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Exploring Human-Human Teaming and Human-Machine Interaction in a Collaborative Virtual Learning Factory

Mrs. Rumena Begum, University of Louisville

I am Rumena Begum, a PhD candidate in the Department of Industrial and Systems Engineering at University of Louisville. I completed my MS in Industrial and Management Systems Engineering from Montana State University, USA, and my BS in Industrial and Production Engineering from Shahjalal University of Science and Technology, Bangladesh. My research interest include human-machine interaction, systems engineering, computational modeling, machine learning, and artificial intelligence.

Dr. Faisal Aqlan, University of Louisville

Dr. Faisal Aqlan is an Associate Professor of Industrial Engineering at The University of Louisville. He received his Ph.D. in Industrial and Systems Engineering form The State University of New York at Binghamton.

Dr. Marci S. Decaro, University of Louisville

Marci DeCaro is an Associate Professor in the Department of Psychological and Brain Sciences at the University of Louisville. DeCaro's research applies principles of cognitive psychology to study learning and performance in educational contexts.

Dr. Hui Yang, Pennsylvania State University

Dr. Hui Yang is a Fellow of IISE, a Professor of Industrial and Manufacturing Engineering, Biomedical Engineering at Penn State, and is affiliated with Penn State Cancer Institute (PSCI), Clinical and Translational Science Institute (CTSI), Institute for Computational and Data Sciences (ICDS), CIMP-3D. He is a recipient of the prestigious NSF CAREER award and Fulbright Award. Currently, he serves as the director of NSF Center for Health Organization Transformation (CHOT).

Dr. Richard Zhao, University of Calgary

Dr. Richard Zhao is an Assistant Professor in the Department of Computer Science at the University of Calgary. He leads the Serious Games Research Group, focusing on games for training and education, including artificial intelligence, virtual reality, and eye-tracking technologies. Dr. Zhao has served as a program committee member on academic conferences such as the International Conference on the Foundations of Digital Games (FDG), the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (AIIDE), the IEEE Conference on Games, and the ACM Special Interest Group on Computer Science Education (SIGCSE) Technical Symposium, and as a reviewer for the ASEE Annual Conference.

Jason J Saleem, University of Louisville

Jason J. Saleem is an Associate Professor with the Department of Industrial Engineering at the J.B. Speed School of Engineering at the University of Louisville. He is also a Co-Director of the Center for Human Systems Engineering (CHSE). Dr. Saleem received his Ph.D. from the Department of Industrial and Systems Engineering at Virginia Tech in 2003, specializing in human factors engineering and ergonomics. Dr. Saleem's research interests focus on the integration of human factors engineering with the development of health information technology (HIT). His research also focuses on provider-patient interaction with respect to exam room computing, as well as virtual care tools and applications. Dr. Saleem also maintains an engineering education research portfolio and in 2024 was awarded a grant by the National Science Foundation (NSF) entitled, 'Introducing a Mixed-Methods Approach to Engineering Students through Human-Centered Design'.

P. Karen Murphy, The Pennsylvania State University

Dr. P. Karen Murphy is a Distinguished Professor of Education at The Pennsylvania State University, where she serves as Associate Dean of Research and Outreach in the College of Education. Dr. Murphy is an elected member of the National Academy of Education and a Fellow of both the American Educational Research Association and the American Psychological Association. Her research focuses on the role of critical-analytic thinking in the processing of disciplinary content, including the development and implementation of interventions such as Quality Talk that maximize the effects of reasoning and classroom discussion on students' problem solving and content-area learning.

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Abstract
The rapid advancements in manufacturing technologies and the growing need for a skilled workforce have emphasized the importance of innovative approaches to manufacturing training. Traditional methods often lack the flexibility to conduct virtual training and collaborative tasks in the event of disruptions (e.g., pandemics) as well as sensor tracking measures to study problem-solving. To address these challenges, this study develops a collaborative virtual learning factory to enhance the learning of manufacturing systems and analyze human-human teaming and human-machine interaction. The development of the virtual factory involves creating a virtual reality environment that simulates the physical assembly of car toys, replicating key manufacturing paradigms such as craft production, mass production, mass customization, and personalized production. The virtual factory offers an immersive and interactive virtual environment where learners can engage with manufacturing systems, gain hands-on experiences, collaborate with peers, and develop problem-solving skills. The virtual factory also incorporates collaborative features such as a voice system for facilitating communication among participants, team-wise performance requirements for proceeding towards subsequent manufacturing paradigms, and interdependency among participants in the production line. This allows participants to work together on manufacturing tasks which enhances teamwork and communication skills. A study was conducted with 30 participants who completed a series of assembly tasks to produce car toys in the virtual factory. Participants' collaboration and interactions with the system were recorded, and both quantitative data including physiological signals (e.g., heart rate and electrodermal activity) and performance measures (e.g., perception of workload and system usability) were collected. Analyzing the data revealed that higher physiological synchrony among the members of a group indicates better performance in task execution, which emphasizes the importance of physiological alignment for team performance. A significant negative correlation ($r = -.60$, $p < .05$) was found between workload and system usability. The study has the potential to improve user experience by enhancing system usability and reducing user workload.

Keywords: Virtual learning factory, manufacturing systems, sensing technology, teamwork, human-machine interaction

1. Introduction

The primary goal of any production system is to achieve an optimally configured and stable process at minimal cost. Achieving this goal requires years of experience or targeted research addressing critical factors, including flexibility, adaptability, and safety [1]. These requirements, combined with the complexities of designing and redesigning human-human teamwork and human-machine interaction, make the process increasingly error-prone [2]. Time-based simulations provide a safe virtual environment for testing and validation, simplifying these complexities. Additionally, simulation-based learning bridges the gap between different disciplines by offering practical insights into how decisions in such disciplines impact each other throughout product development, manufacturing, and market [3]. However, traditional simulations lack the immersive experience needed for end-users to fully engage with the system.

Virtual reality (VR) bridges this gap by enabling highly immersive, interactive experiences, allowing users to engage with realistic, three-dimensional environments that improve learning and data retention beyond the constraints of the physical world [2, 4]. VR can enhance production processes by allowing designers to create virtual prototypes, test multiple design options, and identify issues before physical implementation, which saves them time and reduces cost [2]. Additionally, VR simulations help optimize workflows by identifying inefficiencies in material, equipment, and workforce allocation, ultimately increasing efficiency and minimizing waste. Moreover, VR supports both individual and team-based experiences to enhance collaboration in the virtual workspace. Teams—defined as “distinguishable sets of two or more people dynamically interacting and adapting toward a common goal” [5]—benefit from VR by enhancing interactions, cohesion, and performance [6, 7].

Human-machine interaction (HMI) is critical for ensuring process safety, quality, and efficiency in automated and complex systems [8]. Additionally, system usability is crucial to better align the VR environment with user needs and industry requirements [9]. As automation advances, the human role shifts from a controller to a supervisor, necessitating effective interfaces for communication and decision-making. Well-designed HMI is essential for supporting operators and ensuring efficient operations in dynamic technical environments.

To enhance operator performance and, consequently, overall system efficiency, it is essential to provide effective and interactive training [10, 11]. Therefore, this study develops a VR environment for human-centered production systems and seeks to answer the following research questions:

1) Does physiological synchrony in virtual reality teams impact performance during human-human collaboration?
2) How does the human-machine interaction in VR-based manufacturing environments impact perceived task load and system usability?
3) Does perceived system usability impact perceived workload?

2. Relevant Literature

VR offers a fully immersive environment that enables simulated learning experiences free from real-world distractions and better replicates collaborative scenarios and complex team interactions. Recent studies explored the use of VR in human-human team dynamics by integrating traditional frameworks and sensor-based measures to assess team efficiency and effectiveness, emphasizing factors like team composition, coordination, and prior VR experience [12]. On the other hand, a unified framework was proposed that integrates VR with human-robot simulations to enable human interaction with production equipment to address the challenges in designing flexible, adaptable, and safe human-robot workspaces [3]. By employing event-driven simulations, these frameworks support human-robot cycle time estimation, process planning, layout optimization, and robot control programming.

A study demonstrated the use of VR technology to simulate digital factories and enhance production efficiency by employing simulation software [11]. It showed how VR enables intuitive interaction with factory equipment, facilitating real-time assessment of layout efficiency, material flow, and ergonomics. Results included reduced production time and increased overall productivity, illustrating VR potential as a decision-making tool to improve production processes in digital factory settings. While our study does not focus on factory optimization, such works demonstrate the broader applicability of VR-enhanced collaboration and interaction, reinforcing the practical relevance of our virtual learning environment. A case study of a Simulation-Based Training (SBT) system was designed to train manufacturing operators, focusing on steel plant operations [13]. A hybrid simulation approach combining virtual process models with physical ones and human-machine interfaces to replicate real-time plant dynamics and operator interactions. It demonstrated the potential for enhancing safety and failure prevention and providing a lifelike and effective training experience, i.e., learning effectiveness in a virtual factory setting, which is the focus of the current study. An experimental framework was proposed for formalizing collaboration in virtual environments through VR-powered metaverses [14]. A VR system was developed by incorporating digital twins and avatar models, advanced interfaces, and an online multi-user system. It was tested in a metaverse-based smart factory, and the usability metrics provide insights into real-time user interaction and teamwork dynamics, key aspects of our research. An adaptive simulation method for human-robot collaboration in production engineering using VR was proposed [15], supporting our research on how VR facilitates human-machine coordination and teamwork. Leveraging gaming industry software and open-source approaches, it addresses VR limitations in industrial tools and enables realistic, immersive experiences with advanced hardware. A Unity-based prototype demonstrates feasibility, with future work focusing on formal validation through controlled studies. An immersive and interactive cyber-physical system framework was proposed using VR to enhance human-machine-autonomy collaboration in smart manufacturing [16]. Application of the framework augmented human skills via autonomy and deploying virtual human tasks to robots for automated programming. It showed its effectiveness in improving productivity and collaboration, reinforcing its role in enhancing human capabilities, a key aspect of our research on team performance in a VR factory.

3. Theoretical Framework

The proposed study aims to explore human-human teaming and human-machine interactions within a collaborative virtual reality environment, designed to enhance manufacturing training. Figure 1 represents the Conjecture Map [17] of this study. The high-level conjecture centers on investigating how these interactions impact task performance and collaboration in the VR environment. The design conjecture focuses on the immersive nature of the VR environment, which integrates manufacturing paradigms and collaborative features like voice communication and team-based performance requirements to promote teamwork. Theoretical conjectures examine the role of physiological synchrony in predicting team performance and the influence of human-machine interactions on cognitive load and system usability. This research aims to provide insights into optimizing operator training, enhancing team collaboration, and improving system efficiency in virtual environments.

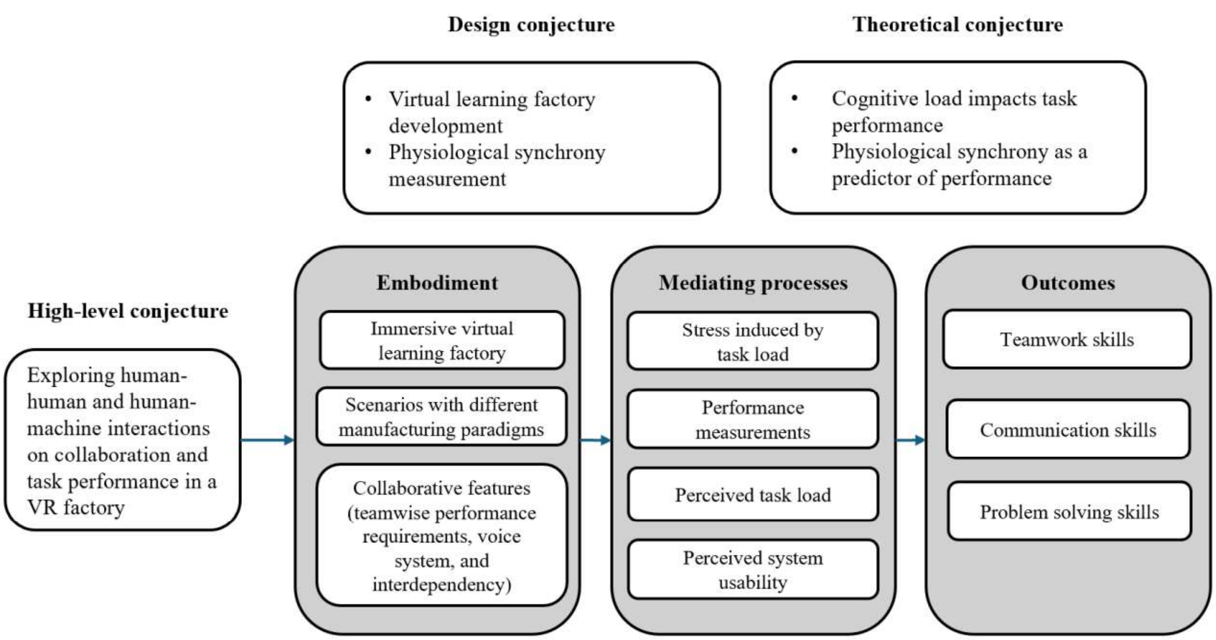


Figure 1. Conjecture map of the research in this study.

4. The Virtual Learning Factory

The virtual factory demonstrates the evolution of manufacturing paradigms, beginning with early-stage craft production and followed by mass production, mass customization, lean manufacturing, and personalized production. There are separate production rooms for each of the paradigms. Figure 2 shows an angled top view of the virtual factory. Additionally, there is a tutorial room with two workstations where participants can practice basic manufacturing tasks and become familiar with the VR environment. There is also a storage room in which the completed products are stored. Figure 3 shows the factory hub.

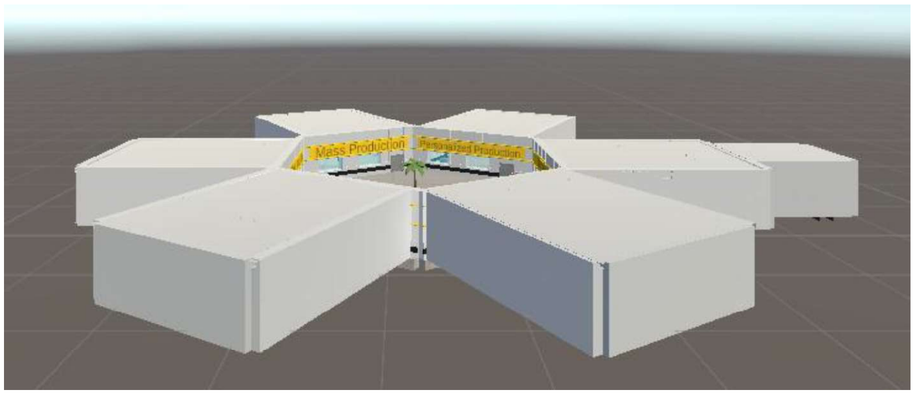


Figure 2. A top view of the virtual factory.

Figure 3. Part of the hub of the production rooms in the virtual factory.

The virtual factory was developed in Unity engine, with multiplayer designed using Photon. Participants can order, build, and package toy cars. The environment is compatible with different headsets, see Figure 4. A user does not need to physically walk around, since the physical space around the user can be limited. By using the controllers, a user can teleport (move instantly) to any location in the room. Every user is represented with a virtual character in a black body suit. However, a diverse set of characters is envisioned to be created in the future, along with the ability for each user to choose their virtual character. As a user works through the simulation, the system tracks the user's eye movements, including fixation points, latencies, and saccades. The eye-tracking data is used to model attention and metacognitive processes.

Figure 4. HTC Vive VR headset (left) and the Oculus Rift headset (right).

Tutorial Room: Once participants enter the virtual factory, they start with the tutorial room, see Figure 5, where they get introduced to the virtual factory with audio instructions on how to interact with the virtual manufacturing system and the different tasks such as ordering, picking up/dropping, and connecting pieces for the car toy.

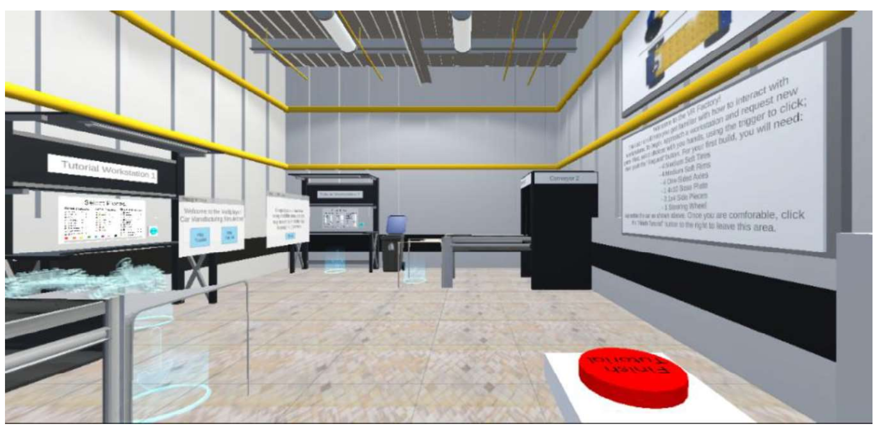


Figure 5. Tutorial room in the virtual factory.

After finishing the tasks in the tutorial room, participants press a button to start the move to the other factory rooms. The tutorial room has a set of instructions and includes two workstations, see Figure 6, each with a designated conveyor belt, assembly table, and trash bin. Workstations feature a selection board with 27 different options available in eight colors. At each station, users interact with a virtual screen displaying various plastic bricks. Selection is performed by pointing at a piece using the controller. Once selected, the chosen parts move on the conveyor belt to the workstation, allowing users to assemble them as needed. Unused components can be discarded in the trash bin. Upon completing the assembly of the car toy, users press the “Finish Assembly” button, and the workstations provide real-time feedback on the price and weight of the assembled build, ensuring that participants meet the required specifications.

Figure 6. Workstation in the tutorial room in the virtual factory.

Storage Room: In the storage room, completed products (car toys) can be displayed, see Figure 7. There is a robot in the storage room capable of using generative AI to guide the users on the assembly tasks.

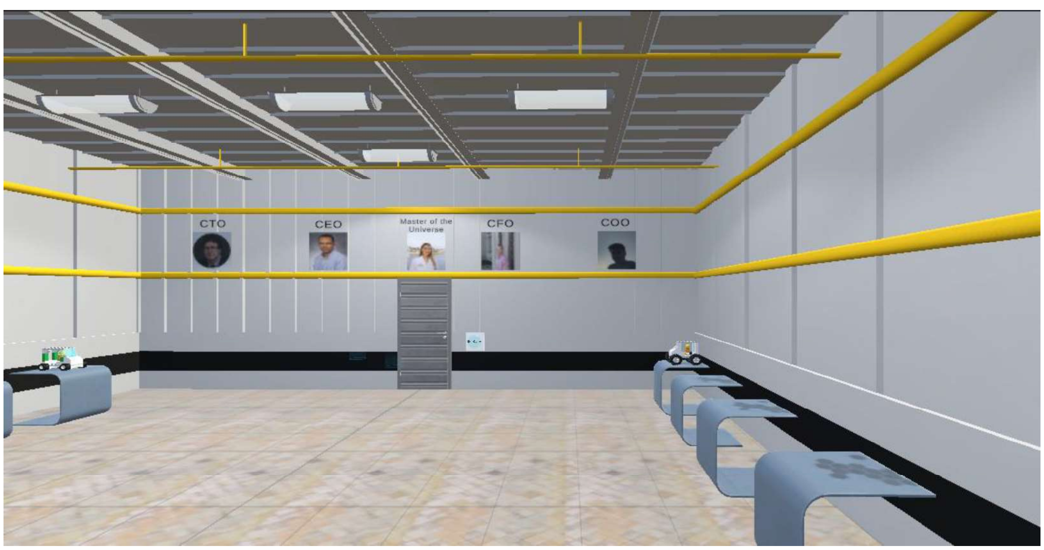


Figure 7. Storage room in the virtual factory.

Craft Production Room: From the VR factory hub, participants can enter the craft production room and see four workstations, as shown in Figure 8. Each workstation has its own set of requirements (see Figure 9) for the toy car (e.g., color, size, tire type, price, and weight). At each station, the participant is presented with a screen of different parts to choose from. The participant then selects the parts and builds the car toy.

Figure 8. Craft production room in the virtual factory.

Figure 9. Craft production room workstation.

Mass Production Room: The mass production room follows the post-industrial revolution traditional layout of an assembly line, see Figure 10. The room has four workstations, each connected by a conveyor belt to move parts between the stations. At each station, a user is tasked with assembling different parts of the car toy, moving from tires to base, side walls, and roof, before passing the subassembly off to the next station. Two available car options can be produced, see Figure 11. In the first station, a user is tasked with assembling the base of the car. In the second station, a user is tasked with assembling the sides of the car. In the third station, a user is tasked with putting the windshield, roof, and steering wheel on. Finally, the last station is tasked with adding the axles and wheels before moving the car toy to the inspection station, where the price and weight of the car toy are checked. Unlike craft production, mass production has a limited number of car toy designs. Further, requirements for completion are much stricter, as pieces must be the right color and located in the correct place.

Figure 10. Mass production room in the virtual factory.

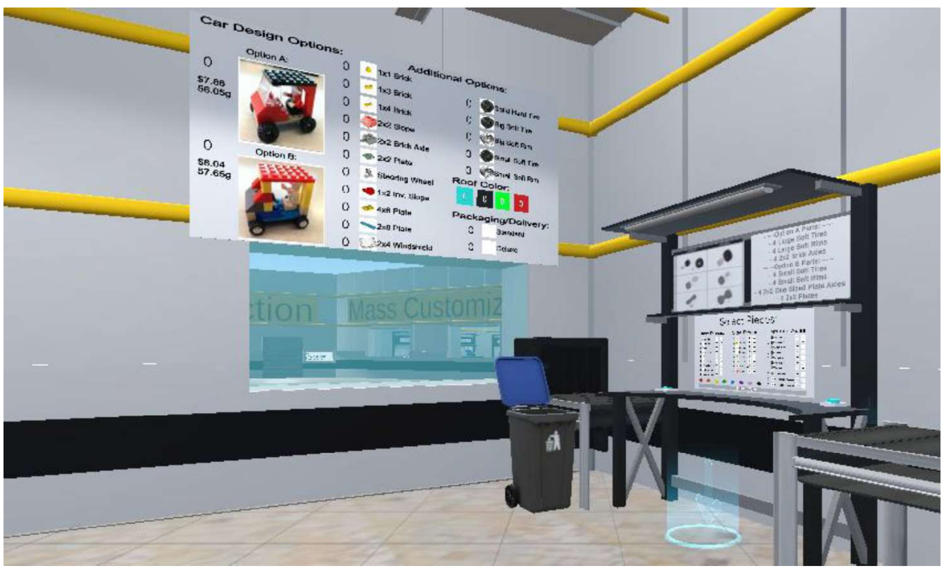


Figure 11. Mass production workstation in the virtual factory.

Mass Customization room: The mass customization room produces a variety of car toys that satisfy specific customer requirements, and at the same time maintains the assembly production system to ensure high production volume. Unlike mass production, mass customization offers the customers a variety of design options to choose from. The mass customization room includes four workstations, each connected by a conveyor belt to move pieces between the stations (see Figure 12). At each station, a user is tasked with assembling different parts of the car according to customer requirements. In workstation 1 (see Figure 13), participants perform the 'axle assembly' task in which they assemble the wheel, axles, and flats. Wheels are of various types – large, hard, or soft. In workstation 2, participants perform the 'frame and chassis assembly' task in which they assemble flats of different sizes to prepare the frame and then assemble the frame with axles to prepare the chassis. In workstation 3, the "hood and fender" assembly, the "windshield" assembly, and then attach them to the axle/frame assembly and the steering wheel.

In workstation 4, the roof is prepared. There are a variety of colors of the roof to choose from based on customer requirements. Finally, the roof is attached to the body sub-assembly received from workstation 3. Once the car is completed, it is moved to the inspection station to determine the price and weight.

Figure 12. Mass customization room in the virtual factory.

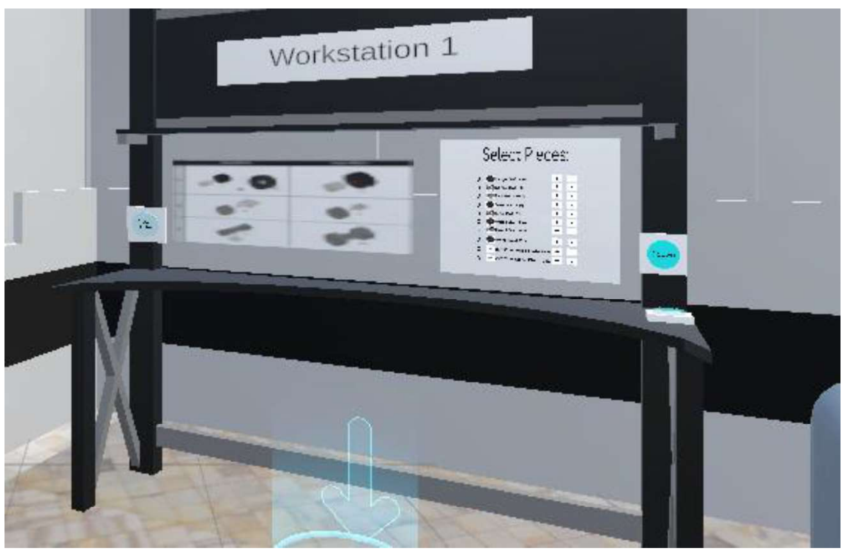


Figure 13. Workstation in the mass customization room in the virtual factory.

Lean Production Room: In the lean production room, teams will have 20 minutes for Kaizen. Areas for improvement include reducing work in progress and waste by physically limiting storage space, balancing line build activities based on takt time, creating visual guides to avoid common mistakes, and combining or reducing positions or stations to improve organization. The lean manufacturing room is shown in Figure 14.

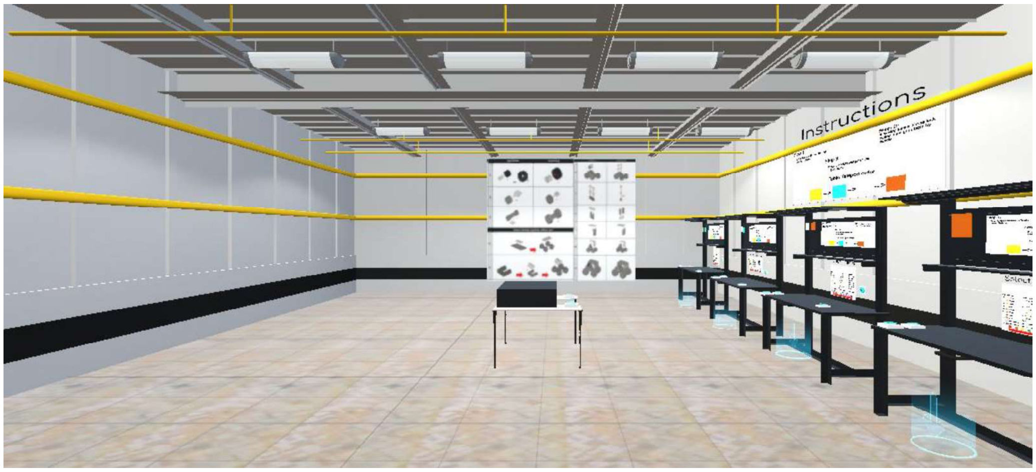


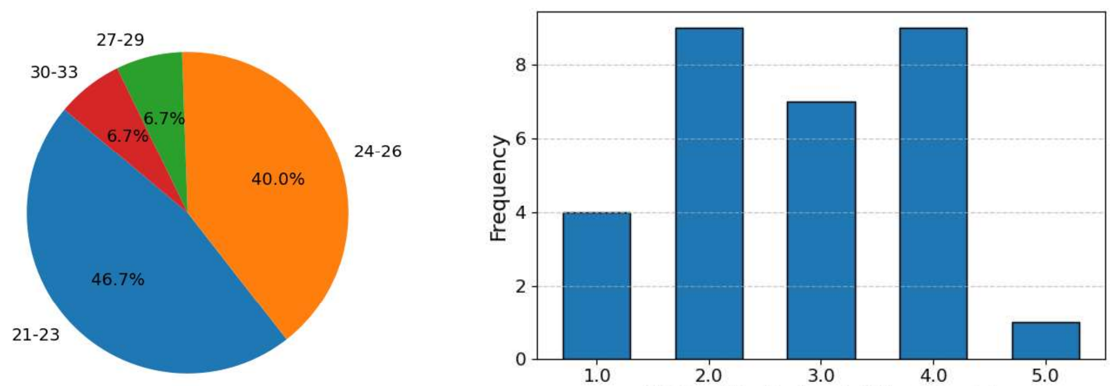
Figure 14. Lean production room in the virtual factory.

Personalized Production Room: The personalized production room produces a high variety of products that fit specific customer needs. Unlike the mass customization paradigm, where customers only select from lists of available options, personalized production involves customers in the design of products they want to buy. The product design has two phases. The initial phase is driven by strategic decisions made by the manufacturer to fit their facilities and strengths. In this phase, the product architecture and module interfaces are designed. In our personalized production room, initial design options are a car with a windshield, a car without a windshield, a sports convertible, or a pick-up truck. Basic modules include a variety of options for “hood and fender assembly”, “body sub assembly”, “roof assembly”, final assembly”. Once the customers select their preferred product features, the final tailored design takes place in the personalized design phase, in which a flexible and reconfigurable manufacturing system is utilized, as shown in Figure 15.

Figure 15. Personalized production room in the virtual factory.

5. Methods

Participants: 30 students (8 females and 22 males) with ages between 21 and 33 years old (mean = 23.17 years, SD = 2.83 years) participated in the study (see Figure 16a). Participants were engineering students with no or varied levels of prior VR experience (see Figure 16b). The study was approved by the University of Louisville's Institutional Review Board (IRB) #22.1089. Participants worked in the virtual factory in groups of three. Participants were provided with a brief introduction about the study, the VR environment, the use of VR headsets and controllers, the eye tracker, and wearable sensors. Participants read and signed an informed consent form and filled out the demographic survey and pre-experiment surveys.



a) b)

Figure 16. a) Age distribution of participants and b) distribution of VR familiarity levels.

Procedure: In this study, along with eye tracking data, participants' physiological data, such as electrodermal activity (EDA) and heart rate, were collected using an Empatica Embrace Plus watch. Participants started experiencing the virtual factory by walking through the tutorial room. After spending 10 minutes in the tutorial room, they moved to the craft production room and occupied three different workstations where they assembled the car toys. First, users selected the required pieces and then moved to the corresponding assembly stations to prepare the toy car. The users then determined the price and weight by pressing the finish assembly button. After spending around 45 minutes in the craft production room, participants completed post-experiment surveys such as NASA Task Load Index (TLX) and System Usability Score (SUS).

Data Collection: The physiological data recorded via the Empatica watches was collected from the Care Lab portal. Videos were also recorded from the virtual factory for each participant's activities. NASA TLX, a 6-question standardized survey with a rating of low to high, was used to determine the perceived task load. Each question asks for a rating of a different aspect of perceived task load, including mental demand, physical demand, temporal demand, performance, effort, and frustration level [18]. SUS, used for system usability assessment, is a 10-question standardized survey with a Likert scale of 0 to 4, where 0 corresponds to "Strongly Disagree" and 4 corresponds to "Strongly Agree" [19].

6. Results and Analysis

6.1 Human-Human Teaming

This study investigated the correlation between team physiological synchrony and team performance. Analyzing the recorded videos, various team performance measures were documented, such as the number of parts assembled correctly. Team physiological synchrony was assessed utilizing EDA and heart rate data. Dynamic Time Warping (DTW) of EDA and heart rate was calculated. DTW measures the similarity between two temporal sequences, even if they differ in speed, length, or timing. It was found that EDA_DTW and HR_DTW were negatively correlated with the average number of parts assembled correctly by the groups (see Figures 17 and 18, respectively). The correlation values are r_s = -0.75 (p = .01) and r_s = -0.63 (p = .05), respectively where r_s represents Spearman's Rho. This indicates that the more synchrony in the EDA and/or HR among the members of a group, the better their performance in assembling correct pieces. However, this does not necessarily imply that synchronization causes improved performance. Instead, it is possible that well-coordinated and high-performing teams naturally exhibit greater physiological alignment due to shared cognitive and emotional states, such as mutual engagement, focus, or stress regulation.

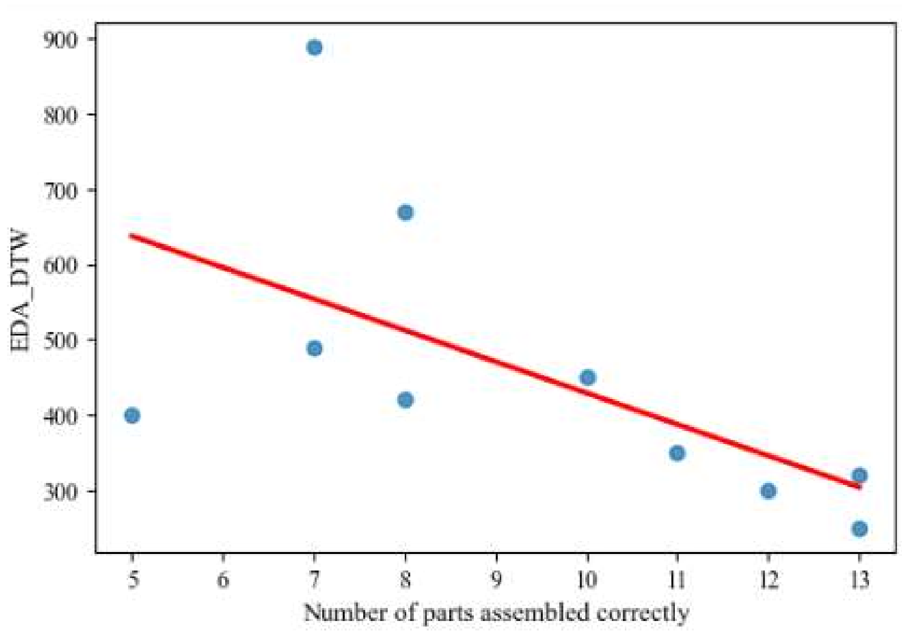


Figure 17. Correlation between Team EDA_DTW and No. of Parts Assembled Correctly.

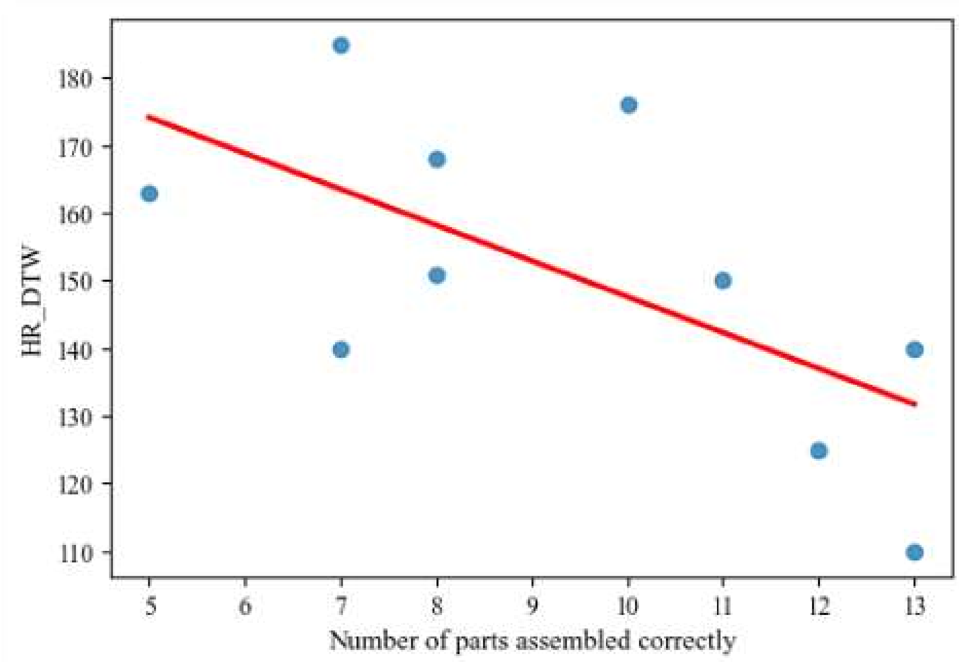


Figure 18. Correlation between Team HR_DTW and No. Of Parts Assembled Correctly.

6.2 Human-Machine Interaction

Workload Perception: As their perception of the different loads varies, participants' scores for the NASA TLX categories were weighted to account for individual preference [16]. This was done by pairwise comparison of the sources of load where participants were asked to select one source of load from each pair. The participant responses to the NASA TLX questionnaire were analyzed as follows (1) calculating the average score for each of the sources of load, (2) calculating the overall weights for each of the sources of load, (3) calculating the weighted score for each of the sources of load by multiplying the average rating by the overall weight of the corresponding source of load and then dividing the product by the sum of the weights, and (4) calculating the load sources' share of the overall workload which sums up to 100%. The average NASA TLX score was 60.76, indicating the workload was moderate.

System Usability: The SUS score is calculated between 0 and 100. The average SUS score was 53.75, indicating a relatively low system usability. Some users may have found the system challenging to navigate, especially if they had limited prior VR experience. Also, latency in interactions and object interaction mechanics may require refinement to enhance intuitiveness.

The NASA TLX and SUS scores were found to be negatively correlated ($r = -.60$, $p < .05$), as presented in Figure 19. This means that by enhancing system usability, user task load can be reduced, thereby improving user experience.

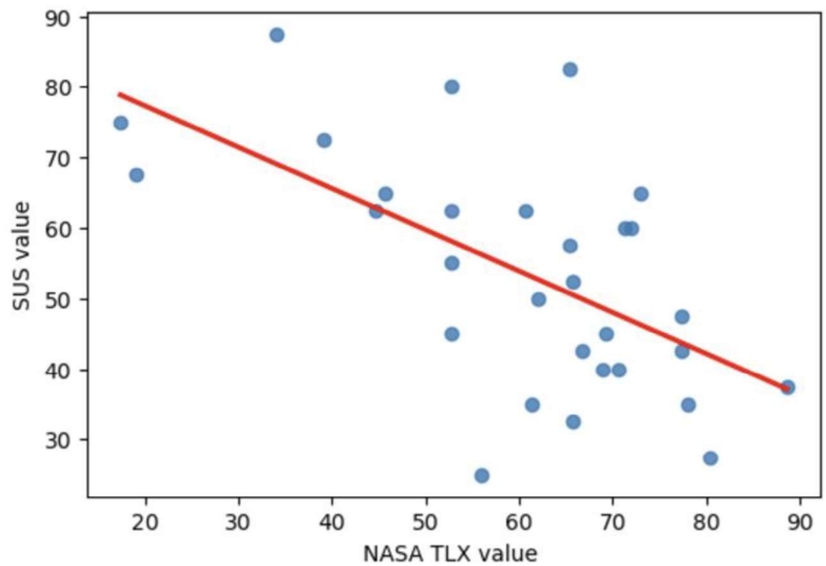


Figure 19. Correlation between NASA TLX and SUS scores.

7. Conclusions and Future Work

This study highlighted the transformative potential of VR in manufacturing by developing an immersive and interactive platform for training and collaboration. The integration of human-human teaming and human-machine within the virtual factory allows participants to engage with key manufacturing paradigms. Though the system usability score is relatively low, it provided insights into the possible reasons impacting participants' perception of the system. To improve usability and enhance user experience, future refinements should focus on optimizing the user interface design for better intuitiveness and enhancing VR interactions by reducing latency and improving object manipulation. Providing comprehensive onboarding and training can minimize the learning curve. Finally, conducting iterative user testing can help to refine task design and system responsiveness.

The findings underscore the importance of VR-embedded task engagement and physiological synchrony, such as alignment in stress responses, in improving group performance during assembly tasks, or vice versa. Future studies could manipulate synchronization by varying stress levels, task complexity, or team composition to analyze the impact on performance. Furthermore, temporal trends can be analyzed to determine whether synchronization precedes or results from high performance. This can be compared with subjective measures of team cohesion to explore underlying mechanisms.

Acknowledgments

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