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RESEARCH ARTICLE

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An intelligent, adaptive, performance-sensitive, and virtual reality-based gaming platform for the upper limb

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Abstract

Stroke is a leading cause of adult disability, characterized by a spectrum of muscle weakness and movement abnormalities related to the upper limb. About 80% of individuals who had a stroke suffer from upper limb dysfunction. Conventional rehabilitation aims to improve one's ability to use paralyzed limbs through repetitive exercise under one-on-one supervision by physiotherapists. This poses difficulty given the limited availability of healthcare resources and the high cost of availing specialized services at healthcare centers, particularly in developing countries like India. Thus, the design of cost-effective, home-based, and technology-assisted individualized rehabilitation platform that can deliver real-time feedback on one's skill progress is critical. This paper describes the design of a novel, multimodal, virtual reality (VR)-based, and performance-sensitive exercise platform that can intelligently adapt its task presentation to one's performance. Here, we aim to address unilateral shoulder abduction and adduction that are essential for the performance of daily living activities. We designed an experimental study in which six individuals who had chronic stroke (post-stroke period: >6 months) participated. While they interacted with our VR-based tasks, we recorded their physiological signals in a synchronized manner. Preliminary results indicate the potential of our VR-based, adaptive individualized system in the performance of individuals who had a stroke suffering from upper limb movement disorders.

KEYWORDS

physiology, stroke, upper limb, virtual reality

1 | INTRODUCTION

Global Burden of Disease estimates that nearly 15 million people suffer from stroke every year with a prediction that 80% of stroke events will occur in low-to-middle income countries such as India by 2050,[1,2] making the incidence of stroke a public health issue. Stroke causes several disabilities such as loss of control on the contralesional side and loss of limb coordination and dexterity of hands. Research studies depict that 80% of stroke patients suffer from upper limb movement disorder, with only 20% achieving some functional recovery during the first 6 months of post-stroke.[3–6] Movement disorder in the upper limb often adversely affects an individual's ability to independently perform activities of daily living, for example, self-feeding, dressing, bathing, and brushing the teeth, thereby making the affected individual dependent on caregivers with subsequently reduced community life. Often, execution of these tasks needs one's shoulder abduction and adduction capability. With stroke, the abnormal joint torque often gets manifested as an inadequate shoulder abduction and adduction capability,[7] which makes it difficult for them to carry out reaching tasks required in activities of daily living. Conventional rehabilitation aims to address such disorders through physical therapy,[8,9] which has been promising for such patients for recuperating limb function. However, this needs one-on-one sitting with skilled clinicians and physiotherapists who can decide the right dosage of rehabilitation and timely access to specialized health care centers offering such services. For middle-income countries like India, limited availability of specialized healthcare resources, the high cost of availing specialized and private-owned services, and limited access to health care centers in rural areas are some of the main deterrents. Even when patients do receive rehabilitation, the upper limb receives scant attention, with a recent systematic review reporting that the average time spent on upper limb activities during a session is 0.9–7.9 min.[10] Also, a perception of treatment regimen as rigid and immutable often leads to exhausting patients' capabilities and motivation.[11]

Faced with these challenges, researchers have been investigating the use of technology-assisted platforms to deliver rehabilitation services that are intensive, quantitative, individualized, and cost effective. For example, investigators have used robot-assisted,[12–15] computer-based,[16–18] and wearable, sensor-based platforms[19] to address rehabilitation needs for individuals with upper limb movement disorder. However, the robot-assisted and wearable, sensor-based platforms such as CyberGrasp, although powerful, are often costly and, in some cases, might pose safety issues for the patient. Thus, computer-based platforms using virtual reality (VR) have been studied for their potential use in rehabilitation. This is because VR offers several advantages, for example, proponents highlighted the capability of VR systems to contribute to repetitive task practice with variations that are often motivating, real-time feedback, safety, controllability, etc.[9,20] Also, VR provides the flexibility to manipulate the rehabilitation paradigm, along with qualitative and quantitative feedback to the therapist and to the patient.[21] This flexibility in designing a suitable rehabilitation paradigm is important for individualized rehabilitation that is critical, given the spectrum nature of the disorder. Thus, in our present research, we have designed a VR-based exercise platform targeting an individual's upper limb movement.

In the recent years, the use of VR in stroke rehabilitation has increased, for example, Broeren et al.[22] developed VR-based 3D games to promote motor skills and pattern of arm movements of patients suffering from left arm paresis; Holden,[23] Saposnik et al.,[24] and Adams et al.[25] showed the importance of designing skill-specific meaningful activities in the VR environment for rehabilitation; Sucar et al.[19] presented VR-based Gesture Therapy platform for upper limb rehabilitation; and Ballester et al.[26] showed the efficacy of the VR-based intervention in enhancing motor skills of the paretic limb in hemiparetic stroke patients. Also, researchers have used VR in conjunction with external peripherals, for example, Wii (Nintendo),[27] Kinect Sensor (Microsoft),[28] and haptic devices,[29] which add to delivering a feeling of immersion in the task environment, thereby making the task motivating.

The currently existing VR-based systems offer exercises that can monitor one's performance in a task. However, tasks are not designed to offer different levels of challenge within the VR environment to the users. Given the spectrum nature of the disorder with varying residual motor abilities in post-stroke, it is critical to individualize the exercise platform such that the task is effective in spite of the individual variability evident in patients with different stroke severities.[30–32] One of the ways can be to design applications that are adaptive to individual capabilities by offering tasks of varying challenges based on individualized performance, similar to that practiced by expert clinicians. The estimation of patient's health condition while performing rehabilitation exercise is done by the clinician's expert eyes that are often subjective in nature and not quantitative. Literature studies indicate that various physiological signals showing cardiovascular, electrodermal ectivity, etc., are often considered as valuable health indicators to the physiotherapist.[33–35] Further, it has also been shown that monitoring physiological indices including heart rate[36] and galvanic skin response[37] is crucial during exercise, which is always helpful for clinicians to understand the patient's physiological profile and their exercise stress level.[38] However, none of the currently existing VR-based systems have investigated the implications of such technology-assisted exercise on one's health as can be evident through the monitoring of physiological indices during exercise. Thus, given the criticality of monitoring the health status or the physiological profile of patient, particularly during rehabilitation exercise sessions, it would be beneficial to make the rehabilitation platform with physiology. With this rationale, in our proof-of-concept study, we have considered physiology as an offline analysis with our performance in a self-adaptive system.

1.1 | Contribution and objectives

The **main contribution** of our present work is the development of VR-based adaptive task platform coupled with a peripheral device such as haptic device. Our VR-based, haptic-enabled task platform can (a) offer tasks of varying challenges based on individualized performance and (b) provide an avenue to monitor one's health status through real-time measure of physiological indices. The current paper focuses on three research objectives: (a) to develop a VR-based stroke rehabilitation platform equipped with force feedback facility, (b) to make the interactive system intelligent such that it can adapt to one's task performance ability by offering tasks of varying difficulty in a controlled manner, and (c) to understand the implications of such a system on an individual's task performance, namely, task progression, task completion time, performance errors, and performance score (PF) while doing a VR-based task. Additionally, we acquired their heart rate and galvanic skin response in a time-synchronized manner for subsequent offline analysis.

This paper is organized as follows. Section 2 describes the system design. Section 3 presents the experimental setup and the methodology used. Section 4 presents the results obtained in our experimental study. Finally, Section 5 summarizes the research findings, limitations of the current study, and the direction of our future research.

2 | SYSTEM DESIGN

Our system is composed of four modules: (1) VR-based task module, (2) physical interface module, (3) task switching rationale, and (4) physiological data acquisition module (Figure 1).

2.1 | VR-based task module

We designed the VR-based tasks using the Vizard software (marketed by Worldviz Llc.) and Google sketch-up (3D modeling program provided by Google). The VR-based tasks were of two different types, namely, (i) *Reaching* and (ii) *Coordination* tasks to trigger abduction and adduction movement of the shoulder joint. In order to facilitate repetitive practice as practiced by physiotherapists and mentioned in physiotherapy guidelines,[30–32] we designed a repository of 48 templates of VR-based tasks (24 each for *Reaching* and *Coordination* tasks) distributed over 3 difficulty levels (DL1–DL3) to avoid monotony of practice. Also, severity of the stroke is one of the important factors that influences the needs and preferences of the individuals who had a stroke.[39] Hence, three difficulty levels were designed while performing the reaching and coordination movements as an initial approximation to make the task effective in spite of the individual variability. However, based on the rehabilitation paradigm, more difficulty levels can be designed.

2.1.1 | Design of VR-based reaching task

For the *Reaching* task, we designed park environments composed of static and dynamic obstacles (e.g., crates and birds, respectively) and target objects (e.g., balloons of different sizes, shapes, and colors) as shown in Figure 2(a). The balloons were located randomly throughout the park with variations in the surrounding environment. The task was to reach out with the help of tabletop-mounted haptic stylus (stylus tip shown as an arrow in Figure 2(a)) and puncture the balloons by avoiding both the static and dynamic obstacles within a specified duration. "Crate"-shaped static obstacles were placed in front of the balloons to increase the difficulty in reaching out the balloons. Any collision of the haptic stylus with an obstacle was counted as an error. The number of balloons (3, 6, and 9) to be punctured within a specified duration decided the task difficulty level (DL1, DL2, and DL3, respectively).

2.1.2 | Design of VR-based coordination task

A car navigation task was designed as the VR-based *Coordination* task. A navigation environment consisted of a car, a track, and dynamic obstacles in the form of pedestrians crossing the track and static obstacles as tree pots at the edge of

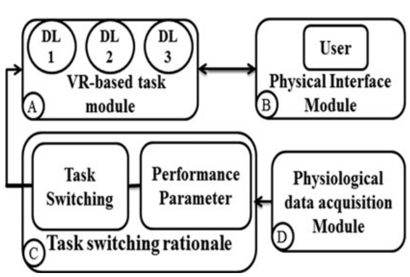

FIGURE 1 System design block diagram. VR = virtual reality, DL = Difficulty Level

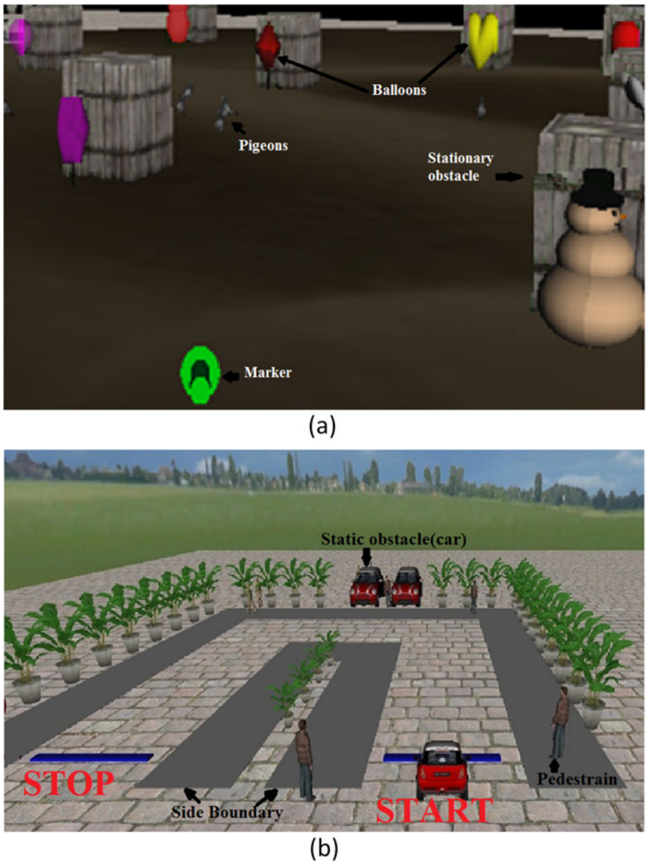

FIGURE 2 Screenshot of VR-based tasks in (a) reaching task and (b) coordination task [Colour figure can be viewed at wileyonlinelibrary.com]

the track (Figure 2(b)). A participant was asked to navigate the virtual car from a start line to stop line drawn on each track within a specified duration with the help of the haptic stylus while avoiding collision with the obstacles. The tracks were of different shapes to challenge the coordination skills of the participants. For example, DL1 task was kept fairly easy with a straight track. Tracks were curved to challenge the coordination skills for increased difficulty. The DL2 task has a semicircular track where the participant would need to continuously change the shoulder movements in order to follow the track and avoid collision with the pillars at the edge of the track. The DL3 has a semisquare track where the participant has to start from the start line, move through a straight track, change hand orientation, follow a straight track, change hand orientation, and finally follow a straight track to reach the end line of the track (Figure 2(b)).

2.2 | Physical interface module

Our participants interacted with the VR-based platform with the help of haptic device ("Phantom Omni" from Geomagic) as shown in Figure 3(a). The haptic device (integrated to the VR-based objects by dynamic linked library) provided tactile feedback to the participants during the interaction. We considered the haptic stylus movement along the x and y directions that maneuvered objects right/left and forward/backward, respectively, in the VR environment. This stylus movement corresponded to the patient's horizontal shoulder adduction/abduction.

In the *Reaching tasks*, one had to translate the haptic stylus on a physical workspace (x, y) of 30 mm × 70 mm for DL1, 60 mm × 70 mm for DL2, 90 mm × 70 mm for DL3 that accounted for an angular displacement range (x(min, max), y(min, max)) of 0°–20°, 0°–52° for DL1, {0°–55°, 0°–52°} for DL2, and {0°–90°, 0°–52°} for DL3 for completing each task (i.e., punching of all the balloons: 3 for DL1, 6 for DL2, and 9 for DL3). Thus, with the increase in difficulty level, the horizontal displacement (along x) varied from 30 mm to 90 mm, and angular displacement range extends from 0° (DL1) to 90° (DL3). Similarly, in the *Coordination tasks*, physical workspace (x, y) varies from (0 mm × 70 mm) for DL1, (60 mm × 70 mm) for DL2, (120 mm × 70 mm) for DL3, which accounted for an angular displacement range (x(min, max), y(min, max)) of {(0°–20°), (0°–52°)} for DL1, {(0°–55°), (0°–52°)} for DL2, and {(0°–120°), (0°–52°)} for DL3

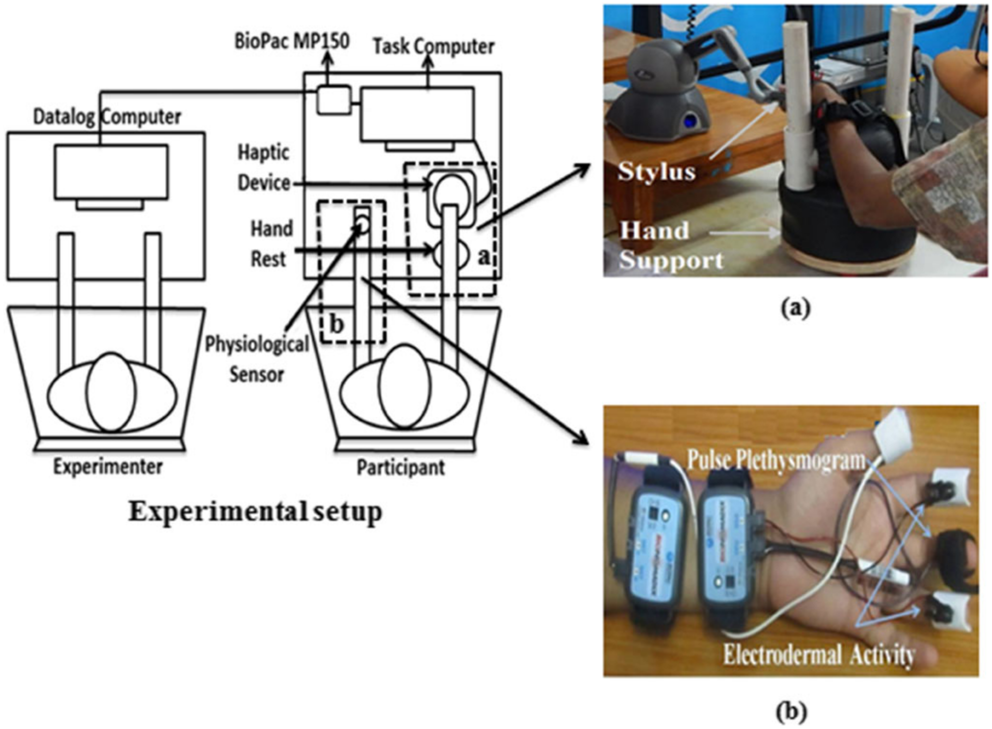

FIGURE 3 Block diagram of physical interface module. PPG = pulse plethysmogram; EDA = electrodermal activity. (a) A participant holding the stylus of the haptic device (b) Setup for sensors PPG and EDA [Colour figure can be viewed at wileyonlinelibrary.com]

for completing each task (i.e., traversing the VR track from the Start Line to the Stop Line). Thus, the horizontal displacement range extends from 0 mm to 120 mm with angular displacement from 0^o to 120^o, keeping the displacement along the z direction at 70 mm and 52^o for all the cases. The idea of variability in range/angular movements was to encourage the participants to make shoulder movements while doing the tasks. Please note that our system was programmed to make one's shoulder movement on a restricted workspace based on the limited movement capability of our post-stroke participants. Although the participants came with some residual shoulder abduction and adduction capability, they faced difficulty in making large displacement of their hand through shoulder abduction/adduction. The patient's affected hand was tied to the haptic stylus with a Velcro belt to prevent it from falling, and his hand was provided with a hand support (Figure 3(a)). We hope that with the knowledge of performance and repeated exposure, this haptic device can be replaced with one that allows increased movement. Additionally, the haptic device was programmed to provide tactile feedback (approximately 1.6 N) to the user upon colliding with an obstacle (static or dynamic) in the VR environment. For our experimental study, we used Equations (1) and (2) and did not use the turret-like movement of the haptic stylus because we did not focus on the roll capability of one's wrist joint, as follows:

$$\Delta \mathrm{Z}_{\mathrm{DIST}} = \mathrm{W_Z}^* \left(z + z_{\mathrm{OFFSET}}\right) \tag{1}$$

$$\Delta \mathrm{X}_{\mathrm{DIST}} = \mathrm{W_X}^* \left(x + x_{\mathrm{OFFSET}}\right), \tag{2}$$

where ΔZ_{DIST} and ΔX_{DIST} represent the distance of the virtual car (for *Coordination task*) or haptic pointer (for *Reaching task*) traversed in the VR environment corresponding to the stylus displacement along z and x directions, respectively. W_Z and W_X are the weight factors used to render a smoother and controlled maneuver of the virtual car/haptic pointer along the track/park environment. The z_{OFFSET} and x_{OFFSET} are the offsets used for getting the coordinates of the virtual car/haptic pointer on a 0–1 scale. These weight factors and offset values were chosen as an initial approximation for our experimental study, and these can be changed in future. For the *Reaching* task, the weight factors and offset values were W_Z (=0.2), W_X (=10), and z_{OFFSET} (=0), x_{OFFSET} (=0), respectively. For *Coordination* task, the weight factors and offset values were W_Z (=0.5), W_X (=4.5), and z_{OFFSET} (=0.5), x_{OFFSET} (=0), respectively.

2.3 | Task switching rationale

Our VR-based system was adaptive to the participant's PF while the participant interacted with the VR-based tasks. Here, a cutoff score of 70% was used in tasks across different difficulty levels, similar to that used for robot-assisted rehabilitation

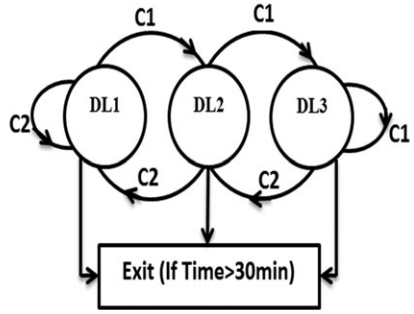

FIGURE 4 State machine representation

tasks, for outpatient clinics, and technology-assisted skill learning.[40–42] The task switching module offered tasks (chosen randomly) of varying challenges (difficulty level) based on one's PF using a state machine representation (Figure 4).[43]

If a participant's performance in a task belonging to a particular difficulty level was "Adequate" (≥70%; condition C1), say DL1, then our task switching module offered tasks of higher difficulty (DL2), except for DL3, because DL3 was the highest difficulty level. If one's performance was "Inadequate" (condition C2), then the module switched to a task of lower difficulty level (except for DL1). Care was taken that different task templates were offered to the participants in order to avoid the feeling of monotony that the participant might experience while performing tasks. While offering tasks of varying difficulty levels, our algorithm also took care on the presentation of *Reaching (R)* and *Coordination (C)* tasks such that an *R* task of lower difficulty level was presented before an *R* task of higher difficulty level. Likewise was the case for *C* tasks. For example, if 1_R, 2_R, 3_R, 1_C, 2_C, 3_C represent *R* tasks and *C* tasks in DL1, DL2, and DL3, respectively, then, if the first task was 1_C; this could be followed by 1_R for "Inadequate" performance or by 2_C (but not 2_R) for "Adequate" performance. This was because the first game offered was 1_C and not 1_R. The task repository was sufficient to offer tasks that ended on completion of 30 min of task performance, similar to that reported in literature.[44]

2.3.1 | Computation of PF

PF was evaluated based on the time (T) taken by a participant to complete a given task and the number of collision errors (E) made by the participant while performing the task. Our algorithm calculated time fraction (TF) and error fraction (EF) from T and E. From our previous pilot study with age-matched healthy participants (n = 6; mean (sd) =48 (18.23) years), we decided the threshold values of T and E as T_{TH} = 50 (Dl1), 80 (DL2), 110 (DL3), respectively, for *Coordination*; T_{TH} = 225 (DL1), 525 (DL2), 825 (DL3) for *Reaching*; and E_{TH} = 5 for DL1–DL3 for both the tasks.

The TF is defined by Equations (3)–(5) as follows:

$$\text{If} \quad T \le T_{TH}, \text{then } TF = 1 \tag{3}$$

$$\text{If} \quad T_{TH} < T \le 2^{*}T_{TH}, \text{then } TF = \frac{2^{*}T_{TH} - T}{T_{TH}} \tag{4}$$

$$\text{If} \quad T > 2^{*}T_{TH}, \text{then } TF = 0 \quad . \tag{5}$$

Likewise was the case for EF.

Speed–accuracy trade-off is critical while taking an errorless (or reduced error) approach, particularly seen in exercises related to upper limb rehabilitation.[45] Keeping this trade-off in mind, as a first approximation, we have considered a weight distribution of 60% for EF and 40% for TF (Equation 6). Although both the speed and accuracy of task execution are important, we allotted more weightage to accuracy than the time taken, because performing a task accurately with less number of errors was considered as more important from the standpoint of rehabilitation. For example, if a individual who had a stroke was asked to brush his teeth, then satisfactory ability to complete brushing is more important than completing brushing unsatisfactorily within a shorter duration.

$$PF = 100 * ((0.6 * EF) + (0.4 * TF)\,. \tag{6}$$

2.4 | Physiological data acquisition module

While our participants interacted with VR-based systems, physiological signals, namely, pulse plethysmogram and electrodermal activity, were acquired by Biopac MP150 (from Biopac Systems Inc.) operated in wireless mode with sampling frequency of 1,000 Hz. The acquired signals were processed to extract two physiological indices, for example, mean pulse rate (PR_{MEAN}) and tonic mean ($Tonic_{MEAN}$) synchronized with VR-based task propagation.[46] We chose these signals, because literature indicates the importance of monitoring these signals as possible window to one's health condition during exercise. Specifically, pulse rate, an important indicator of one's physical fitness, is often used by clinicians in deciding the exercise intensity.[34] Also, tonic activity has been reported to be used as a metric of post-stroke functional recovery.[35] Even for VR-based exercises, investigators have used pulse rate and galvanic skin response to provide additional user state information to the clinician, thereby helping in making informed decisions on the pacing of the VR-based exercises.[33]

3 | EXPERIMENTAL SETUP AND METHODOLOGY

3.1 | Participants

We included six individuals who had a stroke (mean (SD) =50 (8.50) years) in the study. These patients were recruited through referral from a local civil hospital where they were undergoing therapy. Once their questions related to our system were answered, their consent for voluntary participation in the study was sought. The participants' characteristics are shown in Table 1. The study was approved by the Institutional Ethics Committee.

3.2 | Inclusion and exclusion criteria

Patients aged 18–75 years and having a post-stroke period of >3 months were included in the study. Individuals with a history of recent surgery (<3 months) and having a skeletal injury or pace maker were excluded. Patients were also screened by a physiotherapist through the range of motion of horizontal abduction and adduction measures of their shoulder joint on the first day (Fday) to see whether it was less than the corresponding values for healthy adults as reported in the literature.[33]

3.3 | Experimental procedure

The experimental setup (Figure 3) was composed of (a) a chair placed in front of a task computer mounted on a table along with a haptic device, (b) a real-time data acquisition module connected to a data logger computer through an Ethernet port, and (c) a height-adjustable hand support. We invited participants for multiple exposures. However, based on the availability, most of the participants were given 3 exposures on 3 different days. Our study required an involvement of approximately 1 hr on the Fday including the patient's screening by the physiotherapist, signing of the consent forms, task demonstration by the experimenter, and interaction with VR-based tasks. Subsequent exposures lasted for approximately 30 min of the VR-based task. Also, the experimenter informed the participant that he was free to quit from the study at any point if he felt uncomfortable. Although we designed *Reaching* and *Coordination* tasks that were of two different task types, in our present experimental study, we offered both the task types to the participants in each session. The motivation was to expose each participant to a mix of *Reaching* and *Coordination* tasks on each day, similar to that required in real-life scenarios while executing daily living activities. However, care was taken to offer *Reaching/Coordination* tasks while keeping an eye on the fact that the participant was exposed to a task of lower difficulty level before being exposed

TABLE 1 Participant characteristics

Participants	Age (Years)	Affected hand	Post-stroke period (Years)	Days of exposure	Range of motion (in degrees) (Shoulder)
P1 (m)	52	Left	1	3	Ab:0–40°, Ad:0–40°
P2 (m)	48	Right	2	4	Ab: 0–80°, Ad: 0–70°
P3(m)	52	Right	8	3	Ab:0–90°, Ad:0–80°
P4 (f)	35	Left	0.58	3	Ab:0–75°, Ad: 0–60°
P5 (f)	61	Left	1	3	Ab: 0–60°, Ad:0–60°
P6 (f)	52	Left	2	2	Ab:0–75°, Ad:0–60°

Note. m = Male; f = female; Ab = abduction; Ad = adduction.

to a task of higher difficulty level. After completion of each task, our system delivered audiovisual feedback, for example, "Good job!" and PF points (0 –100).

4 | RESULTS

Here, we present the findings of the experimental study carried out with our VR-based task platform that offered tasks of varying difficulty levels based on one's task performance. Specifically, we report our observations on one's task performance measured between the Fday and the Lday of interaction in terms of (a) task progression, (b) task execution time, and (c) accuracy while performing the tasks (i.e., reduced errors). Additionally, we present the implications of VR-based tasks on the participants' physiological indices such as PR_{MEAN} and $Tonic_{MEAN}$.

4.1 | Effect of our VR-based system on participants' task progression

Figure 5 shows the task progression pattern of all the participants for both Fday and Lday along with the distribution of *Reaching* and *Coordination* tasks of varying challenges.

It can be seen from Figure 5 that the pattern of task progression changed considerably on the Lday compared with that on the Fday of interaction for almost all the participants. On the Lday, all the participants were able to reach the highest difficulty level (DL3). Although P2 and P4–P6 also could reach DL3 on the Fday, there was an improvement in performance. For example, although P2, P4, and P5 interacted with the same number of trials on Fday and Lday, the

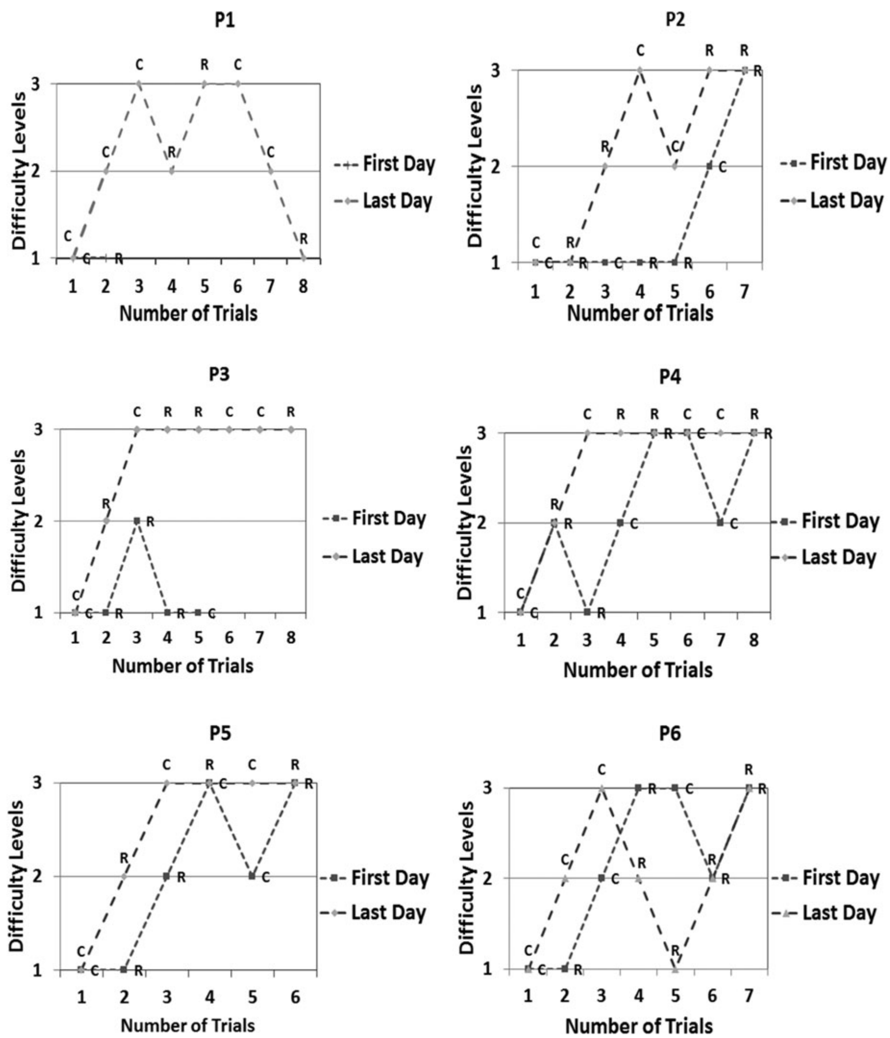

FIGURE 5 Comparative representation of task progression of P1–P6 between the first day and last day. R: Reaching; C: Coordination

number of trials in DL3 on Lday were more than that on Fday. However, for P6, although the number of trials in DL3 on Lday was less than that on Fday, there was a better controlled hand movement in terms of reduced collision error ($\Delta = 32\%$ for DL1, $\Delta = 44\%$ for DL2, $\Delta = 40\%$ for DL3) and improved performance in certain tasks of DL1 and DL2 ($\Delta = 57\%$ for *Coordination* task (DL1) and $\Delta = 14\%$ for *Reaching* task (DL2)).

4.2 | Effect of our VR-based system on participants' task execution time

Improvement in skill learning depends not only on one's capability of completing more task trials (as is evident from the task progression) but also on the ability to achieve improved task execution speed, without compensating for the PF. From Figure 6, we find that on an average, the *Reaching* tasks took more time than the *Coordination* tasks, possibly due to the fact that the *Reaching* tasks required the participants to search the targets distributed throughout the VR environment. Again, for both the *Reaching* and *Coordination* tasks, there was reduction in Task Execution Time from the Fday to the Lday across different difficulty levels, although by varying amounts. The decrease in task execution time indicates increase in speed of execution, which can be considered as an improvement in performance, provided that it comes with decrease in collision errors.

4.3 | Effect of our VR-based system on participants' performance errors

For improvement in skill, one needs to be able to do a task not only with increased speed but also with improved accuracy, that is, fewer collision errors in our case. Thus, we compared the average number of errors performed by the participants while interacting with our VR-based tasks for each difficulty level between the Fday and Lday. From Figure 7, we observe that the group average errors reduced for both the *Reaching* and *Coordination* tasks from Fday to Lday across all the difficulty levels, except DL3 of *Coordination* tasks (for which the error counts were comparable). In fact, the number of collision errors reduced from Fday to Lday for all the participants, except P5 for DL3. A possible reason behind this can be that P5 was hurrying to complete the tasks on the Lday, making more collision errors, as reported by the experimenter.

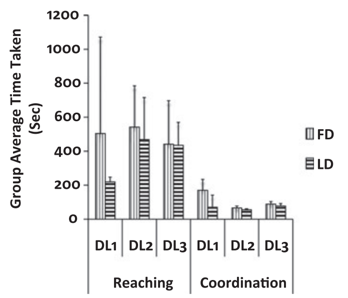

FIGURE 6 Group average interaction time of participants from (a) first day to (b) last day in reaching (R) and coordination(C) task with standard deviation bars. FD = First day, LD = Last day, DL = Difficulty Level

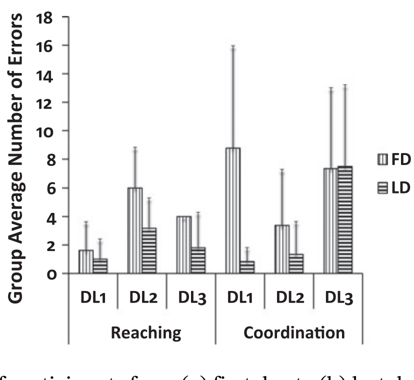

FIGURE 7 Group average number of errors of participants from (a) first day to (b) last day in reaching(R) and coordination(C) task with standard deviation bars. FD = First day, LD = Last day, DL = Difficulty Level

4.4 | Effect of our VR-based system on participants' PF

While our participants interacted with the VR-based tasks, our system computed their PF by using Equation (6). Figure 8 presents the group average PF (%) for both the *Reaching* and *Coordination* tasks on Fday and Lday across all the difficulty levels. There was an improvement in performance (%) from Fday to Lday for all the difficulty levels, except marginal change for DL3 trials of *Reaching* tasks and DL2 trials of *Coordination* tasks. A possible reason behind this can be that the participants took considerable time (that was comparable on Fday and Lday) to complete the DL3 trials of *Reaching* tasks and DL2 trials of *Coordination* tasks (Figure 6). Again, as far as the *Reaching* tasks were concerned, the group showed *Adequate* performance even on the Fday. However, that was not the case for the *Coordination* tasks (except DL2 tasks). A possible reason might be that the number of collision errors was more for the *Coordination* tasks on the Fday (except DL2 tasks) compared with the *Reaching* tasks (Figure 7). As reported by the experimenter, the participants were unable to make controlled maneuver of the VR cars with increased collisions with the walls at the side of the tracks on the Fday.

4.5 | Effect on PR_{MEAN}

Figure 9 shows the variation in the group PR_{MEAN}. On average, the PR_{MEAN} reduced on Lday than that on the Fday for both the *Reaching* and *Coordination* tasks and across all the difficulty levels, except *Reaching* tasks of DL1. This might infer that the participants were more comfortable while interacting with the *Reaching* and *Coordination* tasks on Lday than that on the Fday across the varying task difficulty levels. The increase in PR_{MEAN} on the Lday for the *Reaching* tasks, particularly for DL1, can be attributed to the fact that as the participants were excited to interact with our system (that most of the participants told the experimenter post our study) due to that they pressed themselves hard to perform well in the tasks, with the *Reaching* tasks requiring them to search the VR environment, accounting for maximum increase (%ΔPerformance$_{\text{Fday-to-Lday}}$ = 37% for DL1, 22% for DL2, −3% for DL3) in the % performance (Figure 8) for *Reaching* tasks.

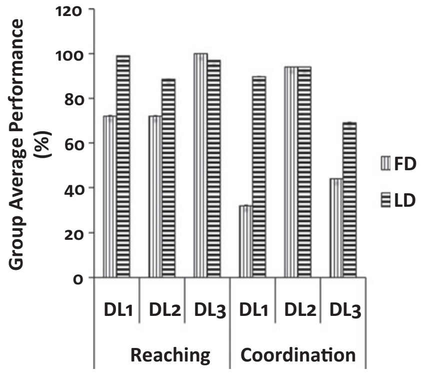

FIGURE 8 Group average performance score (%) of participants from first day to last day. Note that here, standard deviation is very less, therefore not visible. FD = First day, LD = Last day, DL = Difficulty Level

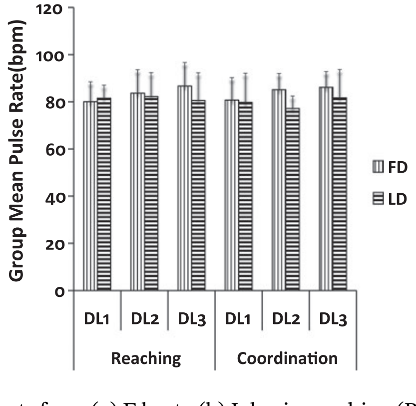

FIGURE 9 Group mean pulse rate of participants from (a) Fday to (b) Lday in reaching (R) and coordination(C) task with standard deviation bars. FD = First day, LD = Last day, DL = Difficulty Level

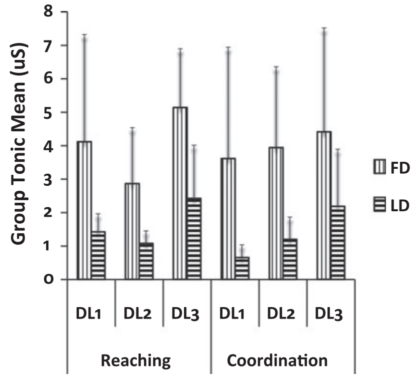

FIGURE 10 Group average tonic mean of participants from (a) first day to (b) last day in reaching (R) and coordination(C) task with standard deviation bars. FD = First day, LD = Last day, DL = Difficulty Level

4.6 | Effect on Tonic$_{MEAN}$

Similar to that for PR$_{MEAN}$, we find from Figure 10 that the participants' group Tonic$_{MEAN}$ indicated that for both the *Reaching* and *Coordination* tasks across different difficulty levels, the participants were more comfortable on the Lday as compared to the Fday.

5 | DISCUSSION AND CONCLUSION

The results of our VR-based experimental study indicate that our system can have implications on one's task performance. Specifically, the preliminary results indicate that the performance improved in terms of task progression pattern, task completion time, performance errors, and PF while doing the VR-based tasks. Additionally, the results on the physiological indices, such as PR$_{MEAN}$ and Tonic$_{MEAN}$, indicate that the participants' improvement in performance across tasks of varying difficulty from Fday to Lday was accompanied with themselves being more comfortable on the Lday as compared with the Fday. The decrease in pulse rate and tonic inhibition, which are valuable indicators of health condition during post-stroke recovery, indicates the potential of such a system to promote rehabilitation while contributing to improvement in health condition and physical fitness. However, in comparison with previous studies,[35] which speaks on tonic inhibition as an indicator of post-stroke functional recovery, similar trends (reduction in Tonic$_{MEAN}$) shown with our system indicate less stress level and further promote post-stroke recovery. Pioneering contributions[13,17–26,32,47] used for stroke rehabilitation are powerful; often employ robots that are costly and heavy, posing financial and safety burdens on the patient; and, in some cases, have been reported to be limited in their ability to have a significant impact on one's daily living activities. Wearable sensors, such as CyberGrasp, used in stroke rehabilitation can provide force feedback to the user; besides being expensive, such wearable sensors often require uncomfortable mechanical plug for mounting on one's hand, making it inconvenient for use by patients. Additionally, these applications were not adaptive to offer tasks of varying challenges to the participants based on their individualized performance in a controlled manner and also do not provide individualized feedback on one's physiological profile, to the participants and also to the clinicians.

Our system is different compared with abovementioned pioneering studies, as users can repeatedly practice specific movements in a variety of environments in a controlled manner to achieve adequate performance; their physiological profile brings the added potential advantage to the physiotherapist, thereby providing a window into the quantitative estimates of one's health status. Passive device does not generate any power, is portable, cost effective, and suitable for home rehabilitation compared with clinical assistive devices having mechanical complexity. Our system also includes audiovisual feedback, as recent studies indicate that learning can be enhanced by visual and/or auditory cues.[17,20]

Although the preliminary results are promising, our study had certain limitations. One of the limitations was a small sample size. However, the **main focus** of our paper was to design an individualized VR-based system that can offer *Reaching* and *Coordination* tasks (frequently used in daily living) to the participants as a technological platform rather than an intervention platform. In order to understand whether our system was operating as desired, we designed a preliminary experimental study with a small sample size and for a limited duration. However, in the future, for a full-fledged intervention study, we plan to carry out a longitudinal study with a larger number of participants. Another limitation of our study was the usage of the haptic device with a limited maneuvering capability. While considering the upper limb movement capability of our participants, we used this haptic device with limited maneuverability. However, in the future, with longitudinal study, we plan to use haptic devices that have increased maneuverability.

With promising results of the present study, we hope that such a system can be used at least as a complementary tool in the hands of the therapists. Also, information on the real-time physiological measures of the patients during exercise can help the therapists to get an estimate of the physiological profile of the patients and accordingly decide the intervention paradigm. The low-cost portable exercise platform can reach households and thereby can be potent to bring in paradigm shift even in rural healthcare.

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Conflict of Interest: The authors declare that they have no conflict of interest.

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