3 Designing Robots That Challenge to Optimize Motor Learning

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Abstract

The purpose of this chapter is to provide the reader with a better understanding of the theory and practice of providing effective levels of challenge for people with motor disability, using rehabilitation robotics to provide the safety and assurance that is necessary to prevent physical harm and mental frustration. First, we describe the therapeutic context with which clinicians encounter the need to design challenge into the motor learning sessions that are typical for individuals who are recovering from impaired movement. Second, we explore the challenge point framework as a major breakthrough in our understanding of the nature of challenge in motor performance and how this challenge contributes to efficacious motor learning. Next, we describe ways in which rehabilitation robotics can be designed and implemented to explore the ways in which people

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with motor disability can learn to move again and how results with these devices suggest extending the challenge point framework to take into account self-efficacy and willingness to practice. Finally, we provide a detailed example of a robotic system that works collaboratively with the clinician to provide physical challenge during walking and balance training in people with poststroke hemiparesis using a library of novel techniques. We conclude by providing further thoughts to engineers and clinicians who collaborate to develop a next generation of rehabilitation robotics that build on the concepts of optimal challenge into the engineering design.

Keywords
Movement rehabilitation • Motor learning • Rehabilitation technology • Challenge • Practice psychology • Self-efficacy • Stroke • Psychomotor performance

3.1 Therapeutic Context of Physical Challenge During the Rehabilitation Process

Impaired motor performance results in disability that becomes a major obstacle to community function in persons with movement disorders such as poststroke hemiplegia, spinal cord injury, Parkinson's disease, multiple sclerosis, head injury, osteoarthritis, postamputation loss of limb, etc. This disability is characterized by functional deficits, such as slow walking, inability to grasp objects, moving in a manner so as to avoid pain, and avoiding situations in life that may result in falls. Often these functional deficits are due to a combination of motor impairments such as reduced muscle strength, slow movement speed, poor balance and coordination, poor aerobic endurance and muscle fatigue, and an inability to move under conditions of environmental distractions due to fear of falling or lack of attention to movement. The inability to move functionally in a complex environment can result in some dire consequences. For example, in the case of persons with gait and balance impairments, there can be a high risk for falls at the home and in the community.

One of the promises of robotic rehabilitation applications is in providing persons with disability the opportunity to be physically challenged in a safe and efficacious manner. While clinicians are very effective at matching the capabilities of a person with disability with the challenge of the exercise, physical limitations in a clinician's strength and endurance can reduce the potential for providing consistently challenging and ever-progressing environments for continued performance improvement. In addition, there are some domains of challenge, such as with balance, strength training, and speed training, where smart machines, such as robots, can provide tireless and adaptable challenging exercise and motor learning environments.

It also may be argued that, unless the person is challenged to perform beyond their current capability, acquisition of new and improved functional movement behaviors will be limited. In fact, in such wide-ranging fields as athletic performance, musical instrument expertise, and chess mastery, the evidence shows that mastery in a task is best achieved with deliberate and persistent practice sessions that push a person to move beyond their current performance limitations. Of course, the physical risks of harm and mental frustration that come along with attempts to move against high-level challenges should cause concern. However, rehabilitation robotics, if designed appropriately, can allow individuals who are learning to move more functionally, to attempt increasingly challenging tasks without fear of harm and with the knowledge that, if they make mistakes during the training, they can learn from the mistakes.

Further, in the case of neurological injury or disease, the concept of challenge must be applied intelligently when used as an adjunct to disorders that may limit ability to recover movement capability. Factors such as impaired sensory input (i.e., proprioceptive, cutaneous, visual, vestibular, etc.), inappropriate coupling of muscle activations, muscle hyper- or hypotonicity, poorly prepared and planned movement sequences, difficulty with starting and stopping movements, and psychological factors (i.e., cognitive status, memory, motivation, etc.). The sections that follow describe the concept of challenge; however, one must always remember that the nervous system can be overstimulated; therefore, a sensitive clinician will always monitor physiologic and behavioral responses when providing challenging learning environments. Optimal challenge conditions in the case of recovery of walking and balance poststroke will be discussed in Sect. 3.4.

3.2 The Challenge Point Framework

Motor performance and motor learning share a fluctuating relationship. A *performance* is usually defined as the outcome of an action. It can be measured at any one time or over a series of short-term intervals. In contrast, the term *learning* refers to performance improvements that "stick"; improvements that are relatively permanent over a longer term. One might assume that good short-term performances naturally lead to good longer-term improvements. But, that assumption does not hold, and in fact, many times the reverse is true—better learning often results from poor performances. Guadagnoli and Lee [1] introduced the "challenge point framework" (CPF) in an attempt to define how the relationship between performance and learning could be optimized.

Motor performance is critically dependent on the difficulty of the task. All other issues being equal, more difficult tasks generally result in less successful performances. However, learning can sometimes benefit from difficulties. Bjork [2] termed these as "desirable difficulties." Clearly, though, not all difficulties are desirable. Guadagnoli and Lee [1] hypothesized that difficulties could be optimized in order to promote the desirable and minimize the undesirable effects.

The CPF hypothesized a systematic attempt to introduce challenges to the learning environment. The critical factors that combined to define a challenge point included the task, the individual, and the practice-related constraints. Some tasks are more difficult to perform than other tasks, and optimal learning conditions are predicted to be associated with levels of task difficulty that are appropriate for the skill level of the learner. The CPF predicted that there are levels of task difficulty that are too easy for some individuals and levels that are too difficult for others. And, although there may exist a level of task difficulty that optimizes learning for each individual at some point in time, the level must be adaptable to changes in the performer that occur with learning (see also [3–5]).

The CPF considered adapted task difficulty as a key component for setting appropriate conditions of practice for learning. For example, an easy task, practiced under random practice conditions, makes performance on the task more difficult in a *functional* sense. Conversely, a difficult task, subjected to physically restricted guidance, makes performance on the task *functionally* less difficult. There are many other practice-related conditions that change the functional difficulty of practice too (such as rote repetition, the provision of feedback, and so on).

The CPF therefore considered the effects of functional task difficulty from a perspective of both performance in practice and the potential for learning that might result. Figure 3.1 illustrates a predicted optimal point at which increasing the functional task difficulty would maximum learning at the least cost to immediate performance. The goal of optimizing the functional task difficulty was to maximize the positive boost to learning combined with the negative detriments to immediate performance. Beyond the optimal point, the framework predicts that performance will deteriorate rapidly at a cost to learning as well. Figure 3.1 illustrates the prediction from the framework that an optimal challenge point would occur at a level of functional task difficulty that was considerably lower for a novice than for a skilled performer.

Let's use golf practice as an example of how the CPF might be useful. For the beginner, striking a golf ball to result in an airborne trajectory is a very difficult task. Repeated failures do not optimize learning—at the beginner stage, learning is facilitated by successful performance. For the novice, physically restricted guidance devices, for example, make the task functionally, less difficult, which should positively influence both performance and learning. The use of physically restricted guidance devices, however, might have the opposite effect for the more advanced golfer. In this case, the learner needs to be challenged by more functionally difficult practice conditions, because the task itself does not bring about the same level of challenge as it did for the novice. Changing golf clubs on each practice attempt, or playing shots out of imperfect lies in the grass, adds a desirable challenge for the more advanced golfer that would optimize the benefits of practice that would "stick" for the longer term (see [6] for more examples).

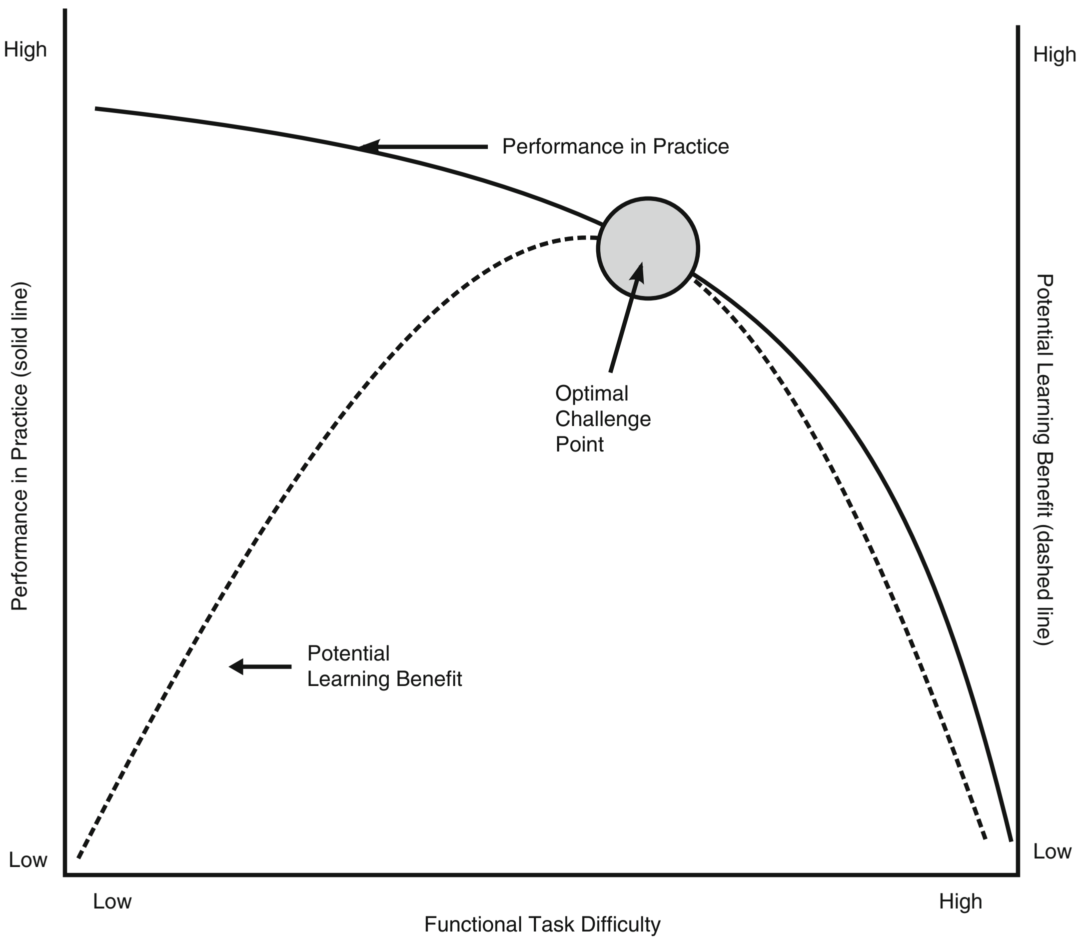

Fig. 3.1 The optimal challenge point predicts the level of functional task difficulty that maximizes learning at the least cost to performance during practice. This optimal challenge point is relative to the individual's abilities and thus changes in relation to the individual's level of expertise

3.2.1 Application of the CPF to Stroke Rehabilitation: A Pilot Study

Some predictions made in the CPF were examined in a randomized controlled pilot trial by Griffiths [7], involving patients in an inpatient stroke rehabilitation program. A small sample of participants, 2–12 weeks poststroke, was assigned to one of three training groups. A control group ($n=3$) received a usual-care, strength training protocol. A second group of participants ($n=3$) were assigned to a condition in which they were encouraged to select a set of specific tasks to be used in therapy with the goal to challenge their current capabilities as much as possible. As performance improved participants were taught how to change the tasks to make them more challenging. The third group of individuals poststroke ($n=5$) also practiced challenging tasks, but these were assigned by the therapist, rather than self-selected. Physical therapy was administered for 15 sessions over a 3- or 4-week period, which was followed by 4 weeks of self-managed physical therapy that usually occurred in the home post-discharge. A number of primary and secondary recovery-of-function assessments were taken at three time periods: pre-intervention (T1), post-intervention (T2, following the 15 sessions of physical therapy), and after the 4 weeks of self-managed therapy (T3). The general goal in selecting the tasks to be performed in the therapy session was that they were to be neither too difficult nor too easy to perform. Note that the difference between the two experimental groups was that in the self-selected group, the participants were taught to determine the tasks that optimally challenged their current skill capability, and in the therapist-selected group, the therapist chose the tasks to optimally challenge the participants' current capability.

The effect of the therapy conditions on the (CAHAI) Chedoke Arm and Hand Activity Inventory, a measure of functional activity performance, illustrated in Fig. 3.2, represents just one of the primary assessments. Many of these other outcomes showed similar effects, although not all were significant due to the small sample and low statistical power. The results for the CAHAI revealed that the self-selected group produced the best recovery-of-function result at T3 (after the self-management period), even though

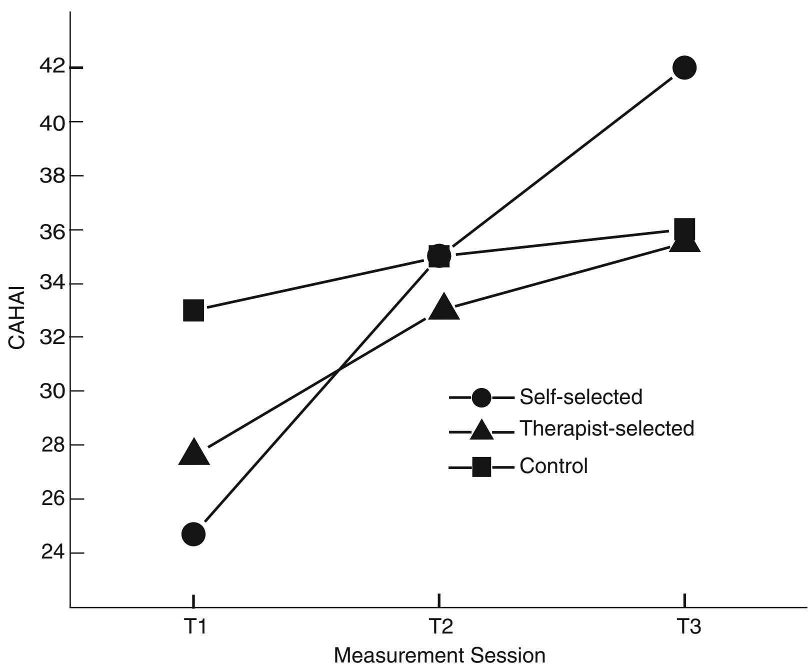

Fig. 3.2 Performance of three poststroke treatment conditions on the Chedoke Arm and Hand Activity Inventory (CAHAI) at T1 (prior to treatment), T2 (after a 15-session inpatient treatment), and T3 (after 4 weeks of at-home self-administered treatment) (From Griffiths [7]; used with permission)

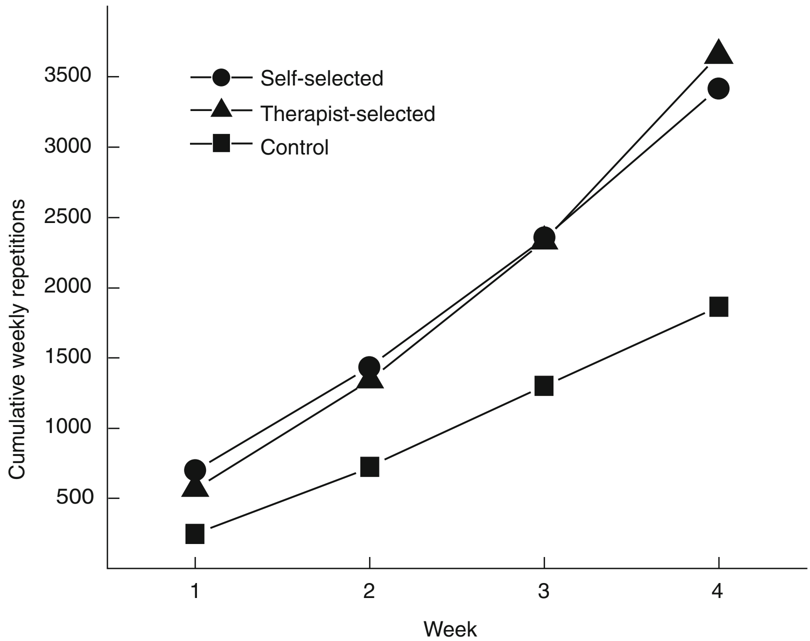

Fig. 3.3 Cumulative number of at-home task repetitions that were recorded (by diary) over a 4-week period treatment period (From Griffiths [7]; used with permission)

the participants in control group were much better at T1. In terms of proportional recovery of function, the self-select group improved by 41.7 % from T1 (pretest) to T2 (after the inpatient therapy) and by 70.0 % when considered from T1 to T3. The patients receiving therapist-selected tasks improved by 19.6 and 28.6 % over these same periods. Both of these proportional improvements were higher than the improvements seen in the control groups (3.0 % and 9.1 % in T1–T2 and T1–T3, respectively).

Perhaps of equal, if not more important, however, were the task repetition records that were observed in the patients' diaries over the 4-week period of self-managed treatment. These findings, illustrated as the cumulative number of task repetitions in Fig. 3.3, revealed that both the self-selected and therapist-selected groups continued the self-managed treatment with a significantly higher dose of training than the control group. This finding was unexpected, and Griffiths suggested that the finding indicated that the increasingly challenging aspects of the therapies resulted in higher, sustained motivation to continue self-managed treatment at home.

Minimally, the findings of this pilot study suggest that a larger trial is warranted. The data support the potential role of providing task appropriate challenges to individuals poststroke during physical rehabilitation, both in terms of recovery of function and in terms of enhanced motivation to continue treatment. The latter finding supports the long-held view in motor learning that *amount and intensity* of practice are the most important determinants of skill improvement. If that statement is true also for recovery of function following stroke (as many believe it to be), then therapy treatment conditions that facilitate recovery of function *and* motivate the individual to continue therapy serve as dual-purpose advantages. The CPF is one possible mechanism that could inform therapy (see also [8]).

3.3 Using Robotic Technologies to Provide Challenge in Rehabilitation Therapy

Based on the prior discussion, it is clear that a key issue in the design of neurorehabilitation therapy technology is to provide appropriate challenge during training. This section describes the evolution of robotic therapy device design to meet this requirement. Two initial strategies have been to provide mechanical assistance for movement and, more recently, to automatically adjust therapeutic parameters using sensors and software algorithms.

3.3.1 Providing Appropriate Challenge by Providing Mechanical Assistance

The first robotic therapy devices were designed to provide mechanical assistance to help individuals complete training tasks (for reviews, see [9, 10]). This strategy mimicked the strategy of active assistance sometimes used by rehabilitation therapists, in which the therapist physically assists the active patient in completing movements. Therapists use active assistance for both the upper extremity, for example, for reach practicing, or for the lower extremity, for example, by providing balance support during overground walking training. Likewise, initial robotic therapy devices for the upper extremity, like MIT-MANUS [10], MIME [11], and the ARM Guide [12], assisted patients in completing reaching movements, while initial devices for the lower extremity, like the Lokomat [13] and the Gait Trainer [14], assisted patients in maintaining balance and achieving a stepping-like pattern of leg motions. These machines physically attached to the patient and essentially tried to work in harmony to achieve desired movements, specified by video games for the upper extremity or using a normative gait trajectory for the lower extremity.

Within the challenge point framework, this strategy of providing assistance can be viewed as a way to make rehabilitation tasks that are overly difficult practicable by individuals with severe impairment. As explained above, making a task practicable may make it more learnable. In addition, making tasks practicable may play a role in motivation. In the words of one participant with a stroke in a study with the arm training exoskeleton T-WREX, “If I can’t do something once, why would I do it a hundred times?” [15].

The motivational significance of robotic assistance was recently confirmed in a study of the FINGER robotic finger training exoskeleton. In this study [16], 30 individuals with a moderate to severe finger movement impairment after chronic stroke were randomized to either a high success or low success group, where success was defined as the percentage of musical notes they successfully hit as they played a computer game similar to Guitar Hero. The FINGER robot adaptively assisted the participants to achieve either an 85 % success rate (high success) or a 60 % success rate (low success). Participants were asked to rate how motivating the rehabilitation training was after each of nine training sessions using a validated scale, the Intrinsic Motivation Inventory [17]. Figure 3.4 illustrates that the participants who received more assistance from the robot, and thus achieved higher success levels, consistently rated the robotic training as more motivating.

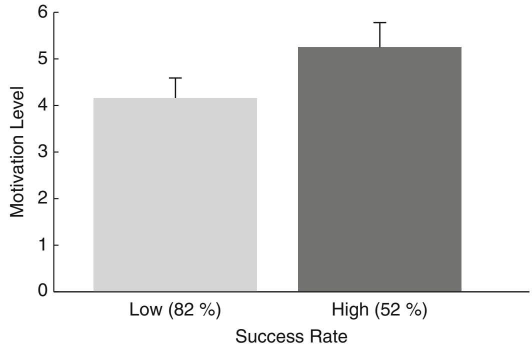

Fig. 3.4 Participants who received more assistance from the robot and thus achieved high success levels (high), consistently rated the robotic training as more motivating

Despite positive motivational effects of active assist robotic therapy, what became increasingly clear with ongoing clinical studies was that there was a danger of over assisting a patient and thereby decrementing the amount of learning that could happen during training. As outlined above, the challenge point theory states that there is an optimal challenge point that is patient specific, which will change with practice. Thus, using the golf example above, physical assisting of the golf swing may be appropriate early in learning but less appropriate as learning proceeds. In two key robotic therapy studies [18, 19], the Lokomat was used for gait training by patients with stroke who were already ambulatory and compared two control groups that trained with conventional gait

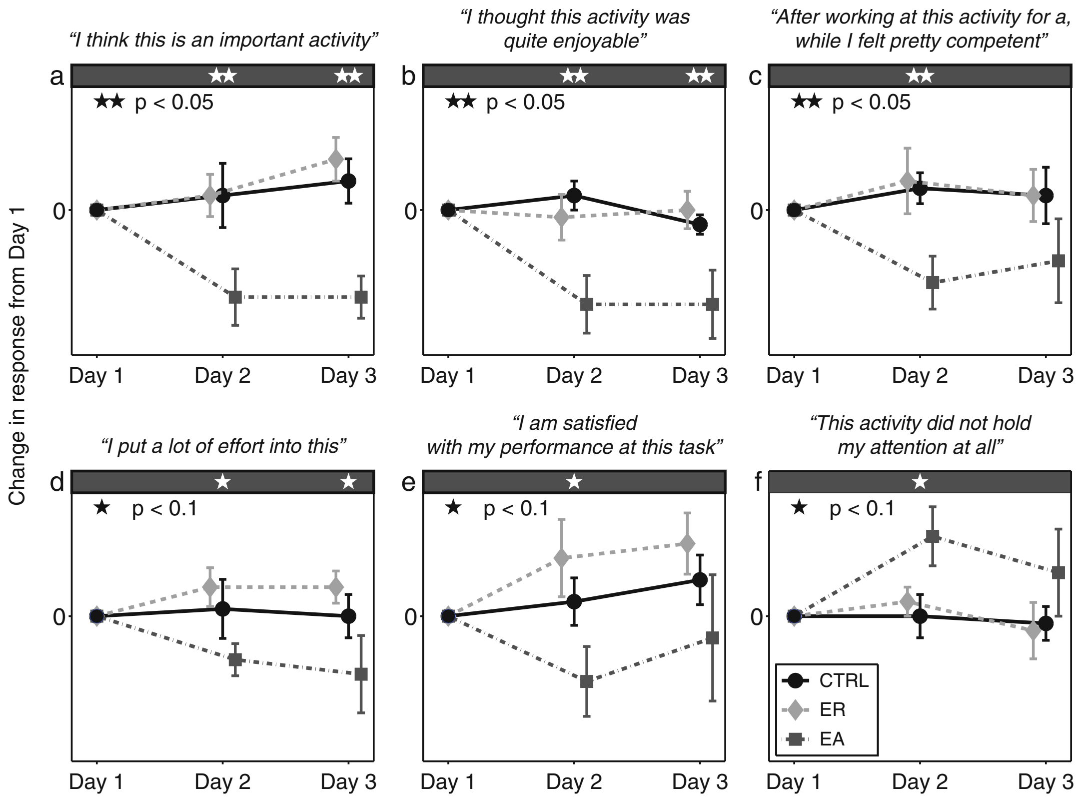

Fig. 3.5 Participants who trained in a virtual golf putting task reported decreased motivation after training with error augmentation and these feelings persisted even days later when errors where no longer augmented. (From Duarte and Reinkensmeyer [28])

training techniques. While patients improved their gait speed through training with the Lokomat, they improved less than via conventional training. One interpretation is that the Lokomat created a training environment with too low of challenge by over assisting the trainee.

Around the same time, research in human-robot interaction with upper extremity robotic training devices showed the intrinsic and automatic capacity of the human motor system to "slack." That is, when interacting with an assistive robotic device, the human motor system will automatically reduce its effort unless precautions are taken [20, 21]. Slacking was shown to be a consequence of the fact that the motor system acts as if it were trying to minimize a cost function with both error and effort terms [22]. When error is small, because, for example, a robotic device is assisting, then the motor system essentially minimizes a cost function with just an effort term. A reduction of effort in the presence of robotic assistance was also shown in a metabolic study with the Lokomat [23]. Reduced effort during rehabilitation training correlates with worse outcomes [24].

In part as a reaction to these findings, other robotic movement training studies began examining the use of error augmentation in training [25, 26]. Error augmentation can be seen as essentially the inverse of active assistance. Instead of a machine that reduces error, the trainee interacts with a machine that amplifies sensed movement errors. Studies of error augmentation with individuals with stroke showed that the technique could correct chronic reaching trajectory abnormalities that persisted throughout normal reaching practice [25], and, importantly, training with error augmentation produced better upper extremity outcomes for individuals with a chronic stroke than a matched amount of reach training without error augmentation [27]. On the other hand, a recent study that used a temporary bout of error augmentation to try to enhance learning of golf putting found that increasing errors decreased trainee motivation, in a way that persisted days after the use of the error augmentation (Fig. 3.5 [28]). Thus error augmentation may have negative motivational effects, an important consideration for training techniques that are to be implemented in real-world clinical and home environments.

What is suggested by these results is that robotic therapy devices should be designed to provide gradable amounts of mechanical intervention. The key question is not whether active assistance, no mechanical intervention, or error augmentation should be used but where, on a continuum of levels of mechanical intervention, each patient should practice. Providing less active assistance to a severely impaired patient can be viewed as a form of error augmentation. Likewise, providing less error augmentation to a less severely impaired patient can be viewed as a form of active assistance. Several studies of robotic training with unimpaired participants already suggest that the effectiveness of active assistance or error augmentation may depend on the initial skill level of the trainee [28–32]. What is needed are ways to adjust the training environment to the challenge point of the trainee.

3.3.2 Adapting Challenge

What is promising for meeting this goal is the fact that adjustability is a fundamental property of robotic therapy technology. And not only are robotic therapy devices adjustable, but they are adjustable in real time based on automated readings from their sensors. Almost from the beginning of robotic therapy, developers began implementing ad hoc algorithms to provide varying amounts of assistance (see review [33]). It cannot be claimed that these algorithms have achieved the goal of automated challenge point selection, but they are first steps, as we survey now.

One of the first strategies tried was to provide assistance for movement only when a threshold of movement was not met within a specified time frame (see [33] for review of strategies to provide assistance). Soon, other algorithms were developed to adapt the forces applied to the trainee or the mechanical impedance of the training environment. These adjustments could be based on the ongoing performance of the trainee, analogous to the way the human motor system adjusts its own arm forces and impedance during interaction with dynamic environments.

For the Pneu-WREX arm exoskeleton, a model-based assist-as-needed paradigm was implemented, in which a sliding adaptive controller was used to build a real-time model of the patient's weakness using a radial basis function representation [20]. In a study of this algorithm, it was shown to be necessary for the robot to include a slacking term itself, to ensure that the patient did not slack [20]. With a robot slacking term, the assistance-as-needed strategy provided a level of mechanical support proportional to the patient's clinical impairment level. Recently, with the FINGER robot, an algorithm was implemented to transition the robot from active assistance to error augmentation based on the game success rate of the patient during training [34].

Besides adapting the forces, it is also possible to adapt game parameters. For example, using the BONES arm exoskeleton, the speed at which a virtual baseball was pitched was varied based on the success of catching the previous ball. In other words, this simple adaptive challenge algorithm altered a task difficulty parameter following each task attempt based on a binary measure of performance (success or failure). Spencer [35] showed that the average success rate can be controlled by adjusting the ratio of up-steps to down-steps, and the rate and variance of convergence can be adjusted by setting the overall step size.

Choi et al. [36] developed a novel upper extremity robotic training system that can automatically switch out objects for the patient to attempt to manipulate. A high-level task scheduler selects the task to practice and adjusts the task difficulty based on the previous performance at the task. Caurin et al. [37] used an adaptive algorithm to select the level of difficulty of a pong game based on measures of the user's motivation and performance during training. Metzger et al. [38] automatically adjusted the difficulty level from one session to the next in a hand rehabilitation program so that patients trained at a target level of 70 % found reductions in both motor and sensory impairments. As a final example of exercise adaptation, Zimmerli et al. [39] matched the difficulty of a reaching task to the capabilities of the patients by controlling the time available for patients to reach a given target.

The algorithms developed so far are primarily based on the premise that task difficulty should be adjusted based on a performance measure. However, as shown in Fig. 3.5, performance levels may not be the same for different individuals at their optimal challenge point. A key question is whether performance, or possibly some other measure, should be the basis for task difficulty adaptation.

3.3.3 Implication of Challenge on Motivation and Self-Efficacy

As implicated in the discussion above, another factor that may be important for determining the optimal challenge level of a motor task is the level of motivation of the trainee. Specifically, the challenge level must be selected so that it maximizes the degree of engagement during practice and, in the case of neurological rehabilitation, motivates patients to use their impaired limbs in unsupervised practice beyond the clinic as seen in Griffiths' pilot study above [7]; this is especially important because of strong evidence that the current doses of rehabilitation training in areas such as stroke are insufficient to drive clinically meaningful improvements [40].

It may be possible to extend the challenge point framework [1] to incorporate the effect of motivation on a trainee's ongoing willingness to engage in motor training. As demonstrated recently in the FINGER study, using an adaptive challenge algorithm to regulate the rate of success during rehabilitation training led those stroke patients that trained with a higher success rate to self-report higher motivation about the task. In a similar implementation of this algorithm, this time tested with a rat model of rehabilitation following spinal cord injury, rats that trained at a lower challenge level and thus reached a higher success rate were more willing to engage in the training task, performing more repetitions in a fixed amount of time [41]. Thus, incorporating measures of motivation and engagement to determine the optimal challenge point may lead to therapies that are more motivating and ultimately increase the willingness to practice both during supervised and unsupervised practice.

This idea is illustrated in Fig. 3.6 where, following the convention of the CPF and including plausible curves for different levels of expertise, the functional difficulty of the task determines the willingness to engage in practice. For a novice, or for someone who has just started rehabilitation training, a lower difficulty level is accompanied by a high level of performance in practice (consistent with the CPF), and the willingness to practice is expected to increase as shown in the rat study above. However, as the trainee—or patient in the case of rehabilitation—gains mastery of the motor skill and transitions to higher skill levels, the engagement in the task and willingness to practice is expected to decrease for lower difficulty levels. On the other hand, as the difficulty is increased, the performance in practice may worsen to a point that leads to frustration and a decreased willingness to practice; this was evident in the recent FINGER study. There is therefore a point where the functional difficulty of the task maximizes the trainee's willingness to practice the task. This point must be combined with the optimal challenge point predicted by the CPF in order to strike a balance between motor performance, motor learning, and motivation.

Considering that for many patients the bulk of rehabilitation occurs away from direct supervision and that in many cases motor capacity exceeds actual performance [42, 43], an important goal of rehabilitation training is then to provide patients not only with the motor capacity but also the motivation to use their impaired limbs during activities of daily living and in unsupervised practice. An important concept to consider in this context is self-efficacy. Self-efficacy relates to a person's belief that he has the capacity to execute a specific action or achieve a specific goal [44]. Self-efficacy has been found to influence people's motivational, cognitive, and affective states [44], and increased self-efficacy has been shown to have positive effects on motor learning [45, 46]. Importantly for rehabilitation, self-efficacy has been shown to influence a person's level of effort,

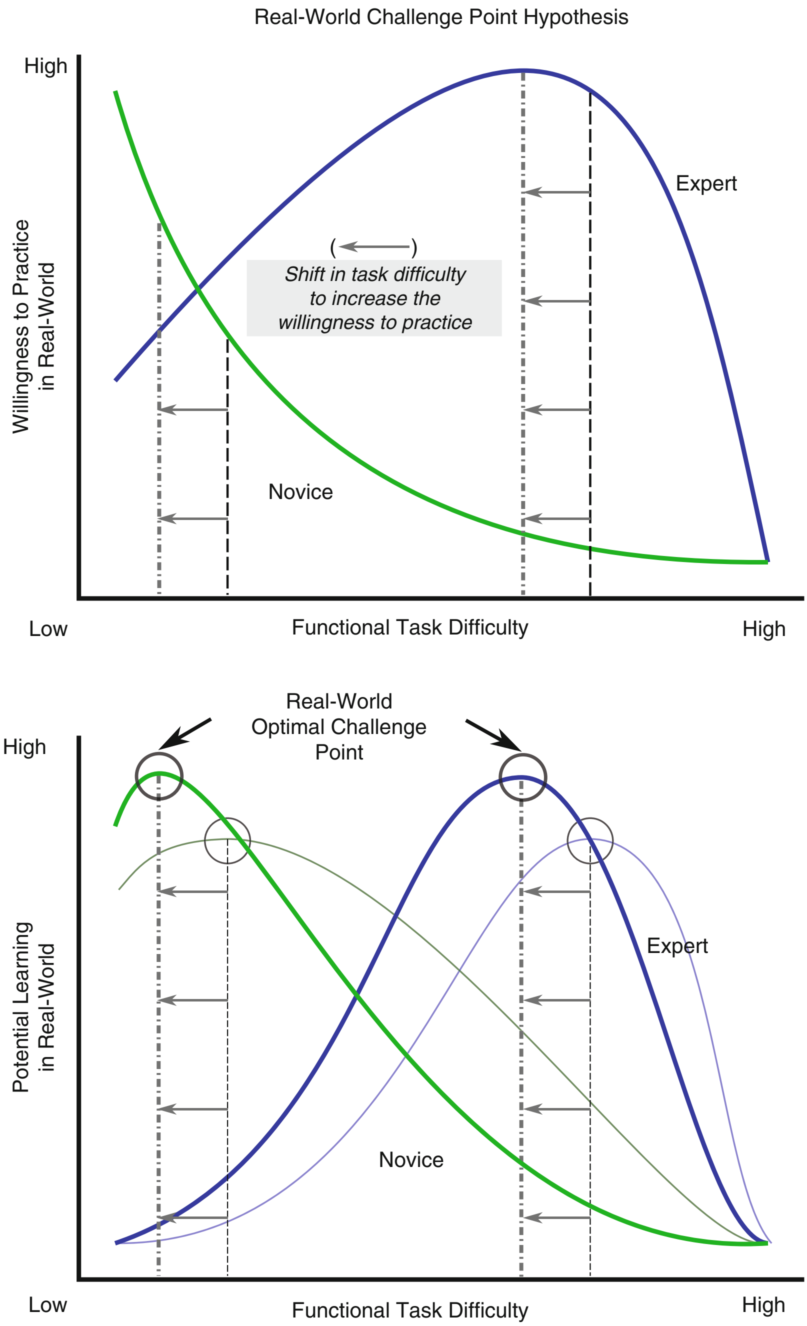

Fig. 3.6 [*Top*] Willingness to practice curves. The functional task difficulty determines the willingness to practice for trainees of different skill levels. For a novice, or someone who has recently begun rehabilitation training, a lower difficulty level means the task is doable and the trainee is likely to have a high willingness to practice. However, as the trainee gains mastery of the motor skill and transitions to higher skill levels, the engagement and willingness to practice is expected to decrease for lower difficulty levels. On the other hand, as the difficulty increases past the abilities of the trainee, then the performance in practice may worsen to a point that the willingness to practice will decrease. [*Bottom*] Based on the challenge point framework by Guadagnoli and Lee [1], the optimal challenge point may need to be shifted toward lower levels of functional task difficulty in order to promote higher self-efficacy levels

persistence, adherence to therapy, and resilience when confronted with failure [47, 48]. Studies of self-efficacy with populations of stroke and spinal cord injury patients have shown strong relations to measures of quality of life and well-being [49–51]. In another study, focused on self-efficacy as it relates to balance and falling, self-efficacy was found to be a strong predictor of ADL performance 10 months poststroke [52]. As a result of these findings, researchers have recommended the development of rehabilitation programs that, in addition to the development of patients' motor capacities, also take into account their level of self-efficacy [47, 49, 53].

In the context of robotic rehabilitation and challenge, it is important to know that the main source of efficacy information about a given task is based on a person's experience of success in performing the task [54]. These beliefs are not based on the person's motor capacity but rather on his beliefs of what he can accomplish with that capacity [55]; this is of special importance when translating motor capacities from therapy to the real world. For example, a patient who may display the motor capacity to reach out for and grab a glass of water in a therapy setting may be limited by fear to perform this same task in unsupervised practice if her level of self-efficacy is low. However, if self-efficacy is increased during therapy, for example, by providing increased assistance from a robotic device to decrease the functional difficulty of the task, then it may increase patient's willingness to use their impaired limbs in their activities of daily living and in unsupervised practice. This idea is consistent with the existence of a threshold of hand and arm function that predicts long-term use of a patient's impaired arm in activities of daily life [56]. Specifically, patients with function above the threshold are more likely to use their impaired arm than those below the threshold. As a result, these patients used their impaired arm outside of training and showed increased recovery. This functional threshold highlights the importance of developing therapies that give patients not only the motor capacity but also the motivation, to use their impaired limbs throughout their daily lives and beyond the rehabilitation clinic alone.

One approach may be to use measures of self-efficacy as feedback to adjust the functional task difficulty during training. Expanding again on the challenge point framework, this may require adjustments of the optimal challenge point—as defined by performance in training and the potential learning benefit—to account for patients' self-efficacy. These adjustments may come at the expense of lower potential learning benefits per unit of practice (as shown in Fig. 3.6) but with the benefit of increasing self-efficacy, motivation, and ultimately patient's willingness to engage in supervised and unsupervised practice, thereby ultimately resulting in greater amounts of learning.

3.4 Expanding Options for Patient Challenge with Rehabilitation Robotics: The KineAssist™-Mobility eXtreme as a Case Study

Robotic rehabilitation systems continue to evolve to be more capable of providing optimal challenge. In this section, we provide a detailed case study of a new rehabilitation robotic system, the KineAssist Mobility eXtreme, which works collaboratively with the patient and provides an extensive library of features for providing physical challenge during walking and balance training in people with poststroke hemiparesis.

Collaboration is an emerging emphasis in robotics that refers to devices that sense human movement and take direction from this movement. In rehabilitation robotics, the term is used to describe mechanized systems that sense the intent of the user and work with the user to accomplish some movement goal. This type of system can be a useful tool for clinicians who are working with clients who are at risk for harm during challenging movements and/or who will likely experience frustration if presented with tasks that are too difficult to achieve. In addition, since the "intent to move" feature of these robots require the person to desire movement, the person is able to develop their autonomy and independence during the rehabilitation process.

Fig. 3.7 Example of robotic device (KineAssist MX, HDT Robotics) that was used to enable to stroke survivors to practice highly challenging balance and walking tasks while also providing safety and stability against falls. (Photo courtesy of HDT Robotics)

The KineAssist™-Mobility eXtreme (MX) is an example of a collaborative device that senses intentional forces at a specialized pelvis interface and drives a treadmill surface to move in the user's intended direction and at an intended speed. The device is used by clinicians to challenge individuals, recovering from mobility disorders, to recover from perturbations, and to improve dynamic balance function during treadmill training that is performed within a locomotor control context (Fig. 3.7). This device addresses the fact that standard Body-weight supported treadmill or BWSTT exercise fails to incorporate progressive resistive gait training, high speed training, perturbation recovery training, and functional balance task training. Also, it is innovative because it enables fully expressed stumbling corrective responses, and it will drive the treadmill belt at speeds that are appropriate for each given specific dynamic task (solid, slippery, and foam surface stepping, front and backward perturbations, step length and step height hurdles, isotonic and isokinetic resistance walking). The implementation of these types of exercises during body -weight supported treadmill training represents a further progression in providing different forms and amounts of robotic challenge in rehabilitation practice that we expect to help generate advancements in the science of balance and walking control in neurologically impaired individuals.

3.4.1 Introducing Challenge During Balance and Walking Training Poststroke

Robotics allows for an exploration of a wide variety of challenging motor learning environments in a safe manner. With respect to poststroke recovery of balance and walking, the major issues to overcome are slow walking speeds and increased risk for falls that people experience when trying to regain function during the rehabilitation process. With slow movement and high fall risk, low propulsive ground reaction forces are generated, balance and stepping reactions are delayed, appropriate target levels of heart rate cannot be reached or sustained, and environmental distractions arrest movement. With the benefit of collaborative robotics, we have focused on developing methods for providing the highest level of challenge to three key areas of balance and walking recovery in stroke survivors—force generation, speed generation, and dynamic balance.

To introduce challenge in each of these three areas, certain key ideas were explored. First, the challenge should involve a motor task with some ecological validity. That is, the task should be meaningful to the person and represent some real-world problem that a person will encounter. Second, the challenge should be gradable, from very low levels of task difficulty to very high levels of task difficulty, so that the level of challenge that is introduced can be scaled up or down depending on the client's abilities. Finally, the intervention challenge should be preceded by an assessment of each individual's highest capacity to perform the particular movement task so that the appropriate level of challenge can be introduced during the training session. This last requirement allows individuals with very different capacities (e.g., age, neurologic deficit, premorbid status, etc.) to be trained at a level that is appropriate for their particular situation.

Force challenge: *Individuals poststroke generate reduced muscle power during walking*. Impairment in muscle strength is an important limiting factor in determining walking speed after stroke. There is a positive correlation between muscle strength and maximum gait speed [57–62]. Specific muscle groups that demonstrate the strongest relationship with walking speed vary greatly among studies, depending on the number of muscles investigated, the parameter used to quantify strength, and the method of documenting gait speed [57–62].

To assess the highest level of force capability, individuals are tested, while walking against various levels of resistance provided to the pelvis by the robotic interface. During the force challenge (FG) walking mode, participants walk on a treadmill belt while attached to the same KineAssist MX. The horizontal forces exerted by the participant, against the pelvic harness, are used by the KineAssist MX to specify the speed of the treadmill belt. In this mode the participant is asked to walk at a comfortable speed while the amount of force required to generate that particular treadmill belt speed is progressively increased. As the participant encounters higher and higher resistive forces, their walking speed begins to slow until they can barely move the treadmill belt with their attempted horizontal force output. We then calculate a theoretical maximum walking force measure that represents the highest amount of force that a person can generate in the forward, propulsive direction during walking. Figure 3.8 demonstrates the results of two participants, one person with no neurological impairment and another person with poststroke hemiplegia. The individual poststroke shows an extrapolated maximum horizontal force value of 120.8 N while the non-impaired person shows a value of 307.6 N. We are now confirming these results in a larger

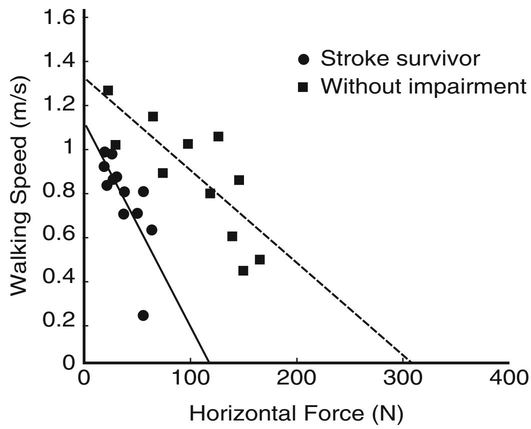

Fig. 3.8 Data comparing two subjects (one without impairment and one individual poststroke) as they walk on the KineAssist MX during progressively higher levels of resistance. As resistance increased, people slowed down until a resistance level was too high to overcome and the velocity nears zero m/s. The stroke survivor reached the zero velocity value at a much lower level of force

number of individuals poststroke and relating the measured parameters to walking speed and mobility participation scores.

Once the maximal propulsive force capability during walking is determined, the individual can engage in a progressive resistive exercise (PRE) regimen where a percent of maximum is applied for a predetermined number of steps. This PRE approach is very common in the strength training literature and enables an exerciser to constantly progress and increase the level of effort that they apply as they get stronger and more able to generate propulsive force during walking.

Speed challenge: *Individuals with poststroke hemiplegia move slowly*. After stroke, most patients walk at speeds that range from approximately 0.2 to 0.8 m/s [63–66] when asked to walk at a comfortable pace; these velocities are significantly lower than age-matched individuals (1.3–1.4 m/s) [64, 65, 67]. Also, when stroke survivors were encouraged to walk at their self-selected maximum walking speed, they achieved walking speeds from 0.3 m/s to 1.3 m/s [63, 65, 66, 68]. This suggests that this population has limited capability to adapt comfortable gait in order to increase walking speed to reach higher functional levels.

To assess the highest level of speed capability, the robotic interface can provide assistive horizontal forces to the pelvis interface so that a person can be "pushed" to walk at faster speeds without the added requirement of needing to generate propulsive forces. Since the robotic system is providing the horizontal propulsive forces, the individual is challenged to move the legs in successive steps at the fastest speeds possible until a speed is found where the person fails to keep up with the treadmill belt, and the device safely catches the person and prevents a fall from occurring. With this method, the clinician can find the fastest speed that a person is capable of achieving while walking.

We compared the "push" mode to the overhead harness treadmill mode in a recent published study [69]. Stroke survivors were able to walk at self-selected comfortable speeds (SSCWS) overground of 0.67 ± 0.04 m/s. Stroke survivors reached significantly faster speeds in the push mode (1.92 ± 0.06 m/s; $p < 0.05$) than on the treadmill (1.67 ± 0.11 m/s; $p < 0.05$), and both were faster than overground (1.19 ± 0.09 m/s; $p < 0.05$), as seen in Fig. 3.9, and show the speed, average step length, and average cadence achieved by participants during the greatest maximum walking speed.

Once the fastest possible speed of walking is obtained, the clinician can then apply sprint training methods to expose the person to brief bouts of high speed sprinting, followed by adequate recovery walking at much slower speeds.

Dynamic balance challenge: *Individuals with poststroke hemiplegia are at high risk for falls due to poor balance and inability to tolerate environmental challenges*. We have selected specific environmental hazards by turning to the current literature related to why people fall in the home or nonclinical environment. Research has identified specific risk factors for falls in people with stroke [70]. Fallers have shown poorer balance [70], lower physical function measures than non-fallers [70], greater standing sway [71], impulsivity [72], and slowed response times [73], in addition to greater postural sway and reduced force generation when standing up and sitting down [74]. Forster and Young [75] found that fallers were more depressed and less socially active that non-fallers. They found that most falls occurred in patients' homes while walking or during transfers. Individuals reported loss of balance, getting their foot stuck, and difficulty performing transfers as reasons why they fell. Hyndman et al. [76] found that repeat fallers had significantly reduced arm function and ADL ability compared with those who did not fall, and the measure of mobility showed a trend for repeat fallers to have greater mobility deficits than non-fallers, although the difference was not significant. However, fallers had a significantly higher depression score.

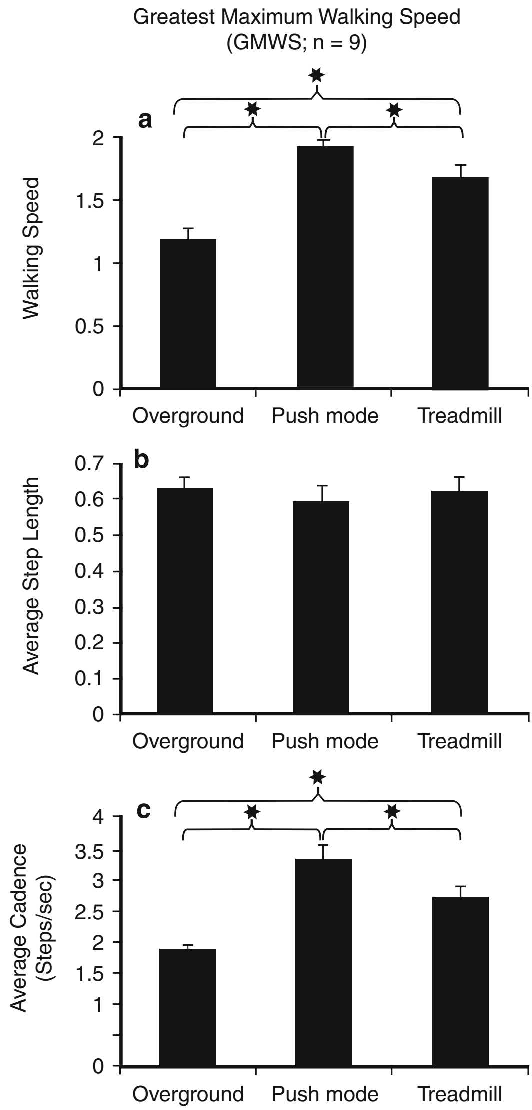

Fig. 3.9 *Bar graphs* illustrating the average top walking speeds that can be obtained by individuals poststroke while in the "push mode" of the KineAssist MX. The second and third *bar graphs* show the average step length and cadence associated with these top speeds

To assess the highest level of dynamic balance capability, we developed nine different dynamic balance tasks that are related to real-world balance activities. These nine tasks are (1) responding to a forward push, (2) responding to a backward push, stepping up onto a step, (3) stepping up onto a compliant surface, (4) stepping onto a slippery surface, (5) reaching forward as far as possible, (6) stepping forward as far as possible, (7) standing up out of a chair, (8) and stepping over a hurdle. Each task is gradable so that there is a very low level to a very high level of challenge. For example, with the stepping onto step task, the height of the step can be made progressively challenging by successively adding one of each platform to the height of the step until a height is reached where the person is no longer able to step up successfully. With each of the nine tasks, we can determine the highest level of performance for the individual.

We determined the concurrent and construct validity of a new balance measure, the KineAssist 9 Task Balance Test (K-9), by comparison to a gold standard, the Berg Balance Scale (BBS). The K-9 represented 9 dynamic balance tasks, such as stepping on to a high step, stepping over a hurdle, forward reaching, and responding to forward and backward pushes, that were tested at a range of levels of difficulty until we determined the highest level where the participant was able to succeed at the task. There was a statistically significant correlation ($R^2=0.632$; $p<0.0004$) between the scores on the K-9 and the BBS in chronic stroke survivors but not with non-impaired subjects. The non-impaired subjects scored significantly higher that the chronic stroke survivors on the K-9 ($p<0.0001$; $t=-6.341$). The K-9 was able to discriminate between subjects with balance impairments poststroke and non-impaired subjects. Thus, the K-9 is a valid measure of balance impairment in the clinic for community-dwelling stroke survivors but now must be tested using the new KineAssist MX.

Once the highest level of performance is reached, then the clinician can choose a level of challenge that will optimize the learning of the task. In our laboratory, we challenge the individual to attempt to succeed at levels which are just one grade above the highest level that they were able to perform during the testing. This approach has resulted in some very successful performances during training week after week (Fig. 3.10).

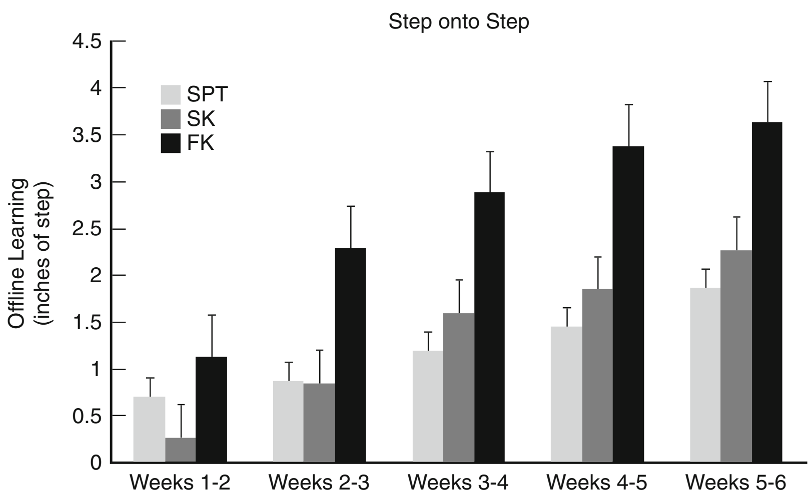

Fig. 3.10 This graph shows the results of a randomized controlled trial (Brown DA et al. 2014, unpublished) for week after week changes in task performance for stepping up onto a step of a specific height. *SPT* clinician-guarded training group ($n=12$), *SK* robot guarded, where the participant was trained on the highest height that they were capable of performing ($n=12$), and *FK* robot guarded, where the participant was asked to perform beyond their initial capability ($n=12$). All participants gained in performance week after week; however, the FK group showed the greatest gains over the 6-week period

Clinicians understand that many neurologic conditions leave an individual with limits to recovery, and adjunctive therapies such as pharmacologic agents and electrical stimulation may help a person to compensate for lost neurologic function. Perhaps the only way to truly recognize a person's limitations to recovery is to provide consistently high challenges to movement and then observe if the behavior can or cannot match the challenge requirements. Our experience seems to suggest that, if given enough time to attempt multiple strategies, stroke survivors have a more expanded capacity to meet higher expectations than might be presumed by considering only physiologic factors.

Conclusion

This chapter described important considerations for design and implementation of rehabilitation robotics in order to enable exercise and motor learning under optimal challenge conditions. In Table 3.1, we have summarized the aspects of challenge that were discussed in this chapter. Individuals engaged in developing new robotics may wish to use this table as a guide for determining the extent to which their system allows for adequate provision of challenge during training. We suggest that there is still much work to be done to design and implement safe and effective robotic tools for allowing optimal motor recovery during the rehabilitation process and forward as the person continues to move toward to the goal of high quality of life. Clearly, more research into the science of motor learning and the ideal conditions for a person to reacquire lost motor skills is needed. New developments in rehabilitation robotics might be best informed by asking questions about how the interface between the person and the machine will facilitate optimal motor learning and exercise training parameters. Elegant mechanical robotic systems that under-challenge, or even ignore, the physical involvement of the user run the risk of facilitating passivity and an expectation for movement assistance, even when the person has great potential to recover function. Rather, the flexibility of robotic systems can be used as a tool to grade challenge. Our challenge to the rehabilitation robotics community is to begin the development of any new project by asking the question, how can a new robot optimize motor learning and exercise effectiveness?

Table 3.1 Summary of factors related to challenge discussed in this chapter

Challenge factor	Robotic application
Random vs blocked practice	Manipulating presentation sequence of task difficulty level
Guidance restriction	Allowing varying degrees of freedom; removing restrictions
Success vs failure	Degree to which failure is allowed to occur
Mechanical assistance	Degree to which the device intervenes to allow completion of movement
Adaptability	Ability to increase/decrease parameters based on performance metrics
Motivation/ self-efficacy	Provision of feedback that facilitates interest and desire to achieve task
Movement validity	Movement reflects true representation of a desired activity of daily living
Biomechanical requirements	Manipulation of key kinematics and kinetic task parameters
Assessment	Identifying an individual's highest performance capacity

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