A Spatially Aware Smartwatch for Decision-Making on the Go

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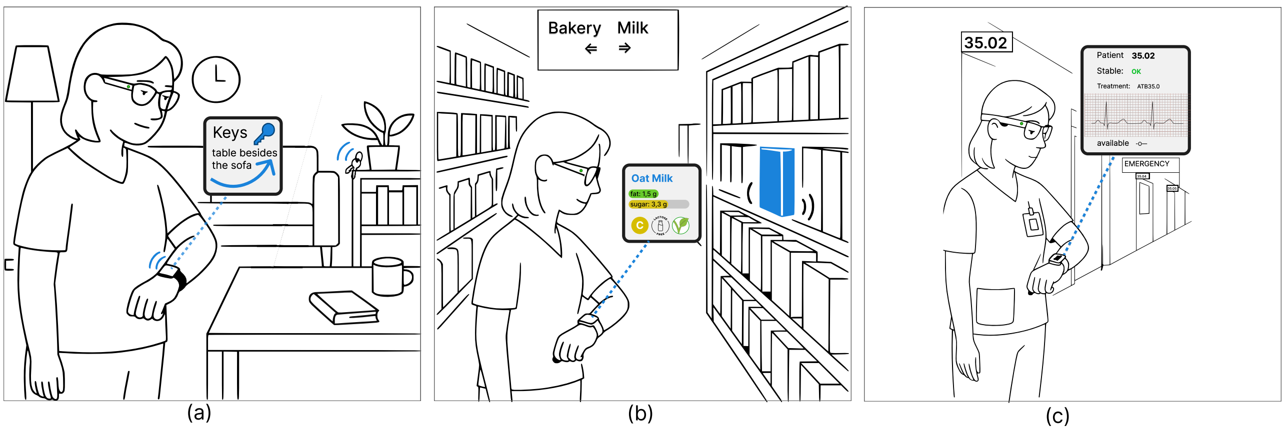

Figure 1: Using a spatially aware smartwatch in real environments: (a) at home, (b) in a grocery store, and (c) in a hospital.

Abstract

Smartwatches enable real-time, interactive access to personal data, facilitating rapid on-the-go data analysis. However, a conventional smartwatch does not provide spatial sensing and context awareness. Therefore, we implemented a spatially aware smartwatch (SAS) as a technology probe to explore how navigation and decision-making tasks benefit from a smartwatch that knows its current location and relative position to nearby objects of interest. We investigate, in a grocery-shopping scenario, how people interact with SAS. We were specifically interested in the acceptance and usability of SAS as a companion device to support daily decision-making. In addition, we compared performance when searching for products with and without spatial awareness. Even though task completion time results were not in general in favor of our technology probe, our findings suggest that using SAS can help reduce perceived stress levels and physical load. Overall, participants' feedback was positive on using SAS in everyday tasks. At the end, we discuss our study, the technology probe's limitations, and potential improvements for future work.

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CCS Concepts

• **Human-centered computing** → **Mobile devices**.

Keywords

Spatial-awareness, technology probe, in-situ interactions, situated visualization, wearable, smartwatch

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1 Introduction

Smartwatches are among the smallest personal computing devices. They represent the convergence of ubiquitous sensing and computing. Diverse personal (e.g., physiological) and environmental (e.g., weather) data can be captured in real time with integrated or external sensors. Quick and easy access to information makes smartwatches indispensable for rapid data analysis and decision-making on the go [7, 8, 22, 23]. Previous work [2, 22, 23, 32, 40] has looked at wrist-worn devices used as fitness trackers and training assistants. However, the day-to-day scenarios that these devices can support are much broader.

Already in the early 1990s, long before the advent of the first commercial handheld computers, Fitzmaurice [20] introduced a handheld display with spatial sensing as a technology probe. Today, the idea of *spatial awareness* as a core capability is deeply embedded in many mobile devices. Even devices with modest computational capabilities, such as commercial smartphones [39] or smartglasses such as Google Project Aria Gen 2[1] (no display, weight: 75 g), provide precise and continuous spatial awareness. Today's smartwatches do not yet provide spatial awareness. However, it seems plausible that a smartwatch (typically around 50 g) capable of measuring its spatial position and orientation as precisely as today's smart glasses can be built soon. With this capability, a smartwatch can provide location-based and situated visualizations [41, chapter 7].

In this paper, we use a technology probe to investigate how a spatially aware smartwatch (SAS) can support its wearer to achieve everyday tasks. People make many conscious decisions throughout the day, ranging from routine choices, such as selecting an outfit or choosing a product, to more critical judgments, such as a physician determining the appropriate treatment for a patient. In many cases, these activities can benefit from contextual information. However, retrieving this information with conventional means, such as a smartphone app, is cumbersome if one needs to take the phone out of the pocket, start the app, and search for the information. In contrast, SAS is instantly available on one's wrist—merely pointing one's watch arm in a particular direction already triggers a spatially aware display of information.

Consider finding specific objects in familiar or unfamiliar spaces, such as finding a hidden key at home (Figure 1a) or a specific product in the aisles of a grocery store (Figure 1b). SAS not only helps find the object, but also provides detailed and up-to-date information (e.g., product characteristics, Figure 1b) and status (e.g., if a product is still available in stock). In professional environments, SAS can help monitor critical data (e.g., frequent status changes, Figure 1c) for quick intervention. Our paper explores the value that SAS, in the form of a smartwatch/headset system, can have as a personal interaction device. We make the following contributions:

- We introduce SAS, a technology probe, implemented by retrofitting external tracking based on a HoloLens to a commercial smartwatch, to carry out a study on its usage for daily decision-making.
- We assess the effectiveness of our SAS when searching for and comparing products in a realistic context, a life-size model of a grocery store with non-trivial size and complexity (300 products).

To our knowledge, our study is the first to explore continuous 3D spatial awareness using a smartwatch. Unlike smartglasses, smartwatches are already widespread, socially accepted, and relatively discreet. Our work clarifies the benefits of a small, but literally *embodied* (i.e., body-worn) interaction device.

2 Related Work

The evolution of networked mobile sensing technologies, such as wrist- and eye-wearable devices, enabled egocentric and spatial data tracking anywhere, anytime. In-situ data sensing helps bridge the gap between the physical and the logical world. In the following sections, we outline prior work on context and spatially aware computing, with a focus on systems that have explored wearable technology and smartwatches, as well as real-world technology probes.

2.1 Context and Spatially Aware Computing

Context awareness refers to the ability of a computer system to sense, interpret, and respond to spatial, temporal, activity-centric, and environmental data [10]. With the growth of mobile and wearable devices, context-aware systems have been applied in domains such as healthcare (e.g., monitoring patient status and adapting interventions [5]), smart homes (e.g., automated energy control and assisted living [12]), or navigation [26].

Spatially aware computing is a special case of context-aware computing focusing on absolute or relative spatial information (i.e., the physical location, orientation, movement, and proximity of entities) or physical referents (i.e., the physical space or object to which the data refers) in an environment. In recent years, spatially aware systems have been used for human-computer interaction (HCI), visual analysis, and in-situ data exploration. Spatial awareness in ubiquitous computing is important for bridging physical and digital data representations, enabling users to manipulate and interpret information through situated, embodied actions. The pioneering work of Fitzmaurice et al. [20] demonstrated how a "palmtop" computer augmented with spatial tracking becomes a lens capable of revealing and interacting in different locations. This idea later became known as situated computing [17, 45] (i.e., computing grounded in the specific environment of use). Previous research has demonstrated multiple advantages arising from the deployment of such systems for situated visual analysis [26, 36] and spatial situated interaction [26, 33, 37].

In their survey on AR for situated visualization, Martins et al. [36] argue that presenting visual data in close proximity to its real-world referents allows users to access relevant information within its contextual environment, enabling more effective and informed decision-making. Other studies [26, 33] explored the use of spatially aware smartwatches in map navigation tasks. Hasan et al. [26] demonstrated the effectiveness of combining two spatially interlinked devices—a smartphone and a smartwatch—for improved analytical performance. Although the dynamic peephole interaction controlled by smartwatch movements [33] did not provide the fastest task completion times, participants preferred it most.

Spatially aware systems enable direct interaction with the physical world, for example, using proxemics or gestures. For cross-device interaction, Rädle et al. [37] found that spatially aware interactions (e.g., flicking and throwing gestures) were preferred over spatially agnostic techniques (e.g., selecting items from a menu). They found that spatial awareness can reduce mental demand, effort, and frustration. Similar results were reported by Hasan et al. [26]. The authors implemented a multi-device interface for map navigation by physically moving a spatially aware smartwatch and smartphone in space. Previous work has also explored different spatial interaction techniques with mobile devices. Langner et al. [35] designed five data transfer interaction techniques between a spatially aware smartphone and a large display.

In our paper, we explore the use of a portable, easily accessible device—a smartwatch— that provides spatial awareness and serves as the sole display and input device to assist decision-making in

[1]https://www.projectaria.com

everyday tasks. However, in contrast to prior explorations of spatially aware smartwatches that relied on static external tracking infrastructures or hand-held devices, our approach targets a hand-free combination of sensing and display, such as Watch Spaces [42], enabling more natural, continuous interaction with the real world.

2.2 Spatial Sensing with Wearable Devices

With the emergence of mobile and wearable devices, recent work has emphasized integrating visual analysis into physical space to provide contextual and situational interactive visualizations that respond dynamically to both analyst and environmental cues. While some of these works focused on the use of augmented reality displays [17, 21, 36], others investigated wrist-worn displays [26, 28, 33, 42, 43], a combination of both [19, 24], or other mobile devices [35].

The most common indoor spatial tracking uses a motion capture system with reflective optical tracking markers attached to devices [26, 33, 35, 42, 43]. Other systems used head-worn displays to complement the input and output space of wrist-worn devices [19, 24], and display situated data visualizations around real-world objects [21]. A key limitation of motion capture systems lies in their limited, bounded sensing area, which prevents spatial sensing outside the calibrated capture space. In addition, they are not well-suited to handling occluded spaces. To avoid such problems, we opted for a head-worn device with continuous tracking to provide our smartwatch with spatial sensing capabilities.

2.3 Technology Probes

A technology probe [30] is an early but faithful prototype used in real-world settings to explore how people might understand, use, and adapt to a new technology. According to Hutchinson et al. [30], it has three goals: understanding users in their natural context, field-testing technology, and inspiring design. This approach has since been widely adopted in HCI research to explore emergent practices around novel systems. In the domain of wearable and mobile computing, prior work has deployed probes directly within users' everyday environments. For instance, a study by Dicianno et al. [29] used a wearable technology probe to support in-home, computer-assisted physical therapy, demonstrating how probe-style deployment enables observation of interactions in natural contexts. Technology probes have also been applied in high-stakes, context-sensitive clinical settings. Kulp et al. [34] adopted a probe approach along with other ethnographic methods to examine how trauma team leaders interacted with a context-adaptive medical checklist during live resuscitation, foregrounding the interplay between dynamic situational context and system usability. More recently, the method has converged with visualization and personal informatics: Jörke et al. [31] developed Pearl, a technology probe that uses a calendar visualization to support user-directed reflection on personal well-being data, illustrating how probe studies can evaluate both the usability and interpretability of data-driven interfaces. In our study, we also adopt a technology probe to test SAS in a grocery store setting, to gather feedback and steer reflection.

2.4 Real-World Application Scenarios

Various authors suggest scenarios rooted in everyday, data-rich environments that offer opportunities to interact with contextual information and surrounding objects during decision-making tasks. Therefore, libraries [46] and grocery stores [18, 45, 46] have been used frequently in previous work. Grocery shopping tasks were frequently imagined [3, 17, 45, 46] or tested in empirical studies [18, 46]. A possible reason why grocery stores were chosen is that they are easier to access than, for example, hospitals [5]. We try to get as close as possible to the real world in a lab study with a purpose-built grocery store with more products ($\approx$ 300) and shelves (23) than reported in previous work (8 [18], 12 [46] products).

3 Concept of a Spatially Aware Smartwatch

Our idea of SAS is a smartwatch that provides *localization*: It tracks egocentric data about its wearer and knows where it is located in a 3D environment—both with respect to the wearer and the surrounding environment. In addition, SAS consults a database that stores information about objects in the surrounding environment. SAS uses this input to display contextual information to support the wearer in daily decision-making.

For example, in Figure 1a, SAS knows where a person left their keys and can provide navigation instructions. It can also support a person during daily decision-making, such as grocery shopping (Figure 1b). SAS can help the wearer find the shelf containing the desired product, locate it on the shelf, and support the person in deciding on the exact product to buy based on product data. SAS can also be used in a professional context, for example, in a hospital (Figure 1c), where it displays detailed information about a patient once a doctor is near the patient's room.

Among the many tasks that can benefit from SAS are localization, navigation, guidance, and visualization. SAS can report on its location with sub-centimeter-level accuracy, in an indoor environment of at least room size. It can support the wearer in navigating to a specific place in an environment (e.g., a patient's room, an aisle in a grocery store, or a bookcase). Once there, it can guide a person in front of an object (e.g., a shelf or cupboard) to find a desired item (e.g., a key, a product, or a book). Finally, SAS can show visualizations based on the current context—for example, visual product comparisons for shopping, patient data in a hospital environment, or statistics about an ongoing sports event. For exploring SAS, we formulated the following research questions:

- **RQ1**: Is a smartwatch with spatial sensing and context inspection capabilities helpful in assisting with navigation and decision-making tasks in real-life scenarios?
- **RQ2**: Does SAS enhance the interaction with the physical world?
- **RQ3**: Does the small form factor of a smartwatch constitute a limitation in displaying contextual information?
- **RQ4**: To what extent does the use of SAS help reduce mental fatigue and stress when making decisions?

In the next section, we will describe the scenario we selected to explore how SAS can be used in practice.

4 Grocery Shopping Scenario

Grocery stores represent data-rich environments in which individuals are required to engage in various decision-making tasks, such as locating specific products or selecting among multiple product alternatives. Therefore, we picked a grocery store scenario to explore the potential of our SAS. The smartwatch serves as the primary

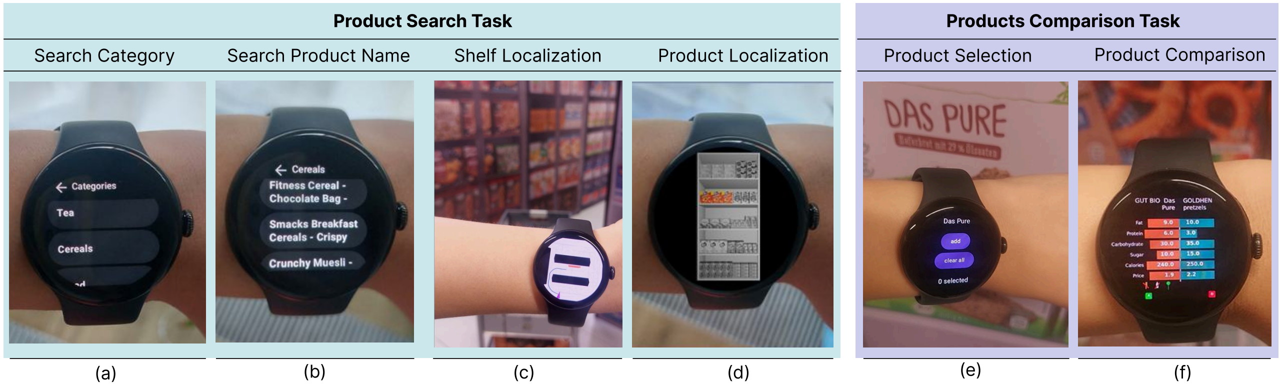


Figure 2: Interfaces for SAS application: product selection from the (a) category list and (b) product names list, (c) shelf and (d) product localization, (e) product selection, and (f) tornado graph showing comparison of two products' characteristics.

input and output device. It enables interaction with context-aware information. For this purpose, the smartwatch displays a variety of lists (Figure 2a and b), diagrams (2c), static images (2d), buttons (2e), and visualizations (2f). The smartwatch supports two tasks, namely, product search and product comparison.

Product Search. The product search task is divided into two phases: 1) locating the shelf that contains the desired product category, then 2) finding the product on the shelf. Participants had to search through a list of product categories (Figure 2a), then a list of product names (Figure 2b) in the selected category, to launch the shelf and product localization.

To find the shelf with SAS, a top-down view of the store's 2D map is shown. The current position and orientation of the person are shown with an arrow (Figure 2c). The arrow is connected to the target shelf (shown in a distinct color) with a line trajectory. Once the person is in front of the shelf in the grocery store, the smartwatch displays an image of the shelf with the target product in color, but all other areas are grayed out (Figure 2d).

Product Comparison. The smartwatch comparison interface features a tornado graph that stacks the characteristics of two products as horizontal bar charts. The graph shows nutrition facts and price information for both products. Icons below the graph show additional information on the nutrition score and other characteristics (e.g., if the product is vegetarian, vegan, lactose-free, or gluten-free).

The product selection is triggered when the ray cast from the hand wearing the smartwatch intersects the product's 2D bounding area (rectangle defined by the top-left and bottom-right y and z coordinates). As confirmation, the smartwatch vibrates and shows the name of the selected product. If nothing happens within a few seconds, participants were instructed to point elsewhere, then back to the product. To confirm the selection, the wearer presses the "add" button or "clear all" to deselect the product (Figure 2e). After selecting two products, the comparison graph is shown. Finally, participants had to select one of the products that fit the comparison criteria by tapping on the corresponding side (Figure 2f).

Table 1: Three localization techniques and how we rate them for different criteria. Good Moderate Bad

Criterion	External motion capturing	SLAM on smartphone	SLAM on XR headset
Accuracy	High	Moderate	High
Infrastructure	Extensive cameras network	None	None
Mobility	Non-portable	Portable	Portable
Practicality	Low (lab setup)	Moderate (Wear phone on wrist)	Moderate (Wear headset)

5 Implementation of the Probe

In this section, we describe the implementation of the localization solution and the software framework.

5.1 Localization

To turn a conventional smartwatch into SAS, we considered multiple ways to retrofit 3D localization with sub-centimeter-level 3D localization to the smartwatch. We wanted to cover an indoor environment of at least 5×5 meters.

The built-in sensing capabilities of current smartwatches do not provide such localization capabilities, because the inertial measurement unit (IMU) alone is insufficient for 3D localization, and its GPS sensor does not work indoors. In contrast, current smartphones combine IMU, camera, and additional processing power for 3D localization using simultaneous localization and mapping (SLAM).

We investigated what kind of device could provide smartphone-like localization in a smaller form factor. A large smartwatch (e.g., Samsung Watch 8 Ultra) weighs about 50–55 g without the wristband. The Google Project Aria Gen 2 smartglasses, which are capable of real-time SLAM, weigh around 75 g. With further advances in wearable sensor miniaturization and embedded computing, we anticipate that a regular smartwatch with SLAM capabilities like the Aria device can be built within a few years. In the interim, our probe simulates the intended functionality with existing technologies to explore the concept of SAS from an HCI perspective. In the following, we compare three possible indoor localization technologies to simulate SAS (see Table 1 for strengths and weaknesses).

- External motion capturing: Systems such as Vicon[2] or OptiTrack[3] use multiple high-precision infrared cameras looking outside-in to track the 3D position of the target (in our case, the smartwatch) fitted with reflective markers. Accuracy is generally high, but occlusions can be problematic.
- SLAM on a smartphone: Localization can be easily performed with the built-in SLAM function (e.g., ARKit or ARCore [39]) on a smartphone. The user wears a smartphone in a fitting sleeve on their wrist next to the smartwatch. We were concerned that using the smartphone camera to point upward rather than forward might affect tracking accuracy. However, an informal experiment with a tablet worn on a sleeve (Figure 3) while walking did not reveal significant tracking instabilities and provides evidence that arm-mounted tracking quality is sufficient in principle and only miniaturization is required.
- SLAM on an extended reality (XR) headset: A headset not only offers multi-camera SLAM, but also hand tracking to approximate the smartwatch position on the wrist. The disadvantage is that a person has to wear the headset in addition to the watch.

Among the three options, we selected the one using an XR headset (Microsoft HoloLens 2) to build our proof-of-concept system.[4] We decided against a stationary infrared tracking system because it is inflexible, and covering all the occluded angles between the shelves would require an excessive number of cameras. Given the choice between a smartphone or an XR headset as a tracking companion device, our informal investigation showed no clear preference for which device was considered more obtrusive. Some individuals preferred to keep the arm unencumbered (except for the smartwatch); others preferred to keep the head unencumbered. We ultimately gave preference to the HoloLens because of its proven and tested tracking performance. We never turned on the headset display and told all participants during the study that they should ignore the headset and focus on the smartwatch. We use the headset to track both the user's head and hands. The origin of the environment is uniquely determined using absolute localization with Bag of World Anchors (BOWA) descriptors [38].

5.2 Software Framework

We use the software architecture illustrated in Figure 4. Our architecture is implemented as a distributed system consisting of a stationary computer acting as a server, a smartwatch, and a headset, all communicating over WiFi using the message queue telemetry transport (MQTT) network protocol. Node-RED running on the server controls the communication. Node-RED is a software framework written in JavaScript on top of Node.js. It excels at orchestrating data flows in distributed systems and has been found to be useful for situated visualization research in the past [21].

A headless application (no display output) is started on the headset. It invokes the Microsoft Mixed Reality Toolkit to read the headset's tracking data and broadcasts MQTT messages over WiFi.

The smartwatch acts as a thin client. It displays images and forwards touch events the user generates to the server. The application

[2] https://www.vicon.com
[3] https://optitrack.com
[4] The Project Aria Gen 2 headset was only released in 04/2026 and was not yet available when this work was performed.

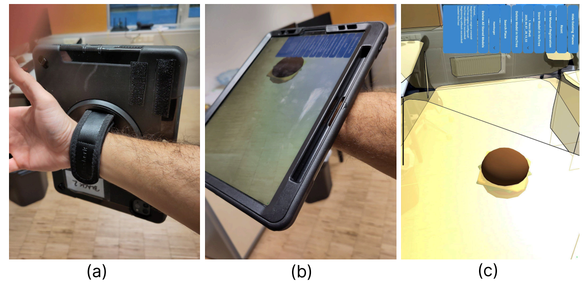


Figure 3: (a) Tracking with SLAM on an iPad worn on the wrist. (b and c) The virtual hamburger remains in its place even after a minute of movement.

logic of the shopping assistant (i.e., shelf localization and product comparison functionalities) is executed in a Node-RED flow on the server. The server collects MQTT messages for tracking and smartwatch input events (e.g., the ID of a selected product) to determine the application state. Then, it renders the appropriate visual output to an off-screen buffer, which is streamed to the smartwatch for display. We generate 2D visualizations with D3.js;[5] the 3D view of the grocery store is created with Three.js,[6] and the navigation path is computed using three-pathfinding.[7]

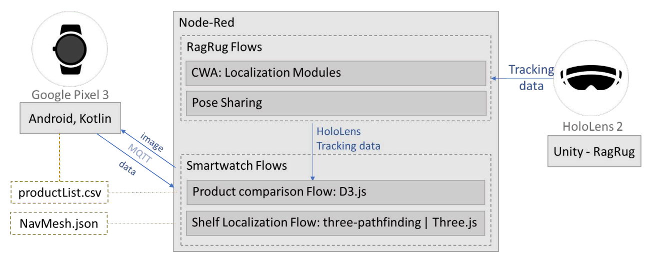


Figure 4: System architecture for our SAS.

6 Evaluation

To test our technology probe and a baseline condition, we built a grocery store (Figure 5) and set two shopping tasks (searching for a product and comparing the characteristics of two products). Given the restricted space and capacity of our grocery store, we chose a between-subjects design for our study to minimize learning biases. Our study was approved by our university ethics committee.

6.1 Tasks and Conditions

Our main goal was to explore our research questions. Given the experimental nature of our prototype, we were primarily interested in determining which interactions worked and were perceived as helpful when performing basic grocery shopping tasks. We compared two main conditions: 1) a baseline condition without any assistance, and 2) SAS. We collected data on participants' performance on the study tasks, as well as their preferences, perceived

[5] https://github.com/d3/d3
[6] https://github.com/mrdoob/three.js/
[7] https://github.com/donmccurdy/three-pathfinding

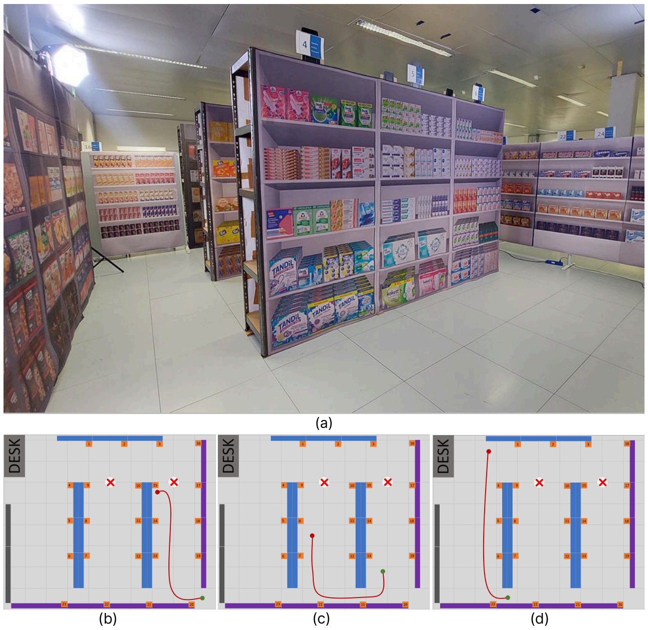


Figure 5: (a) The grocery store shelves with 2D printed products. (b – d) A top-down view of the map of the grocery store setting showing trajectories' starting (in green) and ending (in red) points for each product: (b) product 1: sauce, (c) product 2: cookies, and (d) product 3: pizza. The distractor shelves are highlighted in purple. The red cross indicated the blocked area that we prohibited participants from crossing.

task load, helpfulness, and acceptance of SAS. The first task involved searching for a product in an unfamiliar grocery store, and the second task compared the nutrition facts of two products to select the one that best met a given criterion.

Product Search Task. We gave participants a grocery shopping list with three products to find. For each item listed, we indicated the category of the product and its name as shown on the package. To maintain a consistent walking distance from each product location to the starting search point (i.e., 8–9 tiles, Figure 5b–d), we marked three starting location points on the floor, respectively, for each product. To make the task more realistic, we asked participants to push a trolley full of shopping products while walking the aisles.

Product Comparison Task. After successfully completing the search task, participants were asked to compare the product found with a second product based on a specified condition related to nutrition facts (e.g., select the product containing less sugar). The name of the second product and the comparison criterion were indicated in the grocery shopping list. The second product always belonged to the same category and was displayed on the same or an adjacent shelf, next to the first product (i.e., same row or adjacent row). For the baseline condition, we handed the real products to participants. In the SAS condition, participants had to point toward the two products to select them for comparison. Then, a tornado graph showed nutritional facts and prices (Figure 2f).

6.2 Apparatus and Setting

Apparatus. The study was carried out using a Google Pixel Watch 3 with a round screen of 41 mm, a Microsoft HoloLens 2, and a server PC (CPU: i7-7700, GPU: GeForce RTX 2070, RAM: 32 GB) running Oracle Linux Server 9.6.

Grocery Store Setting. We purposely built a grocery store that covered an area of 25 m^2. We started with a virtual reality model, which served as a digital twin. Then, we recreated the digital twin as a physical environment in our research lab. From our product database, we extracted data such as package photos, names, prices, and nutritional attributes for about 300 products from a real supermarket website. Package photos were applied to box-shaped containers placed on shelves using a 3D modeling application (Blender). The products were sorted into categories, and up to three categories were placed on a shelf. As is customary in a real grocery store, individual products are repeated up to five times in a row. The shelves are 100 cm wide and 200 cm high, with five boards each.

The shelves were arranged in three aisles to ensure a reasonably complex environment with a fair amount of occlusion. The store is made up of a total of 23 shelves—including eight as distractors (Figure 5b–d). Most of the products on display are food products (240/289 products) (Figure 5a). Each shelf is identified with a unique ID displayed on a sign at the top of the shelf, together with the product categories.

6.3 Participants

We recruited 30 participants (15 per group) via university mailing lists, personal networks, and direct recruitment. Seven participants identified as women, and 23 as men. Eighteen participants were between 25 and 34; 10 were between 18 and 24, and two participants belonged to the age range of 35 to 44. The majority of participants had a master's (12) or bachelor's (10) degree, six had a high school diploma, one had a doctorate (PhD), and one had a secondary school diploma. When asked about their previous experience with smartwatches, 12 participants from the SAS condition reported having used a smartwatch before, including five who owned one and used it regularly. From the SAS condition, 13/15 participants were right-handed, and one wore a watch on the right wrist.

6.4 Study Procedure and Design

After signing the consent form, participants were randomly assigned to one of the conditions. Then, we introduced them to the tasks. Participants in the SAS condition started with a training session to become familiar with SAS. After confirming that they understood the tasks, participants performed the two study tasks. In the end, they were asked to complete a questionnaire inspired by NASA-TLX [25] and SUS [9] questions. Participants reported on their preferences and experiences with both conditions by answering follow-up open-ended questions. All collected data was anonymized, protecting participants' privacy.

7 Results

This section reports study results, including the task completion time for the product's search and comparison tasks under the different study conditions, and ratings of the perceived task load and

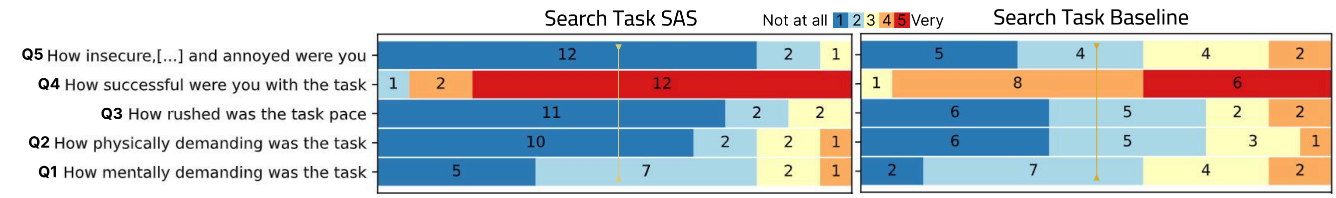


Figure 6: Participants ratings for the search task using questions related to the task load. Q4 is reverse-anchored: higher values indicate better perceived success. The yellow line shows the median.

usability for SAS. To evaluate and refine the technology probe, we gathered qualitative data capturing participants' subjective preferences, acceptance of the system, and perceived helpfulness.

Following recommendations for establishing a modern evaluation methodology [14, 15], we report our inferential statistics using *interval estimation* rather than p-values. We measured Task Completion Time (TCT) for the SAS condition, starting from the moment the product name was selected from the list (Figure 2b) until the frontal view image (Figure 2d) was pressed—indicating that the product was found. For the ∅ baseline condition, the TCT was measured with a stopwatch. We report sample means for 180 trials in total: 90 trials (15 participants × 2 tasks × 3 trials) for each group using 95% confidence interval (CI) estimation [6, 11, 13, 15] using BCa bootstrapping [16] with 10,000 bootstrap iterations. In addition, we report the differences between means to compare the two conditions. We adjusted the CI of the mean differences for multiple comparisons using Bonferroni corrections [27], highlighted as red error bars. When reading a CI of mean differences, we interpret a non-overlap of the CI with 0 as evidence of a difference.

7.1 Product Search Task

For this task, we report and compare the results of the two study conditions (full results are in the supplemental material). We read the TCT results with caution due to the small sample size.

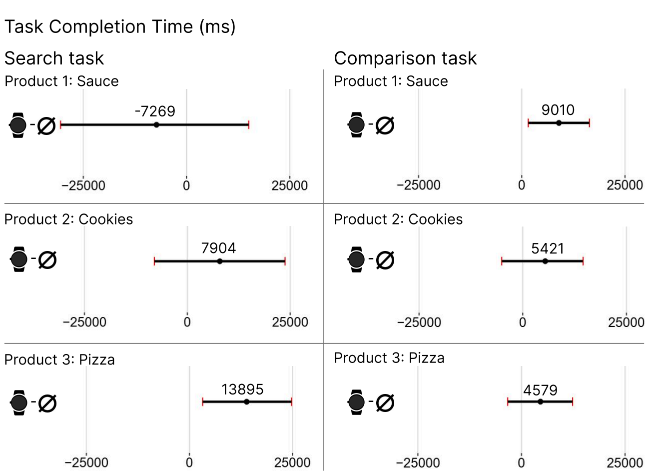
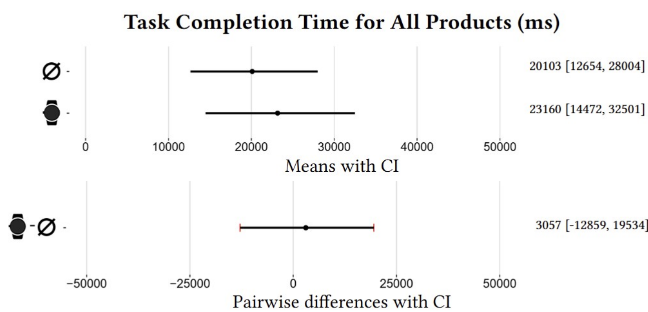


Figure 7: Mean TCT pairwise differences for search (left) and comparison (right) tasks for the 1st, 2nd, and 3rd products.

Table 2: Means (top) and pairwise differences (bottom) between the two conditions of TCT while searching for the three products. Legend: ∅ Baseline and SAS.



Completion Time. All participants were successful in finding the three products from the grocery shopping list. In general, the results do not show evidence of differences in mean TCT between the two conditions (mean TCT ∅: 23.2 s and : 20.1 s (Table 2)). However, the mean TCT for individual products differed across conditions. On the one hand, participants from the ∅ baseline condition took on average 7.2 s longer than the SAS condition to find the first product (mean TCT ∅: 33.3 s and : 26.1 s). However, the results do not show any evidence of a difference between the two conditions for the mean TCT for the first product. On the other hand, the mean TCT for the second and third products was shorter with the ∅ baseline condition, with 7.9 s for the second product (mean TCT ∅: 17.4 s and : 25.3 s) and almost by 3× with 13.9 s for the third product (mean TCT ∅: 7.6 s and : 21.5 s, Figure 7). The pairwise differences between the two conditions for the third product show weak evidence of a difference, indicating that participants were faster with the ∅ baseline condition than with the SAS condition.

Task Load. To measure the perceived workload for the two conditions, participants were asked to fill out a questionnaire inspired by NASA-TLX and using a 5-point Likert scale (1 = not at all, 5 = very). For the two conditions, participants reported that the product search task was not mentally demanding (median: 2). In contrast, with the ∅ baseline condition, the physical load of the task was rated higher (median: 2) compared to the SAS condition (median: 1). Similarly, participants felt more rushed and stressed (median: 2) when performing the search task with the ∅ baseline condition than the SAS condition (median: 1). When asked how successful they were with performing the task, participants reported being

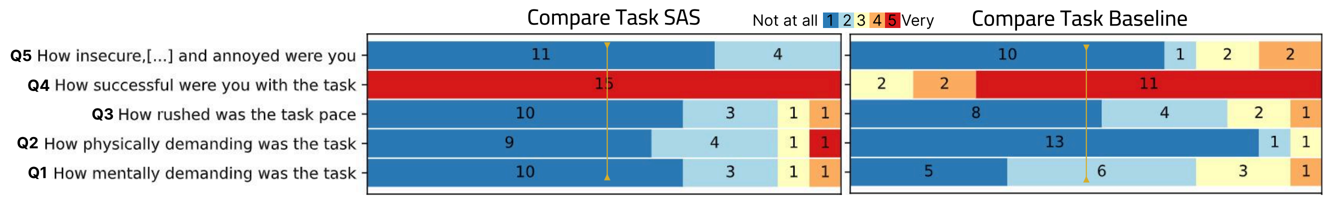
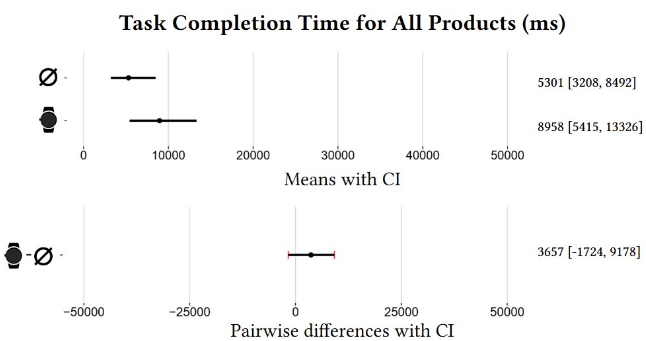


Figure 8: Participants ratings for the comparison task using questions related to task load. Q4 is reverse-anchored: higher values indicate better perceived success. The yellow line shows the median.

Table 3: Means (top) and pairwise differences between the two conditions (bottom) of TCT while comparing two products for the three products. Legend: ∅ Baseline and SAS.



very successful (median: 5) with the SAS and only successful (median: 4) with the ∅ baseline condition (Figure 6).

7.2 Product Comparison Task

For the product comparison task, we report results from the two study conditions (full results are in the supplemental material). We read the TCT results with caution due to the small sample size.

Completion Time. All participants were able to choose the correct product based on the provided comparison criterion. With the baseline condition, participants were 3.7 s faster with the comparison task (mean TCT ∅: 5.3 s and : 9 s, Table 3). However, no evidence of differences was found between the conditions. Similarly, comparing individual products' TCT shows no evidence of difference between the two conditions (mean TCT ∅: 9.6 s and : 15 s for the second product, and ∅: 8.2 s and : 12.8 s for the third product), except for the first product, a weak evidence of a difference indicated that participants were 9 s faster with the ∅ baseline condition than the SAS condition (mean TCT ∅: 5.5 s and : 14.6 s, Figure 7).

Task Load. Participants found that the product comparison task was more mentally demanding with the ∅ baseline condition (median: 2) than the SAS condition (median: 1), but not physically demanding at all for both conditions. The participants did not feel the task was rushed or stressful (median: 1) and expressed that they were very successful in accomplishing the task (Figure 8).

7.3 Spatially Aware Smartwatch: Usability Ratings

To assess participants' experience with SAS (the smartwatch and headset system), we asked them to complete the System Usability Scale (SUS), a 10-item questionnaire that yields a composite usability score ranging from 0 to 100. The SAS condition received a score of 86.66, and is classified as EXCELLENT according to Bangor et al. [4]. Participants' comments about their ratings of the usability of SAS were nuanced. While a few comments pointed at some functional shortcomings and irregularities, such as *"Sometimes it failed to detect the product during comparison check" (S-53),* or *"The navigation is little bit slow but everything else was good " (S-81),* most of our participants described SAS as *"intuitive and easy to use" (S-63),* and found that *"Simple navigation and clear cut comparison made it easy" (S-53).* Participant (S-63) also mentioned that the *"System worked consistent with no sign of technical flaws or faulty recognition".*

7.4 Spatially Aware Smartwatch: Helpfulness and Acceptance Ratings

Participants were asked for feedback on their overall appreciation of SAS to complement the usability evaluation. This includes perceived helpfulness in supporting task completion and their willingness to adopt SAS in real-world contexts. The participants rated SAS as very helpful (median: 5) in finding a product at the grocery store and comparing the characteristics of two products. Furthermore, they were open to using SAS in public spaces without feeling that it could be socially awkward at all (median: 1). However, they were more reluctant to perform the product selection task with SAS, pointing to a product in public (median: 2).

8 Discussion

In this section, we summarize the findings of our study and discuss opportunities emerging from our technology probe with respect to the four research questions defined in Section 3.

RQ1: Is a SAS helpful in assisting with navigation and decision-making tasks in real-life scenarios? We assess the helpfulness of SAS using TCT measurements and participants' subjective ratings. The chosen tasks illustrated indoor navigation and decision-making in a realistic usage context (i.e., an unknown grocery store). The results showed that, with the help of SAS, all participants successfully located the designated shelves and found products that matched the search criteria. When designing the study, it was important that participants were unaware of the grocery store's products and locations. In the baseline condition, this circumstance was valid only during the first product search. In contrast to the SAS condition, participants did not have any indication of shelf location for the baseline; therefore, the majority of participants (13/15 participants) had to navigate and scan almost all the shelves and read the products' category signs—placed on top of each shelf—to find the searched product. This procedure resembles a typical product search task in an unknown supermarket or when the aisle configuration changes. This was reflected in many participants' comments in the post-study questionnaire. One participant reported: *"Like a supermarket you don't know—orientation takes some time" (B-12).* Another one mentioned: *"I took pretty long to find the first item. However, during that search I got a decent overview of the entire store, which helped me to find the next items much faster" (B-29).* When asked whether they have learned about the location of products from the grocery list while performing the search task, 14 (10: Yes and 4: Maybe) reported that they (might) have learned about products locations." It is likely that the relatively small supermarket size—with only three aisles, which most participants already inspected when searching for the first product—influenced the mean TCT results during the search task for the second and third products, in the baseline condition. Generally, the recorded TCT results help estimate the average time required for the given tasks. However, they cannot be generalized to different usage contexts or even grocery stores with a larger number of shelves, products, and different arrangements.

In general, participants confirmed in the post-study interview that SAS was helpful. SAS participants reported more confidence and a positive perception of both tasks compared to no smartwatch. One participant commented: *"The smartwatch provided the correct navigation and precise placement of products on the shelf" (S-53).* Another participant mentioned that the smartwatch's navigation instructions were clear *"The navigation is really nice, I know exactly where to go" (S-99).* Regarding the comparison task, one participant mentioned: *"Much easier to compare with the graphs provided on the watch" (S-53).* Also, one participant expressed their motivation to use such a tool for his daily shopping: *"I use a smartwatch to track my exercise, my sleep. So I was rather fascinated that shopping features can be added to it, which can save time when I go to the supermarket and spend hours searching for the right products" (S-15).* In a similar vein, more than one participant expressed that the use of SAS, particularly in the study context, was both meaningful and helpful. One noted: *"The idea of the system feels great considering how big the supermarkets are, so it feels best to use when one already has the list of items to buy" (S-53).* Another one stated: *"It allows [a] user to efficiently navigate through cutting down search aisles and compare products to best meet customer needs" (S-26).* Interestingly, the use of SAS in the context of buying groceries revealed additional perceived benefits among participants, specifically to support more conscious shopping behavior: *"You focus more on the products that you need [...] I might buy groceries more efficiently without looking at other options" (S-36).*

Participants received the idea of our SAS well. Those who own a smartwatch appreciate using their personal device to help with mundane tasks and are starting to envision how they will use it and adapt it to their grocery habits. This feedback motivates us to investigate the SAS concept further for usage scenarios that require everyday guidance and assistance.

RQ2: Does SAS enhance the interaction with the physical world? We assessed this research question with the SUS questionnaire and qualitative feedback on the pointing interaction. When performing the navigation and comparison tasks, participants performed different interaction techniques to select the products. In general, participants rated the SAS usability high. While the product name was selected from a list by tapping on the touchscreen of the smartwatch, the physical products displayed on the shelf were pointed to by the participant's arm wearing the smartwatch. First, using touch interaction on the smartwatch to select and scroll through product categories and names was perceived as quite time-consuming, especially when the item list is long: *"It just feels like it takes a little bit more time tapping on the smartwatch" (S-02).* and *"The selection of the product is a bit mentally demanding when the list of products is long" (S-95).* Second, the feedback we received on the pointing interaction was quite nuanced. On the one hand, it demonstrates great potential for using spatial interactions with SAS. Indeed, because our spatial tracking approach is centered around the hand, which is the primary natural interaction medium with the physical world, to grasp, point to, or touch objects, it provides a wide range of spatial interaction options. One participant mentioned: *"It was fun to select the products by pointing towards them" (S-95).* However, some were hesitant to use such spatial interaction in public spaces: *"It would be a bit weird to go close to the products and point out for the comparison task" (S-53).* Another participant thought that the interaction might be time-consuming, especially if the person is in a hurry. The reluctance of certain participants to use SAS when surrounded by other people was not surprising, because social acceptance of spatial interactions in public environments remains a challenge that prior work has highlighted [1, 46]. This opens new research opportunities for designing hand-based spatial interactions with SAS that are intuitive and suitable for public use.

RQ3: Does the small form factor of a smartwatch constitute a limitation in displaying contextual information? We assess this research question using qualitative feedback from participants. Smartwatches have displays with a diameter of 4.2–4.4 cm. This size directly affects how much information the smartwatch can display at once, requiring careful interface design that emphasizes the most important information.

For the two tasks we studied, our SAS did not show too much information per screen—only a top-down view of the store map and a tornado graph, showing different nutrition facts as proportions. Few participants commented on the smartwatch or the size of the information displayed. However, one participant mentioned *"still a bit small numbers, but generally easy" (S-36).* We assume that most participants focused on reading the graph's proportions rather than the exact values. Another commented: *"Clear bar graph comparison made [the task] easier, didn't need to check the values" (S-53).* We received a few comments expressing concern about elderly people reading information on such a small display. Accessibility was not our main focus for this first exploration. Future work should consider a more inclusive design for elderly and vision-deficient individuals [44]. Although it was possible to pinch the screen of the smartwatch to zoom in on the content, there are other opportunities to further test spatial interactions by moving the smartwatch up and down to zoom in and out of the content.

Smartwatches are generally underestimated. Larger devices usually occupy at least one hand and are less suitable for extended mobile use. Our investigation confirms that, despite their small display area, smartwatches can show the necessary information for navigation and search tasks. We leave the exploration of more elaborate gestural interactions for future work.

RQ4: To what extent does the use of SAS help reduce mental fatigue and stress when making decisions? We assess the task load using a NASA-TLX-inspired rating. In line with previous findings [37], SAS helped reduce perceived task workload and stress levels. In general, the assistance of a smartwatch reduced stress, particularly for the search task. In fact, participants felt the urge to perform the task faster and were more rushed and frustrated in finding the products in the baseline condition. One participant commented: *"I felt a bit stressed because I had to process a lot of information in a short amount of time to complete the product search" (B-29).* This statement explains the slight increase in the physical load rating, because participants had to walk the store aisles with the trolley and look everywhere, especially when locating the first product. Another participant commented: *"I was annoyed that I overlooked the first product. Sometimes, I was unsure if I found the correct product, and I had to cross-check with the grocery list" (B-38).* In contrast, when using SAS, participants were more relaxed: *"good pace and supportive instructions" (S-63).* It seems that participants were more content with finding the product, because they had the necessary information about their own and the product's location. Based on how participants rated their success, we think that SAS boosted their confidence in their performance.

Our main focus was the extent to which SAS can support and enhance daily tasks, especially when involving decision-making under stress and uncertainty. The preliminary feedback from our exploratory study confirms the potential value of having our SAS.

9 System and Study Design Limitations

In the following, we summarize limitations related to the current prototype and study design and outline potential improvements.

Influence of the Used Headset on Task Load and Comfort. Even though all the interactions and information were mediated via the smartwatch, in the SAS condition, participants had to wear a HoloLens 2 to ensure spatial tracking. Some participants described the HoloLens as "*bulky,*" and they expressed their preference to use lightweight smartglasses or a standalone smartwatch instead. However, using the HoloLens did not hinder perception of the shelves or the products (8 votes: no hindrance, 7: slightly or sometimes—mainly due to the visor tint). Although wearing the HoloLens had no direct impact on task workload (SAS mental and physical loads were lower than or equal to the baseline), its use may nonetheless affect social comfort and acceptance in daily-life settings.

Toward Building a Standalone and Lightweight SAS.. The current prototype relies on a bulky headset and a distributed infrastructure, limiting the usability of SAS in real-life settings. In the near term, this can be addressed by replacing the HoloLens 2 with the lightweight Aria 2 glasses. In the longer term, the same sensing hardware (of the Aria glasses) can be embedded in a commercial smartwatch to transform it into a standalone SAS. Additionally, the emergence of public spaces equipped with built-in outside-in spatial tracking infrastructure (e.g., Amazon Go[8]) could offload much of this technological burden.

Interaction Modalities Vary Between Conditions. Both search and comparison tasks presented different interaction styles, accommodated to each condition's specificities. Most likely, these differences have impacted the TCT results. For the search task, we assume that the mean TCT for the SAS condition could have been shorter if direct input were applied, instead of scrolling through two lists. The list navigation time to select the product to look for was estimated to be ≈15 s for the first, and ≈9 s for the second and third products.[9] Similarly, the pointing interaction is estimated to take ≈8 s until the comparison visualization is displayed on the smartwatch: ≈3 s to detect the pointed to product, in addition to ≈5 s to confirm the selection and wait for the comparison visualization to load on screen, compared to less than 1 s to flip the two products and see their nutrition facts information. Ultimately, the interaction time with the application and the overall user experience can be improved by enabling direct interactions (e.g., voice input) and centralizing all necessary information on the smartwatch (e.g., a shopping list that lets users select products directly on the smartwatch).

Sample Diversity and Study Setting. Future work should aim for a larger and more demographically diverse sample: ensuring better gender balance and including participants with visual impairments to evaluate data accessibility and readability on small displays. Moreover, future investigations should extend the study setting scale (i.e., larger grocery stores to minimize the learning effect) and test higher-stakes environments, such as hospitals, that might produce stronger effects on performance and task load.

10 Conclusion

SAS received high usability ratings and, according to participants, provided effective assistance with the study tasks. Additionally, it helped ease the workload and reduce the stress caused by spatial disorientation in large or unfamiliar environments. Although our current SAS prototype has some technical limitations, such as latency in updating the real-time navigation map, participants generally received it well.

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References

[1] David Ahlström, Khalad Hasan, and Pourang Irani. 2014. Are you comfortable doing that? Acceptance studies of around-device gestures in and for public settings. In *Proceedings of the International Conference on Human-Computer Interaction*

[8]https://www.justwalkout.com/

[9]Time estimate was based on time measurement tests conducted with nine people

with Mobile Devices & Services. Association for Computing Machinery, New York, NY, USA, 193–202. doi:10.1145/2628363.2628381

[2] Fereshteh Amini, Khalad Hasan, Andrea Bunt, and Pourang Irani. 2017. Data representations for in-situ exploration of health and fitness data. In *Proceedings of the EAI International Conference on Pervasive Computing Technologies for Healthcare*. Association for Computing Machinery, New York, NY, USA, 163–172. https://doi.org/10.1145/3154862.3154879

[3] Abhaya Asthana, Mark Crauatts, and Paul Krzyzanowski. 1994. An Indoor Wireless System for Personalized Shopping Assistance. In *First Workshop on Mobile Computing Systems and Applications*. IEEE Computer Society, New York, NY, USA, 69–74. doi:10.1109/WMCSA.1994.8

[4] Aaron Bangor, Philip Kortum, and James Miller. 2009. Determining what individual SUS scores mean: adding an adjective rating scale. *Journal of Usability Studies* 4, 3 (2009), 114–123.

[5] Jakob Bardram, Thomas Hansen, Martin Mogensen, and Mads Soegaard. 2006. Experiences from Real-World Deployment of Context-Aware Technologies in a Hospital Environment. In *International Conference on Ubiquitous Computing*. Springer International Publishing, Cham, 369–386. doi:10.1007/11853565_22

[6] Lonni Besançon and Pierre Dragicevic. 2019. The Continued Prevalence of Dichotomous Inferences at CHI. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–11. doi:10.1145/3290607.3310432

[7] Tanja Blascheck, Lonni Besançon, Anastasia Bezerianos, Bongshin Lee, and Petra Isenberg. 2019. Glanceable Visualization: Studies of Data Comparison Performance on Smartwatches. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (Jan. 2019), 630–640. https://doi.org/10.1109/TVCG.2018.2865142

[8] Tanja Blascheck, Lonni Besancon, Anastasia Bezerianos, Bongshin Lee, Alaul Islam, Tingying He, and Petra Isenberg. 2023. Studies of Part-to-Whole Glanceable Visualizations on Smartwatch Faces. In *IEEE Pacific Visualization Symposium*. IEEE Computer Society, Los Alamitos, CA, USA, 187–196. doi:10.1109/PacificVis56936.2023.00028

[9] John Brooke. 1996. *SUS – a quick and dirty usability scale*. CRC Press, London, UK, 189–194. doi:10.1201/9781498710411

[10] Guanling Chen and David Kotz. 2000. *A Survey of Context-Aware Mobile Computing Research*. Technical Report. Dartmouth College, USA. doi:10.5555/867843

[11] Andy Cockburn, Pierre Dragicevic, Lonni Besançon, and Carl Gutwin. 2020. Threats of a Replication Crisis in Empirical Computer Science. *Commun. ACM* 63, 8 (2020), 70–79. doi:10.1145/3360311

[12] Diane Cook and Sajal Das. 2004. *Smart Environments: Technology, Protocols and Applications (Wiley Series on Parallel and Distributed Computing)*. Wiley-Interscience, USA. doi:10.5555/1036248

[13] Geoff Cumming. 2013. *Understanding the new statistics: effect sizes, confidence intervals, and meta-analysis*. Routledge, New York, NY, USA.

[14] Geoff Cumming. 2014. The New Statistics: Why and How. *Psychological Science* 25, 1 (2014), 7–29. doi:10.1177/0956797613504966

[15] Pierre Dragicevic. 2016. Fair Statistical Communication in HCI. In *Modern Statistical Methods for HCI*, Judy Robertson and Maurits Kaptein (Eds.). Springer, Berlin, Heidelberg, Chapter 13, 291–330.

[16] Bradley Efron. 1987. Better bootstrap confidence intervals. *Journal of the American statistical Association* 82, 397 (1987), 171–185.

[17] Neven Elsayed, Kim Marriott, Ross Smith, and Bruce H Thomas. 2024. Situated Analytics Process and Mantra. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, Article 292, 9 pages. doi:10.1145/3613905.3650814

[18] Neven ElSayed, Bruce Thomas, Kim Marriott, Julia Piantadosi, and Ross Smith. 2016. Situated Analytics: Demonstrating immersive analytical tools with Augmented Reality. *Journal of Visual Languages & Computing* 36 (2016), 13–23. doi:10.1016/j.jvlc.2016.07.006

[19] Nuno Estalagem and Augusto Esteves. 2024. Between Wearable and Spatial Computing: Exploring Four Interaction Techniques at the Intersection of Smartwatches and Head-mounted Displays. In *Proceedings of the Symposium on Eye Tracking Research and Applications*. Association for Computing Machinery, New York, NY, USA, 1–7. doi:10.1145/3649902.3656365

[20] George W. Fitzmaurice. 1993. Situated information spaces and spatially aware palmtop computers. *Commun. ACM* 36, 7 (1993), 39–49. doi:10.1145/159544.159566

[21] Philipp Fleck, Aimee Sousa Calepso, Sebastian Hubenschmid, Michael Sedlmair, and Dieter Schmalstieg. 2022. RagRug: A Toolkit for Situated Analytics. *IEEE Transactions on Visualization and Computer Graphics* 29, 7 (2022), 3281–3297. doi:10.1109/TVCG.2022.3157058

[22] Fairouz Grioui and Tanja Blascheck. 2023. Heart Rate Visualizations on a Virtual Smartwatch to Monitor Physical Activity Intensity. In *Proceedings of the International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*. INSTICC, SciTePress, Setúbal, Portugal, 101–114. doi:10.5220/0011665500003417

[23] Fairouz Grioui, Tanja Blascheck, Lijie Yao, and Petra Isenberg. 2024. Micro Visualizations on a Smartwatch: Assessing Reading Performance While Walking. In *IEEE Visualization and Visual Analytics (VIS)*. IEEE Computer Society, Los Alamitos, CA, USA, 46–50. doi:10.1109/VIS55277.2024.00017

[24] Jens Grubert, Matthias Heinisch, Aaron Quigley, and Dieter Schmalstieg. 2015. MultiFi: Multi Fidelity Interaction with Displays On and Around the Body. In *Proceedings of the Annual ACM Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 3933–3942. doi:10.1145/2702123.2702331

[25] Sandra Hart and Lowell Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In *Human Mental Workload*. North-Holland, Amsterdam, Netherlands, 139–183. doi:10.1016/S0166-4115(08)62386-9

[26] Khalad Hasan, David Ahlström, and Pourang Irani. 2015. SAMMI: A Spatially-Aware Multi-Mobile Interface for Analytic Map Navigation Tasks. In *Proceedings of the International Conference on Human-Computer Interaction with Mobile Devices & Services*. Association for Computing Machinery, New York, NY, USA, 36–45. doi:10.1145/2785830.2785850

[27] James Higgins. 2004. *Introduction to modern nonparametric statistics*. Thomson Learning, –.

[28] Tom Horak, Sriram Karthik Badam, Niklas Elmqvist, and Raimund Dachselt. 2018. When David Meets Goliath: Combining Smartwatches with a Large Vertical Display for Visual Data Exploration. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3173574.3173593

[29] Kevin Huang, Patrick J. Sparto, Sara Kiesler, Asim Smailagic, Jennifer Mankoff, and Dan Siewiorek. 2014. A technology probe of wearable in-home computer-assisted physical therapy. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 2541–2550. doi:10.1145/2556288.2557416

[30] Hilary Hutchinson, Ben Bederson, Allison Druin, Catherine Plaisant, Wendy Mackay, Helen Evans, Heiko Hansen, Stéphane Conversy, Michel Beaudouin-Lafon, Nicolas Roussel, Loïc Lacomme, Björn Eiderbäck, Sinna Lindquist, Yngve Sundblad, and Bo Westerlund. 2003. Technology Probes: Inspiring Design for and with Families. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA.

[31] Matthew Jorke, Yasaman S. Sefidgar, Talie Massachi, Jina Suh, and Gonzalo Ramos. 2023. Pearl: A Technology Probe for Machine-Assisted Reflection on Personal Data. In *Proceedings of the International Conference on Intelligent User Interfaces*. Association for Computing Machinery, New York, NY, USA, 902–918. doi:10.1145/3581641.3584054

[32] Sarina Kashanj, Xiyao Wang, and Charles Perin. 2024. Visualizations on Smart Watches while Running: It Actually Helps!. In *IEEE Visualization*. 41–45. doi:10.31219/osf.io/2fa56

[33] Frederic Kerber, Antonio Krüger, and Markus Löchtefeld. 2014. Investigating the effectiveness of peephole interaction for smartwatches in a map navigation task. In *Proceedings of the International Conference on Human-Computer Interaction with Mobile Devices & Services*. Association for Computing Machinery, New York, NY, USA, 291–294. doi:10.1145/2628363.2628393

[34] Leah Kulp, Aleksandra Sarcevic, Richard Farneth, Omar Ahmed, Dung Mai, Ivan Marsic, and Randall S. Burd. 2017. Exploring Design Opportunities for a Context-Adaptive Medical Checklist Through Technology Probe Approach. In *Proceedings of the Conference on Designing Interactive Systems*. Association for Computing Machinery, New York, NY, USA, 57–68. doi:10.1145/3064663.3064715

[35] Ricardo Langner, Ulrich von Zadow, Tom Horak, Annett Mitschick, and Raimund Dachselt. 2016. *Content Sharing Between Spatially-Aware Mobile Phones and Large Vertical Displays Supporting Collaborative Work*. Springer International Publishing, Cham, 75–96. doi:10.1007/978-3-319-45853-3_5

[36] Nuno Cid Martins, Bernardo Marques, João Alves, Tiago Araújo, Paulo Dias, and Beatriz Sousa Santos. 2021. Augmented reality situated visualization in decision-making. *Multimedia Tools and Applications* 81, 11 (2021), 14749–14772. doi:10.1007/s11042-021-10971-4

[37] Roman Rädle, Hans-Christian Jetter, Mario Schreiner, Zhihao Lu, Harald Reiterer, and Yvonne Rogers. 2015. Spatially-aware or Spatially-agnostic? Elicitation and Evaluation of User-Defined Cross-Device Interactions. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 3913–3922. doi:10.1145/2702123.2702287

[38] Fernando Reyes-Aviles, Philipp Fleck, Dieter Schmalstieg, and Clemens Arth. 2023. Bag of World Anchors for Instant Large-Scale Localization. *IEEE Transactions on Visualization and Computer Graphics* 29, 11 (2023), 4730–4739.

[39] Vedala Venkata Satyadev. 2025. *Building AR Apps with ARCore and ARKit: Master Augmented Reality App Development with ARCore and ARKit for Immersive and Interactive AR Experiences*. Orange Education Pvt Ltd, Delhi, India.

[40] Alexander Schiewe, Andrey Krekhov, Frederic Kerber, Florian Daiber, and Jens Krüger. 2020. A Study on Real-Time Visualizations During Sports Activities on Smartwatches. In *Proceedings of the International Conference on Mobile and Ubiquitous Multimedia*. Association for Computing Machinery, New York, NY, USA, 18–31. doi:10.1145/3428361.3428409

[41] Dieter Schmalstieg and Tobias Höllerer. 2016. *Augmented Reality - Principles and Practice*. Addison-Wesley Professional, Indianapolis, IN, USA.

[42] Keitaro Tsuchiya, Kaiyuan Lin, Takuro Nakao, and Kai Kunze. 2019. Watch Spaces: A Spatial User Interface for Smart Watches. In *Proceedings of the International Conference on Human-Computer Interaction with Mobile Devices & Services*. Association for Computing Machinery, New York, NY, USA, Article 62, 6 pages. doi:10.1145/3338286.3344412

[43] Dirk Wenig, Johannes Schöning, Alex Olwal, Mathias Oben, and Rainer Malaka. 2017. WatchThru: Expanding Smartwatch Displays with Mid-air Visuals and Wrist-worn Augmented Reality. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 716–721. doi:10.1145/3025453.3025852

[44] Zack While, Tanja Blascheck, Yujie Gong, Petra Isenberg, and Ali Sarvghad. 2024. Glanceable Data Visualizations for Older Adults: Establishing Thresholds and Examining Disparities Between Age Groups. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, Article 987, 17 pages. doi:10.1145/3613904.3642776

[45] Wesley Willett, Yvonne Jansen, and Pierre Dragicevic. 2017. Embedded Data Representations. *IEEE Transactions on Visualization and Computer Graphics* 23, 1 (2017), 461–470. doi:10.1109/TVCG.2016.2598608

[46] Qian Zhu, Zhuo Wang, Wei Zeng, Wai Tong, Weiyue Lin, and Xiaojuan Ma. 2024. Make Interaction Situated: Designing User Acceptable Interaction for Situated Visualization in Public Environments. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, Article 196, 21 pages. doi:10.1145/3613904.3642049