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Unlocking context-aware mobile map adaptation: a VR navigation user study

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ABSTRACT
As maps have become indispensable for many of our everyday mobility activities, research on context-aware mobile map adaptation has become increasingly relevant. Empirical evidence on the effectiveness of the design of context-aware mobile maps is still underexplored, but increasing slowly. We report on a virtual reality study with 54 participants where we assessed mobile map adaptation for map-assisted navigation tasks. We manipulated environmental context (i.e. light and heavy traffic) and map adaptation, comparing an adapted map that masked task-irrelevant points of interest (POIs) with a non-adapted map that provided all available POIs. Participants were asked to search for and navigate in the virtual environment to varying POIs (e.g. restaurant, coffee shop, etc.). Heavy traffic affected participants' task completion time, particularly locomotion time, and significantly increased participants' self-reported cognitive workload, agitation, satisfaction, and control. The adapted map provided only partial evidence for its ability to support map users to complete the navigation tasks in heavy traffic. We found participants' individual and group differences, predominantly their sense of direction, as significant human factors to consider for designing maps that assist navigation tasks.

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Mobile map design; map adaptation; map use context; navigation; spatial ability; virtual reality

Introduction

Maps on mobile devices have become integral to everyday activities. They are commonly used to find spatio-temporal information on-the-fly (e.g. locating a restaurant and its opening hours, etc.), to receive live updates on traffic congestion, or to receive navigation instructions while hiking. Unlike paper maps, GPS-equipped mobile maps offer dynamic and interactive features that can cater to the needs of individual users and their use contexts (Reichenbacher & Bartling, 2023).

Prior research spanning transferable design (Griffin et al., 2017), responsive and mobile-first design (Roth et al., 2024), neuro-adaptive design (Fabrikant, 2023b), location-based services (Huang et al., 2024), and context-aware map adaptations (Reichenbacher & Bartling, 2023) has enriched our understanding of contextual factors, including those of map users and their specific use tasks, in shaping mobile map design and adaptation. Beyond the map user, map use context can encompass a spectrum of information about the environment, concurrent activities, and the mobile map itself, necessitating tailored adjustments in map design (Griffin et al., 2017; Reichenbacher & Bartling, 2023). For instance, a visually impaired map user may benefit from a tailored color palette, while a map user driving on busy streets may prefer navigation assistance that prioritizes traffic-related information on the mobile map.

To identify contextual factors of map use situations, Griffin et al. (2017) present a map use context taxonomy and discuss how to discern relevant map use context elements for identifying transferable aspects of map design across different map use situations. Bartling et al. (2023) offer a comprehensive taxonomy for map use context elements, their acquisition, and application, and emphasize the importance of evaluating not only static but also dynamically changing map use context.

Various prior related studies delve into different facets of the map user, including user preferences (Wilson et al., 2010), user characteristics (Bartling, Havas, et al., 2021), and users' cultural differences (Gartner et al., 2024; Ranasinghe et al., 2018), among others. These studies examine predominantly static aspects of map users, that is, where user factors tend to change infrequently and/or only slowly (if at all).

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Related studies exploring dynamically changing context attributes have included, for example, GNSS positioning (Huang, 2016), location data quality (Ranasinghe & Kray, 2019), seasonality (Sarjakoski & Nivala, 2005), spatial tasks (Bartling, Robinson, et al., 2021), visuospatial attention or cognitive states (Fabrikant, 2023b; Göbel & Kiefer, 2019), among others.

Notably, a study by Savino et al. (2020) assessed map use interaction patterns with participants using Google Maps, and thus, provided insights into the dynamics of mobile-map-assisted spatial tasks during real-world map use "in the wild." These authors have found that users interacted with the map primarily by manipulating the map view (i.e. panning, zooming, viewing the map). Google Map users typically first manipulated the map, searched for and examined a location on the map, and then navigated to that location in the real world. Hence, for these types of mobile map users, mobile map-assisted navigation typically comprises, first, a place-based search, then a basic map manipulation for detailed location exploration, followed by real-world navigation and wayfinding.

Map use context during wayfinding and navigation

Navigation tasks can be either aided or unaided by external aids such as maps, signage, and street names (see Wiener et al. (2009) and Dalton et al. (2019) for taxonomies of human wayfinding). In our spatially enabled society, GPS-equipped mobile maps have become ubiquitous tools for aiding navigation tasks (Dahmani & Bohbot, 2020; Ishikawa, 2019). During navigation tasks, the cognitive processes and task characteristics in map-aided wayfinding differ dramatically from unaided wayfinding tasks (Wiener et al., 2009). For instance, during aided wayfinding tasks, the decision-making, memory, learning, and planning processes that are essential for successful navigation and spatial learning are outsourced to the map aid (Wiener et al., 2009). Recent research has shown that while GPS-equipped mobile maps are often effective for reaching the intended destination, over-reliance on such navigation aids negatively influences wayfinders' short- and long-term spatial learning of the environment, and deteriorates their innate spatial abilities (Dahmani & Bohbot, 2020; Ishikawa, 2019; Ruginski et al., 2019; see also the review by Miola et al., 2024). A proposed solution to mitigate the negative effects of map-based navigation aids on spatial learning is to improve and adapt their design based on users' spatial abilities, preferences, and context of use (Ruginski et al., 2022).

Prior empirical studies evaluate dynamic user factors such as users' cognitive load and visuospatial attention when performing map-assisted wayfinding and navigation tasks, which can depend on dynamic and rapidly changing environmental contexts (Fabrikant, 2023b). For example, pedestrian wayfinding with noise distractions in crowded areas or traffic-congested environments can significantly impact users' cognitive load and attention allocation when navigating (Mavros et al., 2022; Varshney et al., 2024). Traveling through these environments can result in a heightened sense of stimulation, resulting in increased perceived stress and attentional overload for map users (Bilotta et al., 2018; Bitkina et al., 2019; Grassini et al., 2019). Navigating through both virtual and real cities influences map users' levels of cognitive load and visuospatial processing, indicated by empirical studies of users' brain activities (Cheng et al., 2023; Hilton et al., 2025; Kapaj et al., 2024).

Evaluating map use context for adapting the map design

Evaluating whether differences in the map users' abilities and map use contexts, in general, would benefit from an adjusted map design is a helpful approach to informing context-aware map design decisions. Roth et al. (2017) emphasize the value of generating new insights about context-associated mobile map use and mobile map design in field studies and verifying these insights in controlled lab or online studies. In field studies, methods such as observing or shadowing users during mobile map interactions, employing mobile eye-tracking and other mobile sensory devices like mobile EEG, and recording smartphone usage and mobile map app interactions (Hilton et al., 2025; Kapaj et al., 2023, 2024; Savino et al., 2020; Zingaro et al., 2023) offer valuable insights into how users engage with mobile maps "in the wild" in different contexts, and for different tasks.

Kircher et al. (2017) proposed a semi-controlled study design, which provides the opportunity to control aspects of an experiment, such as the study conditions, experiment tasks, and the experiment procedure. While the study runs in a lab setting, its semi-controlled nature allows participants degrees of freedom to complete the experiment tasks (i.e. participants are allowed to choose how they complete the task). This increases the potential for observing naturalistic participant behavior while eliminating potentially confounding environmental variations. Virtual reality (VR) environments offer unique opportunities to investigate naturalistic map use behavior during spatial tasks within realistic yet controlled simulated environments (Cheng et al., 2022).

Commonly accepted explicit measures of usability, such as efficiency, effectiveness, or user satisfaction, can be extended with implicit measures to unobtrusively evaluate context-aware mobile map design. Implicit measures such as those collected with psycho-physiological sensors (e.g. eye-tracking, skin conductance, EEG, etc.) can be leveraged to evaluate map use behavior, for example, to capture cognitive load or (split) visuospatial attention allocation (Cheng et al., 2023; Fabrikant, 2023b; Kapaj et al., 2024). In addition to sensor-derived metrics, map use behavior can be analyzed by, for example, measuring the engagement with the visualized map information using interaction logs (Bartling et al., 2022; Rodden et al., 2010). Evaluating map interactions reveals behavioral patterns (Fabrikant et al., 2008) in an unobtrusive way. User interaction logging is common in controlled lab studies, but can also be found in highly realistic, uncontrolled map use studies "in the wild" (Savino et al., 2020; Zingaro et al., 2023).

Unobtrusively measuring and evaluating users' perceptual and cognitive states across changing map use contexts can support unobtrusive adaptations of mobile maps. For example, Göbel and Kiefer (2019) empirically evaluated gaze-based adaptations for interactive maps using eye-tracking, and Kiefer et al. (2017) evaluated different map adaptation types by assessing usability and user control.

Directed specifically to research mobile-first and responsive design features in mobile maps, Roth et al. (2024) propose research opportunities and provide evidence-based guidelines for adapting mobile maps based on mobile context. In addition, Fabrikant (2023a, 2023b) proposes research opportunities and a related evidence-based framework for mobile map adaptation that considers the mobile map's design and its adaptation to be a function of the user in their map use context (Figure 1). This framework allows for adapting the mobile map display to individual user differences, such as the user's neurocognitive resources, during map-assisted activities in changing contexts such as, for example, dynamically changing traversed environments (i.e. crowded streets, light or heavy traffic densities, etc.) (Fabrikant, 2023b). Because user factors such as preferences, attitudes, cultures, available cognitive resources, and visuospatial attention, and other individual and group differences can significantly affect map use behavior, spatial orientation, and spatial learning, they play crucial roles in effectively adapting a mobile map to its users.

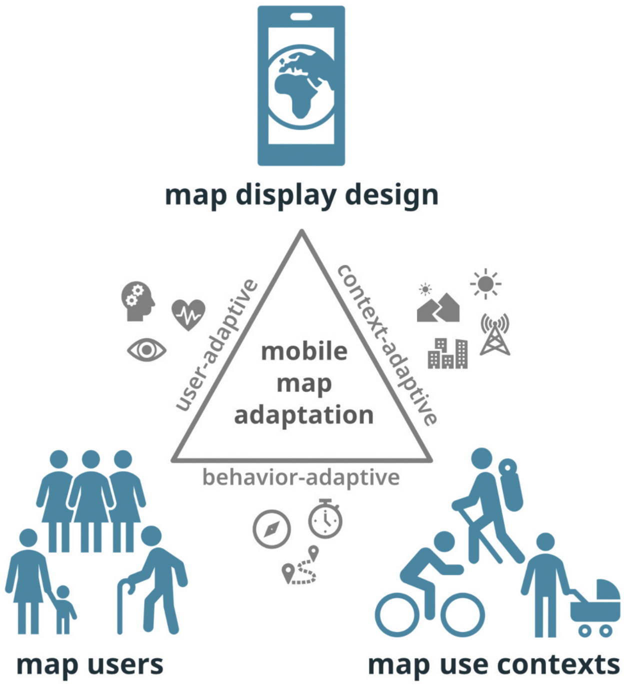

Figure 1. Context-aware mobile map adaptation: an evidence-based research framework, considering user-, behavior- and context-adaptive research dimensions to inform map design (Fabrikant, 2023a, 2023b).

The present study

In this study, we aim to contribute empirically to the approach outlined by Fabrikant (2023a, 2023b) and evaluate mobile map adaptation for map-assisted navigation tasks in varying environmental contexts as one example of map use context. In this study, the mobile maps displayed on a smartphone serve as navigation aids – that is, dynamic navigation aids that support participants' navigation and decision-making in the virtual environment – rather than as a static representation of space (see Materials subsection for more details on the VR-navigation aid positional synchronization). Similar to Kiefer et al. (2017), we were interested in comparing a non-adapted mobile map with an adapted mobile map. Following the approach by Savino et al. (2020), we aimed to evaluate map user behaviors implicitly, including their interactions with these different types of maps. To do so, we applied a semi-controlled study design (Kircher et al., 2017), where we controlled the experiment conditions and tasks; however, the participants were free to choose how they would solve these tasks in the experiment. This provided a relatively high degree of naturalistic map use behavior. We leveraged a virtual environment (VE) to study the role of environmental context in an urban setting. We used traffic density (i.e. number of cars and pedestrians) as a map use context element that typically varies dynamically when traversing an urban environment (Figure 1).

Specifically, we aimed to evaluate whether and how mobile map adaptations enhanced the completion of map-assisted navigation tasks under different traffic conditions. We asked the following questions: a) How do task completion time and map use behavior of study participants differ between traffic densities when using an adapted mobile map? b) Do study participants perceive differences in cognitive workload when using the adapted mobile map compared to a non-adapted map?

Based on prior research, our empirical data analyses were guided by two preregistered hypotheses (AsPredicted #144043, created on 18 September 2023: https://aspredicted.org/K5N_C5V):

(H1) Heavy traffic will increase users' self-rated cognitive load, self-rated agitation, and task completion time, and decrease mobile map interactions. We hypothesize that walking through traffic-dense areas will not only decrease efficient task completion due to traffic impediments, but also due to participants' increased cognitive load (Mavros et al., 2022; Varshney et al., 2024), which limits map use interaction behavior (Wilkening & Fabrikant, 2013).

(H2) Adapted mobile maps, compared to non-adapted mobile maps, when used in traffic-dense environments, will decrease map interactions and users' self-rated cognitive load and agitation, thus decreasing task completion time. Here, we hypothesize that an adapted map will assist participants in cognitively demanding environmental situations to complete the tasks more easily (Kiefer et al., 2017).

This study expands and builds upon preliminary results presented in Bartling et al. (2024).

Methods

Participants

To determine the required sample size, we conducted a power analysis using a linear mixed-effects model in R (v.4.3.2) with the *lmerTest* package (v.3.1–3; Kuznetsova et al., 2017). The model was based on a 2 × 2within-subjects design for task completion time. Assuming a medium interaction effect size ($\eta^2 = 0.06$) between the two conditions, traffic density (i.e. light and heavy traffic) and map adaptation (i.e. non-adapted and adapted map), the power analysis indicated that a minimum of 48 participants would be needed to achieve 80% power. To account for potential data loss, we increased this number by 10%, resulting in a minimum of 54 participants joining this within-subjects design study (see data availability for the study's preregistration report).

Of the 54 participants (33 females), 23 participants reported an age between 18–24 years, 29 participants were between 25–34 years, and the remaining two participants were between 35–44 years. Participants reported being regular users of mobile maps, with 36 participants using mobile maps more than four times a week, 15 participants between two and four times a week, and three participants using mobile maps a maximum of once per week.

Ethical approval for this study was provided by the Ethics Committee of the University of Zurich (no. 23.04.01), and participants gave written informed consent before starting the experiment. Participants were recruited through several channels, including posters in University buildings, digital announcements on the University website, e-mail lists for University staff, alumni, and students, and through invitations to colleagues. The experiment inclusion criteria were healthy adults aged between 18 and 65 years, with English language proficiency and no history of neurological disorders, such as epilepsy or migraines. The experiment lasted approximately 80 minutes, and participants were compensated with CHF 20 upon completion.

Experimental design

We used a 2 × 2 within-subjects factorial design, with mobile map adaptation (non-adapted and adapted) and traffic density (light and heavy traffic) as independent variables (see Table 1). That is, each participant completed all four experiment conditions, whose order of presentation was balanced using Latin squares. Several dependent variables were recorded in the study: task

Table 1. Experiment conditions with map task scenario plot lines and respective map-task-relevant POI categories for the navigation destinations in the urban VE.

Condition:	Mobile map adaptation:	Traffic density as environmental context:	Map task scenario plot line:	Map-task-relevant POI categories:
1	Non-adapted map	Light traffic	Visiting a friend	Supermarket, attraction, coffee shop, restaurant
2	Adapted map	Light traffic	Attending a conference	Coffee shop, hotel, kiosk, attraction
3	Non-adapted map	Heavy traffic	Visiting a city for holidays	Attraction, kiosk, supermarket, coffee shop
4	Adapted map	Heavy traffic	Attending a workshop	Hotel, coffee shop, attraction, supermarket

completion time, map interactions as recorded in map event logs, time spent actively using the map, self-reported workload, self-reported felt emotions, and self-reported perceptions of the experimental conditions.

Map-assisted navigation task

For each condition, participants were asked to complete a sequence of four map-assisted navigation tasks. We devised several plot lines (Table 1) where participants traveled to an unfamiliar city by train and had to navigate from the train station to a designated destination: a friend's house, a conference venue, holiday accommodation, or a workshop location. For each condition, participants were tasked with visiting four different points of interest (POIs), something akin to running errands guided by a mobile map. The tasks were presented through a pop-up text message on the mobile map. These messages were phrased similarly (i.e. participants were asked to go to a POI category in the VE), but participants were directed to different POI categories, with the order depending on the condition (Table 1).

Despite being provided with a specific task prompt, participants had the freedom to select which particular POI within that category to visit. For example, when the task prompted participants to go to a coffee shop, the mobile map depicted several coffee shops from which the participants could choose one to navigate to when completing the task. Each task involved two navigation phases (Montello, 2005): a navigation planning phase where participants decided where to go using the mobile map, involving map interactions such as map view manipulations (e.g. zooming and panning), and POI searching and selection, and a navigation locomotion phase where participants followed a map-suggested route to their chosen POIs in the VE.

To ensure participants completed all conditions within a reasonable time, we allocated a maximum of 16 minutes per condition. This was generously defined by calculating the mean task completion time of five pilot study participants multiplied by three standard deviations. We communicated to the participants that they had sufficient time to complete the conditions and instructed them to complete all tasks as efficiently as possible. As the 16-minute condition cutoff time neared, participants received a warning message on their mobile map. If they exceeded 16 minutes, the scenario was marked as incomplete.

Materials

VR environment

We used a Cave Automatic Virtual Environment (CAVE) at the Department of Geography at the University of Zurich to display the urban VE. This corner CAVE is a room-sized, stereoscopic 3D projection system projected over three walls (Figure 2; see geo.uzh.ch/en/units/giva/services/cave-automatic-virtual-environment.html for more information on the setup). Participants were seated in the center of the CAVE, with a distance of 1.5 m to each wall, and used a foot pedal to move in any direction in the VE (Figure 2a). Their horizontal field of view (FOV) was 200 degrees, and their vertical FOV was 90 degrees. Participants' head height in the CAVE was at around 1.1 m height from the

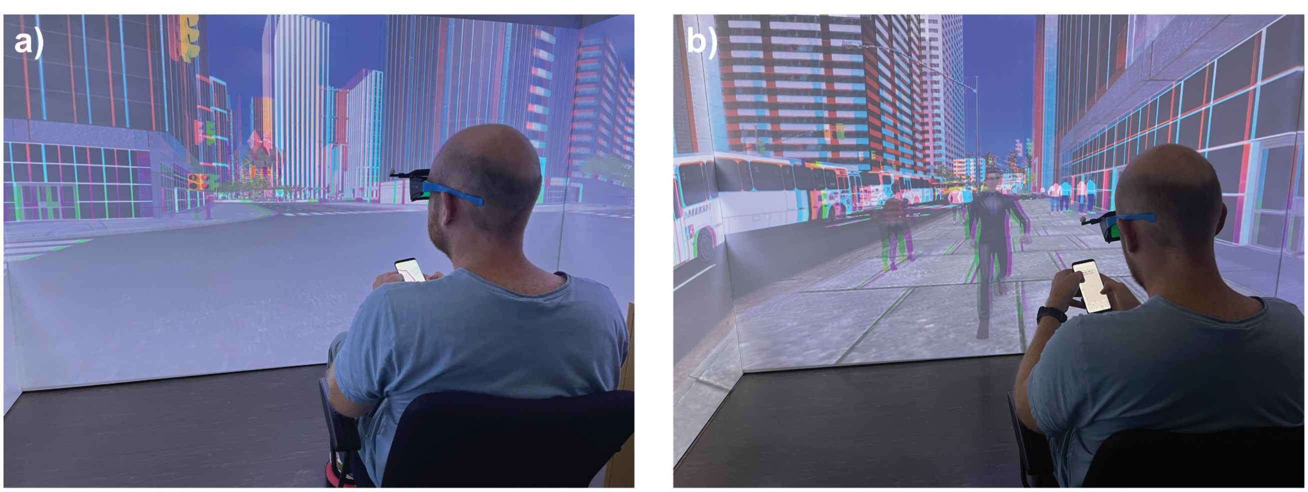

Figure 2. The 3-wall corner CAVE with a study participant sitting in its center wearing goggles for stereoscopic viewing and holding a mobile map app. The participant traverses the VE in a) the light traffic condition with few pedestrians and motorized vehicles and b) the heavy traffic condition with increased numbers of pedestrians and motorized vehicles.

ground and was projected in the VE at around 1.6 m from the VE ground (i.e. simulating an upright person in the VE).

We created the VR environment with Unity (v.2021.3.24), using the "Fantastic City Generator" tool to simulate an American-style gridded city without noteworthy, distinctive landmarks. We included experiment-relevant POIs by adding attractions as 3D models (e.g. churches, statues, museums; see Figure 3a) for an example); for supermarkets, coffee shops, restaurants, hotels, and kiosks, we added banners to buildings displaying their names, and 3D chairs (Figure 3b), and shopping carts (Figure 3c) to suggest their function.

We used the Unity Transport package to build a mobile map app client on a smartphone and connected the client to the VE, which acted as the server. We thus achieved real-time synchronization of participants' positions in the VE and their positions shown on the hand-held Samsung Galaxy S8 smartphone (OS Android 8) on which users' map interactions were recorded with the map client.

To replicate a dynamically changing environmental context in the VE, we manipulated car and pedestrian densities. Like Bitkina et al. (2019), we created two levels of traffic density (light and heavy traffic), adjusting the number of motorized vehicles (i.e. cars and buses) and pedestrians in the environment (Mavros et al., 2022). This approach sought to mirror real-world urban environments, where navigators frequently encounter fluctuating levels of traffic and pedestrian activity, particularly around transportation hubs, shopping districts, and city centers. The light traffic condition (Figure 2a) was characterized by a few pedestrians and vehicles and minimal traffic noise. In contrast, the heavy traffic condition (Figure 2b) included 30 times more pedestrians and 20 times more cars than the light traffic condition, leading to a more traffic-dense, louder environment. Traffic noise was simulated by applying talking sounds to each pedestrian and motor and honking sounds to each vehicle.

Mobile map adaptations

We designed a mobile map by digitizing the main street layout, buildings, park areas, and POIs from the VE in Inkscape (v1.2.1). The POI design was inspired by the Google Maps POI symbology to account for participants' familiarity with this style. The designed map symbols were exported as individual SVG files and imported into Unity to create the mobile map app.

We developed two mobile maps, a non-adapted map (Figure 4a) and an adapted map (Figure 4b), which increased the visual salience of task-relevant POIs from the target POI category for the given task. Both maps featured several functionalities: a search bar to query POIs (Figure 4a) & 4b), a button to track the participant's position on the map using their position in the VE (upper right button in Figure 4a)–4c), and a button to open the most recent task message (upper left button in Figure 4a)–4c). Whenever participants clicked on a POI, they could enable the navigation mode to display a route to the POI (Figure 4c). When in navigation mode, participants could track their movement using the compass button (lower right corner in Figure 4c), or they could exit navigation mode (red "x" button in Figure 4c).

The non-adapted map displayed all POIs with 100% opacity. Whenever participants used the search bar of the map, POIs matching the search query kept their 100% opacity, while all other POIs were displayed with 50% opacity, thereby highlighting the queried POIs (Figure 4a). We chose to vary the opacity values of POIs to encode the geographic relevance of the map information, as suggested by Olivieri and Reichenbacher (2023). In contrast, the adapted map was designed to reduce the map information's complexity by making task-irrelevant POIs less visually salient, which is a similar approach to the map adaptations

Figure 3. Urban VE with POIs: a) a museum as an example of the attraction POI category; b) a coffee shop POI category; and c) Migros as an example of the supermarket POI category.

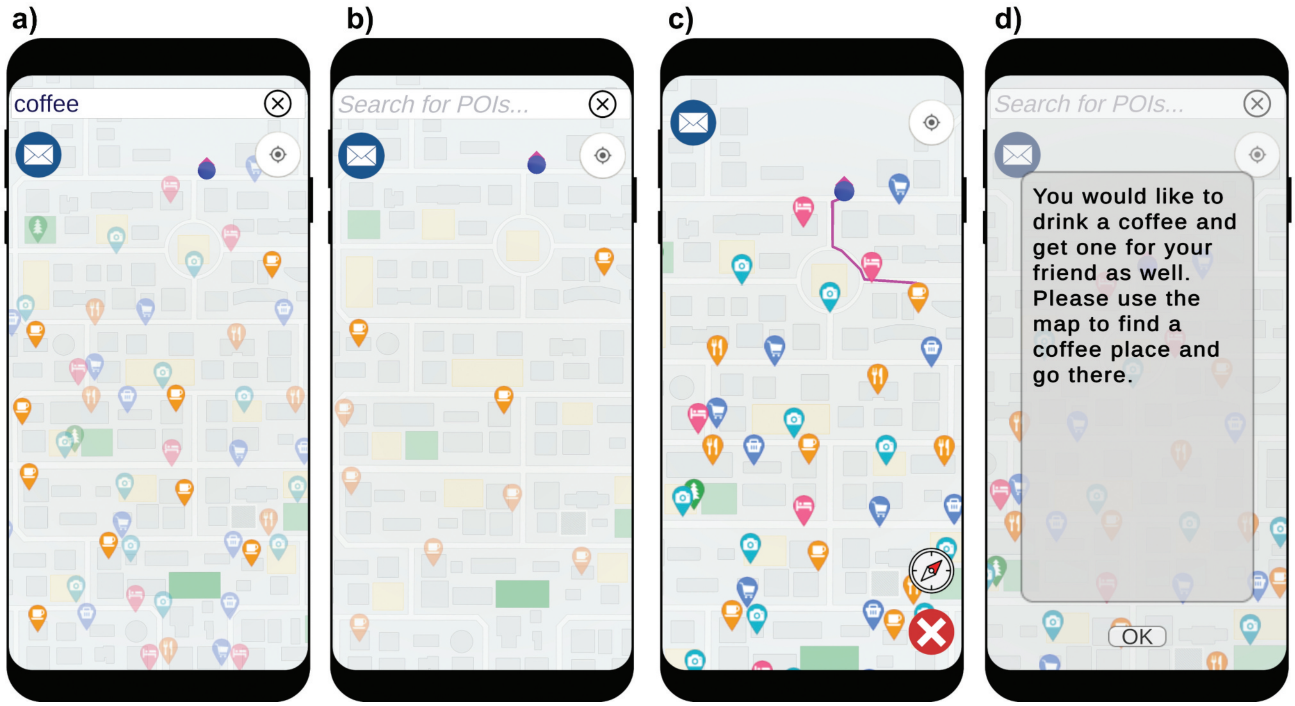

Figure 4. Mobile map functionalities showing: a) search results for a coffee shop on the non-adapted map; b) map view of the adapted map based on the task prompt to visit a coffee shop; c) navigation route to a coffee shop on the non-adapted map; and d) navigation task message.

evaluated in Kiefer et al. (2017) (Figure 4b). The adaptation of the map information was determined by 1) the task and 2) the participant's location in the VE. All task-irrelevant POI categories were removed from the map, i.e. if the task prompted the participants to go to a coffee shop, only POIs of that category were displayed. In contrast, other POI categories, such as supermarkets, restaurants, etc., were given 0% opacity (i.e. presenting "chunks" of information as proposed by Crease 2014). Then, based on the participant's location in the VE, the three nearest POIs were displayed with 100% opacity, whereas all other POIs were displayed with 50% opacity.

Map event logs

Map event logs, including participants' interactions with the map, were logged and stored in a CSV file, together with a timestamp for the interaction and the participant's position in the VE. Nineteen types of map events were logged, including task-mandatory and task-optional user interactions, and system logs. Task-mandatory user interactions consisted of interactions that participants had to carry out to successfully complete the tasks. Here, participants had to accept a task (i.e. they pressed the "ok" button in the task prompt message; Figure 4d), select a POI to start the navigation mode and draw a route to the POI, and complete a task by pressing the "yes" button on a pop-up message that inquired whether the POI was the participant's final destination. This message appeared once participants reached the POI in the VE. The navigation task began when participants pressed the "ok" button of the task prompt at the start and ended when they reached the designated POI in the VE. To differentiate between the navigation planning and locomotion phases, we marked the event when participants selected a POI on the map and activated the navigation mode. All actions before that event were considered to be navigation planning, and those after were considered to be navigation locomotion. The locomotion phase concluded either when participants arrived at the desired POI or when they stopped the navigation mode on the mobile map. In the latter case, participants returned to the planning mode to select a new POI as their destination.

Task-optional user interactions varied depending on how participants used the map as a navigation aid. Participants could pan, rotate, and zoom the map; use the search bar and click on a search-suggested POI; select and deselect a POI; use the self-localization button; use the track & follow button during navigation mode; exit navigation mode, and use the last task message button. In addition to task-mandatory and task-optional user interactions, we recorded system logs, including error and warning messages (e.g. when a participant neared a scenario cutoff time or when a participant set a task-irrelevant POI as a navigation target).

Participants were free to interact with the mobile map whenever and however they desired during the experiment. After ten seconds of not actively using the mobile map, the map display would turn off. Participants had to reactivate the mobile map to continue using it. Map reactivation was used as a proxy to indicate active map usage by the participants.

Questionnaire measures

We employed five digital self-report measures in addition to a demographic questionnaire (i.e. age range, gender, and general map use experience). First, participants' self-reported environmental spatial ability was assessed with the standardized Santa Barbara Sense of Direction (SBSOD) scale (Hegarty et al., 2002). Second, we employed the NASA Task Load Index (NASA TLX; Hart and Staveland 1988) to assess participants' perceived task workload. NASA TLX is a widely used, standardized questionnaire that records users' mental, physical, and temporal demands, performance, effort, and frustration. Third, we used the Self-Assessment Manikin (SAM) questionnaire to capture users' emotional responses to the scenario task in terms of satisfaction, agitation, and sense of control (Bradley & Lang, 1994). Fourth, we used Likert-scale and open-text questions in a questionnaire provided after each condition to capture participants' perceptions of the presented VE and map adaptation. These questions elicited participants' perceived ease of completing the presented tasks, their ease of locomotion in the VE, and how helpful they thought the map was for task completion. Fifth, we employed an open-text questionnaire after all conditions were completed to record participants' general perceptions of the conditions, of perceived differences in the provided map adaptations, and how they used the map in the experiment.

Procedure

The experiment was conducted in English during October 2023. Participants were welcomed to the CAVE lab, where, after informed consent procedures, they completed the demographic and SBSOD questionnaires. Next, participants were seated in the center of the CAVE and underwent a training session to get familiar with the VE and the functionalities of the mobile map app. After this, they independently completed a training navigation task using the mobile map app. Then, they completed the map-assisted navigation experiment, which included the four conditions presented in the Latin-square-balanced order. During each condition, participants received guidance through pop-up messages on the mobile map, providing details of the scenario's plot line and the scenario's task prompts.

After each condition, while seated in the CAVE lab, participants completed the NASA TLX, SAM, and the condition perception questionnaires. Following a short break, participants continued with the next condition, repeating the same procedure until they completed the fourth and final condition. After all experiment conditions were completed, the experimenter orally asked the fifth questionnaire's questions (i.e. post-experiment perceptions and general remarks). Participants' answers to this final questionnaire were audio recorded. After the experiment, participants were debriefed and compensated for their participation.

Analysis

For statistical analyses of the quantitative data related to each condition (i.e. map event logs, self-reported NASA TLX workload, self-reported felt emotions from the SAM questionnaire, and self-reported condition perception), we performed outlier removal using the interquartile range (IQR) method. We removed observations whose values were more than three times below the 1st quartile or more than three times greater than the 3rd quartile. As suggested by Bolton et al. (2023), we analyzed NASA TLX dimensions individually.

We then created linear mixed effects (LME) models in R (v.4.3.2) using the *lme4* package (v.1.1–35.3; Bates et al. 2015). Because we chose to record participants' ages in age brackets (i.e. 18–24, 25–34, and 35–44 years), and only two participants fell into the 35–44 age group, we excluded the age variable from the statistical analysis for robustness. To determine the best-fit model that would converge for each dependent variable, we began with a model that included the dependent variable as a response variable with no fixed effects and a maximal random effect structure informed by the experimental design (Barr et al., 2013). In case this model failed to converge, we iteratively simplified the random effects structure until convergence was achieved. We used ANOVA to compare the converged models and to determine the best-fit model based on the lowest Akaike Information Criterion (AIC). After determining the best-fit model for each dependent variable and before adding the fixed effects, we centered the continuous variables at the mean value and sum-coded the dichotomous categorical variables to −1 and 1. Then, we included the experimental conditions (i.e. traffic density and map adaptation) and the control variables, gender and SBSOD score, as fixed effects. We also added two-way interaction effects between the two experimental conditions, and for each experimental condition, with each fixed effect. We used the *emmeans* package (Lenth et al., 2024) for post-hoc analyses of the LME models' significant interaction outcomes. For this, we used the *pairs()* method to compare the estimated marginal means of the interactions between factor-to-factor variables and the *emtrends()* function for factor-to-covariate interactions to compare the covariate variable slope trend estimates on each level of the factor variable. To calculate the p-values (significance threshold set at $p < .05$) for the LME models and post-hoc analyses, we used the *summary()* function of the *lmerTest* package (Kuznetsova et al., 2017) with the Satterthwaite method for calculating the degrees of freedom, as it produces acceptable levels of Type I error (Luke, 2017).

For each dependent variable, we ran analyses with the entire dataset, including both navigation phases. For the task completion time, the time of active map use, and the map event logs, we additionally divided the dataset into two subsets to distinguish the planning and locomotion phases for the LME.

Results

The experiment manipulated one environmental context factor, light and heavy traffic, and one mobile map adaptation factor, non-adapted and adapted mobile map. Below, we report only the significant effects of each of these experimental factors, discuss them with respect to our guiding hypotheses (H1, H2), and report on the control variables gender and SBSOD score as participants' individual and group differences. Comprehensive results can be found in the respective Supplementary Material.

Traffic density

Task completion time

All participants ($N = 54$) completed all four given tasks for each condition within the maximum allotted completion time (16 minutes). Of the total recorded 864 task sessions, one was missing due to technical issues. On average, participants completed a task in 97.9 seconds ($SD = 49.7$). Participants took, on average, 91.4 seconds ($SD = 44.2$) in light traffic and 104.4 seconds ($SD = 54$) in heavy traffic.

As each task included both a planning and a locomotion phase, we analyzed task completion separately for the two phases. On average, participants spent 13 seconds ($SD = 8.7$) on the planning phase and 82.9 seconds ($SD = 47$) on the locomotion phase for individual tasks across the conditions. The average time spent on the planning phase was 13.3 seconds ($SD = 9.2$) for the light traffic condition and 12.9 seconds ($SD = 8.1$) for the heavy traffic condition. For the locomotion phase, the light traffic condition yielded an average duration of 76.5 seconds ($SD = 41$) and 89.4 seconds ($SD = 51.6$) for the heavy traffic condition, respectively.

The LME models (Tables S1 and S2) revealed a positive significant main effect of the heavy traffic density on the overall task completion time ($\beta = 6.92$, $p < .001$) and on the locomotion phase duration ($\beta = 6.85$, $p < .001$). Hence, heavy traffic increased the task completion time, particularly during locomotion, which is in line with our first hypothesis (H1).

Map interactions

While there were no significant main effects for map panning & rotating, map zooming, and selecting a search-suggested POI, we found a positive marginally significant main effect of traffic density on using the search bar ($\beta = 0.34$, $p = .028$). This suggests that participants used the search bar more often in heavy traffic than in light traffic (Table S5), and thus contradicts our first hypothesis (H1). All LME models and additional information on the recorded map event logs are reported in the Supporting Information S1 and Supporting Tables S3-S5.

In addition to evaluating participants' map interactions, we were interested in how actively participants engaged with the mobile map during task completion. We recorded 6,430 screen lock activation/deactivation events. We used these events to calculate the percentage of time spent using the mobile map actively during task completion. The LME model (Table S6) revealed a significant negative main effect of the traffic density condition on active map use ($\beta = -2.07$, $p = .008$), supporting our first hypothesis (H1). This indicates that the map was used less actively in heavy traffic than in light traffic during the locomotion phase.

Post-condition self-reports

The LME models (Tables S7-S9) indicated significant main effects of traffic density for all NASA TLX dimensions, with heavy traffic predicting higher scores for mental demand ($\beta = 6.78$, $p < .001$), temporal demand ($\beta = 9.73$, $p < .001$), physical demand ($\beta = 5.90$, $p < .001$), effort ($\beta = 7.07$, $p < .001$), and frustration ($\beta = 11.73$, $p < .001$), and lower scores for performance ($\beta = -3.47$, $p < .001$). As the heavy traffic condition has a significant main effect on all NASA TLX dimensions, indicating that heavy traffic increased participants' perceived task workload, these findings support our first hypothesis (H1).

For the SAM variables, the LME models (Tables S10 and S11) showed that heavy traffic predicts increased agitation ($\beta = 0.85$, $p < .001$), and decreased satisfaction ($\beta = -0.53$, $p < .001$) and control ($\beta = -0.39$, $p < .001$), which is consistent with our first hypothesis (H1).

The LME models (Tables S12 and S13) indicated that heavy traffic leads to decreased ease of locomotion in the VE ($\beta = -0.49$, $p < .001$) and ease of task completion ($\beta = -0.27$, $p < .001$), which is consistent with our first hypothesis (H1). In contrast, no significant main effect of traffic density was found for the perceived helpfulness of the map. A summary of the qualitative post-experiment perceptions and remarks can be found in the Supporting Information S2.

Interaction of traffic density and map adaptation

Task completion times

On average, participants completed the light traffic conditions with the non-adapted map in 88.2 seconds (*SD* = 41.9) and with the adapted map in 94.6 seconds (*SD* = 46.3). In contrast, they completed the heavy traffic conditions with the non-adapted map in 101.7 seconds (*SD* = 54.3) and with the adapted map in 107.1 seconds (*SD* = 53.6).

For the planning phase in light traffic, participants took an average of 14.5 seconds (*SD* = 10.2) with the non-adapted map and 12.2 seconds (*SD* = 8) with the adapted map. In heavy traffic, they took 14.4 seconds (*SD* = 8.4) with the non-adapted map and 11.4 seconds (*SD* = 7.5) with the adapted map. During the locomotion phase in light traffic, they took an average of 72.5 seconds (*SD* = 37.7) with the non-adapted map and 80.4 seconds (*SD* = 44) with the adapted map. In heavy traffic, they took 85.8 seconds (*SD* = 52.4) with the non-adapted map and 93 seconds (*SD* = 50.6) with the adapted map.

Contrary to our second hypothesis (H2), the LME models (Tables S1 and S2) revealed no significant interaction effect between traffic density and map adaptation on the task completion time.

Map interactions

For zooming, the LME model (Table S4) revealed a significant interaction effect between heavy traffic and the adapted map during the planning phase ($\beta = -0.82$, $p = .004$) but not during the locomotion phase. Post-hoc analyses on the interaction effect between traffic density and map adaptation during the planning phase revealed a significant influence on participants' zoom behavior. Specifically, the differences in estimated marginal means between the non-adapted and adapted maps were significant in heavy traffic (*emmeans* = −1.93, *SE* = 0.81, *t* = −2.38, $p = .019$) but not in light traffic (*emmeans* = 1.34, *SE* = 0.81, *t* = 1.65, $p = .102$).

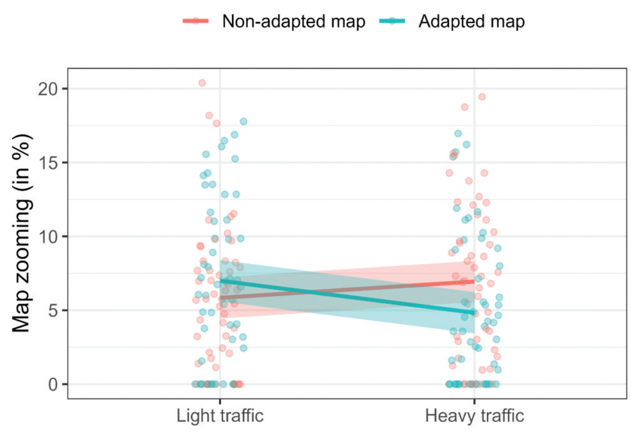

Figure 5. Post-hoc analysis revealed that the adapted map led to less zooming. The dots visualize participants' individual data points according to the map type across the traffic density condition. Data points around 0% indicate participants who did not zoom during a scenario task. Map zooming is shown as a percentage of all map events logged for each participant.

This indicates that participants zoomed significantly less when using the adapted map in heavy traffic than they did in light traffic during the planning phase (Figure 5), which is consistent with our second hypothesis (H2). However, contrary to our second hypothesis (H2), we found no interaction effect between traffic density and map adaptation on the panning & rotating map interactions, the use of the search bar, selecting search-suggested POIs, or on active map use (Tables S3, S5, and S6, respectively).

Post-condition self-reports

Contrary to our second hypothesis (H2), none of our LME models for the NASA TLX dimensions (see Tables S7-S9), SAM variables (Tables S10 and S11), or post-condition questions (Tables S12 and S13) revealed any interaction effect between traffic density and map adaptation.

Participants' individual and group differences: gender and spatial ability

In addition to traffic density and its interaction with the map adaptation, we found user factors, that is, participants' individual and group differences (i.e. gender and SBSOD score) to be significant predictors for task completion time, map interactions, and post-condition self-reports. In the following section, we report only on significant findings. Comprehensive results can be found in the Supplementary Material.

Task completion time

The LME model revealed significant main effects of gender ($\beta = 1.72$, $p = .012$) during the planning phase and of the participants' SBSOD score ($\beta = -4.92$, $p = .024$) during the locomotion phase (Table S2). These results indicate that female participants spent more time in the planning phase compared to male participants, and navigators with better spatial abilities spent less time on locomotion compared to those with lower spatial abilities.

Map interactions

While no individual differences were significant predictors for map panning & rotating, and map zooming (Tables S3 and S4), the LME models (Table S5) indicated that female participants used the search bar more frequently ($\beta = 1.00$, $p = .013$) and selected search-suggested POIs more often ($\beta = 0.73$, $p = .006$) than did male participants. Additionally, the LME model (Table S6) indicated that participants with higher SBSOD scores had less active map use ($\beta = -5.47$, $p < .025$).

We found an interaction effect between gender and map adaptation for search bar use and select search-suggested POI (Table S5). Female participants were more likely than males to use the search bar ($\beta = 0.41$, $p = .014$) and select search-suggested POIs more often ($\beta = 0.29$, $p = .007$) when using an adapted map than a non-adapted map. Post-hoc interaction analyses revealed that the differences in estimated marginal means between the non-adapted and adapted map were significant for male participants (*emmeans* = -1.58, $SE = 0.50$, $t = -3.15$, $p = .002$) but not female participants (*emmeans* = 0.05, $SE = 0.39$, $t = 0.12$, $p = .901$; Figure 6a) for search bar use. A similar pattern for male (*emmeans* = -1.198, $SE = 0.32$, $t = -3.75$, $p < .001$) and female participants (*emmeans* = -0.05, $SE = 0.25$, $t = -0.197$, $p = .844$) was observed for selecting search-suggested POIs (Figure 6b). These results indicate that male participants used the search bar and selected search-suggested POIs less frequently when using the adapted map, compared to female participants (Figure 6).

Post-condition self-reports

For the NASA TLX dimensions, the LME models (Tables S7 and S8) indicated that higher SBSOD scores predicted lower temporal demand ($\beta = -6.24$, $p = .006$), physical demand ($\beta = -7.11$, $p = .014$), and effort ($\beta = -6.24$, $p = .008$). Female participants had lower scores on the performance dimension (Table S9) compared to male participants ($\beta = -3.90$, $p = .045$). No individual differences were significant for the SAM variables, agitation, and satisfaction (Table S10). The LME model (Table S11) for the SAM variable control suggests a marginal interaction effect between traffic density and gender. Female participants seem more likely than males to perceive control during heavy traffic ($\beta = 0.23$, $p = .040$). Post-hoc interaction analyses revealed that gender was a predictor of perceived control, as the differences in estimated marginal means between heavy and light traffic were significant for male participants (*emmeans* = -1.23, $SE = 0.34$, $t = -3.61$, $p < .001$) but not female participants (*emmeans* = -0.31, $SE = 0.27$, $t = -1.16$, $p = .250$). This indicates that the perceived level of control is different between female and male participants, with male participants perceiving more control in the light traffic condition than in the heavy traffic condition (Figure 7).

The LME model revealed a potential further interaction effect between map adaptation and SBSOD (Table S11), with participants with higher SBSOD scores

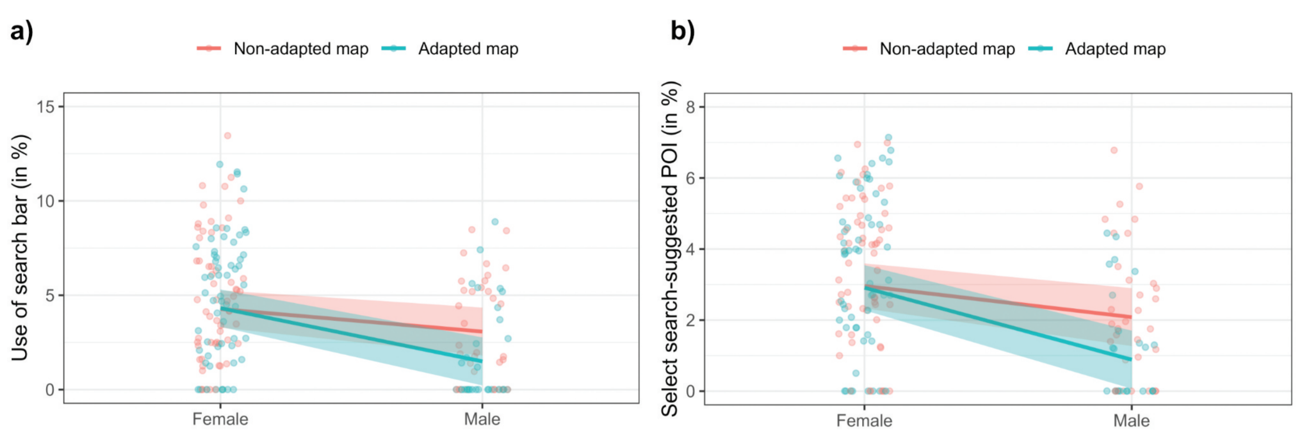

Figure 6. Post-hoc analysis revealed that male participants used a) the search bar and b) selected search-suggested POIs less than females when interacting with the adapted map. The dots visualize participants' individual data points according to the map type and across gender. Data points around 0% are those participants who did not use the search bar or select search-suggested POIs during a scenario task. Both map interactions are shown as a percentage of all map events logged for each participant.

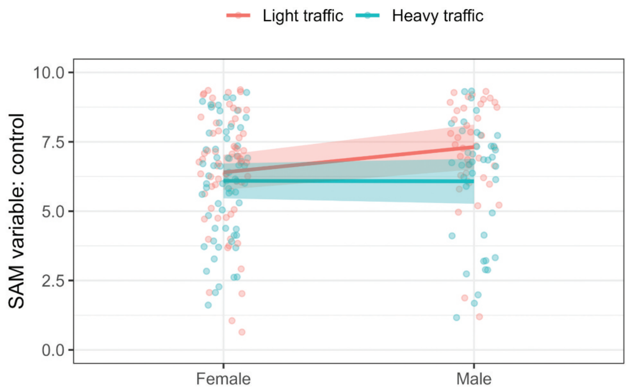

Figure 7. Post-hoc analysis revealed that the level of perceived control was higher for male participants in the light traffic condition than in the heavy traffic condition. The dots visualize participants' individual data points according to the map type and across the traffic density condition.

perceiving less control with the adapted map than with the non-adapted map ($\beta = -0.20$, $p = .046$). Post-hoc analyses revealed no significant influence of the SBSOD score slope trend estimates on participants' perceived control when using the non-adapted map (*emtrend* $= -0.039$, $SE = 0.24$, $t = 0.16$, $p = .870$) or the adapted map (*emtrend* $= -0.36$, $SE = 0.24$, $t = -1.52$, $p = .130$). The contrast between the two slopes revealed a significant difference ($\beta = -0.40$, $SE = 0.2$, $t = -2.02$, $p = .046$), showing that the non-adapted map had a marginal advantage of 0.4 in terms of perceived control per unit increase in SBSOD score compared to the adapted map (Figure 8).

In terms of participants' post-condition self-reports, the LME models (Table S12) revealed that participants' with higher SBSOD scores seem to be linked to increased ease of locomotion in the VE ($\beta = 0.17$, $p = .040$) and increased ease of task completion ($\beta = 0.20$, $p = .011$).

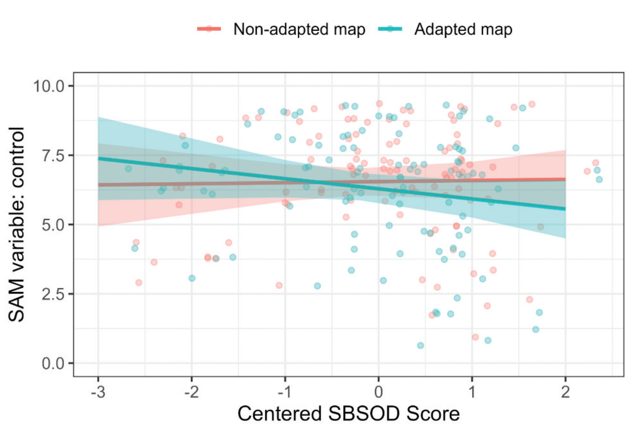

Figure 8. Post-hoc analysis revealed that participants with higher SBSOD scores perceived more control when using the non-adapted map than the adapted map. The dots visualize participants' individual data points according to the map type and across the traffic density condition.

Discussion

Our research aimed to contribute empirically to the outlined three-pronged research framework (Fabrikant, 2023a, 2023b), suggesting that the design of mobile map adaptations should be a function of the context of map use (i.e. environment, modality, etc.) and the map user (i.e. individual and group differences, etc.). Specifically, we evaluated how mobile map design (non-adapted and adapted mobile maps) interacts with the environmental context of mobile map use (i.e. light and heavy traffic), the map task context (i.e. navigation planning and actual navigation), and the individual and group differences of map-assisted navigators.

We evaluated how these factors affected participants' mobile-map-assisted navigation performance (i.e. task completion time) and map interaction behavior (i.e. zooming, panning, etc.) in an urban VE, comparing high and low traffic densities. We were guided by our two hypotheses: (H1) heavy traffic increases self-rated cognitive workload, felt emotions, and task completion time, and decreases map interactions; and (H2) adapted mobile maps used in heavy traffic decrease self-rated cognitive workload and felt emotions, map interactions, and task completion time.

Traffic density

Consistent with our first hypothesis (H1), we found that the heavy traffic condition significantly affected self-reported workload negatively, increased participants' agitation, and decreased satisfaction and control. The participants reported significantly less ease of locomotion in the VE and ease of task completion in heavy traffic. Accordingly, we found that heavy traffic increased task completion times. However, while the locomotion phase duration was significantly longer in heavy traffic, we found no main effect on the planning phase duration. Hence, the effect of traffic density was probably most notable and impactful during the locomotion phase, when participants were moving through the VE. These findings align with previous research, which shows that crowded and traffic-dense areas increase users' stress, cognitive load, and attention levels (Bilotta et al., 2018; Bitkina et al., 2019; Mavros et al., 2022).

We found no evidence that heavy traffic decreases participants' map interactions, as hypothesized. We found that the search bar was used significantly more often during the planning phase in heavy traffic than in light traffic. This contrasts with Wilkening and Fabrikant (2013), who found that an increase in task difficulty using 3D geobrowsers (or, in our case, an increase in traffic density) led to an increase in cognitive demands, which results in map users wanting to invest less "cognitive cost" for map display interactions. Perhaps the search bar was used more often during heavy traffic as participants tried to find the destination POIs efficiently. However, we found no significant increase in selecting search-suggested POIs, which indicates that even though participants pressed the search bar, they did not actually use the search bar to find their destination POIs.

As we found no other differences in map interactions between the studied traffic densities, we attribute this result to the different task phases, planning and locomotion, and their respective task requirements. While participants were required by the task to interact with the map during the task planning phase (i.e. they needed to select a POI first to then navigate to it in the VE), this was not the case during the locomotion phase (i.e. where map interactions were optional). Heavy traffic density probably had the most impact on participants' behavior during the locomotion phase, as indicated by the significantly longer duration of the locomotion phase. Hence, the planning phase was perhaps not as affected by the traffic density condition, which is why no clear differences in map interactions between the traffic densities appeared. However, we found that the map was used significantly less actively; that is, the map display was turned off longer during the locomotion phase in heavy traffic than in light traffic. This is in line with Wilkening and Fabrikant (2013), stating that users interact less with a map display in situations of increased cognitive demand.

We also found that, irrespective of the experimental conditions, participants predominantly selected the closest POI to navigate to and did not spend time studying the map or selecting other POIs farther away from their start location. This could be another reason why we found no clear differences in map interactions between the traffic density conditions.

Interaction of traffic density and map adaptation

Contrary to our second hypothesis (H2), we did not observe changes in self-rated cognitive workload, felt emotions, or task completion times when comparing the two map types in the heavy traffic condition. These findings contrast with previous empirical studies suggesting that adapted maps, compared to non-adapted maps, reduce task completion times and self-reported cognitive load (Kiefer et al., 2017; Wilson et al., 2010; Zhao et al., 2020). Several factors might explain our diverging results.

Kiefer et al. (2017) compared static 2D city plans and metro maps sampled from various cities with adapted maps that increased the visual salience of task-relevant map features (e.g. POIs, public transport routes). The graphic density difference and the difference in information complexity in Kiefer et al. (2017) study was much stronger than in our evaluated maps. While our maps were interactive, the POIs did not provide any further task-relevant information (e.g. opening hours, restaurant type, etc.), and thus, our graphic POI adaptation was probably too subtle for the studied task at hand and map use context. This aligns with Zhao et al. (2020) review, suggesting that when information complexity between evaluated maps differs significantly, the adapted, that is, a visually decluttered map, more effectively supports map users in completing spatial tasks. Another reason might be that we also leveraged the well-known Google Maps-inspired POI symbology, familiar to many map users, whereas related empirical map adaptation research deployed less familiar, customized POI symbols (Göbel & Kiefer, 2019; Kiefer et al., 2017; Wilson et al., 2010; Zhao et al., 2020). In both our tested conditions, the familiar POI style changed only in transparency, which appears not salient enough for the studied map use context.

Additionally, in contrast to Kiefer et al. (2017), who asked participants to complete several different complex spatial tasks in their study (e.g. finding a specific POI or identifying a public transport route with a minimum number of stops), we employed only one relatively simple task (i.e. selecting any POI that belongs to a POI category), which was similar to the task posed by Göbel and Kiefer (2019). Similar to our results, Göbel and Kiefer (2019) found no significant difference between their non-adapted and adapted maps in terms of task completion time. This suggests that task complexity is another relevant factor when evaluating the effects of different map designs.

Unlike maps evaluated in previous research (Kiefer et al., 2017; Savino et al., 2020; Wilson et al., 2010), both of our maps were less detailed and covered a smaller geographical extent. The POIs in both of our map types provided identical locational information but lacked additional details (e.g. customer reviews, product price range, opening hours, etc.). As participant 44 stated: "In reality, I just want to know some customer reviews of the coffee shop, but in this scenario, I just choose to go to the nearest place." This participant's statement aligns with previous findings that map users seek a rich map exploration experience and information retrieval (Savino et al., 2020). This is another good example of the importance of the multifaceted geographic relevance (Reichenbacher et al., 2016) in mobile map users' decision-making during navigation planning, where POI topicality is taken into account along with spatial-temporal proximity. Because our maps only provided spatial proximity information for POIs within a POI category, this was the criterion that participants used as a selection criterion. Indeed, 28 out of 54 participants reported in post-experiment interviews that they chose the nearest POI (see Section 3 of Supplementary Material for details). Future work will focus on analyzing participants' trajectories in the VE to study their perceived navigation behavior further.

As mentioned earlier, irrespective of the map type, participants did not choose to explore the map beyond identifying the nearest POI from their current VE location. Participants panned, rotated, and zoomed the map to select the nearest POI. Consistent with previous findings (Savino et al., 2020; Wilkening & Fabrikant, 2013), these interactions were the most common, regardless of the map type, while fewer participants used the search bar or selected search-suggested POIs. We did not collect sufficient data to be able to perform statistical analyses on further optional map interactions (see Table S14). Participants zoomed the adapted map significantly less often during the navigation planning phase in heavy traffic, which provides support for our second hypothesis (H2). As map zooming was probably one of the most relevant interactions for identifying the nearest POI, the adapted map supported participants effectively during the planning phase, as it also emphasized the three nearest POIs. A visually decluttered display, such as our adapted map that visualizes only task-relevant POIs, leads to a more efficient visual search (Beck et al., 2012; Grison et al., 2017). In our case, this also led to a reduced need for map zooming on the adapted map.

Participants' individual and group differences: gender and spatial ability

Across all the experiment conditions, and as previous work has already suggested (e.g. Hegarty et al. 2023 and Fabrikant 2023a), we found individual (i.e. sense of direction) and group differences (i.e. gender) to be key drivers for map-assisted navigation task completion. Our findings showed that higher SBSOD scores predicted shorter locomotion durations. Similarly, we found that participants with higher SBSOD scores used the map less actively during the locomotion phase compared to participants with lower SBSOD scores. This finding aligns with previous research that suggests that low spatial ability wayfinders use the map more actively as they lack confidence in their spatial skills (Hejtmánek et al., 2018; Kapaj et al., 2024; Koletsis et al., 2017). Furthermore, high spatial ability participants reported greater ease of VE locomotion and task completion and self-reported a lower workload (regarding physical and temporal demand and effort). Participants with higher SBSOD scores also perceived higher levels of control when using the non-adapted map compared to the adapted map, and participants with lower SBSOD scores. This aligns with previous research, which finds that a good sense of direction improves navigation performance and spatial orientation (Ishikawa, 2022; Kapaj et al., 2024). Faster task completion may be attributed to spatially confident participants taking shortcuts in the VE when traveling to a destination POI. In the post-experiment reflection, 27 out of 54 participants noted that the map-suggested routes followed the major street network in the VE without considering possible shortcuts between buildings (see Section 3 of Supplementary Material for details). Several participants reported deviating from these suggested routes to find shorter paths to reach their destination. It is possible that participants with a better sense of direction were more inclined to take these shortcuts or deviate from the map-suggested routes. Other previous research has suggested that less confident participants are more risk-averse and, therefore, less likely to choose a shortcut (Varshney et al., 2024). Further analyses of the VE-related navigation trajectory data are, however, out of the scope of this study. We found that female participants took longer to complete the navigation planning phase than male participants. This might be connected to female participants using the search bar and selecting search-suggested POIs significantly more frequently than male participants overall, and specifically when using the adapted map. These findings indicate an increase in the amount of map exploration behavior compared to male participants. This might be linked to increased spatial anxiety of females during spatial orientation and wayfinding (Lawton & Kallai, 2002; Mendez-Lopez et al., 2020) or could point to reported male over-confidence in spatial decision-making tasks (Wilkening & Fabrikant, 2011). Accordingly, male participants perceived higher levels of control in light traffic than in heavy traffic, compared to female participants. Female participants also reported significantly poorer self-perceived performance across the study conditions. These gender differences are consistent with previous findings related to spatial abilities and navigation performance (Boone et al., 2018; Coutrot et al., 2018).

Limitations and future research directions

For the first time, we have developed a CAVE VR system that synchronizes with a mobile map on a standard smartphone, serving as a navigation aid to support wayfinding and decision-making within an urban VE. This real-world navigation aid substantially increases the ecological validity of mobile map-aided navigation studies in VR, and thus significantly extends prior used virtual tools to serve as map proxies that provide only limited ecological validity. This innovation demonstrates great potential for future empirical studies on map-assisted navigation in VR-simulated environmental contexts, offering a valuable tool for evaluating mobile map adaptations. As with any empirical study, the presented research comes with limitations that could be considered for future research.

While we counterbalanced the order of conditions, the plot lines (e.g. "visiting a friend") were not counterbalanced between the conditions but were associated with them. This presents a limitation, as the results might have been influenced by these plot lines. Future studies should consider this potential issue and counterbalance both the plot lines and the conditions.

Another limitation concerns the environmental context within the VE. Participants remarked negatively on the virtual pedestrians' random behavior, such as randomly spawning (i.e. appearing) in front of them, running into them, or changing walking directions unpredictably, which contrasts with real-world pedestrian behavior. Previous studies have indicated that the behavior and cues of virtual pedestrians, such as following behavior, impact participants' behavior (Torrens & Kim, 2024; Zhao et al., 2020). Future research could aim to create more realistic pedestrian behavior within the VE. Additionally, modifying traffic conditions to establish and control for evenly distributed traffic density across the VE is recommended. This could be achieved by defining the number of virtual pedestrians and cars per area unit within a certain distance of the participants.

To enhance the map exploration experience, we recommend that future studies substantially expand the quantity of geographic features and available POI information on the maps. Map-assisted navigation scenarios could be developed that incentivize participants to explore the map and the VE. Examples include scenarios where participants run errands that fit their preferences and interests, or sightseeing scenarios that simulate tourist behavior and encourage participants to learn about the VE. These scenarios could include tasks of varying complexity to evaluate task variations. Furthermore, future research should consider other environmental factors known to affect map use behavior, such as time of day, seasonality, weather, and crowd movement directions, which may necessitate mobile map adaptations.

For the adapted version of the mobile map, future studies could evaluate different versions of map adaptations with varying degrees of information complexity to identify the level at which an adapted map becomes meaningful. We found that the two navigation task phases, planning and locomotion, required different map interactions, suggesting that future research could design map adaptations tailored to these specific parts of a navigation task. More sophisticated POI recommendations could also be developed based on context-relevant factors, e.g. user's interests in attractions, food preferences, real-time information on traffic jams, waiting queues, etc (Halder et al., 2022). Given that sense of direction was a significant predictor of task completion time and map use, future POI recommendations could also be personalized based on such user factors.

Future studies could employ user-centric measurements, such as eye-tracking or psycho-physiological sensors (e.g. EEG), to assess users' real-time attentional, cognitive, and emotional states while performing map-assisted spatial tasks in different map use contexts (Fabrikant, 2023a, 2023b). Understanding users' states in specific contexts and task phases (e.g. navigation planning and locomotion) could inform the development of real-time adaptive maps that support users in completing spatial tasks efficiently and effectively.

Lastly, although the current study recorded location data within the VE for each map interaction, analyzing these data was beyond its scope. In future research, we plan to examine location-associated map use behavior to provide valuable insights into how maps are used in different spatial contexts and whether participants predominantly select the nearest POIs for task completion.

Conclusion

This study empirically evaluated how 1) mobile map adaptation (i.e. POI density and saliency), 2) varying environmental context (i.e. traffic density), and 3) map users' individual and group differences (i.e. gender and spatial abilities) influenced their task performance, map use behavior, self-reported cognitive load, and felt emotions during map-assisted navigation tasks. The study employed an innovative and novel experimental design in the CAVE lab at the Department of Geography at the University of Zurich. Environmental contexts were presented in naturalistic virtual environments, and participants' mobile map use behavior was unobtrusively captured using a physical smartphone.

Our findings suggest that while perceived cognitive load, agitation, satisfaction, control, task completion time, and navigation locomotion duration increase in heavy traffic, they do not necessarily impact efficient task planning performance or map use behavior. This emphasizes the importance of considering both self-reported and performance-based measures in such empirical studies. We found that the adapted map supported participants in identifying the nearest POI in heavy traffic density with fewer map zoom interactions. However, the difference in design between the two maps, non-adapted and adapted, was too subtle, leading to participants being supported by the maps in similar ways.

Unobtrusively collecting map interactions on a mobile phone in a VE provides great potential for evaluating naturalistic map use behavior in a VR lab. However, the semi-controlled nature of our study requires geographically detailed and information-rich maps to better encourage participants to explore the maps in a manner that is similar to their typical map use behavior.

Depending on the task and map information complexities, studies show different effectiveness of map adaptations for spatial decision-making. Therefore, map adaptations should be carefully designed and should be meaningful and fit the users in their map use contexts. They should also be observable, transparent, predictable, and controllable to be fully effective, underlining the challenge of designing successful adaptations (Bouzit et al., 2017; Gullà et al., 2015; Kiefer et al., 2017).

The study results support previous findings that user factors, particularly a good sense of direction, significantly facilitate users in efficiently completing navigation tasks. This provides further support for the importance of user factors as a key driver to be considered for context-aware mobile map adaptation. With this study, we contribute to the three-pronged research framework (Fabrikant, 2023a, 2023b) considering the design of mobile map adaptations as a function of the map user in their map use contexts.

Practical implications of this work extend to scenarios where the consideration of map use context (e.g. human factors, environmental context, etc.) is critical. For instance, in emergency and disaster response situations, first responders could benefit from context-aware maps that prioritize task-relevant information, enabling less cognitively demanding evaluations of map data for quicker decision-making (Kapaj et al., 2023). Similarly, navigation through hazardous environments could be adjusted to the responders' individual spatial abilities, providing the responder with the easiest routes to emergency sites while accounting for route complexity and route length.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

This study's preregistration, data, and analyses (R-code) are available online at the Open Science Framework repository: https://osf.io/xfu34.

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