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Analysis of Adaptive Problem-Solving in Multiplayer Virtual Reality Manufacturing Systems

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Abstract

The dynamic nature of modern manufacturing systems necessitates adaptive problem-solving approaches that respond to rapid changes and complex challenges to improve productivity. This research explores multiplayer virtual reality (VR) environments for adaptive problem-solving in manufacturing settings. Existing VR studies often focus on specific organizational contexts, isolating technological or social factors rather than integrating both. This approach limits our understanding of VR's potential to support adaptive problem-solving in diverse, realistic environments. We address this gap by examining how VR allows users to dynamically respond to varying task complexities and promote collaborative problem-solving across industries. The study investigates how task transitions affect physiological and cognitive engagement of participants during task execution. In a simulated production environment, ten teams of three participants were asked to design and assemble toy cars. Participant tasks were distinguished by having high, medium, or low complexity. Some of these tasks include ordering from a workstation, assembling car toy components, or teleporting around the production environment. Throughout the simulation experiment, electrodermal activity (EDA) data was collected to assess stress and engagement during task execution. By analyzing physiological responses, this research investigated correlations between task complexity and adaptive problem-solving capacity, as well as patterns in task transitions. The findings contribute to understanding how VR environments can enhance team performance, adaptive thinking, and efficient decision-making in manufacturing. This research highlights VR's potential as a tool for advancing collaborative problem-solving in complex, real-world production environments.

Keywords

Adaptive problem-solving, Virtual reality, Manufacturing; Electrodermal activity, Team performance, Task transition.

1. Introduction

Manufacturing serves as a key driver of economic growth. As industries evolve with technological innovation, adaptability has become increasingly vital. Manufacturers must continuously adapt to unforeseen challenges while maintaining high levels of efficiency and productivity, which requires professionals who can quickly assess complex situations, adjust strategies in real time, and create innovative solutions. Thus, adaptive problem-solving, which involves dynamic reactions to varying scenarios, can be identified as a necessary skill.

Virtual teamwork and immersive technologies are transforming organizational change, performance, and learning [1]. As virtual reality (VR) continues to spread through various sectors, from entertainment to education, healthcare, and beyond, the need to understand the nuances of human behavior and adaptation within these digital environments becomes increasingly paramount. VR enables real-time tracking of cognitive and physiological responses, offering increased insight into how people react under varying degrees of task complexity. Exploring how individuals and teams collaborate to solve problems and navigate these immersive virtual worlds can yield valuable insights that can inform the design and development of more effective and engaging VR applications [2, 3]. The use of VR provides an effective means of investigating adaptive problem-solving within a controlled yet dynamic environment [4].

2. Problem Description

Traditional problem-solving approaches in modern manufacturing have shown limitations when addressing dynamic production challenges [5]. Ineffective adaptive responses can result in inefficient and reduced productivity. This study navigates VR as a tool to explore adaptive problem-solving by simulating manufacturing scenarios, allowing participants to engage with different complex tasks and analyze their physiological response to transitioning between these tasks. The study explores the interaction between task complexity, physiological engagement, and adaptive problem-solving behavior in VR manufacturing settings.

3. Related Research

Despite limited short-term gains, Kittel et al.'s 360° virtual reality usage helped umpires better remember what they learned and felt more realistic. The researchers recommended looking into how VR might affect umpires' actual performance on the field [2]. Understanding the role of agency in virtual environments, Wei et al. explored how perceived control of avatars whether human or computer-controlled influenced prosocial decision-making in VR [6]. This highlights a gap in VR learning: the lack of adaptive approaches. To address this, Wojitok et al. proposed a framework for an adaptive VR learning environment that emphasizes personalization through user modeling, emotion detection, and interaction optimization. Though theoretical, this framework suggests promising directions for future research to develop and evaluate these components in VR learning applications [4].

Several studies have investigated the promising potential of VR for emergency training. Sharma et al. created a collaborative virtual reality system with 3D models and simulated agents to study how people make decisions during big-city evacuations [7]. Their work showed that practicing emergency drills in this virtual setting helped train personnel, resulting in faster real-world response times. While virtual reality has been shown to enhance problem-solving capabilities, the specific effects appear to vary. Araiza-Alba et al. found that immersive virtual reality significantly improved children's problem-solving skills compared to traditional methods [8]. Chen et al. revealed that VR-assisted problem-based learning enhanced vocabulary and motivation, although it did not significantly improve problem-solving performance among English language learners [3]. In contrast, Jin and Lee compared problem-solving approaches using desktop and virtual reality tools in apartment design. Their study suggests that desktop tools were more effective for space utilization, while VR users produced a wider variety of designs [9]. Additionally, Hwang et al. examined the effects of peer learning behaviors in virtual reality on geometry problem-solving, finding that collaboration in VR significantly enhanced problem-solving skills [10].

The current state of VR research highlights several critical areas that warrant further investigation. Key challenges include accurately modeling human behavior within immersive environments, providing rich multisensory experiences, and effectively replicating the complexity of real-world scenarios. Our research addresses these limitations by designing and evaluating a collaborative VR environment that simulates real-world manufacturing tasks. By integrating biometric data (e.g., heart rate and electrodermal activity) and behavioral logs, our study provides a multi-layered understanding of adaptive problem-solving strategies in team-based VR settings. Additionally, our approach includes a larger and more diverse participant pool, enhancing the generalizability of the findings. The multiplayer aspect further contributes to modeling complex human interactions in dynamic environments, offering insights that bridge the gap between controlled VR studies and real-world applications in smart manufacturing.

4. Methods

4. 1 Virtual Environment Setup

This study was conducted within a VR craft production environment for toy car manufacturing. The simulation, developed in Unity with Photon for multiplayer functionality, featured four workstations, each having its own set of instructions for the toy car build (pictured in Figure 1). Additionally, a product checker was integrated to verify build accuracy based on price and weight. Building a toy car involved 12 steps (detailed in Table 1), with tasks varying in cognitive and manual effort depending on complexity level. Complexity levels were assigned through a survey study.

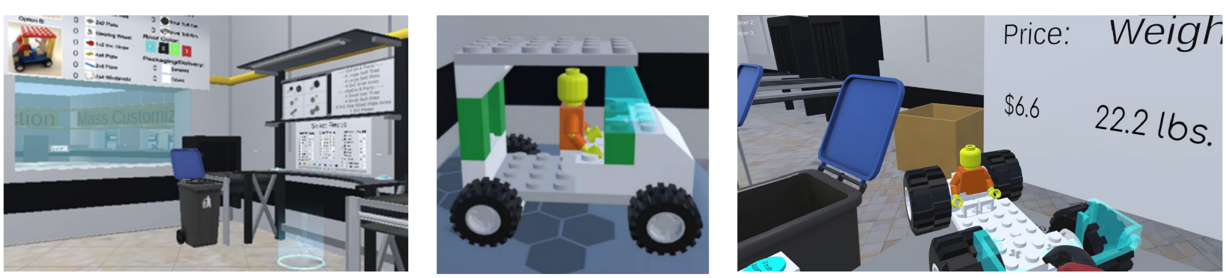

Figure 1: Snapshots of a workstation in the craft production room (left), a sample toy car (middle), and checking the price and weight of the toy car.

Table 1: Summary of Task Complexity Levels.

Task Name	Complexity	Task Name	Complexity
Teleport to workstation	Low	Assemble Windshield	Medium
Check instructions and select parts	Low	Assemble steering wheel	High
Pick and organize parts	High	Assemble driver set	High
Assemble tires and wheel hubs	Low	Assemble roof	Medium
Assemble wheels and axles to base	Medium	Finalize the toy car assembly	Medium
Assemble the toy car frame	High	Check price and weight	Low

4. 3 Data Collection and Analysis

Thirty students, assigned into ten groups of three, participated in a simulated VR manufacturing environment where they worked collaboratively on assembling toy cars. Participants completed informed consent forms prior to the study. Demographic data, including age, gender, and prior VR experience, were collected through a pre-experiment survey. Electrodermal activity (EDA) data was selected as a physiological measure of stress and engagement; participants were outfitted with an Empatica Plus wearable device to continuously collect their EDA. In addition, the VR environment and participant's communications were video-recorded for qualitative analysis. Task performance metrics, such as assembly accuracy and task completion time, were collected directly from the VR environment. After completing the VR tasks, participants filled out post-experiment surveys, including the NASA Task Load Index (TLX) and self-efficacy measures. The EDA data was first organized by the correlated task upon collection, and data was then pre-processed and normalized using min-max normalization to ensure comparability across participants. Changes in EDA were calculated between consecutive tasks to identify significant fluctuations, indicating a change in physiological engagement. Significant physiological responses were defined using a threshold of 0.0048 µS, derived from Empatica's recommended 0.05 µS range and normalized to the study's scaled dataset [11]. Task complexity transitions were categorized by complexity levels (e.g., High → Low), and significant EDA changes were analyzed to assess adaptive responses.

Figure 1 provides an overview of the composition of the study sample. Most participants were male (73%) with a smaller percentage being female (27%). The participants were primarily graduate students (47%), with juniors (43%) and seniors (10%) making up the rest. Racial representation in the sample was predominantly Asian (53%), with White participants constituting 30%, Black participants 10%, and Latinx participants 7%. Regarding parental education, 77% of participants reported having parents with a bachelor's degree. Figure 3 shows prior VR experience by demographic group. Graduate students reported the highest familiarity with VR (3.14), indicating they may have had greater exposure to VR technology compared to juniors (2.69) and seniors (1.67). Gender differences were also observed, with male participants having a higher familiarity score (3.05) than female participants (2.29). Among racial groups, Asian participants exhibited the highest familiarity (3.13), followed by White (2.56) and Black participants (2.33), with Latinx participants reported the lowest familiarity (2.00). Interestingly, individuals whose parents do not hold a bachelor's degree had a slightly higher VR familiarity score (3.14) compared to those whose parents do (2.70). These findings suggest that VR familiarity may be influenced by education level, gender, race, and parental education, though findings are not generalizable due to the sample size of this study.

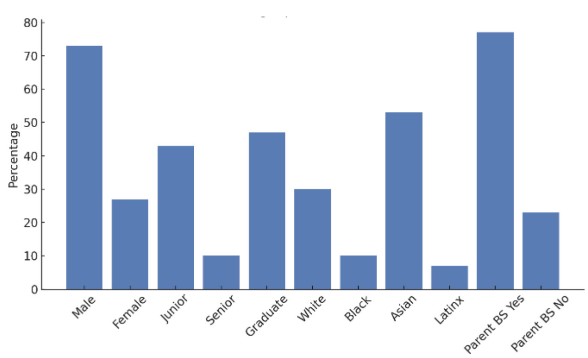

Figure 2: Demographics distribution of the participants.

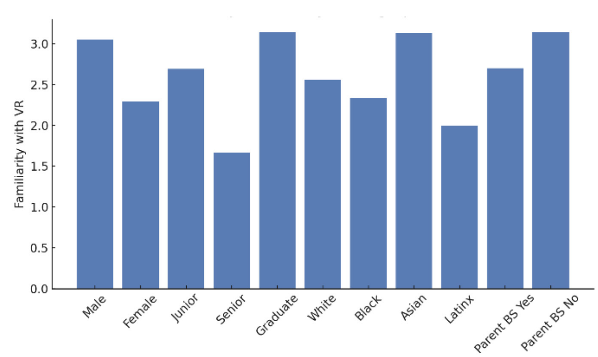

Figure 3: Familiarity with virtual reality by demographic factor.

5. Results

5.1 Statistical Correlation Testing

Statistical testing using the Kruskal-Wallis H test revealed significant differences in EDA changes across transitions ($H = 27.14$ and $p = 0.0007$). This non-parametric test was selected due to the non-normal distribution of EDA data across groups. Post hoc Mann-Whitney U tests with Bonferroni correction showed further insights. Two significantly different pairs were identified: High → High vs. Low → Low ($p = 0.0101$), and Medium → Low vs. Low → Low ($p = 0.0076$). The results indicate distinct physiological responses in these specific transitions.

5.2 Electrodermal Activity Changes During Task Transitions

Significant fluctuations in EDA were observed across different task complexity transitions. Figure 4 presents the percentage of transitions resulting in significant EDA increases or decreases relative to total transitions. Imbalances in transition frequency were observed, with some transitions occurring more frequently than others, as shown in Table 2. For example, Low → Low transitions were the most common with 42 occurrences, while a High→ High transition only occurred three times. This imbalance reflects the structured nature of task sequencing, where participants often completed consecutive tasks in a similar order, repeating certain transitions more often than others.

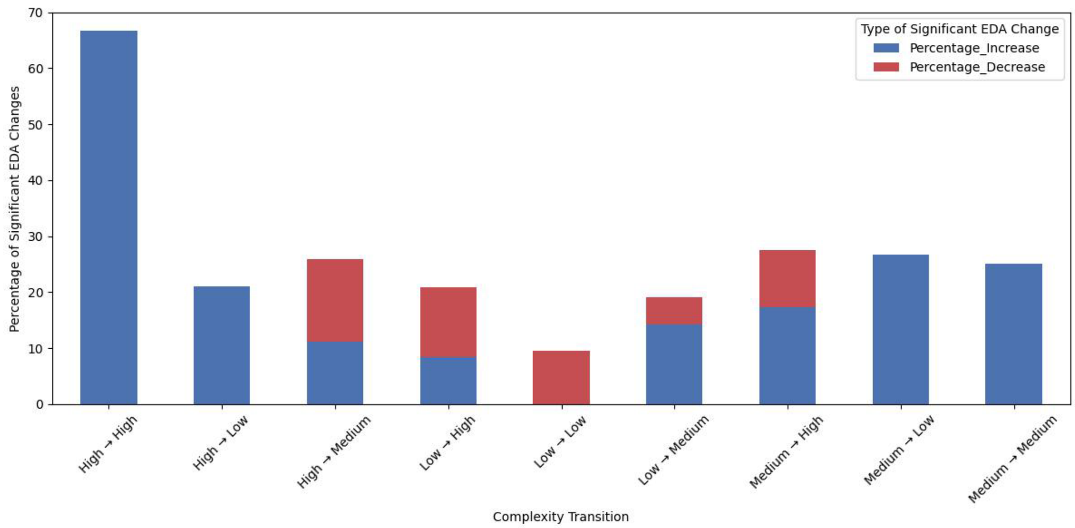

Figure 4: Percentage of significant EDA change during transitions between tasks.

Table 2: Significant EDA changes by task transition

	High to High	High to Low	High to Medium	Low to High	Low to Low	Low to Medium	Medium to High	Medium to Low	Medium to Medium
Total Transitions	3	19	27	24	42	21	29	15	12
Total Significant Changes	2	4	7	5	4	4	8	4	3
Percent Significant Changes	67%	21%	26%	21%	10%	19%	28%	27%	25%
Significant Increases	2	4	3	2	0	3	5	4	3
Significant Decreases	0	0	4	3	4	1	3	0	0

The data presented in Figure 4 and Table 2 reveals important distinctions in physiological response patterns. High → High transitions, while rare, showed the highest proportion of significant changes overall (67%), consisting entirely of EDA increases, indicating that maintaining high complexity levels can also elicit substantial physiological responses. Transitions such as High → Medium and Medium → High showed more moderate proportions (26% and 28%, respectively), with more balanced distributions of increases and decreases. In contrast, Low → Low transitions had the lowest percent of significant EDA changes (10%), with all four being decreases in EDA, suggesting reduced physiological reactivity during a low-complexity task. Notably, transitions involving reductions in complexity, such as Medium → Low, showed a predominance of EDA increases, as reflected in Figure 4.

5.3 Correlation Between EDA Changes and Performance

Figure 5 showcases a comparison of percent changes in normalized EDA during task transitions by participant performance level. Three performance metrics were considered: part selection accuracy, assembly accuracy, and car completion score. These metrics were summed and averaged per participant to achieve a composite performance score. Participants were classified into high and low performance based on the median performance value. As shown in the plot, lower performers (blue) are shown to exhibit greater variability in percent EDA changes, with a wider range and more extreme outliers. Some extreme outliers in the low-performance group exceeded the graph's y-axis range and are not visible in the plot window. In contrast, high performers (green) display more stable physiological responses, with percent changes closer to zero and fewer extreme deviations.

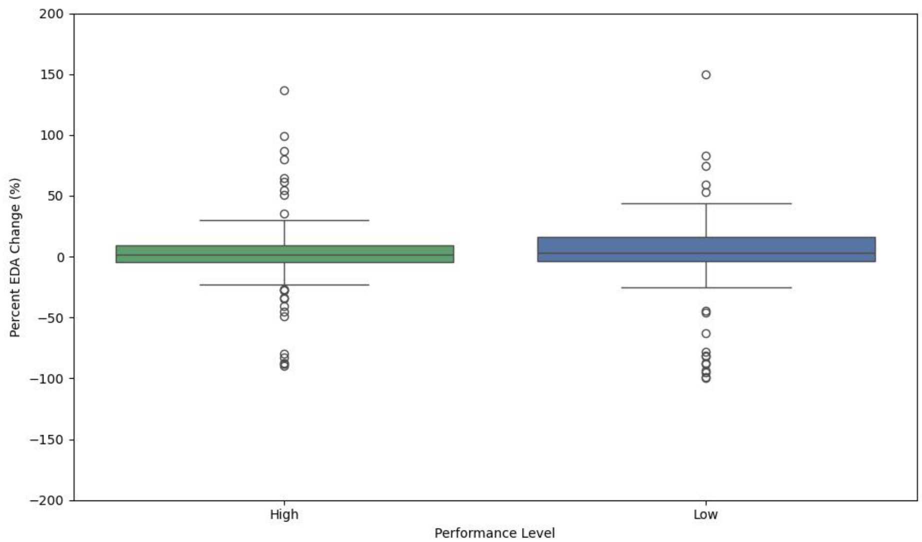

Figure 5: Comparison of percent EDA changes during task transitions between high and low participant scores.

6. Conclusions

The findings of this study offer insights into the relationship between task complexity, EDA responses, and adaptive problem-solving behaviors within multiplayer virtual reality manufacturing environments. The analysis of EDA fluctuations during task transitions highlights how physiological responses are influenced by changes in cognitive demands and task structure. EDA responses varied substantially by transition type, revealing consistent physiological patterns across the dataset. Transitions that sustained high-complexity tasks (High → High) produced the strongest engagement, with 67% of transitions showing significant EDA increases, although this trend should be interpreted with caution due to the small sample size. Downward transitions such as Medium → Low and High → Low also elicited consistent increases, suggesting that cognitive downshifting may trigger engagement, potentially due to abrupt shifts in effort or task context. In contrast, Low → Low transitions showed only decreases in EDA, indicating disengagement during repetitive low-effort tasks. Transitions into higher complexity (e.g., Low → High) resulted in more mixed responses, potentially reflecting anticipatory coping or familiarity. Collectively, these trends suggest that both sustained challenge and task simplification can elevate physiological engagement, while repetition in low-demand contexts suppresses it. The boxplot analysis presented in Figure 5 comparing EDA changes in task transitions between high and low performers revealed that low performers had greater physiological variability and more extreme outliers, while high performers showed more stable responses. This suggests that high performers may possess more effective adaptive strategies, enabling them to better regulate physiological arousal during task transitions, even when faced with complex or rapidly changing tasks. The presence of extreme outliers in the low-performance group indicated that some individuals may struggle with adaptive regulation, in turn emphasizing difficulties in maintaining consistent cognitive control and focus. This relationship between EDA variability and performance emphasizes the importance of regulating stress and engagement levels to optimize performance in dynamic environments.

Statistical testing supported the observed trends. A Kruskal-Wallis H test confirmed significant differences in EDA changes across transition types ($H = 27.14$, $p = 0.0007$), and post hoc comparisons revealed that both High → High and Medium → Low transitions differed significantly from Low → Low transitions. However, other task transitions did not have statistically significant results from the post hoc comparisons. These findings reinforce that not all task shifts are equal in their physiological impact and show the importance of transition structure in adaptive performance. While this study provides valuable insights, it is important to acknowledge limitations. The reliance on EDA as the sole physiological measure may overlook other relevant indicators of cognitive and emotional stress. Future research should explore measurements such as heart-rate analysis and eye-tracking, to gain a more comprehensive understanding. Additionally, EDA data was limited to a small sample size which affects the generalizability of the findings. Finally, stress may occur due to outside factors, so while the study identifies a correlation between EDA fluctuations and adaptive problem solving, it cannot conclusively establish a causal relationship. This research highlights the potential of VR environments as powerful tools for studying adaptive problem-solving in manufacturing contexts. The ability to track real-time physiological responses provides a nuanced view of how individuals navigate complex tasks, offering practical implications for training programs aimed at enhancing cognitive flexibility and stress management in high-stakes industries. These findings can inform the design of adaptive training in manufacturing, emphasizing the need to manage cognitive load during task transitions.

Acknowledgments

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