific dietary recommendations. To motivate our prototype, we discuss related literature on technological approaches to promote healthier food choices (Sect. 2), followed by the presentation of our prototype (Sect. 3). We then detail the prototype's evaluation where participants had to choose grocery products in an offline supermarket scenario with and without our system (Sect. 4), and present the results which show that ShoppingCoach significantly improves compliance with dietary recommendations and reduces decision time (Sect. 5). Finally, we discuss these results and provide future avenues for this work (Sect. 6).

2 RELATED WORK

2.1 Enhancing Adherence to Dietary Recommendations

To help people make healthy food choices, FBDGs provide culturally adapted and science-based recommendations [26], such as *Dietary Guidelines for Americans, 2020-2025* [42]. Referring to these FBDGs, dietitians can support clients to make healthy food choices through personalized dietary recommendations, considering individual needs and preferences [27]. The diet counseling process has been proven to be effective in managing diet-related NCDs [4, 20], but is limited by the restricted clinical resources and the burden on clients for food tracking (e.g., with diaries) and compliance (e.g., by using FOP or back-of-package food labels). The point-of-sale presents another potentially valuable opportunity for promoting healthy eating through nutrition education or environment modification [12, 32] through strategies such as simpler FOP labels and the provisioning of monetary incentives [12, 32]. The FOP food label Nutri-Score, for instance, informs consumers about the overall nutritional value of foods in a simple and understandable way [14, 25]. The nutrient profiling system underlying Nutri-Score is based on the content of nutrients and other elements per 100 grams of a food/beverage, such as sugar content and sodium content [14]. By referring to the Nutri-Score on the package, consumers may thus make healthier food choices at the point of purchase. In online grocery shopping settings such as on supermarket websites, information and position nudges are effective in supporting healthy food shopping [19, 31, 34, 46]. However, FOP food labels may achieve a small degree of success (maximum of 2.0% shift in healthiness of food purchases) at assisting shoppers to buy healthier food [17, 51].

2.2 Interventions using Augmented Reality

In offline shopping settings, AR is increasingly used to display virtual labels and dietary recommendations on top of or next to physical products [35]. While earlier applications mostly use smartphone-based mobile AR [2, 24], more recent examples have employed AR head-mounted displays to display nutrition and health-related information in AR [1, 18, 23, 28, 44]—this is typically shown in addition to FOP or back-of-package labels on the physical product, and contains information about food scores (such as Nutri-Score), macronutrient composition (e.g., sugar content), ingredient lists, and sustainabiliy-related data such as the product's carbon footprint. These systems do not yet exploit the potential to *personalize* recommendations, for instance by accommodating allergies, specific diets (e.g., veganism, planetarism), and restrictions arising from medical conditions (e.g., after bariatric surgery [49]). While AR apps offer the advantage of presenting information directly overlaid on physical products, they usually add multiple virtual elements to each product in scenarios where users examine individual products (e.g., [24, 44]). In a typical offline supermarket setting, however, products are usually arranged on shelves alongside many other items. Thus, introducing excessive information through AR in such contexts may lead to perceptual overload for participants. This might also reduce the effectiveness

of the displayed information, since "attention to [nutrition] labels decreases with an increasing number of additional design elements appearing on the front of the packaging" [7, p.71].

2.3 Diminished Reality to Reduce Visual Clutter

To promote healthier food choices more effectively, an alternative to *emphasizing* recommended products (e.g., [1]), might therefore be to *de-emphasize products that are not healthy* for a given customer. A reduction of the visual clutter in offline shopping setting might be beneficial since mental processes cannot optimally work in the presence of *visual clutter*, i.e. when the amount of items and the way they are organized (or represented) degrade human performance [48]. This reduction can be achieved by emphasizing task-relevant visual details and suppressing others [8] that are semantically less relevant [30] or perceptually redundant [6]. Previous research shows that visual interfaces with reduced clutter improve human visual search performance [5] and increase the salience of items that are being advertised or retailed [29]. One method to reduce visual clutter in a scene is DR, which describes the concealment of selected parts of a physical scene or their replacement with computer-generated content [33, 40]. DR can counteract visual clutter in various ways such as by altering the opacity of objects or introducing blur which reduce the (visual) saliency of undesired objects without causing semantic gaps [15]. In previous research, DR has been implemented using video see-through devices [40], and recent examples demonstrate its use in Virtual Reality [15] and hand-held devices [13]. However, applications of DR with optical see-through devices are still underexplored [40], mainly due to technical shortcomings of these devices that do not yet allow the convincing perceptual diminishing of physical objects [15]. Previous research focused on testing the feasibility and user acceptance of various DR techniques in generic tasks [15, 53]. They found, e.g., that changing the *opacity* (or *transparency*) of objects is one of the most effective and aesthetically pleasing DR techniques [15, 53]. Building on the surveyed related work across the fields of dietary recommendations, AR, and DR, we investigate how DR on an optical see-through AR headset can be used to increase adherence with shopping suggestions and to reduce unhealthy food choices.

3 THE SHOPPINGCOACH PROTOTYPE

We propose the ShoppingCoach system that helps users make healthier food choices by visually diminishing the salience of unhealthy products. ShoppingCoach is able to detect grocery products in front of the user, and selectively diminish their visual appearance based on the products' macro-nutrient composition that is merged with a user-specific dietary recommendation (e.g., "Reduce sugar from cereals."). It consists of an AR HMD, an Object Detection component, a Product Database, and a Dietary Recommendation Database. Figure 2a gives an overview of the system, and we provide more details about its components in the following. The AR HMD's camera feed provides the input for the Object Detection component, which detects grocery products and returns the products' IDs and bounding box coordinates on the 2D video frame. ShoppingCoach then looks up a detected product's nutritional composition in the Product Database and compares the macronutrient composition of the product with the user's current dietary recommendations. The system next calculates a level of relevance for each product, taking into account the deviation of the product from the recommendation to the user. This level is then used to control the visual opacity of the physical product in front of the user via a virtual overlay whose opacity is adjusted accordingly.

3.1 Product Database and Dietary Recommendations

We selected four food categories—crisps, cereals, chocolate, and pasta—that meet specific criteria: practical packaging, convenient storage, extended shelf life, and a wide range of nutritional profiles. From each category, one *reference product* (with which the other products were compared), along with four healthier options and four less healthy alternatives were included for the user study. For each trial in the user study, only the *reference product*, two healthier alternatives, and two less healthy alternatives were used. Here, the term *healthy* refers to a specific nutrient that we regard for each category based on a dietary recommendation such as "Reduce sodium from crisps." or "Increase fiber from pasta.". The recommendations were designed by nutritional experts from a collaborator hospital, and are used by these domain experts in clinical projects. The food data comes from a database maintained by the study group that is sourced from publicly available data from supermarkets. It contains detailed nutrition information for products, including Nutri-Score-related information. The AR HMD in our prototype receives this information through a Web API by specifying a product ID (i.e., a product's Global Trade Item Number (GTIN) [22]. To ensure data accuracy, nutrition information for all products has been verified with the nutrition labels on the food packages.

3.2 Object Detection Component

The ShoppingCoach prototype uses a custom trained YOLOv7 [52] model to detect grocery products in the user's field of view. We trained our custom YOLOv7 model on a NVIDIA Tesla T4 GPU with 36 classes consisting of grocery products in the aforementioned four categories with 100 images per class. To evaluate the model, we divided our dataset into a training (80% of all images) and validation subset (20%). The test on the validation set resulted in an overall recognition precision of 99.2% and a recall of 99.8%. The mean Average Precision (mAP) scores of 99.4% at an Intersection over Union (IoU) threshold of 0.5 and 97.6% across the range IoU=[0.5, 0.95] further indicate the robustness of our model. The object detector accesses the video feed of the HL2 front camera through the Mixed Reality Device Portal API [36] and processes the video frames with a frame rate of approximately 30 frames per second on an NVIDIA GeForce RTX 3060 on an external computer. Once a product is recognized, its GTIN and the bounding box coordinates of the detected product on the 2D video frame are returned to the AR HMD.

3.3 Diminished Reality Component

We developed an application for the Microsoft HoloLens 2 (HL2), using Unity 2022.3 and MRTK v2.8.3 [39]. The application connects the object detection component with the nutrition data and recommendations, and finally diminishes the salience of physical products with virtual overlays. After the HL2 application receives

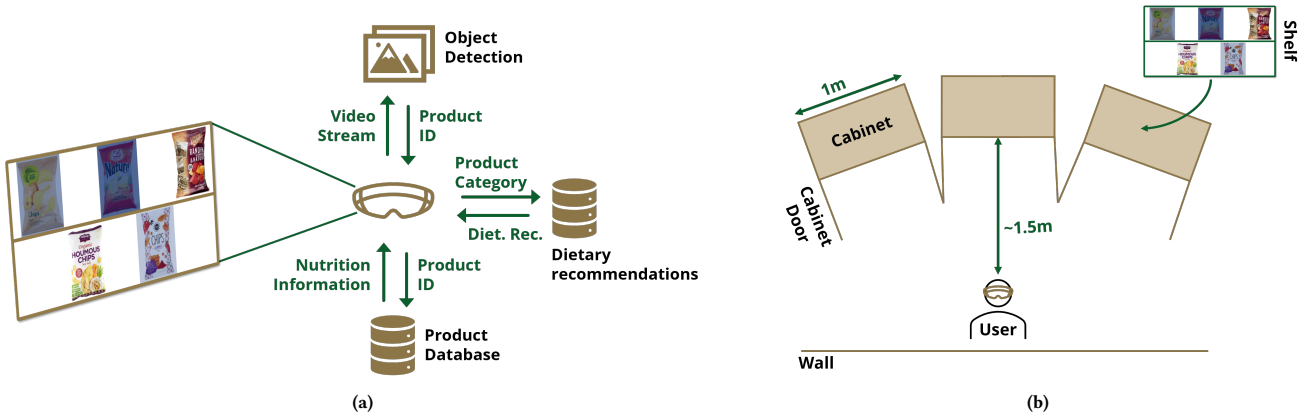


Figure 2: (a) The system overview of ShoppingCoach. It consists of a HL2 on which the central algorithm runs which communicates with the Object Recognition, and the two databases for dietary recommendations and products. (b) The experimental setup of our evaluation where a participant is sitting in front of three cabinets while wearing a HL2. Each cabinet contains five products on two shelves per condition.

the GTINs of the detected objects, it queries the product database to retrieve each product's nutritional composition. It next considers the user-specific nutrition recommendations to determine whether the product's appearance in the user's field of view should be diminished: If the recommendation is, e.g., "Reduce sugar from chocolate.", products with a higher sugar content per 100 grams than the reference product will be visually diminished according to how much more sugar they contain. Here, we first calculated an opacity score between 0 and 1 based on the difference between the current product's nutrient's amount relative to the reference product's one. An opacity score of 1 means that the virtual overlay will be fully opaque. To place a virtual overlay on the physical product, we used the product's 2D bounding box coordinates to calculate a 3D position. To this end, the 2D bounding box coordinates are transformed into a ray from the origin of the HL2's camera pointing away from the HL2. Using a combination of Unity's `Physics.Raycast` and MRTK spatial mapping [38] , the point at which the casted ray collides with the spatial mesh (i.e., a representation of the geometry of the user's environment created by MRTK's Spatial Awareness System [37] is used as the 3D center position of the overlay. In addition to determining the 3D coordinates of the product's center, we use this technique to calculate the coordinates of each of the corners of the bounding box. This allows us to adjust the size of the virtual overlay approximately to the size of the physical product. The previously calculated opacity score is then applied to the overlay's material to correctly diminish the physical product in front of the user. These steps to add a virtual overlay are repeated for each product that is currently in the HL2 camera's field of view.

4 EXPERIMENTAL EVALUATION OF SHOPPINGCOACH

We evaluated the ShoppingCoach prototype in a controlled experiment to test the following hypotheses: (H1) The usage of ShoppingCoach leads to a higher compliance with provided dietary recommendations; (H2) When using ShoppingCoach, participants need less time to choose a product.

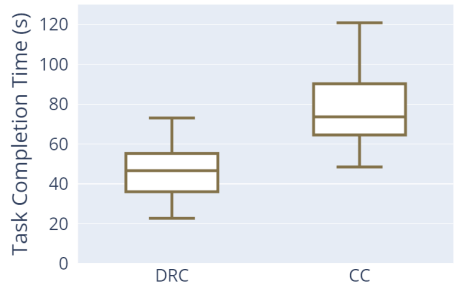
4.1 Participants

For our study, we recruited 12 male university students (half of them with corrected vision; age: $M = 22.75, SD = 1.66$). Two-thirds of the participants pursue studies in the field of Business Administration, Finance or Economics. Most study on a Bachelor's level (N=9). On a 5-point Likert-scale, the participants indicated a familiarity with AR or Virtual Reality (VR) devices of 2.25 ($SD = 1.48$). They rated their consideration of nutritional content when deciding what to eat with an average of 3.66 ($SD = 1.07$), their understanding of nutritional information with an average of 3.42 ($SD = 1.38$), and their confidence in making healthy purchasing decisions at supermarkets with an average 3.42 ($SD = 1.31$). Four participants indicated having used a nutrition app while grocery shopping before. According to our university's regulations, no formal approval from the university's ethics committee was required for this experiment.

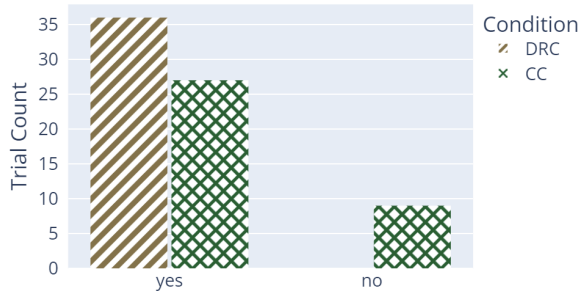
4.2 Experimental Procedure

In a within-subject design, we compared two conditions: the Diminished Reality condition (DRC) and the control condition without DR (CC). We did not incorporate an AR condition, as our primary aim was to assess the viability of DR as an approach before introducing additional variables. In DRC, the grocery products were visually diminished according to the mechanism described in Sect. 3.3, while in CC the participants perceived the products visually un-mediated. In both conditions, the participants were permitted to touch and inspect the physical products. In DRC, the diminishing overlay was projected over the products only once and remained static. Thus, participants had the freedom to examine the products without any obstruction by taking them into their hands.

Upon arrival, participants received a printed information sheet and consent form. After giving consent, each participant filled out a pre-study questionnaire about demographic data and grocery



(a) Task completion time per condition



(b) Followed recommendations per condition

Figure 3: (a) Box plots of the task completion time (in seconds) per condition (N=12). (b) A histogram indicating in how many trials the participants chose a product that followed the given recommendation per condition.

shopping habits. Afterwards, the participants were familiarized with the HL2 and the experimental setup. We asked participants to wear the HL2 in both conditions to mitigate potential confounding effects. However, the HL2 did not display any content in CC. Each participant completed a block of three trials per condition, where we randomized the order of conditions across participants. During each trial, the participants were seated on an office chair in front of three cabinets (see Figure 2b). Each cabinet contained two shelves in which five distinct grocery products were randomly distributed: the *reference product*, two healthier ones, and two unhealthier ones. In a trial, participants were given a nutrition recommendation to follow, a *reference product* to compare with, and were then asked to select one product from a given category (see the setup in Fig. 2b). After the system detected the products and placed the virtual overlays (where, in the CC, no content was shown on the HL2), we measured how long the participants took to select a suitable product. At the end of each trial, participants answered a questionnaire about their confidence in their product choices and the perceived healthiness of these products. After the DRC-block, the participants additionally reported about the usability of the ShoppingCoach based on the System Usability Scale (SUS) [9]. The experiment lasted approximately 50 minutes per participant.

5 RESULTS

The results of our experiment confirmed both hypotheses: Confirming (H1), participants always chose a product following the given recommendation in DRC. In CC, participants chose on average 0.25 ($SD = 0.44$) products (out of a total of 3) that violated the given recommendation (see Fig. 3b). Among the 12 participants, four consistently followed the recommendations in CC, while eight chose one product incorrectly, and one chose two products that did not adhere to the recommendations. Confirming (H2), the participants in DRC needed significantly less time in seconds ($M = 46.51, SD = 13.8$) to choose a product ($t(70) = -8.24, p < 0.001$) than in CC ($M = 78.25, SD = 18.5$, see Fig. 3a).

The average SUS score indicated by the participants was 63.96 ($SD = 18.94$). According to [3] this score is in the marginal part (50 to 70 on a scale from 0 to 100) of the *Acceptability Range* and is classified as *Good* (between *OK* and *Excellent*). In DRC, the average helpfulness-rating of ShoppingCoach was given as 3.50 ($SD = 1.24$) out of 5. We found a significant moderate negative correlation between participants' reported understanding of nutritional information on product packaging before the study and their satisfaction with the shopping experience in DRC (Pearson's $r = -0.649, p = 0.022$). Participants' satisfaction with their shopping experience was higher after DRC ($M = 3.92, SD = 0.67$) than after CC ($M = 3.5, SD = 1.31$), although the difference was not significant ($t(22) = 0.78, p = 0.447$). Similarly, participants' confidence that they had followed the recommendation was higher in DRC ($M = 4.17, SD = 0.93$) than in CC ($M = 3.83, SD = 1.11$), but the difference was not statistically significant ($t(22) = 0.67, p = 0.52$). Participants rated the similarity of their shopping experience with their usual experience higher in DRC ($M = 3.25, SD = 1.54$) than in CC ($M = 2.67, SD = 1.30$), yet this is not significantly different ($t(22) = 1.34, p = 0.206$). In DRC, participants rated the perceived healthiness of the chosen product compared to the reference product slightly higher ($M = 3.75, SD = 1.35$) than in CC ($M = 3.50, SD = 1.31$), although there was no significant difference in the comparison ($t(22) = 0.45, p = 0.65$).

6 DISCUSSION

The experimental evaluation showed that ShoppingCoach can indeed increase participants' compliance in following dietary recommendations, with a significantly reduced task completion time, even though the participants were not very familiar with AR/VR devices. The moderate SUS score ($M = 63.96$) suggests room for improvement in the usability of our prototype. It is important to note that our prototype lacked extensive interactive elements, potentially impacting the significance of the SUS score in assessing overall usability. Since the satisfaction of the shopping experience and the perceived similarity with their usual shopping experience in DRC was not significantly different from CC, participants do not seem to see their experience negatively impacted by the diminishing of the physical products. Thus, the approach of using DR in this scenario might be viable and worth exploring further.

Results from the preliminary study should be interpreted in light of the following limitations: First, the small (N=12) and homogeneous (in terms of gender, age and profession) sample may restrict the generalizability of the study results. To achieve more robust results, a larger and more heterogeneous sample is needed. Second, we had six trials per participant in the experiment, but only four food categories, and thus two product categories appeared in

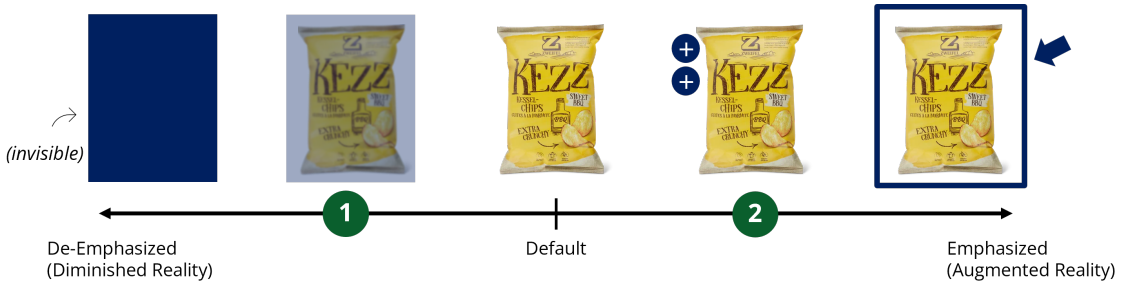


Figure 4: A spectrum that shows how physical products can be emphasized using AR, or de-emphasized using DR. ShoppingCoach currently diminishes products visually to discourage selecting them (1), while we plan to implement a separate AR condition that emphasizes those products that are healthy (2) for a customer.

two conditions, instead of one. Nevertheless, no product appeared twice except for the *reference product*, because there were enough products available in each category. To achieve more robust results, more food products from different categories should be included. However, we might not be able to extend the categories to a great extent, considering the criteria as described in Section 3.1. Third, the arrangement of the product shelf in the experiment differed from typical supermarkets, in terms of number and placement of products, the absence of price information, and other environmental factors such as lighting and sound. However, our objective was to gather initial evidence on the effectiveness of DR in a simulated shopping scenario and therefore, we used a simplified scenario.

We intend to use the system presented in this work as a starting point towards a more comprehensive exploration of (de-) emphasizing objects in a user's surroundings to (not) recommend certain objects. Figure 4 shows a spectrum of how the emphasis and de-emphasis of objects could be realized using AR and DR. The current version of ShoppingCoach investigated how the diminishing of unhealthy physical products can discourage participants to choose them (see (1) in Fig. 4). In a future version of ShoppingCoach, we plan to further explore the delivery of product recommendations, including emphasizing products using AR (see (2) in Fig. 4). De-emphasizing a product via DR would usually have the aim to discourage a consumer from choosing this product, while emphasizing a product via AR can be used to encourage or discourage a consumer to choose this product. Furthermore, the (de-) emphasis of a product does not have to be exclusively health-related; it can also address other preferences, such as aspects of sustainability or origin of products.

7 CONCLUSION

In this work, we presented ShoppingCoach, a prototype which visually diminishes physical products in an offline shopping scenario using a virtual overlay to prevent unhealthy food choices. The results from a controlled experiment show that ShoppingCoach enables users to be significantly more compliant with dietary recommendations and also significantly faster in choosing a suitable product. These findings suggests that DR may indeed be a viable method to assist users in choosing healthier products. Going forward, we plan to increase the number of food products, food categories, and the sample size for more robust results. We also plan to improve the system's usability, and implement an additional AR mode in ShoppingCoach, which will display virtual labels next to the physical products.

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