Enhancing Operational Decision-Making with Adaptive Head-Mounted Display Interfaces

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ABSTRACT

This research explores the advantages of adaptive interfaces in Head-Mounted Displays (HMDs) for enhancing decision-making in complex environments like operational command centers. Traditional interfaces display information at fixed locations, requiring frequent shifts in focal distance. Adaptive interfaces can automatically adjust display information like presenting information at the user's point of attention and aim to minimize these shifts. Using virtual reality, we assessed an adaptive interface technique utilizing a user eye tracking, to allow pertinent information to be placed in response to the user's eye gaze, in a command-center exercise involving route planning and resource management. We hypothesized that an adaptive interface employing this technique would improve decision-making quality and speed, and increase gaze switches between the map and screens due to closer information proximity. Results showed no significant difference in decision quality or speed between adaptive and non-adaptive conditions. However, participants in the adaptive condition had shorter dwell times and more frequent gaze switches. This suggests the adaptive interface facilitated more efficient information retrieval. The null effect on response time might be due to task complexity; faster decisions may benefit more from the adaptive interface. Our findings highlight the complexities of integrating adaptive interfaces in high-stakes environments and underscore the need for further research to refine these techniques. As mixed-reality technologies advance, these insights will guide the design of more efficient user interfaces.

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INTRODUCTION

The advent of mixed-reality technologies, including augmented and virtual reality (AR/VR), has opened new frontiers in the design and implementation of user interfaces, particularly in complex operational and planning environments. In high-stakes settings, decision-making speed and quality are paramount, particularly when the users need to make decisions based on an abundance of information. Traditional command center style interfaces, which are typically static and require users to shift focus frequently between various information sources, can significantly hinder performance by increasing cognitive load and decision-making time. Adaptive interfaces, on the other hand, have the potential to offer a transformative approach to address those concerns. By dynamically presenting information at the user's point of gaze (including perceptual depth plane)—where the eye is naturally focusing—these interfaces aim to streamline the user experience in mixed-reality (MR) head-mounted displays (HMDs).

We aim to evaluate use of state-of-the-art eye-tracking technology to measure eye vergence and then adaptively present information within the user's immediate field of view. Through this technique, information that is relevant for the task may be more readily accessible by minimizing costs associating with shifting eye gaze and attention and thereby reducing the user's cognitive workload. This research is crucial as it seeks to improve the interface design and downstream decision making in scenarios where quick and accurate decisions are critical..
For example, imagine a rescue operation using an adaptive interface in an MR HMD while managing a large scale operation. Instead of looking away from the main operational view to check data on different screens, the relevant information—like asset movements, environmental conditions, supply statuses, and threats—would appear directly in their line of sight, just where they need it at that moment.

In order to explore the best use cases of such environments, we aimed to virtually simulate a complex decision-making environment with route planning and resource management in an immersive 3D environment with dynamic information feeds. Here we chose a family vacation planning exercise as the analog for this purpose.

Participants assume the role of a family member coordinating real time travel logistics for their relatives. These fictional relatives move across a virtual map and communicate with the user through text messages to request assistance with challenges and obstacles they encounter. The user's task is to manage resources (time and money) effectively to ensure that the relatives reach the airport within a six-hour time window (in game time) and retain a specified amount of money. By measuring the decision speed and quality, we aimed to explore and quantify the potential benefits of an adaptive interface in a simulated VR environment that replicates a large scale command center-type task. This scenario includes elements such as blocked roads, unexpected demands on resources, and equipment malfunctions, corresponding to obstacles and threats that professionals might face in the field. The family vacation scenario was designed to mirror the decision-making and resource management challenges faced in a large-scale, command-style operation (disaster management, search and rescue, city evacuation, etc.) in a controlled environment that participants could understand with the goal of exploring the potential benefits of an adaptive HMD interface.

Overall, in this research, we aim to address research questions about the efficacy of adaptive interfaces: "Do eye-gazed-based adaptive interfaces enhance decision-making speed and quality?" We aim to offer empirical evidence and practical insights that could shape the future design of user interfaces in mixed-reality systems and suggest ways to explore further adaptive techniques. Broader impact we aim in this research is to address evolving demands of modern command center-style operations and other high-stakes decision-making scenarios through mixed reality technologies.

BACKGROUND AND RATIONALE

Effective user interface design hinges on the system's ability to adapt to and enhance the user's existing skills and physiological metrics to reduce cognitive load and fatigue. Research suggests that interfaces can be improved by minimizing distractions that can interfere with user tasks and by ensuring that the system's outputs are aligned with the user's cognitive and behavioral expectations (Oviatt, 2006). Furthermore, it is important for interfaces to support a variety of representational systems so users can interact with and process information efficiently. This can facilitate higher-level cognitive functions such as planning and decision making. The concept of adaptive interfaces has been widely explored across different technologies. Greenber and Witten (1985) investigated how a computer system can modify its interaction based on a user model to meet individual needs. The findings indicated that, within the constraints of their study, adaptive interfaces could enhance usability. Miller et al. (2005) highlighted several key advantages of adaptive systems, including their ability to reduce human workload by automating decision-making and operational tasks, increase responsiveness to changes, simplify user interactions, and offload complex tasks to allow humans to focus on aspects of work that require critical judgment with higher cognitive functions. Yelizarov and Gamayunov (2014) developed and tested an adaptive visualization interface that dynamically adjusts the information display to mitigate cognitive overload and enhance decision-making efficiency in safety-critical environments. These studies collectively underscore the significant potential of adaptive interfaces in enhancing user experience and operational efficiency across various domains and motivate the need for further exploration of effective adaptive interfaces.

Traditional (i.e., static, non-adaptive) user interfaces, particularly in augmented reality (AR) and virtual reality (VR) settings, which typically present information at fixed locations, may necessitate frequent shifts in focus both physically and cognitively, which can cause cognitive load and thereby slow down the decision-making process. For example, Gupta (2004) highlighted the difficulties users face when switching between real-world and virtual information displayed at far-off distances or optical infinity in AR and VR settings. Their findings suggest that user task performance improves significantly when the focus depth of virtual information aligns with that of real-world stimuli by reducing the need for frequent focal adjustments (Gupta, 2004). Aligned with this research, Arefin et al. (2023) explored the use of eye vergence angles (EVA) and interpupillary distance measurements to predict perceptual depth changes in AR/VR head-mounted displays (HMDs). Their research showed that it is possible, in principle, to tailor AR displays to the user's current focal depth, potentially minimizing the need for focal depth switching and reducing visual strain (Arefin et al., 2022; Neubauer et al., 2020). Further empirical studies by Arefin and colleagues demonstrated that increased focal distance switching exacerbates eye fatigue and diminishes task performance in AR settings. These studies underline the physiological costs associated with traditional AR display methods, which often do not account for the user's focal depth dynamically (Arefin, et al., 2022; Villavicencio et al., 2023; Arefin et al., 2023; Cohen Hoffing et al., 2023; Cohen Hoffing et al., 2020). Therefore, developing adaptive AR/VR interfaces that dynamically adjust to the user's focal depth may be crucial for improving user performance and reducing eye strain.

OBJECTIVES AND HYPOTHESES

Incorporating previous research on eye tracking and focal plane switching, we explored integrating eye tracking features into an adaptive system that can respond to the user’s eye gaze and thus can reduce costs associated with focal plane switching. Participants engaged in complex decision-making tasks, such as route planning and resource management, while interacting with a large 3D virtual map surrounded by dynamic information feeds. The core of our investigation was a comparative analysis between traditional, non-adaptive displays—where information is fixed at certain locations around the user—and adaptive displays, which adjust the information's position based on the user's current gaze, to test the following hypotheses:

- H1: Decision-making quality will be higher in the adaptive interface condition than in the non-adaptive condition.
- H2: Participants using adaptive interfaces will demonstrate faster decision-making times compared to those using non-adaptive interfaces.

- H3: Participant’s using adaptive interfaces will switch their gaze between the map and screens more frequently due to the accessibility (closer spatial proximity) of the screens to the real-time gaze point and the relative ease of information retrieval.

METHODOLOGY

Participants

We recruited 60 adult participants who were fluent in English and had no uncorrected visual impairments. Participants were mainly recruited from local communities using online platforms such as Craigslist and university email lists.

Experimental Design

We utilized a between-subjects design, where participants were randomly assigned to one of two conditions: an adaptive interface or a control (non-adaptive) interface. The between-subjects design reduced participant fatigue and meant the same scenario could be used for both conditions. Using the Meta Quest Pro, participants were immersed in a VR environment designed to simulate an augmented-reality enhanced operation command center. This simulation involves a central 3D map surrounded by multiple virtual information displays, which participants use to perform tasks such as route planning and resource management. The key differentiator between conditions is the interface adaptiveness:

- **Control Condition (Non-Adaptive Interface):** Participants in the control condition interacted with a traditional interface where informational displays (weather updates, traffic conditions, and communications from virtual characters) were fixed at specific locations around the perimeter of the virtual map. Participants had to physically turn their heads or shift their gaze to view these displays, which simulated static screens displaying information.

- **Experimental Condition (Adaptive Interface):** In the adaptive condition, the information monitors were positioned dynamically based on the participant's immediate point of attention and depth estimation based on their gaze, using eye-tracking technology integrated into the VR headset. For example, if a participant was looking at a particular route on the map, related information like weather conditions and character communications appeared on monitors placed in close proximity to that area. This adaptive feature aimed to reduce the need for significant head movements as well as focal plane switching.

PROCEDURE

Participants first underwent an initial briefing about the study's purpose and the general activities they would engage in. After providing informed consent, participants were equipped with VR headsets and introduced to the simulated operation center environment. They first completed two tutorial events that were designed to help them get familiar with the tasks. The experience uses a detailed virtual map of Hawaii, designed by importing 3D Bing map data within the Unity game engine environment to create a realistic 3D virtual tabletop map within a command center style environment.

Scenario, Tasks, and User Interaction

Participants were tasked with assisting virtual characters as they navigate through various routes on the map, managing resources, and responding to real-time events such as weather changes or traffic updates. Fig 1a and Fig 1b display the control and adaptive conditions, respectively. Participants interacted with the system through verbal commands to the facilitators. For example, when instructed to choose a route for a character due to a flooded path, a participant would verbally communicate their decision to the facilitator, who would then update the system accordingly by entering the desired choice. Then, the participant would observe the resulting changes in virtual character position and their remaining resources. The user's task is to monitor and manage resources (time and money) effectively to ensure that the characters reach the airport within a six-hour time window and retain a specified amount of money. Each decision impacts these resources, with "good" decisions costing $25 and "bad" decisions costing $60.

There were three monitors that the participants were asked to utilize to obtain information critical to their decision making process. In the control condition, these three monitors were positioned on the virtual wall above the far side of the map. In the adaptive condition, the interface adapts to the user’s eye gaze by positioning the monitors on the map in front of the user. The monitors displayed the information they needed to help make decisions for each of the virtual characters. The monitor on the left is for communications (e.g., requests or spot reports from the virtual characters, the center monitor alerts users to weather conditions on the island, and the third monitor on the right will display traffic and other important local information to the user.

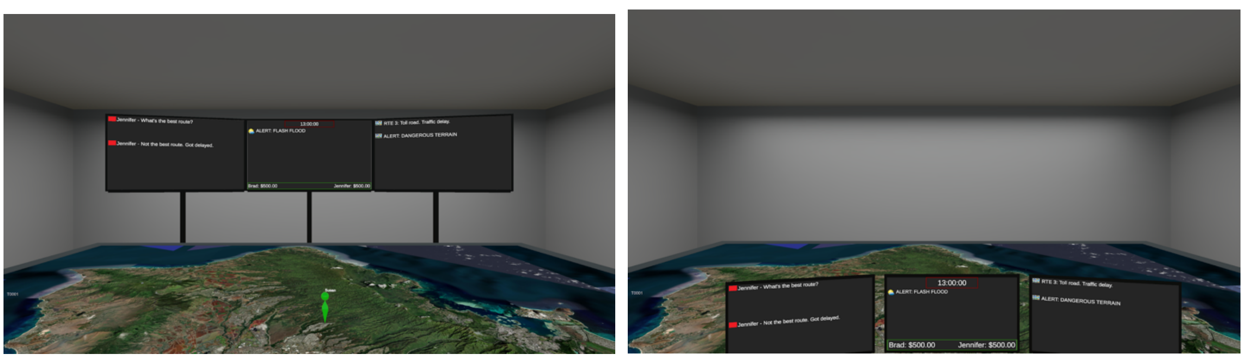

Fig 1. Control condition where the monitors are displayed on the virtual wall (left), and Experimental condition where the monitors are displayed dynamically depending on where the user’s gaze is currently focused on the map (right).

DATA ANALYSIS

A total of 60 participants were recruited for this study, with 31 assigned to the adaptive condition and 29 to the control condition.

Decision Events Analysis

We analyzed 9 decision-making events, each of which involves key choices about the characters' navigation, such as determining routes or selecting proximity to transportation options. Figure 1 illustrates the type of information displayed to participants during a sample decision event. Each decision event offered three possible choices: one optimal and two suboptimal. Decisions were coded as binary outcomes where a good decision was encoded as '1' and poor decisions as '0'.

Time Analysis

The time taken to make each decision, “decision-making time,” was logged from the moment task-relevant information was displayed, to when the facilitator enters the decision to the system after the participant verbally communicated their decision to them.

Eye Behavior Analysis

The Meta Quest Pro has a built in eye tracker that allowed us to determine, at each time point, where the participant was looking. Unity has built in ray casting methods that allow a ‘ray’ to be projected directly forward from the gaze point and return the first object that intersects with the projected ray. Using this method, we could determine when participants were looking at the map versus the screens, and importantly, when gaze switched from the map to a screen and vis versa. We computed several variables associated with eye behavior including: (i) Total time spent looking at the map or at the screens, (ii) Average period of time individuals fixated on the map and on the screens before switching to a new object (fixation dwell time), and (iii) A count of the number of switches between the map and the screens (left, middle, and right screen). Participants with more than 50% missing eye data (n=6) due to technical malfunction or miscalibration were dropped from the analysis leaving a final sample of 54 participants in the eye behavior analysis.

Hypothesis Testing

In order to test the first hypothesis, that decision-making quality will be higher in the adaptive interface condition, we analyzed the decision quality by calculating the frequency of good decisions (coded as '1') across all decision events for both groups. We first conducted a nonparametric Wilcoxon rank sum test to compare the decision quality between two conditions. Then, a chi-square test was conducted to determine if there was a statistically significant difference in the decision-making score distributions between the adaptive and control conditions. To test the second hypothesis, that participants using adaptive interfaces will demonstrate faster decision-making times compared to those using non-adaptive interfaces, we compared the average decision-making time of the participants in each condition. We used the Welch Two Sample t-test to evaluate the statistical significance of the difference between the conditions. To compare eye behavior metrics, we used a 2 x 2 (condition x object) Analysis of Variance (ANOVA) for the outcome variables overall fixation time and dwell time, and used a two-sample t-test to compare the total number of attention switches between the adaptive and control conditions.

RESULTS

Decision Quality Distribution

Participants' decision quality was measured by a "decision score," the average score of their decisions during the simulation. The average of these decision scores was M=0.58, SD=0.21 for the adaptive condition, and M=0.62, SD=0.21 for the control condition. A Wilcoxon rank sum test with continuity correction revealed no significant difference in decision quality between conditions (W=420.5, p=.668).

Figure 3 displays a box plot illustrating the distribution of decision scores across participants in each condition. A chi-squared test of independence was conducted to compare the percentage of good decisions between the adaptive (M = 0.58, SD = 0.21) and control groups (M = 0.61, SD = 0.15). The results indicated no significant difference in the distribution of decision quality between the groups, $\chi^2(1, N = 60) = 0.59$, $p = .441$.

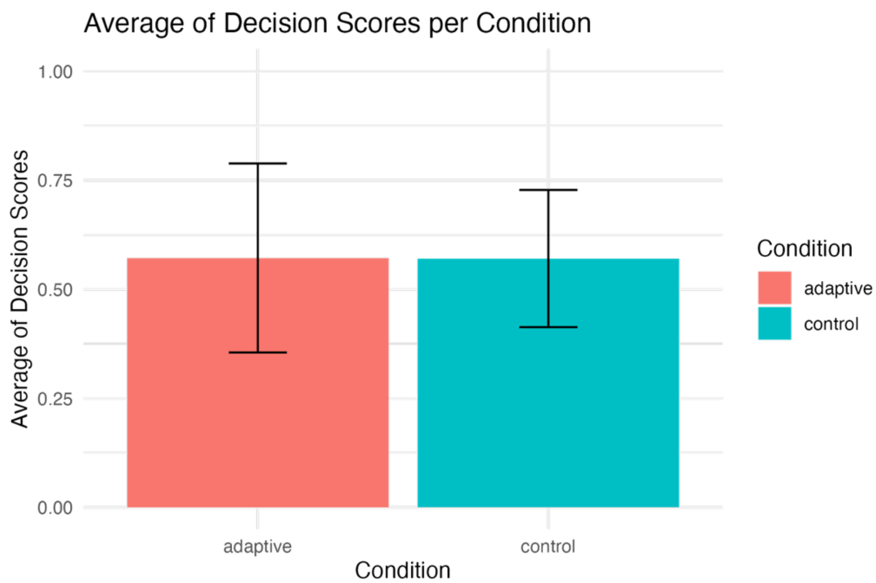

Fig 3. The box plot for average decision scores for both adaptive and control groups.

Decision Time Analysis

Participants' decision-making time was measured by the average interval from the onset of event-related information display to the point when the participant verbally communicated their decision. The average decision time was M=35.44 seconds (SD = 18.64) for the adaptive condition and M=36.94 seconds for the control condition (SD = 18.67). A Welch Two Sample t-test indicated no statistically significant difference in the time spent making decisions between the adaptive and control conditions, $t(56.78) = -0.65$, p=.51 (with 95% CI [−10.64 , 5.42]).

Event-Specific Time Analysis

Figure 4 illustrates the average time spent on each decision event per condition. Event JB001, which required participants to process information for both characters while maintaining awareness of the map, presented a particular challenge. Although the average times for this specific event were longer in the control condition, the difference was not statistically significant (W=343 , p=.117).

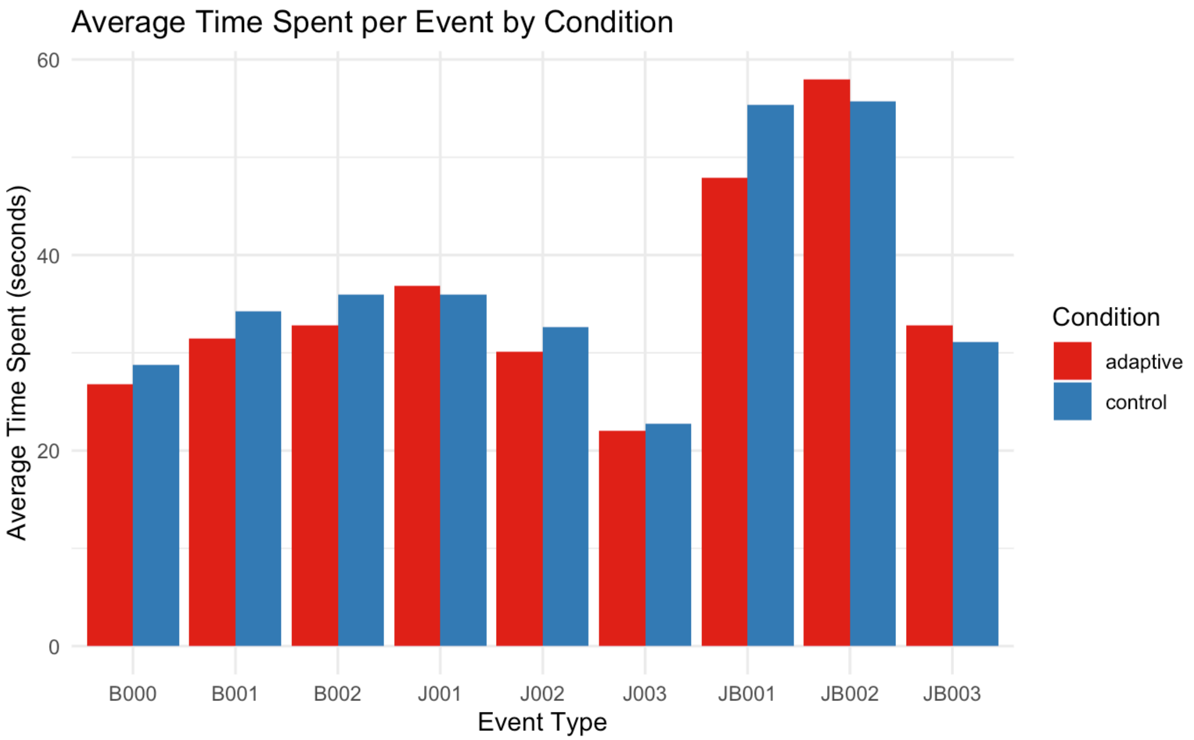

Fig 4. Average time spent for each decision event per condition, with event codes beginning with 'B' corresponding to character Brad and 'J' to Jennifer. JB events are more challenging as the user needs to process information for both characters.

Eye Tracking Analysis

To test the hypothesis that participants in the adaptive condition would spend more time processing information on the screens, we first examined the total time spent looking at the map versus the screens in each condition (Figure 5a). In the control condition, participants on average spent 6.45 minutes (SD=1.3) looking at the map and 6.3 minutes (SD=1.6) looking at the information screens. In the adaptive condition, participants spent on average 6.05 minutes (SD=1.8) looking at the map and 7.09 minutes (SD=1.97) looking at the information screens. An Analysis of Variance (ANOVA) comparing Condition (adaptive vs control) x Object (screen vs. map) revealed a non-significant effect of Condition ($F(1,104)$ =0.37 , $p = 0.0545$) and Object ($F(1,104) = 2.025$, $p = 0.155$) but a trending interaction ($F(1,104) = 3.36$, $p = 0.070$). This result shows that participants in each conditions spent a similar amount of time overall processing information from the screens and referencing the map to support the decision-making task.

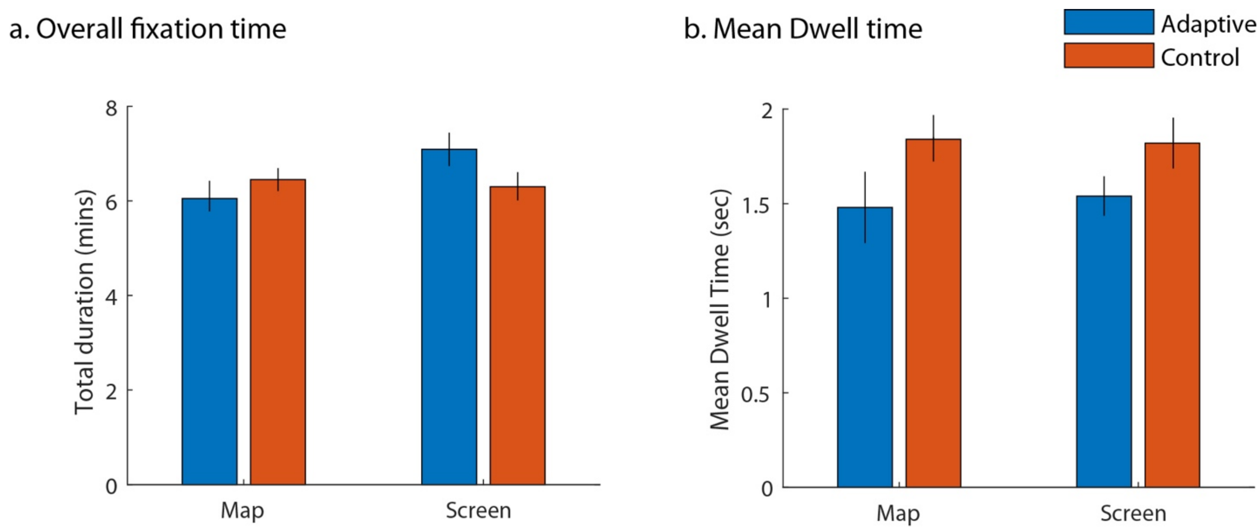

Figure 5. Bar graphs showing overall fixation time (a) and mean dwell time (b) for the adaptive (blue) and control (red) conditions, separated by object (map versus screen).

Next, we examined average fixation dwell time as an indicator of user's allocation of attention (Figure 5b). For each fixation on the map or screen, we determined the amount of time spent on average before the user switched fixation to a different object. In the control condition, average participant dwell time on the map was 1.84 sec (SD=0.69) and dwell time on a screen was 1.82 sec (SD=0.72). In the adaptive condition, average participant dwell time was 1.48 sec (SD=1.05) on the map and 1.54 sec (SD=0.58) on a screen. An ANOVA comparing Condition (adaptive vs control) x Object (screen vs. map) revealed a main effect of Condition ($F(1,104) = 4.44$, $p = 0.038$) but non-significant effect of Object ($F(1,104) = 0.02$, $p = 0.890$) and interaction ($F(1,104) = 0.08$, $p = 0.778$). The main effect of condition suggests that participants in the adaptive condition deployed their attention more efficiently by leveraging shorter duration fixations onto the map and the screens to achieve the same level of performance as the control condition, likely aided by the closer proximity of screens to gaze position in the adaptive condition.

Finally, we examined the frequency of attentional switches between the map and screens in the adaptive and control conditions. To do this we counted the number of gaze switches that occurred from the map to each of the three screens (left, middle, right) and from the three screens to the map (Figure 6a). The count data is represented in 2D histogram images showing the source (where the fixation started) along the vertical axis, and the target (where the fixation switched to) along the horizontal axis. The pattern in the images show a high frequency of switches between the map and screens (and vis versa), and much fewer switches among the three screens (left, middle, right). We calculated the total cumulative count of switches between the screens and the map. In the control condition, the average total count of attentional switches was 503 switches (sd=205) and in the adaptive condition it was 612 switches (sd=207). A two-sample t-test revealed that there were significantly more attentional switches in the adaptive compared to the control condition ($t(52)=1.93$, $p=0.05$). This result coincides nicely with the dwell time results indicating that participants in the adaptive condition maintained the same overall level of gaze time on the map/screens by decreasing dwell time but increasing the number of attentional switches between them.

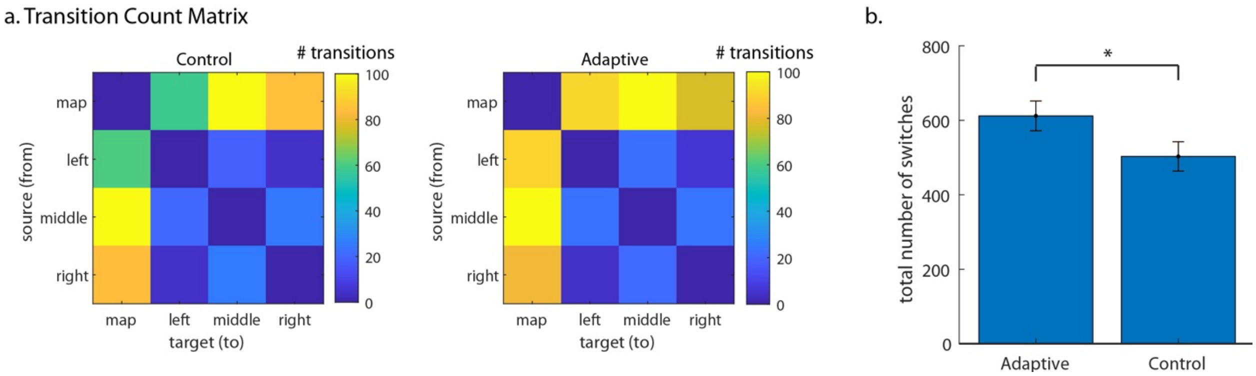

Figure 6. 2D image histograms (a) showing the count of transitions from each "source" along the y-axis to each "target" along the x-axis for the control (left) and adaptive (right) conditions. The diagonal is all zero because by definition it is impossible to switch from one object to itself. The bar graph (b) shows the cumulative number of switches among the map and screens for each condition during the experiment.

CONCLUSION

The results of this study highlight the complexities involved in integrating adaptive interfaces within MR head-mounted displays, particularly in high-stakes environments like an operation command center. Despite the theoretical advantages of adaptive systems in reducing cognitive load and enhancing decision speed by aligning information presentation with the user's perceptual depth, our findings did not demonstrate a significant difference in decision-making quality or speed between the adaptive and non-adaptive conditions. However, our results did show interesting differences in eye behavior, which is perhaps a more sensitive measure of task-related differences in this study. Our results showed that participants in the adaptive condition compared to the control condition spent more time processing screen information as revealed by the increased amount of time spent looking at the screens relative to the map compared to the control condition. We also found that participants in the adaptive condition compared to the control condition spent overall less time dwelling their attention on the screens and the map and a corresponding higher frequency of switching back and forth between the screens and map. These results are in line with previous research that suggests participants will work to minimize working memory (i.e. remembering fewer instructions) load by increasing 'locomotive effort' (i.e. look at instructions more by increasing magnitude and frequency of head and eye movements). (Williams and Störmer, 2021)

Together, these results can be interpreted similarly - in the control condition participants adapted by increasing their fixation dwell time and switching less frequently (likely at the cost of increased working memory) due to the increased locomotive cost of switching gaze to a relatively farther distance on the back wall. Conversely, in the adaptive condition because decision related information was readily available with lower locomotive effort on both the map and screens, participants could reduce the amount of information in working memory by offloading memory every time they fixated on the screens. Though we did not find a behavioral difference in response time, participants did exhibit different eye movement behaviors between conditions suggesting the use of compensatory mechanisms or attentional strategies to meet the task demand. Practically, what this may mean for interface design is to take into consideration human's natural propensity to adapt to the task and task environment and do so in a manner that aligns with these adaptive behavioral 'rules' in mind. If we take to be true the logical axiom that humans are naturally efficient, then designing an interface that allows one to maintain the human adaptive behavioral 'rule' to minimize working memory, should lead to a more efficient use of the human.

This outcome resonates with earlier studies that question the effectiveness of certain adaptive techniques. Further research should explore improving adaptive systems by investigating different adaptive variables. For instance, Findlater and McGrenere (2004) explored the implications of personalization in software applications and emphasized that while adaptive systems aim to automate decision-making, they may not align with user expectations for control and efficiency. Those systems often lead users to prefer adaptable UIs that offer greater control and faster interactions under specific conditions (Findlater et al., 2004). Furthermore, Miller et al (2005) also addressed the implications of adaptive versus adaptable user interfaces (UIs) on decision-making, highlighting that adaptive systems, though beneficial in reducing workload and increasing operational speed, could potentially reduce user engagement and lead to over-reliance and decreased situational awareness. In contrast, adaptable systems, which allow users more control, might indeed increase cognitive engagement and user satisfaction. Such systems can underscore the critical trade-offs between automation and user control in system design (Miller et al., 2005).

DISCUSSION

Ultimately, our study offers insights about reevaluating how adaptive elements can be integrated and potential limitations of such systems. We aim to better understand how to design systems that effectively reduce cognitive load without distracting users and without sacrificing user control and engagement by continuing to refine these technologies. Our study also underscores a significant use case for immersive technologies in large-scale, command center-type applications. One of the critical challenges we identified is managing information overload and making sense of an operating picture. While previous research primarily suggested using MR technology with lower echelon personnel, our research design offers insights about its potential utility in command center environments. Embedding 3D maps with dynamic information in these settings can provide valuable insights and inspire further research into the application of immersive technologies beyond traditional 'boots on the ground' scenarios.

The null results about behavioral variables (decision-making performance and speed) observed in our study are not necessarily conclusive indicators of the general adaptiveness or effectiveness of the adaptive interfaces. We speculate that the null effect on behavioral response time could be attributed to the complexity and duration of the decision-making tasks. It's possible that the rapid attentional shifts afforded by the adaptive interface would be more beneficial for faster and easier decisions, a hypothesis that future research could explore. Moreoever, these results may have been influenced by the specific adaptive technique employed, which heavily weighted certain aspects over others. Despite our expectations, the lack of significant differences in decision-making quality and speed between the adaptive and non-adaptive conditions suggests that the adaptive technique used in this study may not have been optimal. The null results highlight the need to continue to test and refine additional adaptive techniques. Based on these outcomes, future research should consider extending the study period and employing alternative adaptive techniques, such as those mimicking eye gaze more effectively and/or other display modalities. Such techniques could potentially enhance decision-making by providing more intuitive and contextually relevant information displays. Additionally, we aim to explore the differences between *adaptive* systems, where the system controls the information presentation, and *adaptable* systems, where the user has control. This distinction could provide deeper insights into user preferences and performance outcomes.

Our study also examined eye behavior differences and showed that participants in the adaptive condition had shorter dwell times on objects (map vs. screens) and correspondingly higher quantities of attentional switches between the map and screens. As the adaptive interface aimed to present the screens closer to the user's gaze point, the interface enabled more frequent information retrieval with less locomotive effort. These findings suggest that adaptive interfaces did influence how users allocated their attention and managed cognitive load. The increased frequency of gaze switches in the adaptive condition indicates that participants could offload memory by frequently referencing information on the screens, thus reducing load on working memory and cognition.

While our study did not find significant differences in decision-making quality and speed, the observed differences in eye behavior highlight the complexities and challenges of integrating adaptive interface systems to reduce cognitive load of the user. These findings emphasize the need for continued research and refinement of adaptive techniques to better support user needs and operational demands. Our research explored the potential best use cases and affordances of adaptive displays in order to to minimize cognitive load and enhance decision-making efficiency. We plan to conduct additional user studies to explore different adaptive techniques and their impact on decision-making. Understanding the trade-offs between these approaches will be crucial in designing effective interfaces. Future research will compare *adaptive* systems, where the system controls information presentation, with *adaptable* systems, where the user has control. We also aim to further explore comparing different adaptive techniques and exploring the nuanced dynamics between adaptive and adaptable systems to determine which configurations most effectively support user needs in various settings.

Given these insights and our study's outcomes, it becomes evident that the choice between using adaptive versus adaptable systems is not merely about technological capability but also about aligning with user preferences and operational demands. Therefore, next we aim to explore the differences between adaptive and adaptable systems.

References

Arefin, M. S., Swan II, J. E., Hoffing, R. C., & Thurman, S. (2023). Mapping Eye Vergence Angle to the Depth of Real and Virtual Objects as an Objective Measure of Depth Perception. *arXiv preprint arXiv:2311.09242*.

Arefin, M. S., Swan II, J. E., Cohen Hoffing, R. A., & Thurman, S. M. (2022, June). Estimating perceptual depth changes with eye vergence and interpupillary distance using an eye tracker in virtual reality. In 2022 Symposium on Eye Tracking Research and Applications (pp. 1-7).

Findlater, L., & McGrenere, J. (2004, April). A comparison of static, adaptive, and adaptable menus. In Proceedings of the SIGCHI conference on Human factors in computing systems (pp. 89-96).

Greenberg, S., & Witten, I. H. (1985). Adaptive personalized interfaces—A question of viability. Behaviour & Information Technology, 4(1), 31-45.

Gupta, D. (2004). An empirical study of the effects of context-switch, object distance, and focus depth on human performance in augmented reality (Doctoral dissertation, Virginia Tech).

Hoffing, R. A., Thurman, S. M., & ARMY RESEARCH LAB ABERDEEN PROVING GROUND MD ABERDEEN PROVING GROUND United States. (2020). The state of the pupil: Moving toward enabling real-world use of pupillometry-based estimation of human states. Army Research Lab Aberdeen Proving Ground MD Aberdeen Proving Ground United States.

Hoffing, R. C., Thurman, S., Coyne, J., Sibley, C., Enders, L., & Roy, H. (2023). Leveraging the pupillary light reflex for cognitive pupillometry: An initial characterization of the PLR in two data sets. Journal of Vision, 23(9), 5839-5839.

Miller, C. A., Funk, H., Goldman, R., Meisner, J., & Wu, P. (2005, July). Implications of adaptive vs. adaptable UIs on decision making: Why "automated adaptiveness" is not always the right answer. In Proceedings of the 1st international conference on augmented cognition (pp. 22-27).

Neubauer, C., Schaefer, K. E., Oiknine, A. H., Thurman, S., Files, B., Gordon, S., ... & Gremillion, G. (2020). Multimodal physiological and behavioral measures to estimate human states and decisions for improved human autonomy teaming. Report. CCDC Army Research Laboratory.

Oviatt, S. (2006, October). Human-centered design meets cognitive load theory: designing interfaces that help people think. In Proceedings of the 14th ACM international conference on Multimedia (pp. 871-880).

Safayet Arefin, M., Swan, J. E., Cohen Hoffing, R., & Thurman, S. (2023). Mapping Eye Vergence Angle to the Depth of Real and Virtual Objects as an Objective Measure of Depth Perception. arXiv e-prints, arXiv-2311.

Villavicencio, N., & Cohen Hoffing, R. (2023). Estimating User Gaze Depth Perception in Real-Time for Extended Reality Environments.

Williams, J., & Störmer, V. S. (2021). Working memory: how much is it used in natural behavior?. *Current Biology*, *31*(4), R205-R206.

Yelizarov, A., & Gamayunov, D. (2014, August). Adaptive visualization interface that manages user's cognitive load based on interaction characteristics. In Proceedings of the 7th international symposium on visual information communication and interaction (pp. 1-8).