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Conference Paper · October 2019

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Impact of Mixed Reality Food Labels on Product Selection

Insights from a User Study using Headset-mediated Food Labels at a Vending Machine

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ABSTRACT

The rise in diet-related non-communicable diseases suggests that consumers find it difficult to make healthy food-related purchases. This situation is most pertinent in fast-paced retail environments where customers are confronted with sugar-rich or savory food items. Counter-measures such as front-of-package labelling are not yet mandated in most regions, and barcode scanning mobile applications are impractical when purchasing groceries. We thus applied a mixed reality (MR) wearable headset-mediated intervention (N = 61) at vending machines to explore the potential of passively activated, pervasive MR food labels in affecting beverage purchasing choices. Through conduction of a between-subject randomized controlled trial, we find significant, strong improvements in nutritional quality of the selected products (Energy: -34% KJ/100ml, Sugar: -28% g/100ml). Our post-hoc analysis suggests that the intervention effect is especially effective with existing food literacy. This study motivates further research on MR food labels due to the promising, observed intervention effects.

CCS CONCEPTS

• Consumer health • Human computer interaction (HCI) • Information visualization • Empirical studies in visualization

KEYWORDS

Mixed reality, Nutri-Score, Food labels, Product selection

ACM Reference format:

Klaus Fuchs, Tobias Grundmann, Mirella Haldimann and Elgar Fleisch. 2019. Impact of Mixed Reality Food Labels on Product Selection: Insights from a User Study using Headset-mediated Food Labels at a Vending Machine. In *Proceedings of ACM MADiMa '19, October 21, 2019, Nice, France*. ACM, New York, NY, USA. 8 pages. <https://doi.org/10.1145/3347448.3357167>

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MADiMa '19, October 21, 2019, Nice, France

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ACM ISBN 978-1-4503-6916-9/19/10...\$15.00.

DOI: <http://dx.doi.org/10.1145/3347448.3357167>

1 Motivation

Unhealthy food choices are a known risk factor that contribute to the increasing prevalence of non-communicable diseases and premature deaths [44, 45]. In particular the consumption of sugar-sweetened beverages in this context have been highlighted [30, 35]. Consequently, dietary intake has become a recognized public health priority [10], and support for healthier food selection behavior is of key importance to achieve changes in consumer behavior and population health [23].

To address this issue, selected national regulators have begun to introduce front-of-package labels (FoPL), that indicate the degree of nutritional quality for a packaged food item. The important advantages of FoPL in comparison to back-of-package (BoPL) declaration of nutrients and daily intake estimates are their color-encoding and immediate visibility before making a purchase. Such FoPL include most notably the Multiple Traffic Light (MTL) and the Nutri-Score (NS) [22, 38] and have been shown to positively influence food choices [22, 25]. Despite growing evidence between FoPL and healthier food choices, most consumers cannot benefit from FoPL today, as only very few countries have successfully implemented FoPL at significant scale. Multiple barriers to FoPL label adoption exist. First, regulators may be confronted with resistance from retailers, brands or manufacturers who worry about negative economic impacts due to increased administrative and logistical efforts associated with the introduction of mandatory food labels. Second, companies and retailers that offer potentially 'negatively' labelled foods fear declining revenues [41]. Third, societies and public debates might turn against regulators, since individuals may dislike being patronized by regulators about dietary consumption. Consequently, only few countries have successfully managed to introduce FoPL, including Australia with the Health Star Rating (HSR) [38], France with NS or England with the MTL label [22]. As a result, today most consumers cannot yet benefit from easy-to-compare FoPL on their food choices.

As a result of these developments, a series of barcode scanning mobile Health (mHealth) applications have been developed with the intent to display support healthy food choices, for example by displaying FoPL in absence of such regulation [6, 9, 31]. These apps are seen as an inclusive and scalable support system for healthy food [7]. However, the prevalence of such apps remains limited and many suffer from self-selection bias [27] and low rates

of retention [36]. Several factors appear to limit the impact of such technology-based interventions. First, the manual activation hinders continuous usage [16], as users must actively remember to manually scan barcodes of all purchased products. Second, to actively scan a barcode requires aligning smartphone and products, requiring both hands of the consumer, which is usually impossible, as customers are usually not hands-free during shopping, e.g. carrying bags or products [12, 36]. Third, studies show that current diet-related mHealth are usually primarily retained by users with an above average interest in nutrition [28], an interest that is particularly not often prevalent amongst sociodemographic segments prone to diet-related diseases [13, 27].

In order to overcome the shortcomings of current food label practice and barcode scanning mHealth, there exists thus the potential for the joint application of FoPL and wearable, mixed reality (MR) headsets. MR headsets such as Microsoft HoloLens or MagicLeap One are expected to be increasingly adopted by consumers in the near future and offer multiple advantage in supporting healthy food choices. For example, MR headsets feature multiple continuously active cameras that scan their nearby environment and can discover packaged products through computer vision without requiring active user input [40]. Such MR headsets also allow for the display of three-dimensional visualization of interventions, because spatial computing allows for relative positioning of visualizations to the user's field of view and detected objects, thereby achieving high degrees of presence, salience and immersion, important prerequisites for interventions.

2 Related Work

Computer vision (CV) as an alternative, less intrusive method to scanning product barcodes has been by multiple scholars, offering higher degrees of ease-of-use and pervasive monitoring [11, 15, 36, 42]. Through computer vision [36], wearable MR headsets can detect nearby packaged products and display FoPL, thereby overcoming some of the drawbacks of current barcode scanning mHealth. Specifically, wearable headsets do not require the wearer to manually align camera and product barcode but rather rely on built-in cameras that constantly produce an interpretable video feed [16]. Therefore, they allow the wearer to remain hands-free during object detection is especially important during the usually fast-paced food selection processes. In addition, automatic detection of packaged products through CV do not rely on the customer's salience, involvement or interest in nutrition to remember or remain willing to actively scan barcoded products. Last, but not least, another important advantage of wearables in this context is the possible assessment of packaged products even when a barcode is hidden or absent, as can be the case in vending machines where products are usually positioned front facing and barcodes and ingredient declaration usually remain hidden [32].

To detect packaged product within retail environments from the MR headset's video feed, different approaches have been suggested and validated. Ever since the development of ImageNet [29], increasingly more complex architectures have been developed to recognize objects from images, such as convolutional

neural networks (CNN) (e.g. MobileNet [34], ResNet [17], DenseNet [18]) or more recently, generative adversarial networks (GAN) [3]. Different, recent studies have demonstrated the feasibility to recognize packaged products through computer vision on a large scale from labelled images [14, 26, 39, 40].

Counterintuitively, given the technological feasibility to identify packaged products from images or video feeds automatically, it seems surprising that existing research on MR mediated purchase interventions has so far rather remained in a rather nascent state. Until today, studies on MR-mediated interventions for supporting consumers in selecting healthy food items have so far focused on the general design of such novel interventions, mainly demonstrating early-stage prototypes, or conducting field studies using smartphones rather than headsets. For example, smartphone-mediated MR application have been designed to leverage CV in supporting consumers in identifying vegetables [43], to estimate portion sizes of composed dishes [5, 37], to help users navigate around the supermarket and discover healthy food items [1]. Smartphone-based MR applications were found to be easy-to-use [1], to alter consumer behavior [4, 19], and to positively improve food choices [19], yet still suffer under similar shortcomings when compared to barcode scanning applications, i.e. requiring constant manual holding of the device, seen as inconvenient during shopping.

In contrast to smartphone-mediated MR interventions to improve food choice, headset-mediated MR interventions can be used handsfree by the user. For example, a Google glass based intervention was found feasible to automatically detect vegetables and fruits through computer vision, enabling food monitoring and interventions [21]. El Sayed demonstrated a variance of MR visualizations aimed at improving user performance on search, selection and rank tasks on supermarket shelves [8]. Similarly to smartphone-based applications, also wearable cameras were shown to be effective in monitoring consumption of composed dishes using computer vision [2]. Microsoft even patented a wearable headset able to deliver MR interventions for eating activities [20]. Albeit the overall feasibility of MR headset-mediated interventions on food selection has been shown, little is known about their potential impact on user choice, and about users' opinion on such a system's performance.

Therefore, this study represents one of the first in-the-wild validations of mixed reality mediated purchase interventions aimed at improving food choices. In this exploratory study, we were thus interested to examine the potential of wearable, MR headsets in a common food selection context: vending machines. Specifically, this study assesses whether food cues in form of FoPL can influence the preference and selection for healthy or unhealthy foods. This field study with vending machines examines whether FoPL via wearables lead to more sales of healthy over unhealthy foods compared to regular selection. The aim of this paper is then to describe the development and functionality of the implemented application, report usage and experience statistics, and discuss the implications of our findings.

3 System Design

In the following, the trial setup composed of a vending machine, packaged products, wearable headset and the study application will be introduced. The decision was made to trial mixed reality wearable headsets at a vending machine setup for four reasons. First, vending machines represent sources of predominantly unhealthy food items, especially rich in sugar and saturated fats. Second, vending machine users tend to be prone to consumption of processed foods, a behavior suspected to correlate with diet-related diseases in the long run. Third, the product assortment of a typical vending machine is limited and rather static, so that manually collecting ingredient data is feasible for training of a computer vision-based system. Fourth, in order to develop a mixed reality application, the fixed grid of the vending machine offers an ideal layout that can be used as digital anchor in order to map interventions relative to respective products and the machine.



Figure 1: System setup with user, headset, vending machine.

3.1 Vending Machine

For the trial, we wanted to choose a representative vending machine. We therefore selected Selecta (Figure 1) since they are the European market leader with 125'000 machines worldwide, with which they cater to 5 million consumers a day. Specifically, we conducted the user trial at vending machines at the Zurich main train station in Switzerland, where Selecta claims to reach 10% of the Swiss population daily. Additionally, as most Selecta machines are similarly or even equally assorted, choosing the vending machine as study subject increases the applicability of this study since its impact goes beyond the few machines used in the study and could potentially be reproduced and applied in similar form across vending machines internationally.

3.2 Food Labelling and Focus on Beverages

In terms of designing the mixed reality intervention on improving food selection, we consulted together with dietary experts from the Swiss Society for Nutrition (SGE-SSN). Together with the SGE-SSN's dietary experts, the decision was made to focus the MR headset-mediated intervention on beverages for multiple reasons. First, in particular the consumption of sugar-sweetened beverages have been shown to play a major role in the increased prevalence of diet-related diseases [30, 35]. Second, the Selecta machine offers

a equal distribution of beverage products ranging from healthy (e.g. mineral water) to unhealthy items (Table 1), thereby offering ideal substitutes for consumers to choose from. To label the different food items, we decided to draw on the Nutri-Score (NS) framework [24] for three reasons. The NS includes visual food quality cues that can be displayed with MR. Second, growing evidence exists that already links this form of FoPL with healthier food choices in purchasing environments [23]. Third, the NS framework includes a beverage-specific rating for nutritional quality. Therefore, the intervention relied on a Nutri-Score, when study participants considered purchasing beverage items ("drinks") at the vending machine.

Table 1: Available Products in Vending Machine (N=43)

Snacks	Mean (SD)
Weight (g)	58.2 (26.8)
Price (CHF)	2.77 (0.63)
Snacks in VM by Nutri-Score	Count (%)
A (Healthy)	0 (0%)
B	3 (13%)
C	6 (26%)
D	7 (30.5%)
E (Unhealthy)	7 (30.5%)
Drinks	Mean (SD)
Weight (ml)	400 (118.3)
Price (CHF)	3.18 (0.61)
Drinks in VM by Nutri-Score	Count (%)
A (Healthy)	4 (20%)
B	4 (20%)
C	4 (20%)
D	4 (20%)
E (Unhealthy)	4 (20%)
VM: Vending machine.	

In order to realize the Nutri-Score in its original, intended form, not only the products' nutrients, but also their relative share of fruit, vegetable and nuts requires accounting, as the Nutri-Score credits such ingredients with a bonus on the score. In the context of the vending machine, none of the products fulfilled the minimum criteria of at least 40% though. Although 'snack' items could have been added to the study, we ultimately decided against this inclusion to study the headset intervention's effect in the presence of healthy substitutes (i.e. for snacks, there exists an assortment biased towards unhealthy items which in addition vary strongly in their characteristics, as for example chewing gums might not be a perfect substitute for a chocolate bar). Examining the vending machine content (see product characteristics and NS ratings in table 1), available types of snacks were skewed towards unhealthy Nutri-Scores from B to E.

3.3 Product Selection

For realization of the study, we purchased all products available in the vending machine and manually entered their properties including nutritional composition in a database hosted on a dedicated server. In total, the number of products (snacks and

beverages) available over the course of the trial preparation in the vending machines was 60. However, because of cyclical changes in the product assortment by Selecta, and the focus on beverage items, the final product universe that was available in the user study was a reduced set of 20 products that users could choose from for their purchases (Table 1). Beverages in the vending machines used in this trial contained on average 400ml and had an average cost of CHF 3.18 with a rather small standard deviation, indicating a more or less identical price across different types of beverages. Available types of beverages were equally distributed in regard the degree of nutritional quality according to Nutri-Score from A to E (Table 1) and included mineral water (still and sparkling), energy drinks, energy reduced and sugared soft drinks.

3.4 Headset and Mixed Reality Intervention

This study on MR purchase interventions has been realized on a Microsoft HoloLens device. The implemented study application by the name 'HoloSelecta' was developed as a universal windows platform (UWP) and was developed in Unity (Version: 2017.4 LTS) and C#, .Net Mono and made substantial usage of the Microsoft Holo-Toolkit 2017.4.3, pre Mixed-Reality-Toolkit. The application made use of the following features: MixedRealityCamera-Parent (including Camera, Motion Controller, and Boundary), Default Cursor and Spatial Mapping, Input Manager (with MouseInputControl, TouchInputControl, GesturesInput, EventSystem, and ControllerPointStabilizer).

For the conduction of the in-the-wild field study on the impact of MR interventions on purchase decisions, we needed to ensure a fast detection on products relative to the headset wearer's position, to prevent latencies in object detection to impact the user's decision. Therefore, to guarantee a stable user study without waiting times for the identification of products, we hard-coded the relative position and mapping of products to the fixed vending machine layout. This enabled instant visualization of the Nutri-Scores and product details for a user. This layout is actually equivalent for almost all Selecta vending machine in Switzerland; thus the positions of the hardcoded layout could be re-used for other machines as well. The main visual objects of the app include the machine layout, 49 boxes that surround each possible product, an explanation menu that comprises a start button and introductory explanation text, and a sub-menu, utilized to display nutrients about a particular product. We did in fact also implement the object detection and image classification for the in total 60 possible products that were available in the vending machine during the user study (due to changing assortments), using CNNs and image pooling, thereby achieving high accuracy rates for detection for all products within one second. The approach and performance of the computer vision implementation will be published in a separate study. Given the feasibility of fast, reliable object detection and classification, this study builds on the assumption that in the near future, such detection of packaged products will be available for most retail environments in the near future. The visualized objects, including the Nutri-Score frames and detailed nutrient displays (Figure 2) were designed with FreeCAD and the remaining components (e.g. menus, buttons)

were created from Unity UI elements. To scale all boxes of the layout simultaneously, the boxes are aligned on an invisible quad, which has the side ratios of the original machine. Each box includes a box collider and a script based on the `IInputHandler` and `IInputClickHandler` from the Holo-Toolkit. This script allows feedback to a user clicking on any of the boxes, for example for presenting the nutrients or other data. The board displaying the detailed nutritional information applies the product key to query all the nutrients and the respective colors, and the submenu adjusts the layout accordingly. The layout submenu for treatment (TG) and control group (CG) exist simultaneously, and at setup time either one or the other are set active. The product database is specified as an object in the C# code. Also, the nutrients for the 60 possible products in the Selecta vending machine were cached locally on the HoloLens device to minimize interaction time. At setup time, each box in the vending machine is assigned a product key, which grants access to all the displayed nutrients at runtime. Even if the allocation of products onto boxes changed (e.g. by introduction of a new product), respective changes could be made relatively fast, and the updated app could be re-deployed on the study device within minutes, after retrieving the new product data including nutrients from the study's server. The nutrients include energy, sugar, saturated fat, sodium, protein, fiber, the share of fruit/vegetable/nuts (for calculation of the Nutri-Score), as well as the respective Nutri-Score value ranging from A (healthy) to E (unhealthy). In addition, each product was labeled as being a "Snack" or "Drink" based on the product identifier allocated to each box. Before each new user could use the app, the supervisor prepared the headset and HoloSelecta app. As the entire experiment (i.e. TG and CG) was implemented within one app, the supervisor manually entered the user identifier and user allocation on the headset prior to each new user receiving the headset. In addition, the supervisor selected the menu language (English or German) for each user and re-calibrated the vending machine layout to fit perfectly onto the box grid, using hand gestures to manually position the simulated quad onto the four corners of the vending machine window. The machine transformation (transpose, scale and rotate around the y-axis), is handled through the `TwoHandManipulatable` which is provided with the Holo Toolkit. This allows the tester to transform the quad layout of the machine to create a perfect fit with the real machine.

Besides the manual mapping we also investigated automated tracking through markers, scaling to three-point ray traces and transposing along a sticky surface. However, all of those versions still required the ability to adjust the machine manually, since the spatial mapping tends to be erroneous due to the reflecting glass window in the machine. To support the mapping from virtual to reality, the machine sized quad was displayed with 50% transparency. The spatial map was displayed during the machine mapping to ensure the machine was not hidden behind the spatial map during the experiment. Around 20 times per second the app logs all the interactions of the user, including the center of view, the status of the submenu and which product is selected. This tracking together with the survey is sent to a server for continuous evaluation and stored on-device for persistence.

4 Methodology

4.1 Experiment Design

The aim of the study was to examine the impact of a MR headset-mediated nutrition label, in this case Nutri-Score (NS) on actual food selection. To this end, we conducted a non-blinded, supervised randomized controlled trial RCT with follow-up survey involving 61 users at a vending machine at the main train station in Zurich, Switzerland. During the trial, users were either allocated either to a treatment group (TG) that received the Nutri-Score in color (Figure 2, right) or to a control group (CG) that received white frames (Figure 2, left) during the purchase process.

We used convenience sampling for this study, as users were pro-actively asked for their participation by the study supervisor when they approached the vending machine area. Initially, the supervisor would set a new three-digit user identifier on his laptop. Next, the supervisor would ask the prospective user for a short introductory survey after initialization of the survey with the respective user identifier and user language. The user would enter information on gender, age and education. In addition, the supervisor would guess the height and weight of the user for sampling. The decision not to ask the user directly for age and gender was made in order to not prime the users towards wanting to select healthy food items. The correct weight and height were collected in a post-hoc survey after usage of the HoloSelecta app. After the user completed the introductory survey, the supervisor retrieved the pseudonymized data on his machine. Next, an algorithm decides to place the user into either treatment group or control group based on balanced sampling, such that the sum of differences between the groups for each the basic items (age, gender, (estimated) height, (estimated) weight, education) is minimal, with the goal to have balanced samples between TG and CG. When the user received the HoloLens device, he was presented with a welcome screen and tutorial which explained the control of the app via head movement and clicker by showing an overview of available snacks (and the corresponding Nutri-Scores for the TG, or white frames for the CG). The decision was made to use the HoloLens Clicker for product selections in the app instead of gestures, since gestures by novice users might not have been detected immediately.

After the tutorial, the experiment would require the user to conduct the four following choice tasks. Each task was described on an explanatory screen, before the user was able to begin the task. For the first task, users were asked to *purchase a beverage of their own choice*. Second, users were asked to *select the healthiest beverage*. During each task, the users were only allowed to select one box related to the task. If the user pre-selected any displayed box, he was presented with a submenu that revealed further information, including the nutritional values for the treatment group or general product information for the CG (Figure 2). Via the “Select” button, users were able to purchase their respective selected product and finish the task. The selections made were logged under each user identifier. Finally, the user underwent a final, post-hoc survey including items on usage antecedents and

randomization checks (Table 4). All items were scored using a 7-point Likert scale (1: strong disagreement to 7: strong agreement). The final survey marked the end of the experiment, and each user was awarded the selected items for free.

4.2 Data Analysis

The analysis for general characteristics and education levels of subjects was performed by frequency analysis to obtain frequency (n) and percentage (%). Chi-square and independent sample t-tests were used to test for differences in the background characteristics (age, level of education, BMI) of the experimental and control users. Collected questionnaires were coded into numbered data using a spreadsheet program, and all statistical analyses were performed using Python. Significance between treatment and control group were measured by Mann-Whitney U tests since our sample did not follow a normal distribution. Additionally, we thematically examined user feedback and integrated vignettes into the results and discussion to underscore individual findings whenever possible.

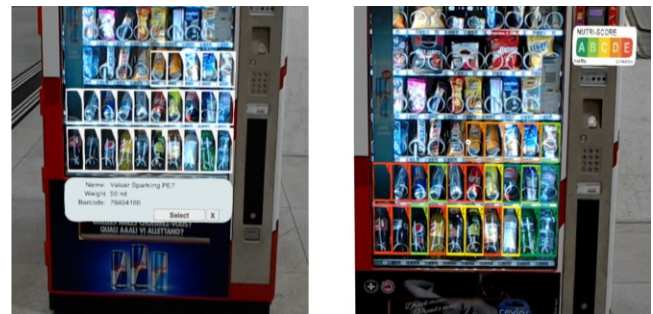


Figure 2: Mixed Reality Intervention: left) CG selecting beverages (with details), right) TG selecting beverages.

5 Results

5.1 Descriptive Statistics

Participants included in the study had a mean age of 29.83 (SD = 13.38) years, 33% were female, and 53% tertiary educated. While 56% of the study participants stated that they rarely use vending machines, 21% of users reported monthly usage and 16% reported weekly or daily usage. We did not find any significant differences between the Treatment Group (TG) (N=31) and Control Group (CG) (N=30) across any of the sample dimensions, indicating a successful randomization for the RCT (Table 2 and Table 4).

5.2 Experiment Results

In regard to *purchasing a beverage of own choice*, significant differences were observed. Users with the Nutri-Score intervention selected products with on average -5.8 Nutri-Score points, with 28% less sugar and 34% less calories per 100ml, albeit only on a 90% confidence interval. The Nutri-Score reduced from 4.8 (CG) down to -0.97 (TG) (Scale -15 = healthy to 40 = unhealthy). Sugar content of the selected beverage reduced from 6.79g/100ml (CG) down to 4.88g/100ml (TG). Energy content of the selected drink reduced from 33.47KJ/100ml (CG) down to 22.03KJ/100ml (TG).

Table 2: Sample Description (N=61)

Age (years)	Mean (SD) 29.83 (13.38)
Weight (BMI)	Count (%)
underweight	2 (3.3%)
normal	46 (75.4%)
overweight	7 (11.5%)
obese	6 (9.8%)
Gender	Count (%)
female	20 (32.8%)
male	38 (62.8%)
other	3 (4.9%)
Education	Count (%)
primary	12 (19.7%)
secondary	14 (23.0%)
tertiary	32 (52.5%)
NA	3 (4.9%)
VM usage frequency	Count (%)
infrequently	34 (55.7%)
monthly	13 (21.3%)
weekly	5 (8.2%)
almost daily	5 (8.2%)
NA	4 (6.6%)
Wearable headset experience	Count (%)
none at all	26 (42.6%)
some (e.g. tried before)	29 (44.3%)
a lot (e.g. frequent usage)	4 (6.6%)
NA	4 (6.6%)
VM: Vending machine.	

Table 3: Comparison between Treatment Group (N=31) and Control Group (N=30) for task 1) Select an item of your choice, task 2) Identify the healthiest beverage available.

Task	Item	Beverages	
		ΔTG-CG	P
1. Select	NS	-5.8	0.009*
	Energy	-11.4 (-34%)	.06
	Sat. Fat	+0.2 (+66%)	.37
	Sugar	-1.91 (-28%)	0.049*
	Salt	0 (0%)	.43
	Protein	+ .11 (+48%)	.38
	Fiber	0 (0%)	.50
2. Identify	NS	-0.8	.27
	Energy	-1.26 (-67%)	.27
	Sat. Fat	0 (0%)	.16
	Sugar	-0.29 (-66%)	.28
	Salt	0 (0%)	.35
	Protein	-0.02 (-100%)	.16
	Fiber	0 (0%)	.50
: significant at 5% level			

Table 4: Nutrients of Selected Beverages for users differing in BMI, Education and Food Literacy

BMI						
	BMI >25kg/m ²			BMI ≤ 25kg/m ²		
	P	TG N=7	CG N=3	P	TG N=22	CG N=26
		M (SD)	M (SD)		M (SD)	M (SD)
NS	0.010	-12.7(6.1)	3.7(3.5)	.068	2.9(8.1)	5.0(8.1)
EN	0.005	0.4 (1.1)	41.3(23.6)	.41	28.8(20.6)	33.2(29.8)
SF	0.017	0.0(0.0)	0.2(0.3)	.07	0.1(0.2)	0.0(0.0)
SU	0.003	0.0(0.0)	7.8(3.0)	.28	6.4(4.3)	6.8(4.6)
SO	.101	0.0(0.0)	0.0(0.0)	.28	0.0(0.0)	0.0(0.0)
PR	0.017	0.0(0.0)	1.7(2.5)	.23	0.5(1.3)	0.1(0.2)
DF	0.5	0.0(0.0)	0.0(0.0)	0.5	0.0(0.0)	0.0(0.0)
FNV	.10	0.0(0.0)	0.0(0.1)	.40	0.0(0.0)	4.6(16.3)
Education						
	Education high			Education low		
	P	TG N=17	CG N=15	P	TG N=12	CG N=14
		M (SD)	M (SD)		M (SD)	M (SD)
NS	.07	-3.3(10.5)	2.7(8.2)	0.049	1.0(10.2)	6.6(6.7)
EN	.29	21.2(24.0)	26.8(31.7)	.07	21.6(20.0)	39.4(25.2)
SF	.24	0.1(0.2)	0.1(0.2)	.34	0.0(0.0)	0.0(0.0)
SU	.31	4.4(4.7)	5.0(4.6)	.07	5.1(5.0)	8.4(3.4)
SO	.45	0.0(0.0)	0.0(0.0)	.47	0.0(0.0)	0.0(0.0)
PR	.40	0.6(1.5)	0.4(1.2)	.19	0.0(0.1)	0.1(0.2)
DF	.50	0.0(0.0)	0.0(0.0)	0.5	0.0(0.0)	0.0(0.0)
FNV	.43	0.0(0.0)	4.0(15.5)	.18	0.0(0.0)	4.3(16.0)
Food Literacy (FL)						
	FL >3.5			FL ≤ 3.5		
	P	TG N=25	CG N=25	P	TG N=6	CG N=4
		M (SD)	M (SD)		M (SD)	M (SD)
NS	0.025	-0.8(10.5)	4.6(8.1)	.13	-1.8(10.3)	6.0(4.9)
EN	.17	23.5(23.2)	32.7(30.3)	.052	16.0(14.6)	42.3(20.1)
SF	.31	0.1(0.2)	0.0(0.0)	.38	0.0(0.0)	0.2(0.3)
SU	.11	5.2(5.0)	6.5(4.6)	.052	3.7(3.4)	9.0(3.2)
SO	.30	0.0(0.0)	0.0(0.0)	0.033	0.0(0.0)	0.0(0.0)
PR	.42	0.4(1.2)	0.1(0.2)	.38	0.1(0.2)	1.1(2.3)
DF	.50	0.0(0.0)	0.0(0.0)	.50	0.0(0.0)	0.0(0.0)
FNV	.10	0.0(0.0)	4.8(16.6)	.27	0.0(0.0)	0.0(0.0)
: significant at 5% level, N varies as answers were skippable						
NS: Nutri-Score, EN: Energy in KJ/100ml, SF: Saturated Fat, SU: Sugar, SO: Sodium, PR: Protein, DF: Dietary fiber, FNV: Share of fruit/vegetable/nuts						
P: P value, M: Mean, SD: Standard deviation						
Healthiest mean values for each nutrient in bold						

When selecting the healthiest beverage, no significant differences between TG and CG were observed. The average Nutri-Score went from -13.48 (CG) down to -14.37 (TG), both very close to the perfect score of -15, as most users correctly selected mineral water to be the healthiest drink, a widely known fact that even most users in the control group were well aware of. Qualitative feedback in both, TG and CG, included spontaneously remembering mineral water being the healthiest, when being asked to identify the healthiest beverage. This correct identification of the two different mineral waters as being the healthiest options seems possible for most users, with only few selecting orange juices to be the healthiest option.

When comparing overweight (BMI over 25kg/m2) to non-overweight users, the intervention seems more effective among overweight users (Table 4), while both, overweight and non-overweight users have seen improved values for sugar, energy and Nutri-Score for the selected beverages when receiving the intervention (TG). When comparing higher educated (e.g. tertiary education) to less educated users, the intervention seems to be supportive for both segments: Less educated users experience a significant improvement of the Nutri-Score of the selected product, while higher educated citizens choose healthier products on average. Similarly, pre-existing food literacy (measured on a food literacy questionnaire) correlates with significant improvements in the Nutri-Score of selected products. Still, also less food literate users experience improvements for Nutri-Score, sugars and energy of the selected products. Further statistical tests comparing overweight versus non-overweight, highly educated versus less educated, food literate versus illiterate receivers of the intervention do not suggest that either group shows significantly better task performance through the intervention.

5.3 Survey Results

All participants filled in a final survey regarding usage antecedents and additional randomization checks. All items were encoded as 7-stage Likert scales, ranging from 1 (strong disagreement) to 7 (strong agreement). All users stated on average positive usage antecedents, with all of the five constructs indicating an average value ranking higher than the neutral value of 3.5 (on usage intention, performance expectancy, social influence, hedonism, or feeling observed). Between all study participants, users with intervention treatment (TG) expressed significantly higher intention for future use (esp. if the app was available on smartphones), to recommend the app, and had a higher opinion about the app. Also, TG users perceived the application's performance significantly higher, i.e. more helpful, educative, enabling faster and healthier product decisions, more supporting for start or maintenance of a healthy diet. Also, social influence was rated higher by TG users, stating that society, friends, family were supportive of such an application. Interestingly, users of both groups felt rather unobserved and claim to have selected their 'true, unbiased' behavior. Also, the users indicate to have enjoyed the HoloSelecta experiment and consider the experience 'fun', and 'exciting'. Both, TG and CG did not differ in food literacy, personal innovativeness, previous experience with wearable headsets. Therefore, neither group had an unfair advantage in selecting healthy food items with the wearable headset (Table 5). Lastly, there were no significant differences in time taken between both groups to complete the four tasks and survey.

Table 5: Survey Comparison between Treatment Group (N=31) and Control Group (N=30)

Construct (# Items)	TG (N=31) mean (SD)	CG (N=30) mean (SD)	P(X)
Usage Antecedents			
Intention (3)	5.84 (1.30)	4.98 (1.55)	.017
Perf. Expect. (5)	5.44 (1.47)	3.53 (1.74)	<.001
Social Infl. (2)	4.77 (1.51)	3.67 (1.44)	.0048
Hedonism (2)	6.35 (0.79)	6.00 (1.17)	.27
Unobserved (1)	5.23 (1.71)	4.79 (1.95)	.29
Randomization Checks			
Innovativeness (3)	5.80 (1.03)	5.60 (1.03)	.27
Food Literacy (2)	5.02 (1.45)	5.11 (1.41)	.44
Wearable Exp. (1)	0.79 (0.99)	0.55 (0.51)	.20
Duration			
Time taken (sec.)	37.2 (20.0)	31.58 (13.7)	.12
Perf. Expect.: Performance Expectancy, Social Infl.: Social Influence, Wearable Exp.: Experience w/ wearable headsets			

6 Discussion

Out-of-home eating is widely considered a part of the modern lifestyle and the public food environment has a central role to play in providing a sense of quality in diets and ensuring public health. Yet, research suggests that out-of-home eating is linked to more energy dense meals, larger portion sizes, and poor nutritional intake, leading to an increase in population rates of overweight and non-communicable diseases. This exploratory study examined the potential of smartglasses to support healthier beverage selections at vending machines, where consumers may intend to purchase unhealthy foods and beverages.

This study sought to implement and validate the potential of mixed reality (MR) headset mediated interventions aimed at improving food selection. Specifically, we found that relatively large improvements were observed in respect to the average Nutri-Score, energy and sugar content for selected beverages when wearing the MR headset and seeing the passively triggered intervention. The identification task revealed that independent of the intervention, most users correctly identified mineral water as the healthiest beverage among the available product in the vending machine. We interpret, that MR interventions may thus be especially successful in rising saliency on topics, where users already have corresponding food literacy and ability to identify healthy alternatives (i.e. mineral water) even without support. To this end, the explorative assessment of the impact on food literate and food illiterate users revealed that primarily food literate users show highly significant improvements in the Nutri-Score of the selected beverages compared to the control group. But still, also less food literate users benefit from non-significant improvements in terms of sugar, energy and Nutri-Score of the selected products.

Furthermore, the usage antecedents collected via post-hoc surveys indicate high degrees for intention to use and performance expectation, as well as hedonic motivation. Concluding, MR headset-mediated purchase interventions have potential to not only become a very effective, but also still very popular purchase intervention in the near future, especially with the expected uptake of MR headsets as consumer devices.

This study contributes to existing work on purchase-related mHealth [6, 7] and FoPL labels [23] that both examine two-dimensional static cues and the degree to which they can affect food decisions. Our findings contribute to this research suggesting that dynamic, three-dimensional environmental cues can achieve a similar effect. Moreover, the proposed solution in this study does not require salience or active input from the users, allowing for a handsfree shopping experience, thereby overcoming one of the strongest barriers of mHealth-based solutions. Also, we examined the impact that such interventions can be effective in influencing beverage purchasing decisions, even when unhealthy beverages were originally intended by visiting a vending machine. These findings also add to literature on priming goals in the context of hedonic eating behavior. While laboratory research has repeatedly demonstrated the food-reducing or food-increasing influence of environmental cues, less is known about environmental cues' impact on actual purchase decisions. Overall, the present findings are in line with priming research, revealing that environmental cues in form of MR induced food labels can influence choices in favor of healthy beverages.

Our findings regarding the potential of food labelling via smartglasses at vending machines are subject to certain limitations of which we believe three limitations warrant special attention. First, we applied a convenience sampling for our study, capturing mainly (male) commuters and travelers, who might not be entirely representative for a population. Further studies could apply a stratified sampling approach. Second, it is possible that the technology and 'single-blindedness' study set-up may have affected the outcome of the study. Although the research supervisor aimed at being neutral and impartial when supporting consumers, especially those who were unfamiliar with smartglasses, certain support or observation may have led users to act differently. However, we found that users who were less familiar with the intervention technology did not significantly differ with respect to nutritional quality of their selected items. Nonetheless, with further investment in the technological set-up of the study, future research designs could allow the user to conduct the tasks feeling less observed. Another limitation of the study is the comparability of findings, especially in regard to current mHealth approaches. While we have mostly theorized about the benefits of wearables over hand-held smartphone approaches, we did not include a smartphone treatment group to examine this aspect. Aside from the theoretical arguments made about the inconvenience of hand-held devices, the placement of products in vending machines would have hindered users in barcode-scanning BoPL's. Future studies however could include

such a treatment group by replicating a MR app on a mobile phone. Such studies would lend itself to compare passively and actively triggered just-in-time interventions (JITAI) [33].

In the future, research is needed to leverage computer vision to scale such MR interventions to supermarket shelves with thousands of products. Also, validation studies are needed for comparing interventions to printed labels (e.g. inside the vending machine) or mHealth interventions aimed at improving food selection. In a distant future, when wearable smartglasses become widely adopted consumer devices, integration of MR interventions into personnel-based counseling programs are expected. In turn, these approaches can complement traditional nutrition interventions in situations where consumers intend to make food purchase selections. Future research can shed light on more comprehensive system designs and different interactions between associations, concepts, goals and awareness, as well as outcomes which could lead to optimized MR-based nutrition interventions. Finally, MR headsets can support development of future FoPL labels, as they can be tested with MR glasses, measuring eye-tracking and gaze. This aspect may be especially useful for the development of new or tailored FoPL labels, allowing to compare different labels without physical changes.

7 Conclusion

To the best of our knowledge, this is one of the first in-the-wild studies that assess the impact of a spatially displayed FoPL (in this case Nutri-Score), displayed in three-dimensional space via a mixed reality (MR) wearable headset. Limited success of public awareness campaigns and health warning with respect to prevention of NCDs require additional measures to alter consumer behavior and to self-manage affective impulses (e.g., temptation, self-control conflicts). The presented study suggests that automated, passively-triggered, non-invasive and hands-free approaches mediated through MR headsets could be meaningful, popular and effective in improving purchase choices. That is, environmental cues in form of wearable MR applications can be applied as interventions for researchers, application developers or policy makers to shape people's behavior towards healthier diets. Interestingly, the introduction of MR-mediated purchase interventions (e.g. FoPL such as Nutri-Score) can also be achieved in regions where FoPL have not (yet) been mandated, potentially due to resistance from industry or regulators. Similar to MR interventions on smartphones, which require manual handling during the shopping process, shown to improve sugar content of chosen products by 32% [19], our study suggests that automated, passively triggered MR headset-mediated purchase interventions can also reduce energy (-34%, TG vs. CG) and sugar content (-28%, TG vs. GC) of purchased products.

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