Situated Brushing and Linking in Virtual and Augmented Reality

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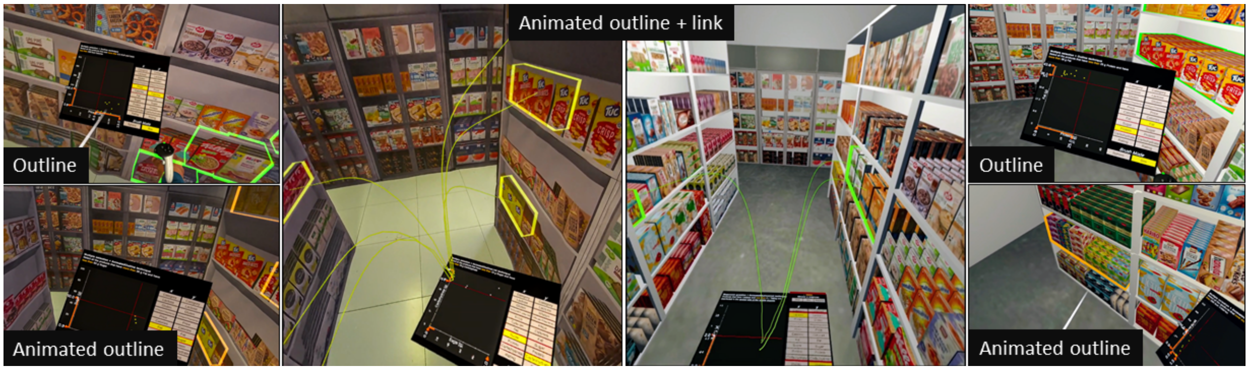

Fig. 1: We leveraged highlighting techniques previously studied to perform brushing and linking tasks in VR and AR. In our user study, users manipulated a virtual tablet to search for products of interest in a synthetic supermarket environment. Center: Visual links are displayed from the data points previously brushed by the user, connecting to the products on the shelves. Top left and right: The *outline* technique highlights the product silhouette. Bottom left and right: The *animated outline* technique shows a gradient hue variation (green to orange) over time. AR snapshots are shown in the left two columns, while VR snapshots are in the right two columns.

Abstract—In traditional visual analysis, brushing and linking is commonly used to visually connect multiple views using highlighting techniques. However, brushing and linking has rarely been used in situated analytics, which uses visualizations to analyze data in the context of physical referents. In situated analytics, data representations must be visually linked to real-world objects. Previous work has assessed situated brushing and linking in a virtual reality simulation of a supermarket scenario. Here, we replicate and extend the previous approach by studying brushing and linking in an actual physical space with augmented reality, while further improving the highlighting techniques. Using a video see-through display, we compare augmented reality with virtual reality. Results suggest that AR performs better in time and accuracy, but the effectiveness of the techniques varies by condition. These results provide a new framing of how the real-world stimuli matter in situated analytics.

Index Terms—Brushing and linking, situated visualization, visual highlighting.

1 Introduction

Traditional brushing and linking techniques are used in visual data analysis to connect elements across data views using visual highlighting [4]. Such visual highlighting techniques rely on visual attributes such as color, outline, or labels. For a more precise linking between elements, there are other approaches using visual links or motion cues.

Physical environments are naturally cluttered, and humans struggle to find and identify relevant objects. Thus, such environments are likely to benefit from brushing and linking. In particular, *situated analytics* [49] helps in decision-making by presenting information visualizations about the physical environment in AR. These applications need effective brushing and linking techniques that link digital information to physical referents while preserving the perceptual characteristics of the real world [14].

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Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x. For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org. Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxxx

While previous work focuses on brushing and linking for 2D interfaces, there is only limited work on the integration of 3D environments using virtual reality (VR) or augmented reality (AR) [13]. Recently, Doerr et al. [8] evaluated situated visual highlighting techniques in a simulated brushing and linking context using VR. The use of VR to simulate AR simplifies the experiment and ensures consistent image quality [18, 29, 32].

However, a synthetic world might not match the richness and dynamics of the real world, and there may be perceptual or behavioral differences in VR compared to AR [55]. Therefore, the extent to which the findings can be transferred from VR to AR remains an open question. Moreover, Doerr et al. investigated fundamental highlighting techniques, from which they extracted design guidelines. However, their paper does not cover a refinement of the highlighting based on these guidelines.

In this paper, we partially replicate, refine, and extend the study of Doerr et al. [8]. While the tasks of the original study were largely kept, we refined the highlighting techniques based on the existing design guidelines. Most importantly, we introduce an additional AR condition to supplement the VR condition of the original study (see Figure 1).

In doing so, we take advantage of the fact that consumer head-mounted display (HMD) technology now offers video see-through (VST) functionality in addition to an opaque VR mode. Hence, we are able to compare the highlighting techniques of the original study using a fully synthetic model under both VR and AR conditions while using the same HMD.

With our study, we expect to obtain more robust insights into the visual perception of situated analytics problems, which brushing and linking techniques work best for a typical situated analytics use case, as well as the fundamental feasibility of simulating AR with a VR display.

In summary, this paper makes the following contributions:

- A user study (N=40) to assess brushing and linking in VR and AR using a synthetic situated analytics environment through a VST device
- Implications of AR simulation in VR on visual guidance research, particularly for situated brushing and linking
- A replication-and-extension study that reveals interesting findings on the validity of AR simulation in VR

2 Background and Related Work

We provide some background in situated analytics (Section 2.1) and brushing and linking (Section 2.1), the two areas that we intend to combine in our work. We also discuss the relation of our work to visual guidance research with an HMD (Section 2.3).

2.1 Situated Analytics

Situated analytics was defined by ElSayed et al. [12] as a combination of visual analysis with the surrounding world using AR technology [49]. Shin et al. [44] structure the field based on data, visualization, platform, physical location, and analytics processes. These situated visualizations allow interactions within real-world contexts since they connect the referent with the users [60].

However, enabling seamless integration of several referents and interaction modalities is a challenge for AR technologies [6]. While the benefits of immersive virtual environments for visualizing complex spatial data can be striking, the advantages of AR can be more difficult to manifest [29]. One of the main reasons is that situated analytics is context-dependent. Several situated visualization researchers have investigated sense-making on human trajectories [37], biomechanical simulations [59], sports training [35], smart objects [57] and smart objects [15].

Even when applications rely on established design patterns for situated visualizations [31], humans do not necessarily focus on the regions of interest intended by researchers [50]. As a consequence, some work proposed region selection [43] and effective guidance [8] for situated analytics contexts.

2.2 Brushing and linking

Brushing and linking is a standard technique in visual analysis and is related to multiple coordinated views [54], i.e., patterns that connect data in two or more views. While brushing means selecting the data of interest, linking refers to highlighting related data in complementary views. In conventional desktop visualizations, highlighting is usually applied by altering the appearance of data points with visual encoding such as colors, glyphs, animations, or lines [19, 27].

Although brushing and linking is widely used on conventional 2D interfaces, its use in AR/VR is still an open research question [26]. A situated analytics survey by Shin et al. [44] shows that brushing and linking techniques have rarely been evaluated in the context of a physical environment. Previous studies on brushing focused on special aspects of real-world interaction, such as the selection of occluded objects [45, 56] or the clutter resulting from linking of dense entities [39]. Doerr et al. [8] compared four highlighting techniques (color, outline, links, and arrows) in a VR supermarket shopping context.

Efficient highlighting needs to minimize visual clutter while keeping a *high contrast* [33]. However, visuals are traditionally geometric shapes that can induce side effects such as attention tunneling [48]. Likewise, the use of *temporal cues* such as motion and flickering [46] offers an effective visual search in real-world contexts. Visual highlighting also has to be able to guide users to targets *outside the field of view* [1].

Mahmood et al. [38] explored the coordination of multiple visualizations embedded in surfaces. Various studies applied brushing and linking to hybrid user interfaces [17, 24, 30, 40] or to physical proxies that represent virtual content [42]. However, the limited field of view of optical see-through devices makes it difficult to use these designs in AR. Video see-through displays can potentially mitigate this problem with a larger field of view. Borowski et al. [2] followed this approach and proposed a toolkit to design visual analysis on demand in AR. Similarly, our prototype uses an HMD with video see-through features to enable exploration either in AR or in simulated AR (using VR).

2.3 Visual guidance

Visual guidance is used to direct users to areas of interest in the environment. The effectiveness of guidance is often demonstrated in 360° videos [20, 50, 53]. Here, information can be lost due to the lack of free navigation in videos [22]. Therefore, different strategies have been proposed to drive the user's attention, like displaying geometric cues and modifying the visual content. For example, Lin et al. [36] used arrows as a hint to support immersive video navigation. Similarly, rectangles and circles have been used to locate out-of-view objects in immersive environments [21].

Mixing multiple visual cues can be beneficial as well. Fox et al. [16] used pointers and outlines to alert people with visual impairments. Some methods modify the real content of the AR displays with respect to saturation, contrast, blurriness [47] or brightness [58], but these approaches can potentially compromise the context. We only use overlaid virtual elements for visual guidance.

3 Study Design

The main objective of this work is to discover how accurately people perform situated brushing and linking in a real environment compared to a simulated one. To answer this question, we extend the work of Doerr et al. [8], which investigates the visual highlighting of products on shelves in a supermarket. For best comparability, we kept the original tasks of their study, but refined the highlighting techniques based on their results and recommendations. In order to compare AR and VR, we performed the study in VST-AR and VR, using an HMD that is able to support both modes. In contrast to the original, we were interested not only in the performance of the highlighting techniques but also in the differences between AR and VR of a visually identical supermarket environment.

3.1 Scenario and dataset

A supermarket is an information-rich environment [3] that is highly familiar to wide audiences. This property makes it a popular use case for situated analytics studies [5, 8, 11, 60]. Since user studies are difficult to perform in the public setting of a real supermarket, previous research relied on small-scale mock-ups of individual shelves [6, 12] or performed the experiment entirely in VR. We target a supermarket model that has as few visual differences as possible between VR and AR. Therefore, we adopted the approach of building the supermarket environment from scratch, using a digital-first strategy: The supermarket model was first modeled digitally and then physically built in the image of the model.

To do so, we first scraped metadata of more than 500 products from a regional supermarket website, including product name, price, description, and high-resolution images. Second, we selected 263 products sold in box-shaped containers, which fit our process of shelf placement. In comparison, Doerr et al. [8] used 98 products. Third, we obtained nutritional information matching the product from online databases, resulting in 10 attributes per product (Figure 1). Finally, we sorted the products into 11 categories to inform the shelf layout.

Each product was modeled as a box in Blender, and the product image was applied as a texture. The dimensions of the boxes were manually adjusted to match the physical products. We organized the products into shelves using the rule that no more than three categories are allowed per shelf. The shelves are 100 cm wide and 200 cm high, with five boards each. We mimicked a typical product arrangement in a supermarket by repeating identical products side by side so that each board is filled with a maximum of five distinct products. We created 15 shelves, which were arranged in five groups consisting of three shelves next to each other, leading to a final layout consisting of three aisles (Figure 2).

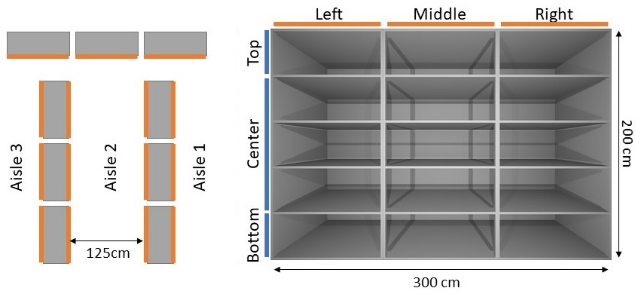

Fig. 2: We built a small supermarket with three aisles, occupying approximately 25 m². Left: Structure of the supermarket model. Right: Shelf model, with the spatial arrangement for spatial judgment tasks.

For the physical model, we acquired 15 steel shelves with dimensions 100×200 cm from a local department store and arranged them in the chosen layout. The front face of each shelf was covered with a poster of the products printed in high resolution (20,000×40,000 pixels). Using actual product boxes on the shelves would have increased the realism, but we preferred posters for multiple reasons: First, posters made the appearance of the AR supermarket more similar to the VR supermarket, because physical packaging materials and local illumination conditions did not affect the look. Second, users could not move the products, which would disrupt the registration of the real world with the digital twin. Third, highlighting techniques could exclusively focus on the front face of the box. Fourth, the effort of building (and changing) the supermarket was significantly reduced without compromising the content: Only the products' frontal appearance had to be modeled. For a more detailed discussion of the limitations of this approach, please refer to subsection 6.3.

3.2 Situated visualization

Similar to the original study by Doerr et al. [8], we used an overview visualization on a virtual tablet held in the user's hand. The overview visualization shows a 2D scatterplot and supports various touch interactions, such as filtering or brushing of the data points (Figure 1, center). Each data point refers to one product. We let the user map arbitrary data attributes to the *x*- and *y*-axes of the scatterplot. Each axis is decorated with two sliders at its ends to allow the filtering of data points. Most importantly, the scatterplot lets the user brush the data points, either by tapping on individual data points sequentially or by dragging a rubber band rectangle to select the data points inside (Figure 3).

3.3 Highlighting techniques

Visual highlighting techniques require coherent strategies to combine visual cues from the virtual and real world, enabling users to perceive areas of interest correctly. The study by Doerr et al. [8] investigated four basic highlighting techniques: using color overlays (thin outlines around the object and full object coloring), arrows, and visual links (leader lines). They found that the thin outlines were useful but often too inconspicuous, while the full object coloring occluded the object details. The arrows were animated, which was rated as too busy by test subjects. The visual links were found to be useful for guiding toward out-of-view objects, but otherwise were too easily overlooked. The paper concludes that outlines combined with visual links may be a potent highlighting technique.

Consequently, we designed three advanced highlighting techniques (Figure 1) that pick up the lessons learned. We choose a fat outline for increased visibility, with or without additional visual links. We excluded the arrows and the full color overlay to avoid the disadvantages mentioned above.

Outline (O) This technique emphasizes only the silhouette of an object, while allowing the interior surface to remain visible [45]. Following the design recommendation of Doerr et al. and the desire for a more suitable *high contrast*, we implemented the outline as a fat green line. However, including a fat contour could occlude the next objects, even more so when the object arrangements are tied to each other.

Animated outline (A) Using a single, static color might interfere with the colors of the background, like a green outline on a green product box. Motivated by the feasibility of *temporal visual cues* for visual guidance [46], we therefore opted for an animated outline that avoids this problem by smoothly changing the highlighting color between green and orange over time. The animation runs continuously and is synchronized for all highlighted products to minimize temporal clutter.

Animated outline + linking (L) While an animated outline ensures high contrast with the background, it does not guide to off-view referents. Hence, we added visual links from the data points in the scatterplot to the corresponding referents [39]. The links are drawn with a curved line and smoothly update for tablet motions (and, with it, the data points). For *out-of-view* products, the line has a visible display portion on the sides to indicate the connection to these referents. Compared to Doerr et al. [8], we increased the curvature of the links and smoothed the transitions caused by the movement of the scatterplot from the activity of natural users (Figure 1).

3.4 Tasks

To ensure comparability, we adapted the tasks of Doerr et al. [8], which involve appropriate interactions for situated analytics [60].

Single Selection: This task requires locating one single referent, e.g., *"Select the product that has the highest fat and has gluten."*

Multiple Selections: This task requires locating multiple referents, e.g., *"Select all the products that have more than 36 g fat and have less than 50 g sugar."*

Spatial Judgment: This task requires the user to judge the spatial arrangement of groups of referents. The user must indicate whether the highlighted referents are located on the left, center, right, and the top, middle, or bottom of the shelves (e.g., *"Products that have less than 3.3 g fat and free lactose are distributed on the top side of the left shelves."*) The spatial arrangement is taken from the perspective of the participant (Figure 2, right); no mental rotation is required. This type of task was chosen to explore whether participants could handle challenging real-world situations.

Each multi-selection task requires 10 products, and the chosen referents were distributed uniformly across the shelves.

4 Experiment

We conducted a within-subjects study with *display context* (VR or AR) and *highlighting technique* (**O**, **A**, or **L**) as independent variables, resulting in $2 \times 3 = 6$ conditions. The experiment was carried out in a 5×3 m wide area in the middle aisle. The participant was asked to stand in the center of the aisle. We included referents from the three shelves to the left and the three shelves to the right. These six shelves contained 101 referents. The remaining seven shelves were used only as decoration and were not included in our study.

From the user's position, only one of the opposing sides of the aisle was visible at any time. The user had to turn the head or body to face the other side. Walking was not necessary to solve the tasks.

The VR and AR conditions were performed at the same location, and the supermarket was shown on the same scale. However, in the VR condition, the user's entire field of view of was filled with the virtual supermarket, while the video see-through was turned off. Thus, the VR and AR conditions only differed in the presentation of the supermarket model.

4.1 Hypotheses

We had the following three main hypotheses for our experiment.

H1: Similar results will be found under VR and AR conditions. Previous studies argue that VR experiments can be representative of AR experiments. However, there is no systematic evidence on how far this transfer of findings from VR to AR goes. We purposely made the VR and AR conditions as similar as possible to uncover any remaining differences.

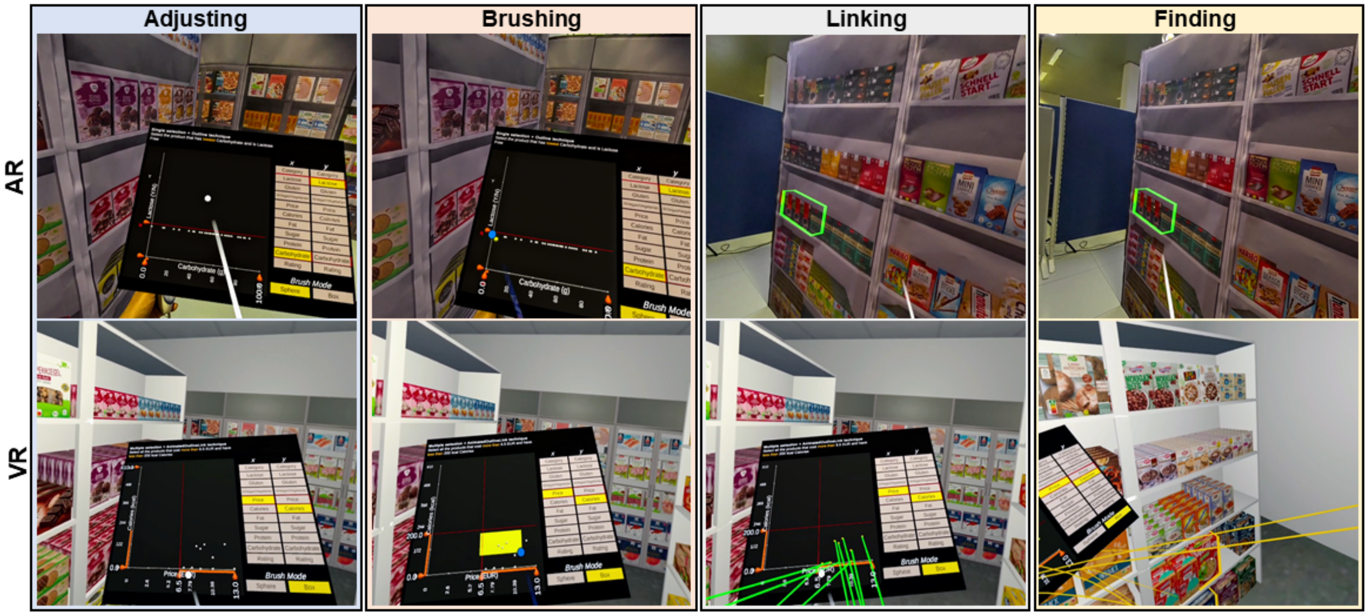

Fig. 3: Brushing on a situated scatterplot in our user study. The top row shows the steps to solving a single selection task using **O** in AR, and the bottom row, a multi-selection task using **L** in VR. From left to right: First, the user adjusts the data dimensions and filters to meet the task requirements. Second, they brush the data points by selecting one-to-one or delimiting regions. Third, once the data points are selected, linked referents are highlighted. Fourth, the user examines the environment to find the highlighted products, confirming by pointing a ray and pressing the trigger on the controller. Link colors are animated by transitioning from green to orange and back.

*H2: **A** will perform better than **O**.* Several works benefit from the use of animation to compare trends, provide visual guidance [51], and direct attention in virtual environments. We expected that completion times and error rates would benefit from animated colors.
*H3: **L** will give the best results overall.* We expected that the additional guidance provided by the visual links would facilitate brushing and linking when out-of-view referents are involved.

4.2 Participants

We recruited 42 graduate students from our university campus, but after observing the recording data, two participants were removed from our analysis due to inattention caused by excessive delay between trial initiation and task execution and a technical problem. The final set of 40 participants (17 female and 23 male) ranged in age from 18 to 44 (eight participants from 18 to 24, 30 participants from 25 to 34, and two participants from 35 to 44). All had normal or corrected-to-normal vision and, if necessary, wore glasses in combination with the HMD. Their reported previous experience with an HMD was no/low for 15 participants and high for ten participants. Of the 40 participants, five reported having no experience with 3D computer games, and three were left-handed.

4.3 Apparatus and implementation

We used a Meta Quest 3 (running Horizon OS 72.0) with touch controllers and Unity 3D (version 2022.3.34f1) with the Meta XR Interaction SDK (68.0.1) to implement the application. The device has a horizontal field of view of approximately 110 degrees. For the study, we ran the application standalone and set the display to have at least 72 fps. In addition, the environment calibration is performed using fixed virtual anchors on the floor squares. For the AR condition, we used the pass-through capability of the device. In addition, a virtual tablet of 40 cm by 31 cm was presented, attached to the controller held in the non-dominant hand. The tablet showed instructions, tasks, and a scatterplot visualization. Brushing on the tablet was implemented by ray-casting from the controller held in the dominant hand. We assigned the trigger and grip buttons on the controller to highlight and de-highlight, respectively.

4.4 Measures

We defined the following primary measures that apply to all 18 tasks featured in our experiment:

(1) Completion time. We measured the time interval from task start to the selection of an answer.

(2) Linking time. We measured the time that the participant's gaze was fixed on the environment, instead of the scatterplot.

(3) Error rate. We determined binary accuracy: In the selection tasks, we determined whether or not the participant was entirely correct in finding the referents on the first attempts. In spatial judgment tasks, the answer is binary. The error rate was directly computed as the fraction of correct answers.

Additionally, we measured *workload*, using NASA-TLX [23], *usability*, measured using Umux-lite [34], and *presence*, measured using the Igroup Presence Questionnaire (IPQ) [52]. All measures are averaged over the number of repetitions.

4.5 Procedure

Our user study protocol was approved by the Committee for Responsibility in Research (Ethics Committee) at the University of Stuttgart. A Latin square design counterbalanced the order of the conditions. Each participant performed six sessions, where they started using one of the three highlighted techniques in the VR condition and later continued in a similar order in the AR condition (or vice versa). Within a condition, the task order was fixed, consisting of one single, multi-, and spatial judgment task per technique. We created six tasks per task type (18 in total) to prevent learning effects. Before the actual experiment, we performed a pilot study (N=5). The results allowed us to improve the clarity of the instructions given to the participants and to accelerate the animation sequences.

The experiment lasted approximately one hour. In total, the experiment collected data from 40 participants $\times$ 2 viewing contexts $\times$ 3 techniques $\times$ 3 task types = 720 trials. After an introduction and signing of the consent form, participants were introduced to the virtual tablet and interaction options. In addition, we showed the supermarket and explained the spatial arrangement inside a shelf (top, center, bottom) and in a group of three shelves (left, middle, and right), used in the spatial judgment tasks. Next, the experimenter calibrated the environment

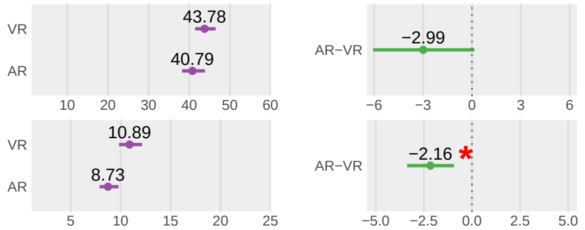

Fig. 4: (left) Mean Completion Time (top) and Mean Linking Time (bottom) in seconds for all conditions and tasks. (right) Pairwise differences. Error bars represent 95% bootstrap confidence intervals. Evidence of differences is marked with an asterisk *. The further away from zero and the tighter the CI, the stronger the evidence is.

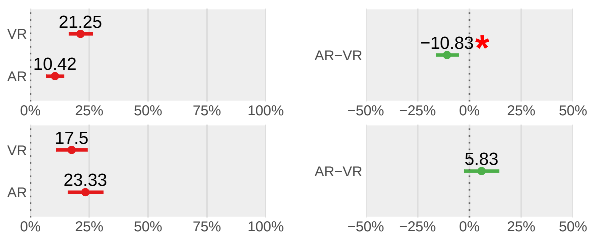

Fig. 5: (left) Mean error rate in % for selection tasks (top) and for spatial judgment tasks (bottom), for all conditions and tasks. (right) Pairwise differences. Error bars representing 95% bootstrap confidence intervals. Evidence of differences is marked with an asterisk *. The further away from 0% and the tighter the CI, the stronger the evidence is.

and adjusted the controller interface to match the handiness of the participant so that they could hold the virtual tablet with the non-dominant hand and interact with the dominant hand. The participants then put on the headset and grabbed both controllers. For each condition, the environment was recalibrated, and the participants went through a training phase, followed by the main trials, including questionnaires and a short semi-structured interview. Finally, participants were compensated with 14 EUR.

During *training* (5-10 minutes), the experimenter explained the tablet interface without active tasks. The participants could familiarize themselves with the features, try the selection of data points using both brushing and filters, and observe the highlighting technique applied to the chosen referents. This training phase used a modified dataset.

In the *main trials* (30-40 minutes), the order of conditions was counterbalanced, but the order of tasks in one condition was fixed: single, multi-selection, and spatial judgment tasks. Before each trial, a text informing about the task was shown on the tablet. Once the participants pressed the start button, the scatterplot was displayed. For the selection tasks, the participants had to select all the highlighted referents by pointing a ray towards the referent and confirming with a trigger button. In the case of the spatial judgment task, the tablet showed three options, "yes", "no" and "maybe". We intentionally included the option "maybe" to reduce guessing, in accordance with Doerr et al. [8]. Once a task was completed, all highlighting was reset, and the participants were required to return to the center of the aisle. After the three highlighting tasks (subsection 3.4), the participants were invited to complete the workload questionnaire. At the end of the condition, they completed the usability and presence questionnaires. After the VR or AR parts of the experiment, they rated the three highlighting techniques.

Finally, participants filled out a demographic questionnaire, and we conducted short *semi-structured interviews* (<5 minutes). Here, we asked some questions about the overall experiment, including preferred techniques and subjective task performance.

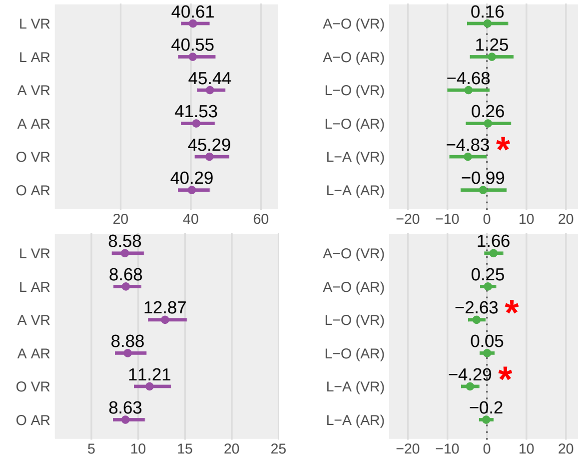

Fig. 6: (left) Mean completion time (top) and Mean linking time (bottom) in seconds per technique. (right) Pairwise differences. Error bars represent 95% bootstrap confidence intervals. Evidence of differences is marked with an asterisk *. The further away from zero and the tighter the CI, the stronger the evidence is.

5 Results

Following recommendations for establishing a modern evaluation methodology [7, 9], we report our inferential statistics using *interval estimation* instead of p-values. *Confidence intervals* (CI) were calculated using *bias-corrected and accelerated bootstrapping* [10]. CI allow for more meaningful interpretations. Pairwise CI that do not overlap with zero correspond to p-values smaller than the significance level, providing the same evidence of differences as in traditional null-hypothesis significance testing. On the other hand, crossing with zero indicates no statistically significant difference. Hence, no p-values are reported, but they can be obtained from CI results [28]. Source code, data collected, and analysis scripts are available as supplementary material[1].

5.1 Overall results across conditions

Figure 4 (top) shows *completion time* for all tasks. Participants took less than one minute to complete each task, being faster in AR (40.79 s) than in VR (43.78 s). No evidence was found that completion times differ significantly between display conditions.

Figure 4 (bottom) shows mean *linking time* for all tasks. Participants spent less than 15 seconds observing outside the tablet for each task. Mean times are shorter for AR (8.73 s) than for VR (10.89 s), indicating that AR is 2.16 s faster than VR.

Figure 5 (top) shows the mean *error rate* for selection tasks. There is clear evidence that AR is less error-prone (10.42%) than VR (21.25%), with an estimated difference of 10.83%.

Figure 5 (bottom) shows the mean *error rate* for spatial judgement tasks. While AR is more error-prone (23.33%) than VR (17.5%) on average, there is no evidence that mean error rates differ between conditions for spatial judgment tasks.

Overall, the findings do not align with **H1**: While completion time and spatial judgment error rate do not show meaningful differences between conditions, AR reduces linking time and is less error-prone than VR for selection tasks.

5.2 Results per technique

Figure 6 (top) suggests that the mean *completion time* in AR is shorter for **O** (40.29 s), followed by **L** (40.55 s) and **A** (41.53 s). However, there is no strong evidence of differences between the three techniques. For VR, **L** performed the fastest (40.61 s), followed by **O** (45.29 s) and **A** (45.44 s). We found evidence of a meaningful difference between **L**

[1] https://github.com/cquijanoch/SituatedBrushingAndLinking

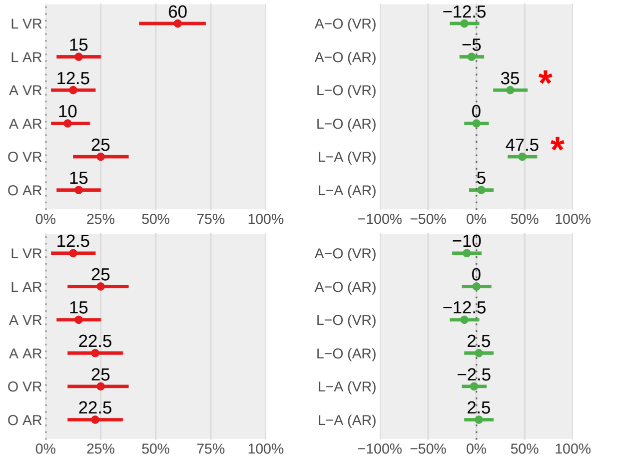

Fig. 7: Mean error rate in % for multi-selection tasks (top) and for spatial judgment tasks (bottom) per technique. (right) Pairwise differences. All error bars represent 95% bootstrap CI. Evidence of differences is marked with an asterisk *. The further away from 0% and the tighter the CI, the stronger the evidence is.

and **A**, with **L** being faster than **A** by 4.83 s. While **L** is the fastest in VR, there are no remarkable differences in AR, on average.

Figure 6 (bottom) shows that mean *linking time* in AR is shortest for **O** (8.63 s), followed by **L** (8.68 s) and **A** (8.88 s). However, there is no strong evidence of meaningful differences between the three techniques. For VR, **L** has the fastest linking time (8.58 s), followed by **O** (11.21 s) and **A** (12.87 s). Evidence shows that **L** is faster than **O** by 2.63 s and **A** by 4.29 s. In addition, differences suggest that **O** is faster than **A** in VR. There are no considerable differences among techniques in AR.

Figure 7 (top) shows that mean *error rates* in AR are lowest for **A** (10%), followed by **L** (15%) and **O** (15%). There is no strong evidence of meaningful differences among the three techniques. For VR, **A** is also less error-prone (12.5%), followed by **O** (25%) and **L** (60%). There is strong evidence that **L** is less accurate than **O** by 35 percent points and **A** by 47.5 percent points. Besides, pairwise differences show that **A** is more accurate than **O**. Regarding spatial judgment accuracy (Figure 7, bottom), while there are no large differences between the techniques, on average, **O** performs better in VR.

Thus, the results align only partially with our hypothesis **H2**. **A** is less prone to error than **O**. However, the participants spent slightly more time with **A**. For **H3**, we found that the completion time and linking time of **L** are the fastest only for VR. However, **L** is more error-prone for VR. Hence, **H3** is partially supported for VR.

5.3 Workload

In addition to time and accuracy, we were interested in investigating possible differences in perceived workload between highlighting techniques using NASA-TLX. Figure 8 suggests evidence of differences in VR only. For mental demand, physical demand, and effort, results indicate that **L** performs better than **A**. The results in Figure 8 also suggest that **L** reduces the physical demand, effort, and frustration compared to **O**.

5.4 Usability and presence

We calculated the System Usability Scale (SUS) from the Umux-Lite [34] filled out after the condition trials. However, as shown in Figure 9, the score for AR (75.31) is only slightly higher compared to VR (75.17), with no evidence of a meaningful difference.

In addition, we explored the presence factors of both conditions and found a similar "sense of being there" mean score of 4.05 for AR and 4.6 for VR. Exploring the presence factors, Figure 10 (left) shows that the sense of being physically present (SP) for VR is higher (4.26) than AR (3.92). For the subjective experience of realism (REAL), results suggest that AR is slightly higher (3.48) than VR (3.24). The involvement (INV) for VR is higher (3.81) than AR (2.11). Figure 10 (center) shows that there is evidence that involvement for VR is greater than AR by 1.7.

5.5 User preferences

Based on our results, all participants quickly learned how to interact with the application to solve the tasks under both conditions. Figure 10 (right) shows participants' responses for their preferred highlighting technique by condition. Most of the participants rated **L** as their first choice in AR (87.50%) and VR (80%). The second choice rating shows that for AR, **A** is the most rated (62.50%), followed by **O** (32.5%), while for VR, **A** and **O** were rated similarly by the participants (45% and 42.5%, respectively).

The responses in the interview section confirmed the previous analysis: Most participants agreed that visual links (L) helped track the referent's location, avoiding searching in other places. However, we found that **L** appears obtrusive. P9 commented that *"the links appear extremely fast and may cause sickness"*; P12 made a similar comment. In addition, P24 added that *"the popup of the links is worse in AR than in VR, in VR it is more smoothly"*. Moreover, P18 commented that *"Link works good when you are selecting few data points"*. P13 emphasized that *"the links distract from checking the surroundings to find the products"*. We also observed that the users looked back once the data points were highlighted and the links were displayed. This behavior happened when the participants applied the rectangle brushing mode.

Regarding the effectiveness of color animation (A), we found that the majority of the participants did not realize the color was animated. However, there is no simple solution. Using a faster animation was suggested by three participants. For example, P17 commented that *"the animation was at first not perceptible"*, and P20 that *"I need to wait for the change of color"*. However, P1 mentioned that *"Animation is too fast. Blinking could cause illness"*. Eight participants suggested different colors: P2, P4, P31, and P37 proposed that the animation should consider the current product and shelf colors. P27 and P33 suggested using colors such as red, blue, pink, and purple, while P11 suggested using colors by product category. In addition, we detected that the participants had difficulty finding green and orange box products, mainly in VR. P3 pointed out that *"it was harder to recognize the green box because the green highlighting color in VR, maybe for this case it makes more sense the AR"*. P20 commented to like *"outline better than the animated one because the color [green] contrasts with crackers [orange] and other products"*. Some participants interpreted the orange color as response feedback. P19 remarked that *"after some seconds, I felt the animated colors looked like a false response"*. P34 pointed out that *"color could change with the gaze, by product independently, instead of as a whole."*.

Participants enjoyed the VR condition due to its high immersion, but also remarked that AR is very promising. P2 pointed out that *"there are benefits of highlighting techniques in AR due to the display of the device"*. P15 also added that *"in AR it is easier to perform the tasks, but VR looks like more fun"*. Furthermore, P7, P17, P18, and P34 complained about the HMD resolution.

6 Discussion

This study compared three highlighting techniques—**O**, **A**, **L**—to perform situated brushing and linking tasks in VR and AR. Since we replicated the work of Doerr et al. [8] only on the conceptual level of feature and design choices, the results cannot be directly compared. Therefore, we discuss our main findings (in the light of theirs, when possible), implications, and limitations of our study.

6.1 Main Findings

Visual highlighting for situated brushing and linking differs between AR and VR. It seems that the visual recognition of the highlighting differed between AR and VR (subsection 5.1). It was more clearly perceived in AR because of the noticeable visual differences between the video-see-through content and the overlays. This advantage resulted in faster and more accurate performance in AR. As long as VR cannot deliver a visual scene representation that is indistinguishable

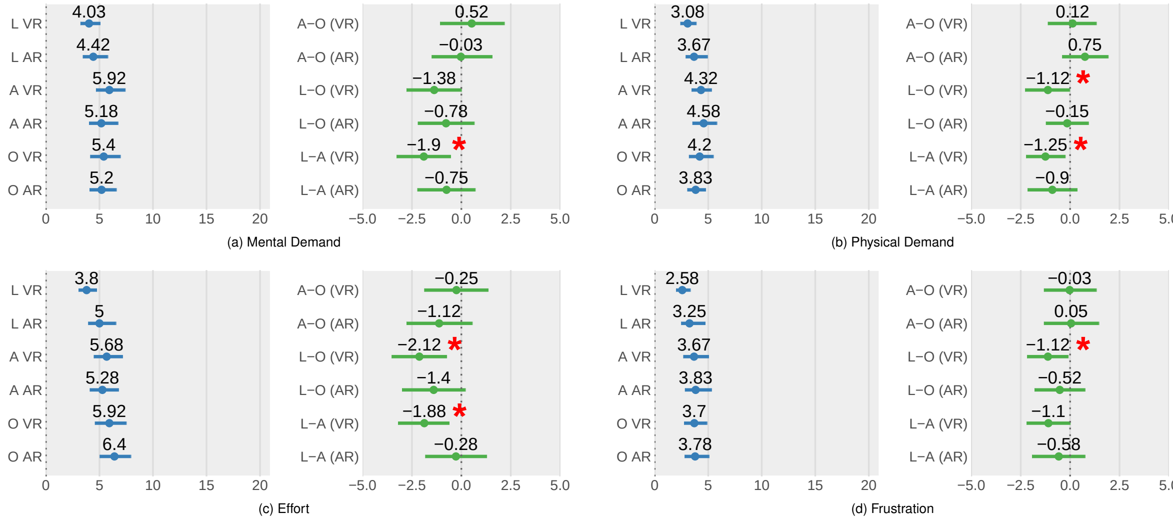

Fig. 8: Results for NASA TLX factors for all conditions and tasks (lower is better). Mean workload factor scores. Pairwise differences. Error bars represent 95% bootstrap confidence intervals. Evidence of differences is marked with an asterisk *. The further away from zero and the tighter the CI, the stronger the evidence is. We did not find evidence of differences for temporal demand and performance factors.

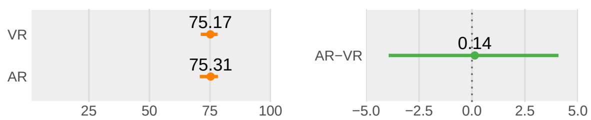

Fig. 9: (left) Mean SUS score evaluated by condition. (right) Pairwise differences. Error bars represent 95% bootstrap CI.

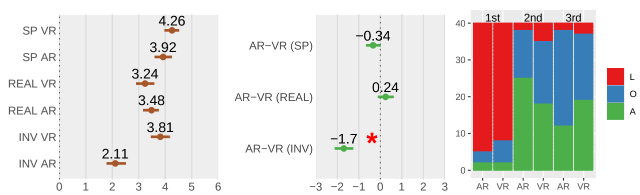

Fig. 10: (left) Mean presence factor scores (INV: Involvement, REAL: Realism, and SP: Spatial presence) for both conditions. (Center) Pairwise differences. Error bars representing 95% bootstrap confidence intervals. Evidence of differences is marked with an asterisk *. The further away from 0% and the tighter the CI, the stronger the evidence is. (right) Distribution of rating choice across the highlighting techniques.

from AR, we must expect performance differences between VR and AR.

L performs faster overall but is less accurate in VR. We assume the visual links assist in achieving the target faster in both conditions; however, the silhouette is difficult to perceive in VR. Hence, the end routing of the link mainly influences accuracy in VR compared to AR. The 3D rendering makes the user perceive one congruent scene in which visual cues affect all content uniformly. The silhouette of the objects was confused with the body of the objects and affected target recognition. This fact is also reflected in the workload results.

A is more accurate but slower than unique color. Although the results do not show strong evidence, the completion time of **O** is lower than that of **A** in both conditions (Figure 6). However, the error rate of **A** is lower than that of **O** for finding referents (Figure 7 top). We assume that this might be due to the chosen color sequence and animation speed. We deduce that, among the outline techniques, **A** is unobtrusive for visual guidance, but time-consuming.

L is most preferred by the participants. Similarly to Doerr et al. [8], visual links are subjectively preferred. However, this technique copies the visual properties of **A** and extends it by a visual line to guide to targets, which limits its comparability. Visual link design should be investigated in more detail to make it more effective.

Highlighting techniques lead to the same spatial judgment. The spatial abilities (not discussed in detail by Doerr et al. [8]) that users exhibited in our experiment did not differ between AR and VR. The results suggest that there are no differences with respect to spatial judgment by display or technique condition yet. The reason could be that all techniques offer a similar level of spatial awareness. In that sense, the AR environment can be replaced by a simulated VR environment without disadvantages in the spatial abilities, as expected from the results obtained in spatial presence research.

6.2 Implications and future work

Visual links cause discomfort and occlusion. As reported in subsection 5.5, multiple artificial marks displayed in a frame cause occlusion and visual discomfort. For example, when brushing multiple data points at once, links add clutter to the tablet interface. Some visual links can be occluded if targets are behind the tablet or the links penetrate the image plane. We propose that visual links should be displayed with a faded-out appearance near their origin to minimize the clutter. In addition, the links could be routed away from the user's gaze direction. Another strategy is to change the origin of the visual links. We always start the visual line from the data points. Other layouts are conceivable, such as starting visual links from the closest edge of the tablet. We also speculate that visual links floating in physical space could be distracting. Especially if **L** connects to an item in a different aisle, it may be better to route visual links on the floor and ceiling. Such a use of 'above' and 'below' has been previously suggested by Satkowski et al. [41]. Besides, the end routing of the link matters for cluttered targets. Adjusting the ending line, which reaches the referents, to be perpendicular and thicker could ensure greater accuracy.

Animated color is unobtrusive but time-consuming. We observed that the animated highlighting color (green to orange) did not optimally consider colorimetry factors. Future studies could evaluate the effectiveness of **A** in situated brushing and linking. For example, a recent study [51] assessed non-obtrusive animation colors for visual guidance on standard displays. However, they did not explore their performance using current VR or AR displays. In addition, following the suggestion of the participants (subsection 5.5), the effectiveness of dynamically changing the color considering the object's own color is an opportunity for future implementations.

Outline techniques require guidance strategies. Both outline techniques cannot highlight out-of-view targets, which limits their application in complex layouts, where targets located in other aisles are occluded (Figure 2). Our experiment only considered a single aisle. In the future, a multi-aisle visualization could use a "magic lens" to reveal referents behind the occluders. This pattern is commonly used in situated analytics [31], but its effectiveness for brushing and linking is currently unexplored.

Brushing and linking physical objects of interest. The current brushing interactions focused on one direction, from the data points to the physical referents. However, in real scenarios, users can interact with the physical environment. As AR leverages the physical environment, users can acquire information about the physical objects on demand. Querying information based on visible objects in unexpected scenarios is challenging to simulate in VR, due to the isolation from the real world, e.g., retrieving information from picking objects. Further work could assess object selection of physical referents in AR [40, 43] to evaluate all directions of situated brushing and linking at once.

Situated brushing and linking in VR We noticed that subtle differences in visual realism between VR and AR can lead to performance differences in an otherwise identical task. In our experiment, AR had the advantage that highlights were more easily identified in comparison to the video background, compared to the synthetic background in VR. This observation suggests that VR simulation has its limits. Users in VR could be influenced by illusion rather than realism [25].

6.3 Limitations

For the AR condition, we built physical shelves but used high-resolution printed posters for the products. As pointed out in subsection 3.1, this procedure has several advantages in terms of costs, flexibility, and reproducibility. However, it also reduces the realism in the 3D perception of the products, possibly affecting ecological validity. We tried to limit this effect by basing the highlighting techniques on the digital 3D models, keeping the spatial arrangement the same in all conditions, and not involving the need for touching products or walking, even in the AR condition, ensuring that the techniques worked the same in VR and AR. However, four of our 40 participants mentioned the use of posters as a limitation, and we cannot completely rule out a negative effect on performance in the AR condition.

Another limitation is the use of only one HMD model, the Meta Quest 3, in our study. Future devices may differ with respect to the field of view, resolution, or distortions. Therefore, special care must be taken when generalizing our findings to arbitrary headsets.

Moreover, the performance results on highlighting (linking) reported in this paper may be affected by errors or misinterpretation in the brushing phase. To avoid interrupting users after each step required in a given task, we considered brushing and linking as a single process judged as a whole. Users who erred during brushing would have likely performed poorly on the linking part, but our experimental procedure did not explicitly split these causes. In addition, additional perceptual and cognitive metrics may be necessary to get a more complete picture of how humans operate in VR and AR.

7 Conclusion

This work evaluates the performance of highlighting techniques for situated analytics. We revisit insights from a previous study by Doerr et al. [8] and address the topics left open in that work. Specifically, we focus on refined highlighting techniques that satisfy the design guidelines put forward by Doerr et al., and we investigate how perception of the brushing and linking changes in a VST-AR setting taking place in a physical supermarket as opposed to a mere virtual one. Our results suggest that VST-AR performs better in task performance and accuracy overall. Likewise, the animated linking performs faster but less accurately in VR only, whereas the use of animated colors improves accuracy compared to static color, albeit at the expense of time.

Acknowledgments

We wish to thank the anonymous reviewers for their comments. Thanks are also due to Fairouz Grioui and Sanan Akther for their participation in setting up the supermarket. This work was supported by the Alexander von Humboldt Foundation funded by the German Federal Ministry of Research, Technology and Space, German Research Foundation DFG (495135767), and Austrian Research Funds FWF (I5912).

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