Mixed-Integer Programming for Adaptive VR Workflow Training

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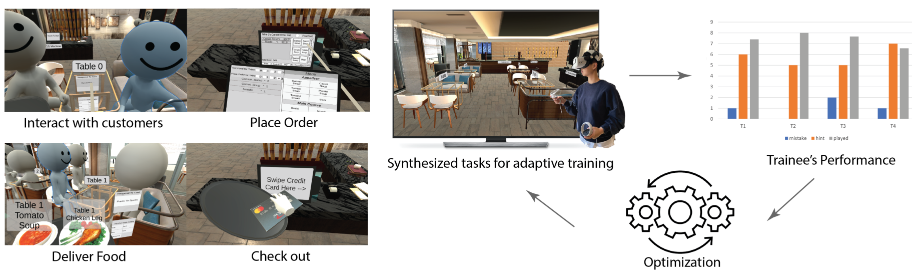

Fig. 1. Four tasks of restaurant service training are shown on the left. These tasks simulate common incidents a restaurant server faces at work. Given the trainee's performance, our approach adaptively generates training sessions. A trainee receives training in the interactive virtual restaurant as shown on the right. In this simulated training environment, the trainee can walk freely, interact with virtual customers, and take requests from tables like working in a real restaurant.

Abstract. With advances in consumer-grade virtual reality (VR) devices, VR training gains unprecedented attention in research and industries. Although the nature of VR training encourages trainees to actively learn through exploring and gathering information in a simulated virtual environment, designing effective virtual training environments is non-trivial. We propose an adaptive approach that guides trainees to develop psychomotor skills in a simulated virtual environment. As a showcase, we demonstrate our novel approach for restaurant service using a game-based VR application. By incorporating the trainee's performance and learning progress into optimization objectives, our approach uses mixed integer programming (MIP) to generate VR training sessions iteratively. Through collecting the trainee's performance in VR training, our approach adapts the VR training sessions by considering the trainee's strengths and weaknesses, guiding the trainee to improve over training sessions. We validated our approach through two experimental studies. In the first study, we compared our approach with a random training task assignment approach and a performance-only MIP approach through performing simulated restaurant service training. In the second study, we compared our approach with the random assignment approach by evaluating trainees' skill developments in restaurant services. The results show that our skill-driven adaptive training approach outperforms the random assignment approach.

Keywords: game design, adaptive training, virtual reality, optimization

1 Introduction

With advances in consumer-grade virtual reality (VR) devices, many companies start to employ VR as a supplement to their workplace training. For example, Walmart uses VR to simulate common and uncommon scenarios that could happen during Black Friday and prepare their employees for all possible upcoming challenges [23]. Similarly, United Rentals, the world's largest equipment rental company, created virtual construction sites to engage their employees in learning customer service skills and raising safety and site awareness [34]. Both examples demonstrate that users can gain practical experience through interacting with and working in a simulated environment.

Compared to traditional training methods (e.g., lecture-based training), VR training appears to have many advantages. It is accessible from anywhere, configurable to anyone, and most importantly, provides an active learning environment for trainees to involve in gathering information, thinking, and problem solving [4, 36]. However, designing VR training is not trivial because active learning does not simultaneously happen in the virtual environment, it requires a delicate design of teaching methods that are constantly adjusted based on the learning progress of a trainee. Such monitoring of trainee progress can help prevent the learning system from assigning a task too difficult too soon, which may discourage the trainee[22, 26]. However, monitoring the progress of individual trainees and manually adjusting difficulty is not ideal as VR training is often applied to a large number of new employees with different skill levels in a company.

This highlights the necessity for adaptive learning, which employs computational techniques to customize learning materials and training based on individuals' needs and performance. [14]. Recent research in adaptive learning has focused on musical tasks [38], machine tasks [11], and academic skills [33] to improve individuals learning efficiency. However, there is a dearth of research to enable psychomotor learning developments. Psychomotor learning refers to the learning process of a person in learning component skills (e.g. how to interact with customers, how to place orders), then compiling these individual psychomotor skills together and automatizing them with higher-level executive functioning (e.g., to work in a restaurant) [7].

Acquiring psychomotor skills in some workplaces is challenging as trainees often have to learn in rapidly changing, intricate environments to gain proficiency, such as performing surgery or flying an aircraft. While VR can simulate these complex conditions, the training may not immediately enable active learning as individuals have unique learning curves. To this end, we propose an adaptive learning approach focused on psychomotor skill development using restaurant service training as a showcase. Our approach is driven by trainee performance on psychomotor skills (e.g., performance in interacting with customers), which are collectively measured and evaluated in an interactive and configurable simulated restaurant. Such an environment encourages trainees to actively gather knowledge about restaurant service responsibility and participate in restaurant service training. By adaptively adjusting training tasks and task difficulty, we provide a full psychomotor learning development experience in an efficient way.

There are four key attributes in constructing personalized adaptive learning: user profiles, competency-based progression, personal learning, and flexible learning environments [25]. Motivated by these design guidelines, we propose a skill-driven adaptive training approach. We build user profiles through pre-evaluation to understand the trainees' skill sets. We evaluate the trainees' progress at each training session by measuring their performances during training. Our approach uses an optimization-based algorithm to create the next training session, taking into consideration the trainee's performance records and their training experience (such as enjoyment). The algorithm balances conflicting training goals (such as being easy but boring vs. being challenging but exhausting) and adapts to each individual's needs, resulting in the creation of a personalized training path to develop their psychomotor skills. By using VR, we enable a flexible active learning environment that supports adaptive adjustment of learning materials. Furthermore, we chose a restaurant as our running example because its workflow is familiar to most people, with a dynamic nature which demands multi-tasking abilities, task priority assessment, and task management. Other workplace training programs and other VR game applications can be adapted into our approach similarly. The main contributions of our work include:

- We present an optimization-based algorithm that considers a trainee's performance and eagerness to adaptively generate training sessions. This approach can be applied to workflow training in general.
- We created an interactive virtual restaurant to simulate restaurant service tasks. This simulated environment encodes many commmon scenarios a restaurant server faces. It also enables trainees to speak and interact with virtual customers. It is configurable and extensible for training staff to prepare for possible challenges in a real restaurant.
- We conducted a user study to compare our adaptive training approach with a baseline training approach. The results show that our adaptive training approach is more effective and efficient.

2 Related Work

2.1 Virtual Reality-based Training

VR training is widely applied in different domains such as retail business [30], workplaces and factories [3, 29], and vehicle control [20, 17], because of its replicability and low cost. For high-risk occupations such as first responders and military and medical learners [27], VR training also provides a mistake-tolerant training environment. We refer our readers to a review on VR training applications for more details [36].

Many current VR training research focuses on knowledge acquisition through training. For example, Li et al. proposed an optimization-based approach for synthesizing construction safety training scenarios, allowing trainees to explore those training scenarios to identify potential hazards [19]. Similarly, Aati et al. developed work zone inspection scenarios for training engineers to inspect the quality of work zone sign placement. They believe this virtual simulator is a safer, cheaper, and more effective way to train inspectors than a field visit [1]. Shao et al. proposed an interactive-learning approach to teach American sign language. Their approach leveraged the third and first-person views for motion demonstration and practice [28]. Moreover, virtual patients have been widely used for testing clinical examination interview skills in the medical field [18, 13]. For example, Tavassoli et al. presented a virtual training platform named JAYLA to teach medical students about symptoms and severity levels of Autism Spectrum Disorder in young children. Through encoding verbal and nonverbal behaviors associated with age-appropriate autism into virtual patients, JAYLA provided a new way to enhance professional training for early detection of autism in young children [31]. Another common use of virtual patients is for training clinicians to acquire social skills needed for clinician-patient interactions. Yao et al. trained a classifier to identify empathy levels of a clinician's responses from their interactions with virtual patients and to provide feedback based on evaluation results [37].

Since VR simulation can provide a blame-free environment, trial and error in VR training provides a powerful learning mechanism, especially for high-risk task training. For example, the Brazilian Navy developed a VR simulator for training landing signalman, who was responsible for visual signaling to the pilot and ensuring general safety conditions of the flight deck area [6]. Since this task is often performed under stressful conditions, VR simulation training can help relieve the burden of making mistakes. Crisis management training, another example that uses VR as a learning tool, has been shown to be efficient in VR. By training through a crisis in a subway station in VR, Conges et al. believed that they could prepare practitioners for real-life crises in cities [5]. Moreover, since VR training provides an accessible and scalable manner of training, it can help manufacturing industry to train inexperienced workers to fill workforce shortages. For example, Ipsita et al. present a VR-based welding training simulator that can be easily adapted and distributed at different scales [12]. Those works either focus on educating trainees through immersive simulation or on the interactions between virtual agents and trainees to improve interpersonal skills. In contrast, we propose an adaptive training approach integrated with virtual reality. Through tracking trainee performances during VR training, our approach adaptively modifies training tasks and adjusts the difficulty level of the next training session to enhance training efficiency.

2.2 Psychomotor Learning

Skill development generally involves complex muscular movement and cognitive control, which requires a substantial amount of practices. Psychomotor Learning refers to the relationship between cognitive functions and physical movement. Playing a sport, driving a car, or dancing are examples of psychomotor learning. Fitts and Posner proposed a three-stage model for psychomotor skills development, comprising the cognitive stage, the associative stage, and the autonomic stage. It describes the learning process of a person in accomplishing the task goals. The process starts from gaining theoretical information and attempting to take actions, then gradually becoming fluent in individual actions with slow transitions between these actions, and finally becoming capable of performing skills seamlessly. They also pointed out an important feature of the three-stage development model: a rapid progression usually happens in the cognitive stage and a slow progression usually takes place towards the autonomic stage [15, 7]. It implied that trainees must take sufficient practice to achieve full psychomotor skill developments. Adaptive training appeals to fast-paced and high-demand work environments for training workforces to be proficient in multiple tasks in a short amount of time.

Merriënboer et al. defined complex learning as the achievement of multiple performance objectives and emphasized the importance of learning how to coordinate and integrate separate skills to achieve goals [32]. It suggests that when designing training for a complex learning environment (e.g., a workplace), one should not evaluate skills separately. They should also consider proficiency in completing tasks using skills in a coordinated and integrated fashion. In our approach we consider psychomotor skill development in our trainees; in particular, our trainees first obtain knowledge of each task (i.e. workflow of each task) and gradually progress through three stages of psychomotor learning. Since our approach uses mixed integer programming to synthesize training tasks targeted at addressing participants' weaknesses, our approach gradually increases the complexity of the multitasking level. To help trainees perform, we evaluate their performance from a complex learning perspective, that is, we evaluate not only the performance of completing each task, but also the ability to coordinate with other tasks through a multitasking lens.

2.3 Adaptive Training and Interfaces

Although research has shown that adding an extra layer of reality can bring effectiveness to training, it is not easy or intuitive for VR/AR creators to encode learning opportunities into AR/VR [2]. On one hand, many research focuses on creating personalized digital space and improving the usability of mixed reality interfaces. For instance, Lindlbauer et al. proposed a context-aware optimization-based approach to automatically control mixed reality interfaces [21]. In particular, this automated process leverages users' cognitive load and information about their tasks and environments to support MR interface adaptation. Inspired by this work, we track a trainee's performance during training and leverage this

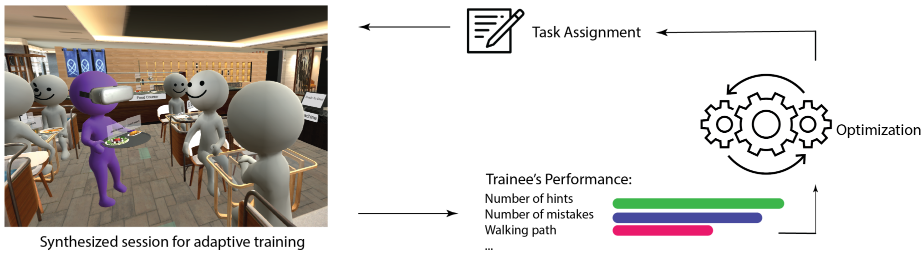

Fig. 2. An overview of our approach. Our approach obtains the trainee's performance metrics from a VR training session, including the number of hints asked, the number of mistakes made, the walking path, and the order of tasks performed. Then it leverages such performance metrics to adaptively generate the next training session through an optimization, aiming to help the trainee improve efficiently. In particular, it adjusts the difficulty levels and appearances of different tasks to keep the trainee engaged with the training.

information to adaptively generate the next training session for the trainee to practice.

On the other hand, a few research investigates different training strategies to improve training performance. For instance, part-task training is often used for training sequential components of a complex task, and increasing training difficulty is effective as long as the increased difficulty is adaptive [7, 35]. Yuksel et al. used an increasing-difficulty strategy to adaptively teach users to learn to play the piano with Bach's music pieces. They measured the learners' cognitive workload in real-time to increase the difficulty level of the music learning tasks [38]. Other research aims to combine multiple instructional strategies to achieve better training results. Huang et al. proposed a system that used a combination of macro and micros-approach for adaptation. They collected learner historical records and real-time input to adaptively teach users to master machine tasks [11]. The previous works focused on evaluating the effectiveness of different training strategies in music and machinery tasks. Inspired by these works, we devise an adaptive training approach to synthesize psychomotor skill training sessions for virtual reality-based training.

3 Overview

To illustrate our approach, we create a virtual restaurant to simulate training in a workplace. This virtual restaurant enables trainees to speak, walk and interact with virtual objects/agents in the environment. We describe the details of the virtual environment, object manipulation, and restaurant tasks involved in Sect. 4. By using this virtual restaurant as an illustrative example, we explain how our approach can generate tasks to train people adaptively with respect to skill development. Fig. 2 shows an overview of our approach.

Since our approach focuses on psychomotor skill development and multi-tasking ability development, we formulate a trainee's learning experience and training record into design objectives (e.g., workflow of a task, number of hints used, mistakes made) as well as a set of constraints (e.g., multitasking difficulty level). We use mixed integer programming (MIP) to solve this multi-objectives optimization problem (Sect. 4.2) while satisfying the constraints. Given trainee performance from the previous training session, our approach assigns different tasks and adjusts their difficulty levels for the next training session, while gradually increasing the multitasking difficulty.

Lastly, we validate our approach through two experiments (see Sect. 5). In the first study, we compared our approach with a random assignment approach and a Performance-Only MIP approach through performing simulated training. The goal of this simulation experiment is to see whether our approach can train trainees to progress more efficiently than baseline approaches given the same trainee with a fixed learning ability. In the second study, we compare our approach with the random assignment approach by training trainees to work in a virtual restaurant. The goal of the second user study is to evaluate efficiency in restaurant skill development and multitask strategy skill development under two different training conditions.

4 Problem Formulation

4.1 Virtual Environment and Interaction

Restaurant Service Tasks. A good restaurant server must excel at communication, front-of-house tasks (e.g., cleaning up tables), time management, and also multitasking. Thus, a restaurant service training not only considers individual skill development but also the ability to combine and use skills in an optimal manner. For our virtual restaurant, we design eight tasks to represent major customer requests restaurant staffs need to handle in their daily work routine. We included regular tasks such as taking orders, delivering food and checkout; and two incident tasks that described some common accidents in a restaurant (e.g. drink dropped, food overcooked). Refer to Table 1 for description of four major tasks.

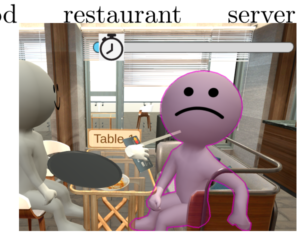

Fig. 3. A snapshot of the "check out" task. The trainee was about to return the credit card to the customer, who was angry as it was taking too long.

Each task has a difficulty level and a property that reveals the characteristic of this task. For example, the "check out" task is time sensitive because this task requires trainees to return the customer's credit card within a time limit, otherwise the customer will be angry at him (see purple agent in Fig. 3). Each task also is associated with a property value, which is used to set up constraints for multitasking level difficulty training (see Sect. 4.3). Please refer to the supplementary material for more details of each task setting. With these constraints, trainees can practice their multitasking ability in training sessions generated by our optimizer.

Virtual Environment. As shown in Fig. 4 (left), our 6m X 6m simulated virtual restaurant contains four tables, one food counter, and one point-of-sale

Fig. 4. Left: the virtual restaurant's layout. Right: the tools for performing tasks in virtual reality. Trainees used the left-hand controller to switch between tools for completing different tasks. They also used the interaction panel to interact with virtual customers and the hint panel to ask about the workflow of a task.

Task Name		Description	Diff. level	Property (value)	Walking Path
1	Ready To Order	Interact with customers and ask what they want to order	3	Talk-centric(1)	Table->POS
2	Want Food	Grab food from kitchen and deliver food to each customers;Grab dirty plates.	3	Service-centric(10)	Table->Kitchen ->Table
3	Reqeust Recipt	Print out receipt and deliver it to the table	3	Time-sensitive(100)	Table->POS ->Table
4	Checkout	Process payment for the customers	3	Time-sensitive(100)	Table->POS ->Table

Table 1. The details of different tasks.

(POS) machine. A trainee can walk freely in this simulated environment. At the beginning of the simulation, the trainee will walk to a table first, interact with customers to get a request, then walk to the POS machine for placing an order, or go to the food counter to get items for the customers. After that, she will go back to the table to deliver the items for completion. During the simulation, each table will have at most one request.

User Interaction and Speech. The trainee uses the left-hand controller for switching tools between a food tray, a clean up tool, and an interaction panel. This interaction panel is used to interact with a customer. See Fig. 4 (right). By pressing the speak button, our program can record the trainee's speech. We use natural language processing from the Wit model [3] for speech recognition in our simulation. The model first extracts the trainee's intention from their speech, then it will check if this trainee's intention belongs to one of the three predefined categories: greeting response, ask for repeat response, and task-specific responses.

[3] https://wit.ai/

If not, it will ask the trainee to speak again. Once the intention is recognized and matches with the current task's desired response, the customer will respond or react. See the supplementary material for responses of different categories. We also include a hint panel underneath the interaction panel. If the trainee is uncertain about the workflow of a task or a message to respond to, he can press this hint button to get the next step information.

4.2 Optimization Approach

Our approach aims to assign tasks with suitable difficulty for each training session while satisfying some training constraints (e.g., multitasking level constraint). We propose an objective with the following sub-objectives: repeated mistake avoidance (M), familiarity with the workflow (W), tolerance of repetition (R) and eagerness (E). M measures the number of mistakes made by a trainee. W measures the number of hints the trainee asked for, which reflects the trainee's familiarity with the current workflow. R measures the number of times a task is repeated in a row. E estimates the amount of eagerness with which the trainee is willing to play this task. Our approach seeks to maximize the overall objective function comprising the sub-objectives. For all tasks $t \in T = \{1, ...n\}$, our approach solves for the following:

$$\max \sum_{t}^{n} \sum_{d}^{m} X_{\mathrm{t,d}} Y_{\mathrm{t,d}} (\lambda_{\mathrm{M}} M_{\mathrm{t,d}} + \lambda_{\mathrm{W}} W_{\mathrm{t,d}} + \lambda_{\mathrm{R}} R_{\mathrm{t,d}} + \lambda_{\mathrm{E}} E_{\mathrm{t,d}}), \tag{1}$$

where $X_{\mathrm{t,d}} \in \{0, 1\}$ is a binary decision variable capturing whether task t with difficulty d will be used in a training session. $Y_{\mathrm{t,d}}$ denotes whether task t has difficulty d. All sub-objective functions are calculated for the current task t with difficulty d, but for simplicity we drop the subscript later on. We empirically set the weight of each sub-objective function as 0.3. Table 2 summarizes the parameters and variables in our formulation.

Repeated Mistake Avoidance (M). Mistakes are a valuable indicator in designing a training session. This objective aims to let the trainee practice more if he exhibits repeated mistakes. It consists of two parts, persistent mistake and usability of task difficulty:

$$E = \delta^{\mathrm{MistPer}} U_{\mathrm{t,d}}^{\mathrm{MistPer}}. \tag{2}$$

First, we want to know on what percentage the trainee persistently made mistakes when doing this task, denoted by $\delta^{\mathrm{MistPer}}$ and formulated as:

$$\delta^{\mathrm{MistPer}} = \frac{1}{e^{\lambda_{\mathrm{MistPer}} (K - n^{\mathrm{t}}/p^{\mathrm{t}})}}, \tag{3}$$

where $\lambda_{\mathrm{MistPer}}$ is set as 2. Presumably, if a task has a large persistent mistake rate, then the trainee needs to work on this task more frequently. K is the largest persistent mistake rate of all tasks from the trainee's performance record. We use this term to evaluate the importance of this task in helping correct mistakes.

Parameter	Description	Variable	Description
m_{t}	number of mistakes made in a task t	$T = \{t_1, \dots t_n\}$	all tasks
n_{t}	number of times task t has mistakes in the training sessions experienced so far	$X_{\mathrm{t,d}}$	binary variable capturing whether task t with difficulty d showed up in training session
h_{t}	number of hints asked in task t	$Y_{\mathrm{t,d}}$	binary variable indicating whether task t has difficulty d
p_{t}	number of times task t was played	λ_{X}	weight of a sub-objective function
R_{t}	number of times of repeating task t in a row		
P_{t}	task t's property value		
S	total number of training sessions		

Table 2. Descriptions of input parameters and variables in our formulation.

Secondly, we define the usability of this task difficulty, $U^{\mathrm{MistPer}}_{\mathrm{t,d}}$, in helping to correct persistent mistakes:

$$U^{\mathrm{MistPer}}_{\mathrm{t,d}} = \frac{(d_{\mathrm{f}} - d_{\mathrm{target}})^2}{0.5\sigma^2}, \tag{4}$$

where σ is empirically set as 0.8. d_{f} is the usability of a task with difficulty d which is defined in Table 1. d_{target} denotes the desired task usability a trainee should practice with respect to the persistent mistake rate of this task. In correcting mistake behaviors, it will be better if we start with an easy level task and then gradually increase the difficulty. Therefore, we set d_{target} as follows:

$$d^{\mathrm{target}} = \begin{cases} 1 & \text{if } n^{\mathrm{t}}/p^{\mathrm{t}} \geq 0.8 \\ 0.6 & \text{if } 0.5 \leq n^{\mathrm{t}}/p^{\mathrm{t}} < 0.8 \\ 0.3 & \text{otherwise.} \end{cases} \tag{5}$$

Familiarity with Workflow (W). This objective evaluates whether the trainee understands and remembers the workflow of a particular task. As suggested by [26], we need to avoid fast progression to a difficult task when the trainee is still uncertain about the basic workflow. Thus, the usefulness of a particular task difficulty, U^{TaskDiff}, is defined as follows:

$$U^{\mathrm{TaskDiff}} = \begin{cases} 1 & \text{if } d = 1 \\ 0.6 & \text{if } d = 2 \\ 0.3 & \text{if } d = 3. \end{cases} \tag{6}$$

In this way, we penalize the assignment of a difficult task to a trainee when he is not familiar with the task workflow.

Secondly, we want to know how much a trainee is familiar with the workflow of a task t, denoted as $\delta^{\mathrm{Familiarity}}$, by measuring the number of hints asked in executing that task and normalizing into $[0, 1]$:

$$\delta^{\text{Familiarity}} = \frac{h_{\text{t}}}{h_{\text{max}}}, \tag{7}$$

where h_{max} denotes the maximum number of hints the trainee asked in doing a task. We empirically set it to be 5. Overall, we have:

$$W = \delta^{\text{Familiarity}} U^{\text{TaskDiff}}. \tag{8}$$

Tolerance with Repetition (R). Repetition is a basic but powerful learning strategy used for training [24]. On one hand, it is desirable to let trainees practice a task repeatedly to strengthen their skills. On the other hand, trainees may lose interest in a certain task after it is repeated too many times. Thus, it is desirable to balance repetition and a trainee's interests during training. In game level design, it is common for game designers to vary game settings to avoid monotonous levels [8, 10]. Inspired by that, we consider the tolerance with repetition and the eagerness to learn to introduce variety to the training.

We include the tolerance with repetition term to evaluate how much a trainee can tolerate training with the same task repeated in a row. It is defined as follows:

$$R = \gamma^{\text{R}_\text{t}} - \sigma^{\text{tolerance}} \text{R}_\text{t}, \tag{9}$$

where R_t is the number of times task t is repeated in a row. γ and $\sigma^{\text{tolerance}}$ determine the amount of decrease in tolerance; they are empirically set as 0.2.

Eagerness to Learn (E). Other than repetition, it is also important to review tasks to reinforce their learning. By introducing occasionally played tasks, we can let the trainee review the tasks while keeping their interests in training. Specifically, we define this term to evaluate how much a trainee is willing to play a task. This term is determined by the appearance rate of a task for the entire training. Our goal is to avoid assigning a frequently appearing task to training sessions. The term is formulated as follows:

$$E = \begin{cases} 0 & \text{if } \delta^{\text{appear}} < 0.4 \\ \Gamma^{\delta^{\text{appear}}} - 1 & \text{otherwise,} \end{cases} \tag{10}$$

where δ^{appear} is calculated by the number of times this task is played over the number of training sessions experienced so far. Γ controls the speed of decay and is empirically set as 0.2.

4.3 Constraints

We introduce a set of constraints to avoid duplicated tasks, limit training session length, and, most importantly, to perform multitask strategy training practice.

Task Duplicates. We avoid task duplicates by enforcing:

$$C_{\text{t}} = \sum_d X_{\text{t,d}} = 1, \forall t \in \{1, ...n\}, \tag{11}$$

where C_{t} denotes the number of tasks appearing in a training session.

Training Session Length. This constraint ensures that each training session has a certain length:

$$1 \leq \sum_t \sum_d X_{\mathrm{t,d}} \leq \delta^{\mathrm{Length}}, \forall t \in \{1, ...n\}, \forall d \in \{1...m\}. \tag{12}$$

For our running example, we set δ^{Length} to 4, meaning that at most four tasks appear in a training session.

Multitasking Level Constraint. In addition to skill level training, we define this constraint to help trainees improve their multitasking performance. When multitasking strategy training is enabled, our approach gradually increases the difficulty of multitasking training based on the trainee's current performance. The difficulty of multitasking level is set as easy, medium, or hard, corresponding to working on two, three, or four tasks at the same time. Presumably, since this constraint will affect the number of tasks assigned in a training session, we include this constraint only when the trainee is familiar with the workflow of all tasks. However, in our user study, we include this constraint in the first training session due to the time limit of our user study. Moreover, our optimizer increases the multitasking difficulty level if the multitasking strategy training score (defined in 6.1) obtained from the trainee reaches the maximum score.

To ensure that each multitasking difficulty level is meaningful, our optimizer selects tasks of different properties from the task list for combination. As shown in Table 1, we associate each task with a property and a property value (e.g., task 7's property is "walk-centric" with property value $Q_{\mathrm{t}} = 1,000$). In this way, some judgments are needed for the trainee before deciding to serve a table:

$$\sum_t Q_{\mathrm{t}} C_{\mathrm{t}} = \delta^{\mathrm{goal}}, \tag{13}$$

where δ^{goal} is from a set of all possible combinations of task property values of a certain difficulty level. For example, if the multitasking difficulty is specified as medium, then the set of all possible combinations of tasks of three, each with different task properties, is $\{111, 1011, 1110, 1101\}$. Then we create a constraint for each δ^{goal} in the set. Our optimizer will generate a solution that satisfies any one of these multitasking level constraints.

4.4 Implementation

We implemented our VR training scenarios using $C\#$ and the Unity game engine. We use the Gurobi solver to solve the mixed integer programming problem[4]. It took less than one second to generate a solution that satisfied the set of constraints with optimized objective values. This solution contains a set of tasks, each with a specific difficulty level. This set of tasks will be used for the current training session. Based on the trainee's performance tracked in the training, our approach uses the MIP optimizer to generate the set of tasks for the next

[4] https://www.gurobi.com

	MIP	Performance	Random		MIP vs. Perform -ance	MIP vs. Random	Perform -ance. vs. Random
Mean (SD)	44.1 (6.6)	49.6 (7.8)	34.9 (5.9)	p-value	<0.001	<0.001	<0.001

Table 3. Descriptive statistics for the simulation experiment. We generated 20 hypothetical trainees to compare the training performance of three different conditions. A performance record is calculated as the sum of the number of hints asked and the number of mistakes made in all tasks. Then we obtain trainees' improvement records by subtracting trainees' final performance records from their initial performance records. The left table shows the average improvement record with the standard deviations in parentheses for the MIP approach, the Performance-Only approach (Performance), and the Random approach. The right table shows the p-values of t-tests for each pair of approaches.

training session. For delivering the synthesized VR training experiences, we used the Oculus Quest2 virtual reality headset.

5 Experiments

5.1 Simulation Experiment

We conducted a simulation experiment to determine whether our approach can train people more efficiently compared to other approaches given the same trainee as input. In this experiment, we focus on the development of individual psychomotor skill components. We compared our approach (MIP) with a random assignment approach (Random) and a performance-only MIP approach (Performance). In the random assignment approach, the optimizer randomly assigned two to four tasks for each training session. In the Performance-Only MIP approach, we only consider the repeated mistake and familiarity of workflow objectives. In general, trainees who received the Performance-Only MIP training had the highest improvement for all tasks in all three conditions; trainees taking the MIP approach has better improvement than those taking the random assignment training. The difference in improvement across the three approaches was significant with $p < 0.05$ for all pairs (see Table 3). Please refer to the supplementary material for more details about this simulation experiment.

5.2 Virtual Reality Training Experiment

We conducted user study experiments to measure the effectiveness of the personalized virtual training sessions synthesized by our approach. We compared trainees' performance under two conditions, adaptive training condition (AT) and random assignment condition (Random). In the adaptive training condition, we first updated trainee performance for each task, then used our optimizer to generate tasks for the next training. In the random assignment condition, we randomly assigned two to four tasks to participants.

Participants. We recruited 26 participants to simulate working in a restaurant. The participants were university students aged 19 to 37, with about 65% of males and 35% females. They were randomly and equally assigned to one of the two conditions. The user study was IRB-approved. We first gave a warm-up session for the participants to get familiar with the virtual environment and the controls. Then we give a pre-evaluation for the participants to evaluate their background knowledge of serving in a restaurant.

The goal of the second study is not only to evaluate mastery of individual restaurant tasks but also trainees' ability to apply multitasking strategies. Therefore, we teach the participants how to combine tasks in an optimal way at the beginning of the training.

Procedure. The participants practiced the multitasking skill for five training iterations. During training, they could request hints if they were uncertain about the workflow of the task either by pressing the hint buttons or talking to the instructor directly. We recorded the number of hints they asked and the number of mistakes they made during the training and also their multitasking performance. There was a two-minute break after each training. During this break, we told the participants about the mistakes they had made and reminded them about the workflow and multitasking strategies for those unfamiliar tasks.

In the end, we gave the participants a post-evaluation that had the exact same task as the pre-evaluation. Akin to the training, we asked them to combine all the tasks using the skills they learned. We recorded their performance. Upon training completion, we asked the participants to fill out a questionnaire. This questionnaire includes their training experience in the simulated restaurant and their enjoyment ratings.

6 Evaluation

6.1 User Evaluation

To help us evaluate the overall performance of our participants, we calculate a final performance score, f_{final}, for the pre-evaluation session and the post-evaluation session, as follows:

$$f_{\text{final}} = f_{\text{strategy}} - 0.1 \sum_{t} (h_{\text{t}} + m_{\text{t}}), \tag{14}$$

where h_{t} and m_{t} are the number of hints and the number of mistakes made by a participant, which we refer to as skill performance record. f_{strategy} evaluates a participant's ability of multitasking, ranging from 0 to 3.

The goal of training multitasking skills is to minimize the average waiting time of customers as well as to improve restaurant server working efficiency. Therefore, a well-trained restaurant server should take multiple tasks from tables and combine workflow of some tasks (e.g., placing an order and printing a receipt at the POS machine) in order to complete tasks in a single run. Since each task has a different property, the order of taking these tasks is critical. A server may want to serve a ready-to-order table first before a check-out table, so that customers who want to check out do not need to wait for the server to help the

		Pre-evaluation	Post-evaluation	Training Improvement
Skill Performance record	AT	10.08(7.58)	1.23(0.86)	8.85(6.64)
	Random	11.85(2.81)	3.77(7.03)	8.08(9.58)
	p-value	0.06	**0.01**	0.50
Multitasking strategy training score f_{strategy}	AT	0.31(0.40)	2.85(0.31)	2.54(0.60)
	Random	0.31(0.23)	2.08(0.58)	1.37(0.53)
	p-value	1	**0.01**	**0.05**
Final performance scores f_{final}	AT	-0.70 (0.55)	2.72 (0.31)	3.42 (0.67)
	Random	-0.88 (0.33)	1.67 (0.68)	2.55 (0.57)
	p-value	0.50	**0.001**	**0.001**

Table 4. Users' overall performance records in completing the pre-evaluation and post-evaluation sessions, and the overall training improvement for both conditions are shown. Specifically, we show skill performance record (the average total number of hints asked and the number of mistakes made), multitasking strategy training score, and final performance score. For each score category, the first and second rows show the means with the standard deviations in parentheses. The third row shows the p-values of t-tests comparing the results of the two approaches. Note that a lower number in the skill performance record indicates better performance while a higher number in the other terms indicates greater participant performance. Compared to the random approach, the AT approach leads to a significantly higher performance score and training improvement.

	I enjoy it	I like it	I feel good physically	It's a lot of fun	I am not at all frustrated
AT	6.5(0.8)	6.4(1.0)	6.5(0.8)	5.8(1.1)	5.8(1.3)
Random	6.1(1.3)	6.2(1.1)	5.8(1.3)	5.7(1.2)	5.2(1.7)

Table 5. The PACES ratings.

ready-to-order table first. Similarly, the order of completing tasks is important. Since customers from a check-out table want to leave right after they receive their credit card, it is important for the server to deliver the credit card to them when he was back from the kitchen (or the POS station). Thus, we define these three metrics to evaluate the ability of participants in handling multiple tasks.

Based on the current virtual restaurant and task settings, we can define an optimal order of tasks a participant take at the beginning as follows: talk-centric task $\rightarrow$ service-centric task $\rightarrow$ walk-centric task $\rightarrow$ time-sensitive task. Similarly, the optimal order of tasks the participant completed is defined as: talk-centric task $\rightarrow$ time-sensitive task $\rightarrow$ walk-centric task $\rightarrow$ service task. Lastly, the participant's optimal walking path is Table $\rightarrow$ POS $\rightarrow$ Kitchen $\rightarrow$ Table. If the participant fails to follow the optimal order (or walking path), she will receive zero on that metric.

Table 4 shows the descriptive statistics and t-test results. As we can see, the average final performance score of the AT approach group is higher than that of the random assignment group. To investigate whether there is a statistically significant difference between the improvement made by the participants in the two groups, we performed two sample t-tests on each component of final performance score ($\alpha = 0.05$). As the results, there was no significant difference in the final performance (F(24)=0.68, p>0.05) or any components of final performance scores before training (skill performance record: F(24)=-1.98, p=0.06; f_{strategy}: F(24)=0, p=1). However, there was a significant difference in the final performance (F(24)=3.83, p<0.001) and so for each component after training (skill performance: F(24)=-3.26, p<0.01; f_{strategy}: F(24)=2.95, p<0.01). We also find significant differences in the overall training improvement (i.e. increase in final performance score) between the random assignment and AT groups (F(24)=2.84, p<0.01). Specifically, a significant difference was observed in the multitasking strategy training scores(F(24) = 2.61, p<0.05) but not in skill performance record. (F(24) = 0.69, p=0.50). Refer to the supplementary material for additional analysis.

This result suggests that participants in both condition groups can master their restaurant skills in five training sessions. However, since there were only four restaurant tasks to learn in 90 minutes, the training might not have been challenging enough for participants in both groups. Moreover, a significant difference was observed in the multitasking strategy training score, indicating that our approach can be highly effective in helping trainees improve not only restaurant service skills but also their ability to apply multitasking strategies.

6.2 Participant Feedback

Physical Activity Enjoyment Rating. We asked our participants to fill out a physical activity enjoyment scale questionnaire (PACES) in both pre and post-evaluation sessions. PACES is a quantitative measurement of the perceived enjoyment level for a physical activity validated by Kendzierski and DeCarlo [16]. We used the short version [9] which consists of five 7-point Likert scale questions. Table 5 shows the results. Overall, the PACES percentage scores of the AT approach are slightly higher than those of the random assignment group. This suggests that the AT approach can lead to a similar level of enjoyment while training people more effectively.

Although all participants had improved after training, not all participants believed that the training sessions assigned to them were carefully selected based on their weakness. Participants from the AT group were more confident in believing that the tasks assigned to them were carefully picked (M=3.8, SD=1.1), compared to those from the random assignment group (M=2.7, SD=1.1). A two-sample t-test shows that there is a significant difference in this rating (f(24)= 2.8, p<0.01).

Example Participants' Performance. To investigate further, we select one participant (P7) from the random assignment group and one participant (P11) from the AT group for comparison. Table 6 shows their pre-evaluation and post-evaluation performances. As we can see, the participant (P7) from the random assignment group got familiarized with task 1 and 7 and had made fewer mistakes

Participant (Condition)	# Hints + Mistakes for Task 1,4,7		Training Session	Multi-Tasking Training Score	
	Pre-evaluation	Post-evaluation		Pre-evaluation	Post-evaluation
P11(AT)	2,2,4	0,1,0	(T2,T7), (T1,T4), (T1,T2,T7), (T2,T4,T7), (T1,T2,T4)	0	3
P7(Random)	2,4,6	1,3,0	(T1,T2,T3,T4), (T1,T2,T7), (T1,T2,T7), (T1,T2), (T2,T4)	0	3

Table 6. Selected participants from the AT approach and the random assignment approach. The multitasking training score has the most influence on the final training score in performance. The participant from the random approach had a difficult time in learning and applying multitasking skills because the multitasking difficulty assigned to him was not adjusted based on his performance. In contrast, the participant from the AT approach received gradually-increasing multitasking difficulty in training and she received a higher multitasking training score.

(or asked fewer hints). However, he was not familiar with task 4 and performed poorly in multitasking. This is likely because tasks assigned by the random assignment approach did not target his weakness for training. Also, random multitask level difficulties were given to the participant. This participant started with a hard level of multitasking difficulty and practiced with an easy level of multitasking difficulty towards the end. This posed extra challenges for this participant to learn and master multitasking. He received 1 out of 3 for the multitasking training score.

In contrast, the AT approach would target all of the participants' weaknesss. The participant (P11) from the AT group was not good at doing task 7 at the beginning and repeatedly made mistakes for task 7. As a result, she was assigned by our adaptive approach to do task 7 three times in the five training iterations. On the other hand, our approach gradually increased the multitasking training difficulty after she showed proficiency at the current multitasking difficulty level. She got 3 out of 3 for the multitasking training score.

7 Discussion, Limitations and Future Work

Our work sheds light upon the novel research direction of adaptive game-based training via virtual reality. Using our approach, trainees can develop psychomotor skills in an efficient way. Driven by a trainee's performance, our approach can generate a suitable task list such that it targets the trainee's weaknesses while keeping the trainee engaged in game-based training. Moreover, other workplaces that require extensive hands-on training prior to work can benefit from game-based training. For instance, simulated medical skill training could be used in conjunction with our approach to provide a personalized training approach that meets individual needs and learning preferences [31, 37]. We demonstrate the hypothetical outcome of the Performance-Only approach if users want to have a results-oriented learning experience. Also, users can activate focus mode using our approach such that only specific types of tasks will be displayed for for training.

Additionally, many workplace training programs focus on developing employees' social skills, such as effective communication, to help them establish and maintain positive social relationships with others. In this paper, we only focus on training verbal communication by identifying the intentions of each sentence. Other nonverbal aspects such as gestures, eye contact, volume, and so forth are also vital in delivering messages. Our approach can incorporate with other communication skill training models [39] to evaluate users' social skill development and adaptively generate training sessions.

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