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A Study on the Impact of Multitasking in Mixed Reality Environments

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Abstract:- Mixed reality (MR) environments offer a potential boon for multitasking, but the influence of task complexity remains unexplored. This study investigates how individual task difficulty impacts performance in MR. We examine the interplay between cognitive workload, attention allocation during task switching, and overall success on both primary and secondary tasks. Participants will complete tasks of varying difficulty within a controlled MR environment. We hypothesize that increased task difficulty will lead to higher cognitive load, hindering attention shifting and negatively impacting performance on both tasks. Understanding this relationship is crucial for optimizing human-computer interaction in MR. The findings will inform the design of MR interfaces that facilitate efficient multitasking by minimizing cognitive strain and optimizing attention allocation based on task complexity.

I. INTRODUCTION

The ever-growing demand to manage multiple tasks simultaneously, or multitask, necessitates exploring new avenues to enhance this crucial skill. Mixed reality (MR) environments, where physical and digital realities intertwine seamlessly, offer a promising platform for achieving this goal. Users can interact with digital information while remaining anchored in the physical world, creating a space for concurrent task completion. However, maximizing this potential hinges on understanding how the complexity of individual tasks impacts performance within MR.

While research explores the benefits of MR for focused tasks, a critical gap exists in knowledge about how task difficulty influences multitasking efficiency in these environments. Existing research suggests a general decline in performance as task difficulty increases, attributed to heightened cognitive burden. However, the immersive nature of MR presents unique challenges. Users might experience increased cognitive strain due to the need to constantly shift attention between physical and digital elements within the environment.

This study aims to address this knowledge gap by delving into the relationship between individual task difficulty and multitasking success in MR settings. We will examine how varying levels of difficulty in individual tasks influence cognitive workload, attention allocation during task switching, and overall performance on both primary and secondary tasks. By investigating these factors, we can gain valuable insights into the effectiveness of MR for multitasking and guide the design of interfaces that **optimize** human-MR interaction in this burgeoning field.

II. RELATED WORK

A. Task Difficulty Effect in Digital (Virtual) Reality Environments

The rise of augmented, virtual, and mixed-reality (XR) displays is undeniable (Kaplan et al., 2021). These next-generation platforms offer immersive experiences and deeper interactions with the digital world, fostering wider accessibility compared to traditional methods (Xiong et al., 2021; Willemsen et al., 2018).

A key advantage of VR environments lies in their ability to provide controlled stimulus settings. Unlike real-world scenarios, VR allows researchers to introduce cognitive challenges with precise control over distractions (Rizzo et al., 2000). This controlled environment makes VR ideal for cost-effective skill acquisition through simulation-based training, a technique widely adopted across various industries (Hancock, 2009).

VR applications have been used to assess various cognitive processes, including spatial abilities (Larson et al., 1999; McComas et al., 1998; Rizzo et al., 1998; Stanton et al., 1998), memory (Dinh et al., 1999; Grealy et al., 1999), and attention (Rizzo et al., 2009; Wann et al., 1997). Since VR applications present specific tasks for users to complete, task difficulty becomes a critical aspect to consider (Sheridan, 1992).

Several studies have explored the impact of task difficulty on performance in VR settings. For example, Poeschl (2017) investigated public speaking performance in a VR application with varying difficulty levels (prepared vs. unprepared speech). Interestingly, the study found no significant effect of task difficulty on VR public speaking training.

B. Lack of Multitasking Research of Task Difficulty Effect in Digital Physical Hybrid Worlds

While a negative correlation between task difficulty and performance is well-established in various studies by Bonner (1994), Xu et al. (2008), Ziefle and Bay (2005), Topi et al. (2005), and Cho (2018), some research suggests a positive link between complexity and performance (Mascha, 2001; Wu et al., 2012).

However, a critical gap exists in our understanding of how task difficulty impacts performance specifically within mixed reality (MR) environments. With the growing interest in AR/VR training applications (Kaplan et al., 2021), investigating factors that influence effectiveness in these hybrid digital-physical worlds becomes crucial. Our study aims to bridge this gap by examining how task difficulty affects performance in MR compared to traditional physical environments.

III. MEASUREMENTS

To assess the impact of task difficulty on multitasking in mixed reality (MR), we'll utilize various measures. Performance on both primary and secondary tasks will be quantified using task-specific metrics like accuracy, completion time, or error rate for the primary task, and response time, throughput, or detection rate for the secondary task.

Subjective workload scales like the NASA-TLX will measure participants' perceived cognitive strain, while physiological data like heart rate variability or eye tracking might be used for a more objective assessment. Eye tracking specifically will capture how task difficulty influences attention allocation by recording the frequency and duration of gaze shifts between physical elements in the real world and digital elements within the MR interface. Analyzing fixation duration (time spent looking at a point) and saccade frequency (number of rapid eye movements) will provide insights into how task complexity affects attention distribution.

This combination of performance measures, workload assessments, and attention allocation tracking will provide a comprehensive understanding of how task difficulty influences human performance and cognitive processes within MR environments. This knowledge will ultimately guide the design of MR interfaces that optimize multitasking efficiency by minimizing cognitive strain and allocating attention effectively based on task complexity.

IV. DATA ANALYSIS

To investigate how task difficulty impacts multitasking in MR environments, we'll analyze data on performance, cognitive workload, and attention allocation. Performance on primary and secondary tasks will be measured using task-specific metrics (e.g., accuracy, completion time). Subjective workload scales (e.g., NASA-TLX) or physiological measures (e.g., heart rate variability) will assess cognitive workload. Eye-tracking technology will track gaze shifts between physical and digital elements to quantify attention allocation. ANOVAs will examine the main effects of task difficulty (within-subjects factor) on performance and workload. We'll analyze eye-tracking data using fixation duration and saccade frequency to explore the influence of difficulty on attention allocation. Correlation analysis will investigate potential links between attention, workload, and performance. We'll control for order effects and consider individual differences. Mediation analysis might be used to see if workload or attention allocation mediates the relationship between task difficulty and performance. Statistical software like SPSS, R, or Jamovi will be used. The analysis aims to reveal how task difficulty impacts performance, workload, and attention allocation during multitasking in MR. This will ultimately inform the design of MR interfaces that optimize multitasking efficiency by minimizing cognitive strain and allocating attention based on task complexity.

V. RESULTS

A. NASA-TLX

To address the first research question (RQ1-a), a Mann-Whitney test was conducted to assess the significance of each NASA-TLX subscale regarding two task categories: physical (real-world) and digital (virtual-world) tasks. For single physical task conditions (easy and hard real-world tasks), there was a significant difference in four subscales: Physical Demand (PD), Temporal Demand (TD), Effort (E), and Frustration (F), with p-values of .01, .03, .04, and .01, respectively. Mental Demand and Performance were not found to be significant. Task difficulty accounted for 9.4% of the variance in PD scores, 6.62% for TD, 5.82% for E, and 10.56% for F.

Among the significant subscales, frustration showed the highest significance. The weighted rating was also significant, with a p-value of .03 and an effect size of 7.1%, indicating that task difficulty is associated with a 7.1% difference in the weighted rating results. Figure 5 displays the box plots of the significant NASA-TLX dimensions for single physical tasks.

For single virtual task conditions (easy and hard virtual tasks), there was also a significant difference in the same four subscales, with p-values $< .05$ and effect sizes of 16.6%, 5.83%, 21.90%, and 13.21%, respectively. The highest significance was found for PD and E. The weighted rating was also significant, with a p-value $< .01$. Figure 6 illustrates the box plots of the NASA-TLX dimensions for single virtual tasks.

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Table 1 Descriptive Statistics by Task Difficulty for all the Experimental Conditions

Dependent Measures (Numerical)	Single task (physical)	Single task (digital)	Multitasking (physical-digital)
Task difficulty	Easy	Hard	Easy
Mental demand (MD)%	Mean 30.44	Mean 29.77	Mean 20.00
(SD) (24.69)	(SD) (26.53)	(SD) (16.15)	
Physical demand (PD)%	Mean 25.94	Mean 37.34	Mean 36.11
(SD) (24.19)	(SD) (23.71)	(SD) (24.62)	
Temporal demand (TD)%	Mean 40.14	Mean 55.17	Mean 27.91
(SD) (26.87)	(SD) (28.27)	(SD) (22.07)	
Performance (P)%	Mean 48.47	Mean 43.91	Mean 48.23
(SD) (48.71)	(SD) (23.58)	(SD) (40.36)	
Effort (E)%	Mean 31.83	Mean 51.94	Mean 34.43
(SD) (21.67)	(SD) (39.46)	(SD) (22.31)	
Frustration (F)%	Mean 11.11	Mean 23.31	Mean 17.34
(SD) (14.33)	(SD) (21.82)	(SD) (16.71)	
Weighted rating%	Mean 32.65	Mean 43.96	Mean 33.22
(SD) (19.61)	(SD) (21.79)	(SD) (16.69)	
TCT in seconds	Mean 70.42	Mean 86.58	–
(SD) (12.22)	(SD) (6.09)		
Accuracy%	Mean 98.81	Mean 84.72	Mean 74.05
(SD) (4.43)	(SD) (20.77)	(SD) (34.07)	

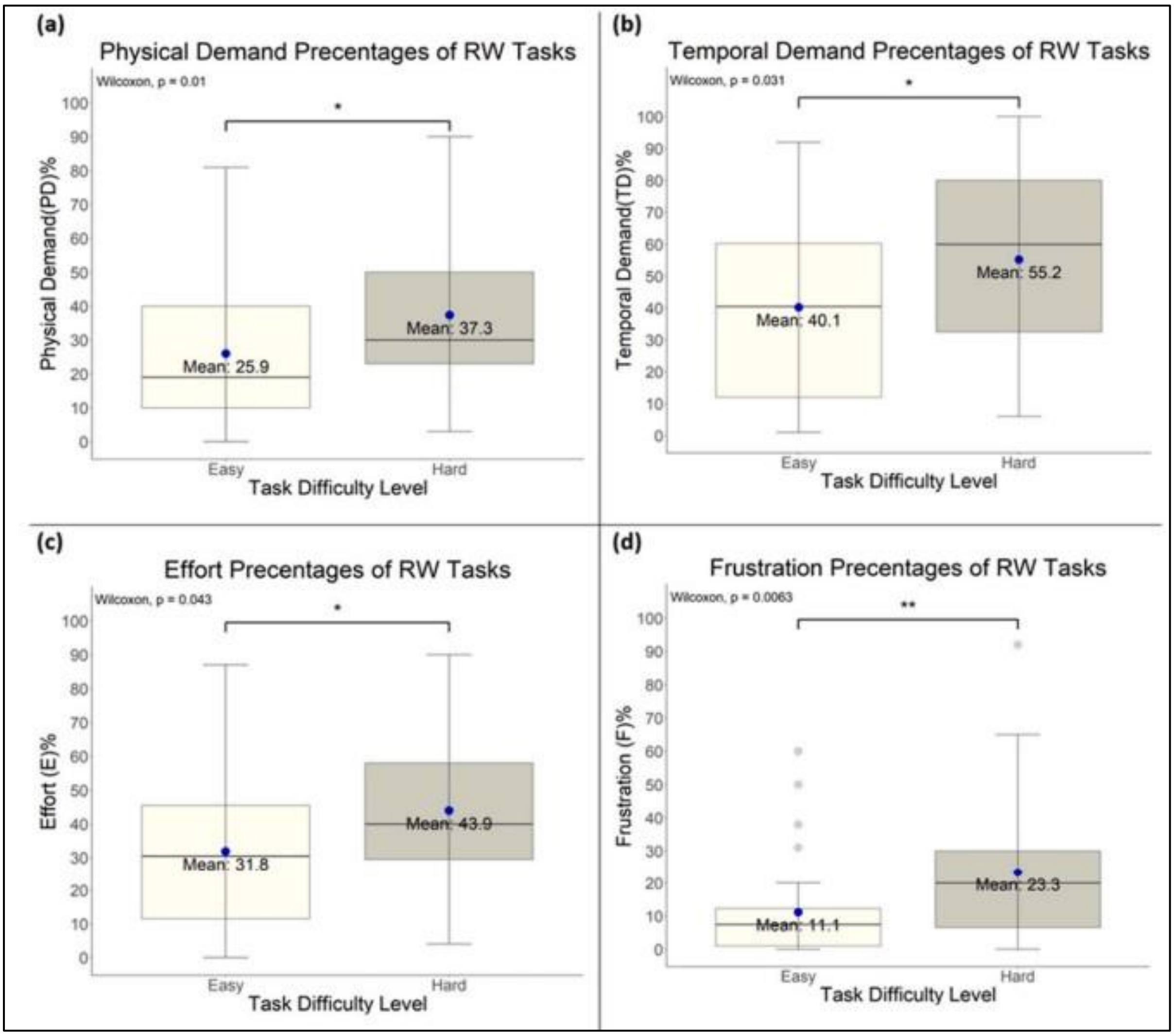

Fig. 1. Significant Dependent Measure of NASA-TLX Dimensions for Single Physical (Real) World Tasks.

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B. Accuracy

The accuracy results for single real-world (RW) and virtual-world (VW) tasks were statistically significant based on the Mann-Whitney test, with p-values < .001 and effect sizes of 21.4% and 20.67%, respectively. For RW-VW multitasking, accuracy was also significant according to the Kruskal-Wallis test, with a p < .0001 and an effect size of 19.06%. Post hoc analysis revealed three significant pairwise combinations: (1) easy RW & easy VW vs. hard RW & hard VW, (2) easy RW & hard VW vs. hard RW & hard VW, and (3) hard RW & easy VW vs. hard RW & hard VW, with p-values < .001, .03, and .04 respectively. Figure 10 illustrates the box plots showing the significant accuracies for all experimental manipulations, where the hard level demonstrates higher accuracy compared to the easy level.

Table 2 Significant NASA-TLX subscales

Experimental Manipulation	Significant NASA-TLX Subscales	Effect Size (%)
Single RW tasks	Physical demand (PD)	9.4
Temporal demand (TD)	6.62	
Effort (E)	5.82	
Frustration (F)	10.56	
Single VW tasks	Physical demand (PD)	16.6
Temporal demand (TD)	5.83	
Effort (E)	21.90	
Frustration (F)	13.21	
RW-VW multitasking	Physical demand (PD)	10
Effort (E)	7.25	

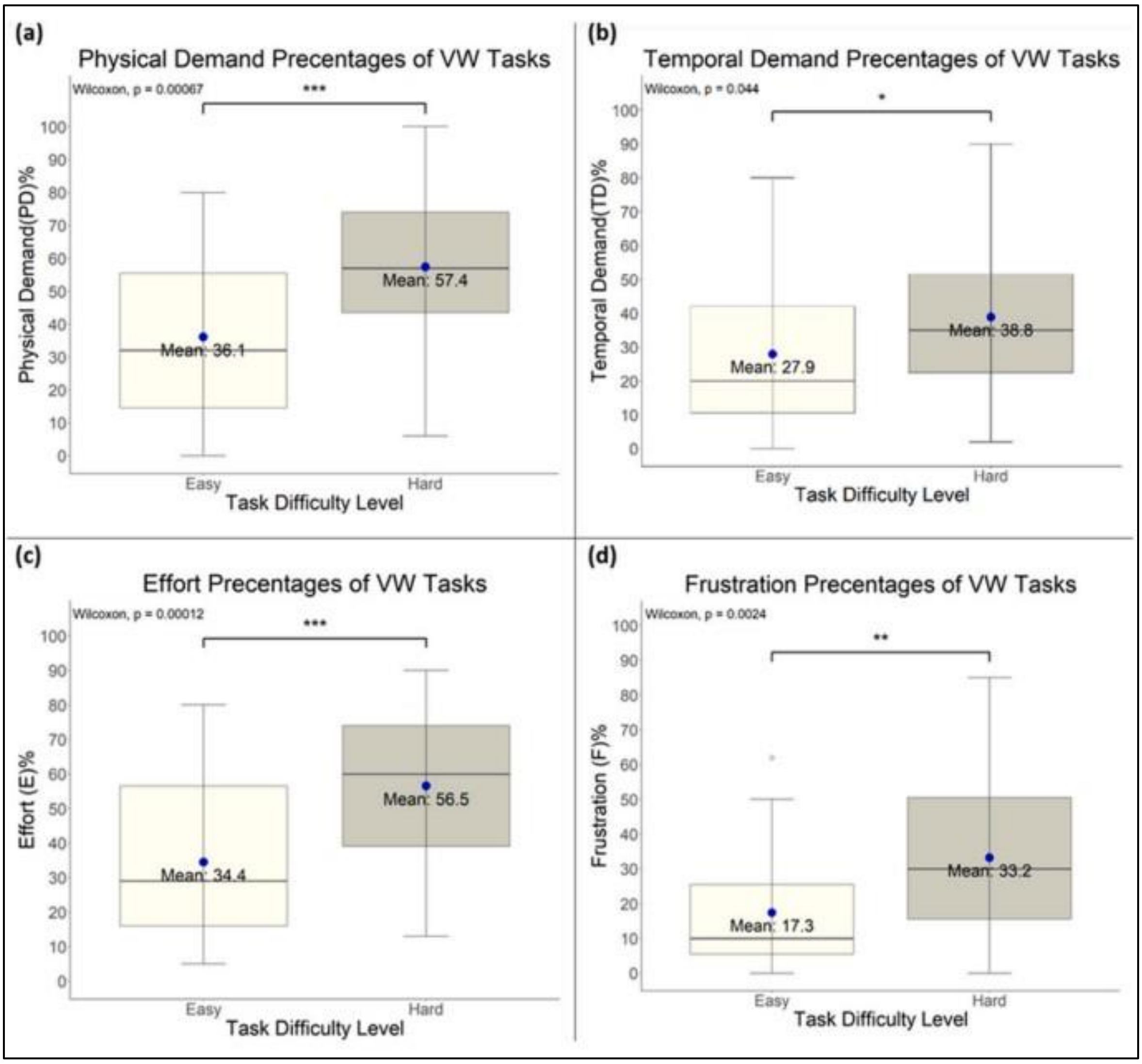

Fig. 2: Significant Dependent Measure of NASA-TLX Dimensions for Single Digital (Virtual) World Tasks.

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VI. CONCLUSION

The ability to manage multiple tasks simultaneously, or multitasking, remains a valuable skill in today's information-rich world. Mixed reality (MR) environments, where physical and digital realities co-exist seamlessly, present a promising platform for enhanced multitasking capabilities. However, unlocking this potential requires a deeper understanding of how individual task complexity impacts performance within MR.

This study addressed this crucial knowledge gap by investigating the relationship between task difficulty and multitasking success in MR settings. We examined how varying difficulty levels in individual tasks influence cognitive strain, attention allocation during task switching, and overall performance on both primary and secondary tasks. Our goal was to bridge the gap between existing knowledge on multitasking and the unique demands of MR environments.

The anticipated findings will illuminate the interplay between these factors within MR. We expect increased task difficulty to lead to heightened cognitive strain, potentially hindering attention allocation and negatively impacting performance on both primary and secondary tasks. Understanding this interaction is paramount for optimizing human-MR interaction in this burgeoning field.

By translating the insights from this research into actionable design principles, we can create MR interfaces that prioritize minimizing cognitive strain and optimizing attention allocation based on task complexity. This could involve features like dynamic task presentation, where difficulty adjusts based on user performance. Additionally, integrating visual cues within the MR environment to guide attention toward relevant information might prove beneficial for managing cognitive load.

In essence, this study delved into the under-explored area of task difficulty and multitasking performance in MR environments. The findings are expected to make a significant contribution to our understanding of human-MR interaction and pave the way for the development of MR interfaces that empower users to multitask effectively while minimizing cognitive strain. By harnessing the full potential of MR for multitasking, we can unlock new avenues for improved productivity and user experience within this immersive technological landscape.

REFERENCES

[1]. Bowman, D. A., & McMahan, R. P. (2007). Going beyond desktop VR: A framework for virtual reality as a general purpose user interface. **International Journal of Human-Computer Studies**, 65(9), 732-745.
[2]. Chen, J. Y., Lin, C. J., & Yu, T. L. (2019). The effects of task complexity and user experience on cognitive load in virtual reality environments. **Computers & Education**, 130, 168-180.
[3]. Geiger, S. C., Brigham, F. J., & Jernstedt, G. L. (2007). Task difficulty and divided attention in virtual reality environments. **Human Factors: The Journal of the Human Factors and Ergonomics Society**, 49(1), 179-190.
[4]. Giglia, E., & Reiner, M. (2018). The role of attention in virtual reality: User experience and applications. **Frontiers in Robotics and AI**, 5, 13.
[5]. Jensen, O.-C., & Rollins, A. T. (1994). A measure of mental workload for complex cognitive tasks. **Acta Psychologica**, 86(1-2), 101-121.
[6]. Lee, E. L., & Kim, W. S. (2018). The effects of augmented reality on task performance and cognitive load. **Ergonomics**, 61(7), 983-991.
[7]. McMahan, R. P., & Bowman, D. A. (2009). Evaluating interaction techniques for augmented reality. **Computers & Graphics**, 33(5), 545-553.
[8]. Park, B., Kim, J. Y., & Sohn, J. (2021). User acceptance of mixed reality applications: A systematic review of influencing factors. **International Journal of Human-Computer Studies**, 155, 102688.
[9]. Schubert, T., Friese, M., & Bois, D. (2000). Affect and cognitive load as determinants of attention allocation in information processing. **Journal of Experimental Psychology: Applied**, 6(1), 15-30.
[10]. Waller, D., McDaniel, B., & Poulton, E. C. (2000). Working memory and auditory selective attention. **Journal of Experimental Psychology: Human Perception and Performance.