

Behavioral Modeling of Collaborative Problem Solving in Multiplayer Virtual Reality Manufacturing Simulation Games

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Engineering is an inherently creative and collaborative endeavor to solve real-world problems, in which collaborative problem solving (CPS) is considered one of the most critical professional skills. Hands-on practice and assessment methods are essential to promote deeper learning and foster the development of professional skills. However, most existing approaches are based on out-of-process procedures such as surveys, tests, or interviews that measure the effectiveness of learning activity in an aggregated way. It is desirable to quantify CPS dynamics during the learning process. Advancements in virtual reality (VR) provide great opportunities to realize digital learning environments to facilitate a learning-by-doing curriculum. In addition, sensors in VR systems allow us to collect in-process user behavioral data. This paper presents a multiplayer VR manufacturing simulation game for virtual hands-on learning experiences, as well as a behavioral modeling method for monitoring the

CPS skills of participants. First, we develop the Virtual Learning Factory, where users play simulation games of various manufacturing paradigms. Second, we collected action logs from a sample of participants and used the same pattern to generate more data. Third, the behavioral data are modeled as dynamic networks for each player. Last, network features are calculated, and a CPS scoring method is driven from them. Experimental results show that the proposed behavioral modeling successfully captures different patterns of CPS dynamics according to manufacturing paradigms and individuals. This detailed assessment contributes to the development of appropriate student-specific interventions to improve learning outcomes.

NOMENCLATURE

P Players (categorical variable)
A Actions (categorical variable)
S Time stamp

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S_α Time stamp for action α
 μ_α Average time taken to complete action α
 $Y(u)$ Learning curve of produced units u
 a Parameter of $Y(u)$ equal to the initial time to produce the first product
 b Parameter of $Y(u)$
 L Learning curve percentage
 $G^{(p)}(t)$ Dynamic graph of player p at time t
 V Node list of all dynamic graphs representing actions
 $E^{(p)}(t)$ Edge list of dynamic graphs $G^{(p)}(t)$
 $M^{(p)}(t)$ Network-feature matrix of $G^{(p)}(t)$

1 INTRODUCTION

A hands-on curriculum is an essential part of engineering education that allows students to practice applying their classroom knowledge and technical skills to solve real-life challenges. Real-world problems are typically ill-defined and require problem-solving skills, referring to the cognitive process of finding a solution even though it is not obvious and uncertain [1]. Collaborative problem solving (CPS) requires two or more individuals to solve the problem together by sharing effort and understanding to develop a solution [2]. In engineering design and manufacturing, CPS focuses on optimizing product design and improving the production process. Fig. 1 illustrates the CPS framework and the pertinent cognitive/social processes. Both technical and professional skills, such as CPS, are indispensable to learning modern manufacturing systems [3]. Thus, experiential instruction in a group setting plays an important role in manufacturing education. For this reason, simulation games have gained the attention of researchers as a way to provide hands-on experiences and practices [4]. A simulation is a representation of a real-world system or process that demonstrates what would happen if the assumed conditions were to occur [5]. In addition, a rigorous assessment method is also necessary to monitor the learning activity and provide an appropriate intervention accordingly to optimize the learning process.

The learning factory concept was introduced and developed by the Manufacturing Engineering Education Partnership (MEEP) to provide a practice-based curriculum that enhances the educational experience in design and manufacturing [6]. However, the resources needed to create and operate learning factories are prohibitive; additionally, concerns over scalability, specificity, and flexibility have been raised [7]. Recent breakthroughs in VR technologies show great potential to realize digital learning factories and bring gamification to engineering education/training [8]. The price of VR devices has dramatically reduced, and standalone VR devices such as META

Quest 2 run without connected computers. VR is featured by its immersive and interactive 3D environment, making it a powerful tool for developing educational simulation games that provide virtual hands-on experience. In addition, modern game engines support the multiplayer function for VR games, which enables efficient implementation of simulation games in a group setting. Moreover, virtual reality (VR) has gained increasing interest as a tool for remote digital education, particularly in light of the COVID-19 pandemic. A recent study has revealed the adverse impact of online education during the pandemic on traditional, hands-on and design-oriented engineering education methods [9]. VR is a promising technology for improving online engineering education by providing virtual hands-on learning experiences.

One of the unique benefits of VR simulation games is the ability to collect data on student behavior and interaction through sensors in VR systems. This sensor-based behavioral data presents new opportunities for developing rigorous assessment methods for evaluating the dynamics of student learning processes, specifically CPS. In contrast, most existing assessment methods rely on surveys, tests, or interviews conducted before or after a simulation game, providing only an aggregated measure of the effectiveness of the learning activity. For instance, a physical simulation game was recently developed to teach key manufacturing concepts such as mass production, lead time, and production cost through hands-on experiences of assembling toy cars [10]. Participants completed a conceptual knowledge survey before the simulation game and subsequent surveys upon completion to measure posterior conceptual knowledge, analytical skills, and CPS. While these out-of-process data have proven useful in evaluating the effectiveness of learning modules, including the car-assembling simulation game, they are limited in their ability to analyze the detailed dynamics of the behavior of learners during the learning process. Additionally, survey-based data carries the risk of response bias from respondents whose answers may not accurately reflect their true thoughts or feelings.

Sensor data track the behavior of learners in the learning process, capturing the dynamics of user behavior, which enables the development of data-driven learning analytics. This paper presents a multiplayer VR manufacturing simulation game and introduces a novel behavioral modeling method to measure CPS from sensor-based in-process data. We developed the *Virtual Learning Factory* and designed a VR manufacturing simulation game for students to experience different manufacturing paradigms and concepts. Our study focuses on a universal type of behavioral data - a log of actions - which records the type and timestamp of each action.

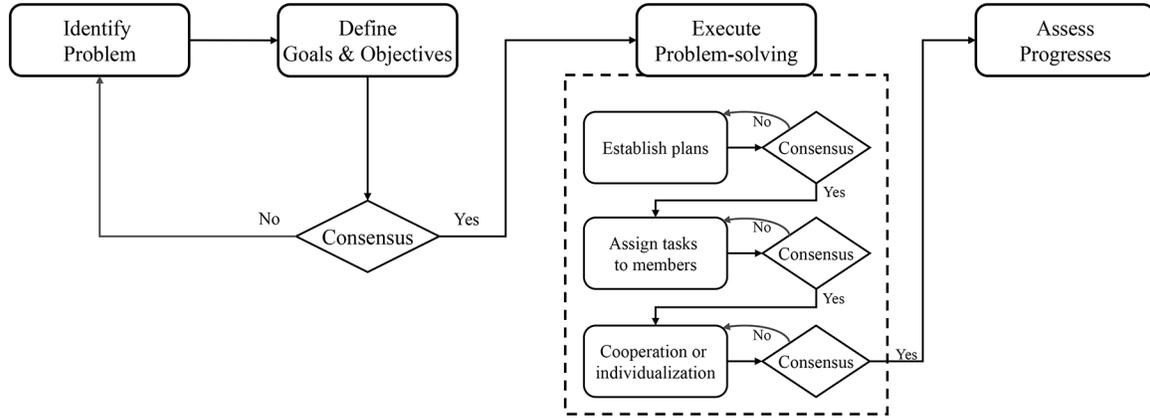


Fig. 1. Flowchart of the typical collaborative problem-solving process

With additional devices, it is possible to collect more specialized types of data, such as eye-tracking or facial-expression data, in VR environments. However, there is an urgent need to develop a learning analytics method for this basic form of data first. We collected action-log data from a sample of participants and used the same pattern to generate more data in two contrasting manufacturing paradigms: craft and mass production. The log data are modeled as dynamic networks for each player to represent user actions in graphs evolving over time. We extract the characteristics of the networks using multiple node-centrality features to form network-feature matrices. The heterogeneous-behavioral-CPS score is defined by the pairwise distance between the network-feature matrices of players, measuring graph similarity.

Experimental results show that the proposed behavioral modeling captures different CPS patterns of players in craft and mass production. By analyzing the temporal dynamics of CPS between students, it is possible to identify the characteristics and intervals of the manufacturing simulation game that have a significant impact on CPS outcomes. This study highlights the potential of VR for gamification in education and learning analytics. The *Virtual Learning Factory* provides immersive virtual hands-on experiences, maximizing the benefits of simulation games in education: learning by doing, promoting motivation, and enjoyment. The multiplayer function connects students from different physical locations. One key advantage of VR educational games is the availability of sensor data on student behavior. Analytical approaches to optimize learning processes have become an essential part of education. A rigorous quantitative assessment of CPS for each learner is crucial to monitor detailed dynamics within the group and develop effective training/learning modules for teaching manufacturing systems. The pro-

posed behavioral modeling of CPS provides a valuable tool to monitor learning processes and provide appropriate interventions.

2 RESEARCH BACKGROUND

2.1 Virtual Reality and Gamification in Education

Recently, VR technology has advanced rapidly and found successful applications beyond the gaming industry. It has shown the unprecedented potential to change our everyday lives in various areas, including education [11], simulation job training [12], cognitive and behavioral therapies [13], and more. Simulations and games have long been of interest to researchers in education due to their benefits, such as learning by doing, engaging learners, and promoting motivation [14]. They also allow students to apply theories learned in the classroom and foster the development of professional skills [15]. VR enhances these benefits by providing immersive and interactive learning environments. In the literature, VR has been utilized for educational gamification including, English [16], art [17], mathematics [18]. This feature is particularly beneficial for the science and engineering fields where practice-based curriculums are essential for understanding the subjects [19]. A major Mexican utility company developed a VR live-line maintenance training program for lineworkers [20]. This study shows that the VR program is effective in teaching highly hazardous activities that carry the risk of electric shocks and requiring costly training infrastructure. VR is also bringing innovations to manufacturing in digital design, training, and maintenance [21]. In manufacturing education, VR e-learning materials were created and tested for demonstrating safety procedures and operations of manufacturing machines, such as CAD equipment, as supplemen-

tal modules for a junior-level manufacturing processes course [22]. A basic multiplayer car-assembling simulation game was developed in [23].

2.2 Behavioral Data in Virtual Reality Environments

Learning analytics is a field of study that involves measurements, collections, and analyses of data to understand the cognitive processes and behaviors of learners as well as relevant contexts, materials, and environments to optimize learning processes [24]. In addition to gamification, another primary advantage of using VR is the availability of sensor-based in-process data on user behavior and interaction. For example, in the Lineworkers Maintenance Program, more than 20 variables such as user profiles, course information, tool selections, and evaluations are collected from the trainees [20]. The authors use machine learning classification and prediction models for the performance assessment. However, this is a supervised learning task that requires a labeled dataset (i.e., post-game evaluations) and usually a large amount of data to ensure performance, which is not always available. There are additional limitations: 1) these models are more concerned with accurate predictions and classifications rather than explaining structures and characteristics of data; 2) they are not able to handle temporal dynamics.

A systematic review study found that the main uses of VR in higher education are for teaching procedural-practical knowledge (33%), such as extinguishing fires, and declarative knowledge (25%), such as memorizing relevant names or concepts [25]. In manufacturing education, VR is often used in limited ways as supplementary material for teaching static knowledge rather than fully simulating the entire process. For instance, VR is used to demonstrate the safety procedures and operations of machines [22]. Little has been done to develop sensor-based learning analytics methods to investigate learner behavior in VR environments. In our recent study, we developed a single-player VR toy-car assembling simulation game and collected eye-tracking data as well as performance metrics such as production time or cost [26]. While a method for modeling problem-solving skills is proposed, it is limited to evaluating final assessment results and does not provide dynamics of problem solving during the simulation game.

2.3 Collaborative Problem Solving

CPS is considered one of the most important 21st-century skills for engineering students to succeed in a fast-paced digital age [27]. A superficial meaning of the term "collaboration" refers to individuals working together, but collaborative works include multiple dimen-

sions, such as metacognitive task regulation, knowledge-building skills, and team communication [28]. CPS is a technical term that includes various dimensions of strategic collaborative problem-solving skills [29]. This essential skill is important in handling complex engineering problems [30], e.g., large-scale manufacturing problems. Although quantitative assessments are essential to rigorously monitor students' learning progresses for detailed insights into CPS dynamics within a group, collaborative learning environments are usually evaluated by out-of-process data or qualitative analyses [31]. For example, the effect of a gamified quiz system for collaborative learning in primary school is evaluated by 5-point-scale surveys [32], and assessment methods of the group effectiveness on problem solving are developed based on questionnaires [33] and surveys [34]. Although out-of-process and qualitative evaluation methods have been useful tools for analyzing collaborative learning, they are not able to capture temporal dynamics in terms of scores, which are necessary for real-time monitoring and providing appropriate interventions.

3 METHODOLOGY

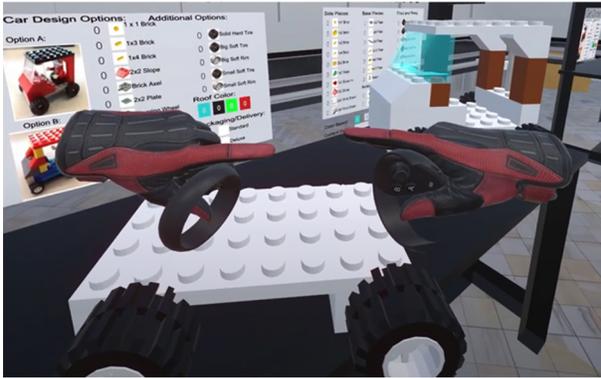
3.1 Virtual Learning Factory

The *Virtual Learning Factory* is a multiplayer VR manufacturing simulation game, enabling users to work together in assembling toy cars. Utilizing the Unity game engine and Photon Unity Networking package, the virtual learning space allows students from different physical locations to join the learning factory and learn different manufacturing paradigms and foster the development of professional skills. During game play, users are immersed in the virtual environment and work in groups to assemble toy cars that satisfy pre-specified customer requirements. The game employs a client-server architecture for synchronous access, with the first computer to launch the game acting as the hosting server. Subsequent computers connect as clients using a room number identifier. This approach reduces costs compared to maintaining a constantly-running server, as the server is created on-demand by the first computer running the game.

The virtual learning space comprises six rooms. Each of the five rooms is designed to experience a different manufacturing paradigm: craft production, mass production, lean manufacturing, personalized production, and mass customization; the final room serves as a storage area for completed toy cars. Fig. 2 shows screenshots of the factory and assembling a toy car from the perspective of a user. Through the simulation game, students assemble toy cars in the five manufacturing rooms, following the specific principles and processes of the corresponding



(a)



(b)

Fig. 2. Screenshots of the Virtual Factory: (a) outside view showing the craft production, mass customization, lean manufacturing rooms, and (b) the perspective of a user assembling a toy car in the craft production room

paradigm. In the craft production room, players assemble toy cars individually. Each student must order all necessary parts, assemble them into functional toy cars, package them, and ensure they are delivered to the customer using their preferred shipping method. This simulation challenges users to work efficiently and effectively alone with marginal collaboration with other students through all stages of the production process, from sourcing materials to fulfilling an order.

In contrast, students collaborate to assemble toy cars in the mass production room, where the entire production process is divided into multiple stations along the assembly line. Users can optimize the assembly line process in the lean manufacturing room by rearranging assembly stations. Players have the flexibility to optimize the assembly line process in the lean manufacturing room by rearranging assembly stations. The personalized production room builds on the concepts learned in the craft production room by introducing the added challenge of as-

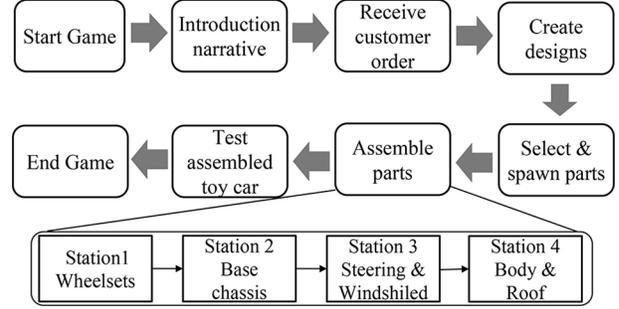


Fig. 3. Scenario of the proposed multiplayer manufacturing simulation game and four stations of the assembly process

sembling a variety of personalized toy cars to meet specific customer orders. Mass customization is a hybrid system in which students collaborate to produce customized toy cars at scale. This simulation allows users to practice balancing the need for efficiency and speed of mass production with the flexibility and customization requirements, which closely mimics the real-world scenario of a manufacturing plant. Fig. 3 illustrates the scenario of the car-assembly game.

3.2 Dynamic Behavioral Modeling

The *Virtual Learning Factory* requires a VR headset, wireless controllers, and base stations to position users in a virtual space and track their motions. This study focuses on simulating two essential manufacturing paradigms, namely craft and mass production. In craft production, users work individually to assemble an entire toy car, implying low collaboration. In mass production, participants divide their work among four stations - wheelsets, base chassis, steering & windshield, and body & roof - to maximize utilization of the assembly line. This represents high problem-solving skills and collaboration.

Action-log data track specific actions of interest and time stamps when they occur throughout the simulation for each user, i.e., a data frame with three variables: player P , action A , and time stamp S . Four players work together for each simulation game in the craft and mass production room, hence P is a categorical variable with four levels, $\{Player1, Player2, Player3, Player4\}$. We track four actions, so A is also a categorical variable with four levels, $\{Spawn, Move, Assemble, Pass\}$. When one of actions in the levels of A occurs, we record the time, referred to as time stamp S , which is the amount of time that has passed since the game started. The time taken to perform each action is modeled probabilistically using an expo-

ponential distribution, such that $S_\alpha \sim Exp(\mu_\alpha)$ where μ_α is average time for action $\alpha \in A$. Note that this is a universal data type available in most digital learning environments, different from pre-designed variables with specific research purposes. This fact makes analysis difficult, i.e., extracting insights from generic data, but meanwhile, it means the proposed method is applicable more broadly. Then, the log for each player is modeled as a dynamic network with the four actions as nodes.

The concept of learning curves is incorporated in the probability models of the time for actions. The production process generally becomes more efficient as a learner gains experience. Learning curves quantify this gain in efficiency as the number of units produced increases. A learning curve, which represents the time required to produce the n th unit, is defined by Eqn. (1). This curve is characterized by two parameters a and b . Usually, learning curves are described by the percentage L of time required to produce twice of unit u as in Eqn. (2). Therefore, parameter a is equal to the initial time to produce the first product, and b is determined by the learning-curve percentage as in Eqn. (3). Fig. 4 shows learning curves with different percentages from 60% to 90% in 10% steps. The efficiency increases exponentially as a student practices more. We assume μ_α follows a learning curve, so that it is a function of the number of units produced as in Eqn. (1), where a_α is the initial mean time spent to take action α .

$$Y(u) = au^{-b} \quad (1)$$

$$L = \frac{Y(2u)}{Y(u)} \quad (2)$$

$$b = -\frac{\ln L}{\ln 2} \quad (3)$$

$$\mu_\alpha(u) = Y_\alpha(u) = a_\alpha u^{-b} \quad (4)$$

Once log data is prepared, they are modeled as dynamic networks for each user. Dynamic networks evolve over time, so they are functions of time as in Eqn. (5) for n players:

$$G^{(p)}(t) = (V, E^{(p)}(t)), \quad p = 1, 2, \dots, n, \quad (5)$$

where $n = 4$ in this case. While a set of nodes or vertices V is fixed as the four actions, the links between nodes (i.e., edges) change over time, so it is a function of time denoted as $E^{(p)}(t)$ for each player p . Continuous time space t is discretized by a time-frame window of

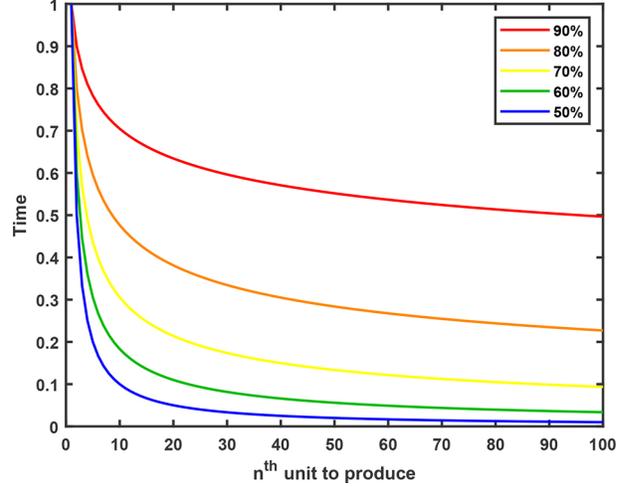


Fig. 4. Examples of learning curves of percentage L from 50% to 90% by 10% steps

size w . Then edges are created and added to $E^{(p)}(t)$ for consecutive actions in a given time frame or reinforced if an edge for these successive events already exists. For example, suppose that moving, assembling, and passing occurs consecutively at time frame i for player 1, and the previous graph $G^{(1)}(i-1)$ already has an edge between moving and assembling nodes but not assembling and passing. Then, a link is created for moving and assembling, while the weight between moving and assembling increases in $G^{(1)}(i)$. This modeling procedure is organized in Algorithm 1. Network modeling enables visualizing the dynamics of actions and, more importantly, engineering features that quantify these time-varying patterns for CPS assessment.

3.3 Heterogeneous Behavioral CPS Score

Now it is possible to apply various graph measures to $G^{(p)}(i)$ for each time frame and player, which calculate the importance of nodes, referring to the actions. Seven features are used in this study: indegree, outdegree, in-closeness, out-closeness, betweenness, page rank, and hub [35]. They are also known as centrality measures in the literature because the importance of nodes is assessed by their connectivity in a network. Given feature matrices at time i , a pair-wise CPS assessment measure between player k and l is defined by the Frobenius norm as in Eqn. (6), where $M^{(p)}(i)$ is a network-feature matrix of $G^{(p)}(i)$. Equation (6) evaluates dissimilarity between two graphs encoded by node-centrality measures. This is based on the idea that the network-feature matrix carries important information about the characteristics of

Algorithm 1 Dynamic Network Behavioral Modeling

Input: 1) Action log data X ($N \times 3$ data frame) consist of three variables:

- Player P
- Action A
- Time stamp S

2) Time-frame window size w

Output: Set of discretized dynamic graphs for each user $p = 1, 2, \dots, n, \{G^{(p)}(i) | i = 1, 2, \dots, T\}$

- 1: Initialize empty edge list $E^{(p)}(t)$
 - 2: Initialize node list V consists of the levels of A
 - 3: Calculate the total number of time frames $T = \lceil t_{\text{end}}/w \rceil$, where $t_{\text{end}} = \max(S)$
 - 4: **for** $i = 1 : T$ **do**
 - 5: Select rows x from X such that $S \in (w(i-1), wi]$
 - 6: **for** $p = 1 : n$ **do**
 - 7: Select rows $x^{(p)}$ from x such that $p \in P$
 - 8: $r \leftarrow$ number of rows of $x^{(p)}$
 - 9: **for** $j = 2 : r$ **do**
 - 10: Create edge e from $A(j-1)$ and $A(j)$ in $x^{(p)}$
 - 11: **if** $e \in E^{(p)}(i)$ **then**
 - 12: Update edge weight $\omega(e)+ = 1$
 - 13: **else**
 - 14: Add e to $E^{(p)}(i)$ with $\omega(e) = 1$
 - 15: **end if**
 - 16: **end for**
 - 17: **end for**
 - 18: **end for**
-

the graph. The proposed heterogeneous-behavioral CPS score is inspired by the observations that players with active CPS show heterogeneous behavioral patterns that likely occur by strategic task division in a collaborative way. Hence the greater the dissimilarity between the two graphs, the higher the CPS score.

$$CPS := \|M^{(k)}(i) - M^{(l)}(i)\|_F \quad (6)$$

$$\|M\|_F = \sqrt{\sum_i \sum_j |m_{ij}|^2} \quad (7)$$

The proposed approach is summarized in Fig. 5. First, we developed a multiplayer VR manufacturing simulation game and collected behavioral data. The action-log data were modeled as dynamic networks for each user. Network features were used to extract information from the graphs and show their time-varying patterns. A heterogeneous behavioral CPS assessment measure was suggested based on graph similarity.

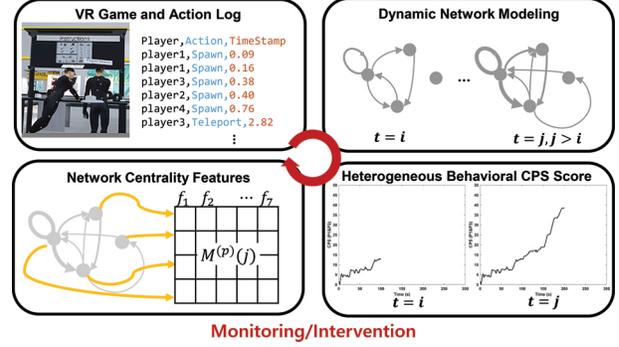


Fig. 5. Illustration of the proposed behavioral modeling

4 EXPERIMENTAL DESIGN AND RESULTS

4.1 Collaborative Problem Solving Assessment

The proposed behavioral modeling method measures CPS scores between pairs of players, rather than joint group effectiveness. This enables monitoring of individual-level CPS dynamics over time. With four players, a total of six CPS scores are available. The number of orders is set to eight as a fair production quantity to compare craft and mass production. If the order number is not divisible by four, some players must be idle in craft production. Mass production, on the other hand, requires a minimum order quantity to operate at full utilization. Fig. 6 shows the pairwise CPS-score lines over the course of the craft and mass production games. The players finished the task in mass production in 92.95 min, which is a few minutes (3 min) earlier for eight orders than craft production with the same learning curve rates, 70%. This time gap will expand rapidly as the order quantity increases.

Dots on the CPS-score lines represent the CPS scores when players complete modules or submodules assigned to them in mass production. Players in stations other than the first must wait for modules from upstream before they can complete their assigned modules. While waiting, Players 2, 3, and 4 produce submodules that can be independently produced. For example, in Fig. 6(a), light blue dots representing the chassis base - the submodule assigned to Player 2 for producing the front module - are actively assembled until approximately 20 minutes into the game. These dots are marked on the CPS-score lines to investigate different patterns and dynamics of CPS.

In general, players show significantly low CPS scores and monotone patterns in craft production. In contrast, mass production exhibits various CPS patterns depending on the combination of players. Fig. 6(a), (c), and (e) - which show CPS among Player 1, 2, and 4 - exhibit

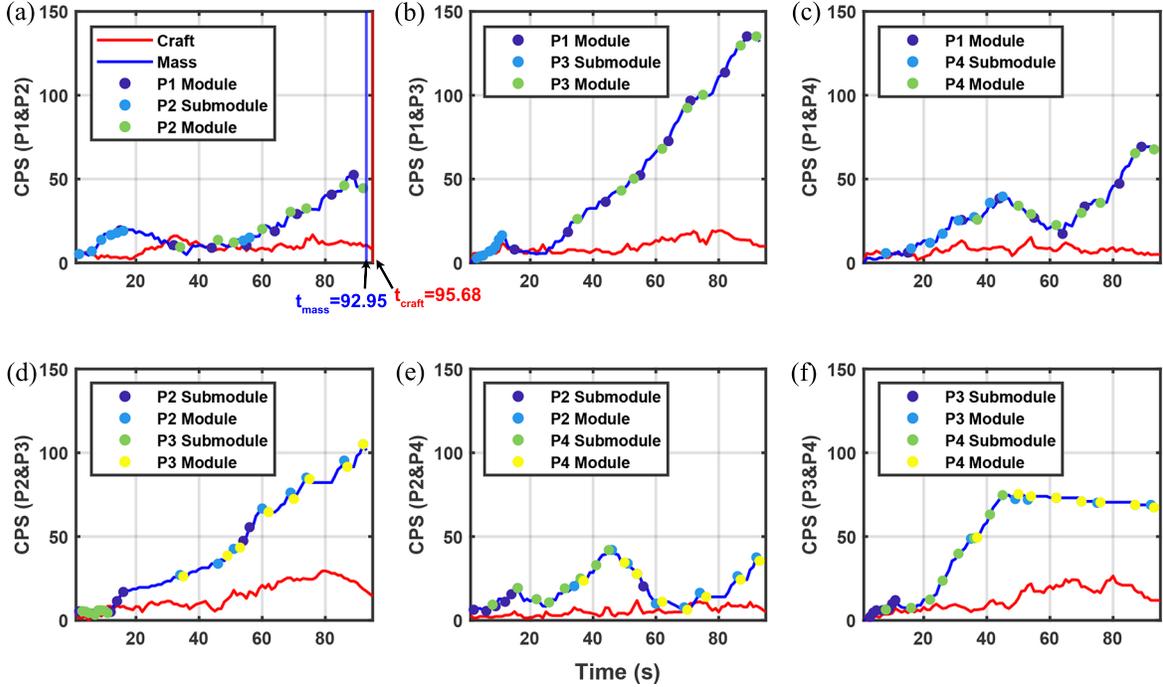


Fig. 6. Pairwise heterogeneous-behavioral-CPS-assessment measures between (a) player 1 & player 2, (b) player 1 & player 3, (c) player 1 & player 4, (d) player 2 & player 3, (e), player 2 & player 4, and (f) player 3 & player 4 in both craft (in red) and mass (in blue) production. Dots on the CPS-score lines represents the CPS scores when modules or submodules assigned to the players are completed in mass production.

a similar bimodal pattern that increases, decreases, and then increases again near the end. The other three plots, Fig. 6(b), (d), and (f), rapidly increase near the 20-min mark, except for Fig. 6(f), which reaches a plateau after 40 minutes. What these three plots have in common is that they all include Player 3.

Only the results for the 70% learning-curve percentages are presented, but we performed a sensitivity analysis to assess the effect of this parameter. Similar CPS patterns were observed in other cases with different learning-curve percentages. We conclude that the learning-curve factor does not significantly affect the CPS levels, and the observed CPS patterns are likely due to the characteristics of the manufacturing paradigms.

4.2 Model Validation

We conducted visual inspections to validate the proposed method. The proposed heterogeneous-behavioral CPS score depends on the assumption that the seven network-centrality features encode node importance and graph structure. We utilize low-dimensional embedding method, namely t-distributed stochastic neighbor embedding (t-SNE), to justify this assumption by visual-

izing the network-feature matrices. It transforms data points in high-dimensional space for visualization in low-dimensional space, while preserving relative distances between data points as much as possible. We embedded $M^{(p)}(t)$ for all p and t in dimension 7 (i.e., number of features) into a plane (2D) as shown in Fig. 7. Data points sharing similar characteristics form clusters. In both Fig. 7(a) and (b), it is clear from the visualization that nodes (i.e., actions) are clustered by their category of action and time, implying network-feature matrices carry essential information about nodes evolving over time.

5 DISCUSSION

We used the dots on the CPS-line plots to understand when CPS increases. First, CPS increases when a player quickly completes submodules shortly after the game starts - see until 20 minutes in Fig. 6(a) and 10 minutes in Fig. 6(b). Second, CPS scores increase rapidly when players alternately complete their assigned modules at different stations. For example, in Fig. 6(b), the CPS plot for mass production increases after 30 minutes when wheelsets (P1 Module) start flowing from upstream (station 1) to downstream (station 3). Because downstream

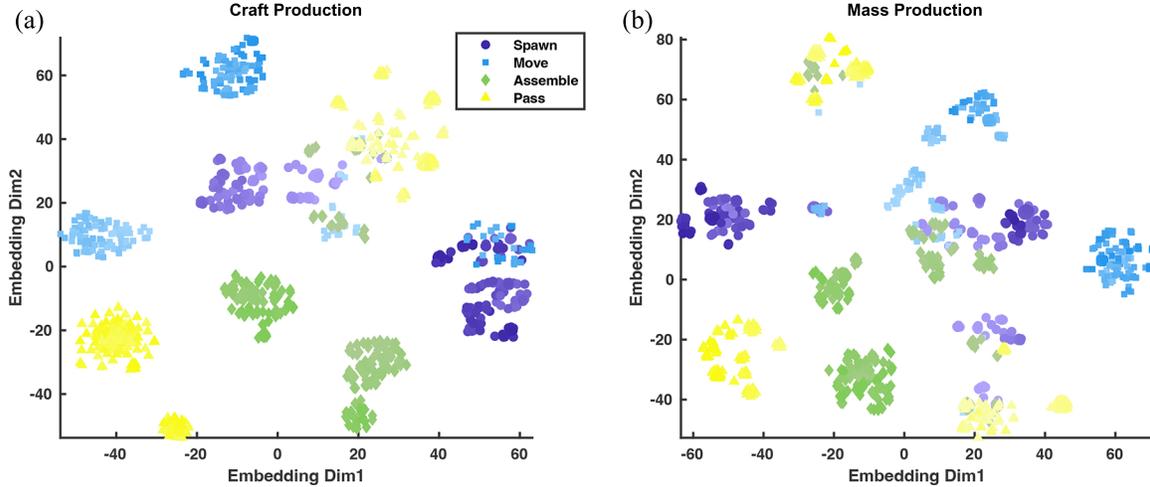


Fig. 7. Scatter plots of low-dimensional embedding via t-SNE of network-feature matrices $M^{(p)}(t)$ for all p and t for (a) craft, and (b) mass production. Color transparency represents the time axis; the more transparent, the earlier.

stations must wait for modules from upstream, submodules that can be produced independently are assembled until the upstream modules arrive.

Although preparing submodules while waiting for necessary modules from upstream contributes to CPS scores, scores change more drastically when modules flow through the stations. This observation implies that the proposed assessment measure successfully captures CPS dynamics from the log data and reveals a strategic division of labor in mass production. Additionally, plots associated with Player 3 (Fig. 6(b), (d), and (f)) exhibit a more rapid increase compared to other plots. To further investigate this observation, we selected a few data frames and visualized the graphs at those time marks.

Graph snapshots of Player 1 and Player 3 were taken at the 10, 40, and 80-min time points (see Fig. 8(a) and (c)) that are points when CPS (P1 & P3) increases. Similarly, snapshots of Player 2 and Player 3 were taken at 60, 75, and 90-min time marks (see Fig. 8(b) and (d)). $G^{(1)}(i)$'s show a different topology compared to the graphs of the other two players and have higher edge weights among Spawn, Teleport, and Assemble. It is likely because Player 1 produces wheels, which require a small number of parts for each but need to be produced in large quantity. In contrast, station 3, for steering & windshield, requires the fewest number of parts but is most dependent on the upstream modules because its main task is assembling the steering and windshield to the base chassis from upstream.

In summary, the proposed dynamic network behavioral modeling approach captures the different characteristics of the two manufacturing paradigms and monitors

the time-varying patterns of CPS among learners. These assessment results can be used to improve the simulation game, for example, by redesigning stations and modules to reduce bottlenecks in station 3. The behavioral modeling results can also be provided directly to students to allow them to optimize the assembly line themselves, fostering a deep understanding of manufacturing systems and the development of CPS.

6 CONCLUSIONS

The goals of our study were to develop 1) a multiplayer VR manufacturing simulation game and 2) a sensor-based dynamic CPS monitoring method. Professional skills such as CPS have recently gained attention for their importance in successful career development and workforce training. Simulation games are considered one of the most effective ways to teach these skills. It is imperative to have a rigorous assessment method to monitor CPS among students and provide appropriate interventions. We developed the *Virtual Learning Factory*, which allows for virtual hands-on experiences that are as effective as their real-world equivalents but much less expensive to implement. This paper also presents a dynamic-network behavioral modeling approach for assessing CPS from action-log data, a type of data commonly found in most digital learning environments. In the future, we plan to explore data from additional sensors, such as eye-tracking data. The log data is modeled as dynamic graphs for each player, with network features calculated to extract time-varying patterns of player actions. The heterogeneous-behavioral CPS score is defined

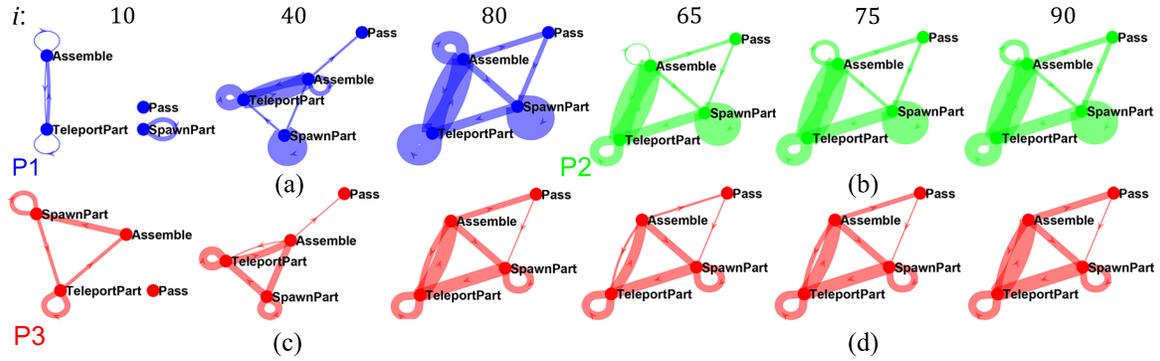


Fig. 8. Snapshots of the dynamic graphs for Player 1 (blue), Player 2 (green), and Player 3 (red). (a) $G^{(1)}(i)$ and (c) $G^{(3)}(i)$ for $i = 10, 40, 80$; (b) $G^{(2)}(i)$ and (d) $G^{(3)}(i)$ for $i = 60, 75, 90$.

by graph similarity between players. Experimental results show that the CPS scoring method successfully monitors individual-level CPS dynamics between players, potentially leading to appropriate interventions to improve learning outcomes.

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