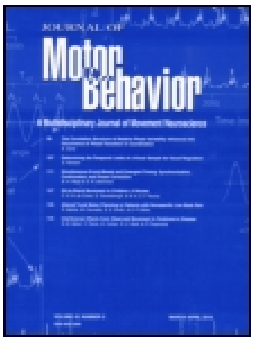

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Challenge Point: A Framework for Conceptualizing the Effects of Various Practice Conditions in Motor Learning

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Challenge Point: A Framework for Conceptualizing the Effects of Various Practice Conditions in Motor Learning

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ABSTRACT. The authors describe the effects of practice conditions in motor learning (e.g., contextual interference, knowledge of results) within the constraints of 2 experimental variables: skill level and task difficulty. They use a research framework to conceptualize the interaction of those variables on the basis of concepts from information theory and information processing. The fundamental idea is that motor tasks represent different challenges for performers of different abilities. The authors propose that learning is related to the information arising from performance, which should be optimized along functions relating the difficulty of the task to the skill level of the performer. Specific testable hypotheses arising from the framework are also described.

Key words: augmented feedback, contextual interference, motor learning

Practice is generally considered to be the single most important factor responsible for the permanent improvement in the ability to perform a motor skill (i.e., motor learning; Adams, 1964; Annett, 1969; Fitts, 1964; Magill, 2001; Marteniuk, 1976; K. M. Newell, 1981; Schmidt & Lee, 1999). If all other factors are held constant, then skill improvement is generally considered to be positively related to the amount of practice. The generalizability of the relationship between practice and skill is so profound that it is sometimes modeled mathematically and referred to as a law (Crossman, 1959; A. Newell & Rosenbloom, 1981). Indeed, the attainment of expertise, the highest level of proficiency in a motor skill, generally requires years of practice (Ericsson, 1996).

In truth, the attainment of expertise is not a goal or a reality for most learners of motor skills. Because of our incomplete knowledge of practice variables, we are often inefficient in our practice sessions. Thus, the limited opportunity for practice, coupled with the potentially small gains in expertise resulting from each session, increases the importance of maximizing the benefits gained whenever practice is undertaken. For over a century, researchers have studied means by which practice conditions can be structured so that they maximize the potential for learning (Adams, 1987); understandably, that issue remains of considerable interest to theorists and practitioners alike. Clearly, the concept of practice as a single, unitary construct that leads to improvements in performance is not a simple one.

In the present article, we offer a theoretical perspective for conceptualizing the effects of practice variables in motor learning (primarily, contextual interference [CI] and knowledge of results [KR]). Excellent reviews of both areas of research are available in the literature, and it is not our purpose to replicate or extend any of them. (For reviews on CI, see Brady, 1998; Magill & Hall, 1990. For reviews on KR, see Schmidt 1991; Swinnen, 1996. For an integration of both CI and KR, see Schmidt & Bjork, 1992). Rather, our present purpose is to explicitly describe a fundamental relationship that we believe applies to both research areas. The relationship involves the effectiveness of CI and KR variables relative to the skill level of the learner and the difficulty of the task being learned.

We present those ideas in the form of a research framework. Although presented as a unique conceptualization, we acknowledge at the very outset that many of the ideas, relationships, and theoretical concepts that emerge as parameters of the framework have appeared, either explicitly or implicitly, in a variety of sources over many years (notably, Lintern & Gopher, 1978; Marteniuk, 1976; K. M. Newell, McDonald, & Kugler, 1991; Wulf & Shea, 2002).[1] As defined by Crick and Koch (2003), "A framework is not a detailed hypothesis or set of hypotheses; rather, it is a suggested point of view for an attack on a scientific problem, often suggesting testable hypotheses" (p. 119). Our goal is to formulate those various ideas within a single conceptual framework—a framework that suggests how interactions

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among several factors within a single experimental protocol might be expected to emerge. As a preview, according to the *challenge point framework*, learning is intimately related to the information available and interpretable in a performance instance, which, in turn, depends on the functional difficulty of the task. Information is seen as a challenge to the performer—when information is present there is potential to learn from it. Three important corollaries arise from that thesis: (a) Learning cannot occur in the absence of information, (b) learning will be retarded in the presence of too much or too little information, and (c) for learning to occur, there is an optimal amount of information, which differs as a function of the skill level of the individual and the difficulty of the to-be-learned task. We begin with a discussion of the relationship between task difficulty and performance by individuals of varying skill levels and follow with a critical discussion of how that relationship affects the information available to the learner during action planning and evaluation. After we discuss those issues we provide a more formal description of the challenge point framework, and we conclude with a presentation of evidence from areas of research that supports the tenets of the framework.

Task Difficulty and Skill

Task difficulty is a variable that is implicit in almost every investigation of motor control and learning. The development of motor task taxonomies to conceptualize task difficulty has a long history, and the present discussion is not intended to update or supplant those previous discussions[2] (e.g., see Fleishman & Quaintance, 1984; Gentile, 1998). Indeed, the concept of task difficulty has been the feature of a large number of studies reported in the motor learning and motor control literature, although it is often included without an operational definition of how it was, or should be, defined. Rather than offer a general or all-encompassing definition of task difficulty, one that would no doubt be less than satisfactory, we follow here an alternative strategy. We assume that investigators fully understand the nature and parameters of tasks that they use in experiments involving CI and KR variables. Given that there are a variety of operational definitions of task difficulty, we suggest that those definitions can be further divided into two broad categories: (a) nominal task difficulty and (b) functional task difficulty. The difficulty of a particular task within the constraints of an experimental protocol would operationally delineate its nominal level of difficulty. The nominal difficulty of a task is considered to reflect a constant amount of task difficulty, regardless of who is performing the task and under what conditions it is being performed. As such, nominal task difficulty includes such factors as perceptual and motor performance requirements (see also Swinnen, Walter, Serrien, & Vandendriessche, 1992). Consider the example of a golfer who is performing a 75-yard pitch shot to a green over a pond of water. Across the entire spectrum of all possible golf shots, that task is one that some would argue is of moderate nominal difficulty. However, the term *level of nominal difficulty* includes only the characteristics of the task, irrespective of the person performing it or the conditions under which the task is performed.

Functional task difficulty refers to how challenging the task is relative to the skill level of the individual performing the task and to the conditions under which it is being performed. For example, it is unlikely that the functional task difficulty of the golf shot just described is the same for both the professional golfer and the weekend duffer. Now let us suppose that the shot is being performed into a strong headwind. That particular shot then becomes more functionally difficult because of the wind conditions, and the increase in difficulty would likely be more severe for the novice golfer than for the professional. Recall that in all those scenarios, the nominal task difficulty remains the same.

In Figure 1, we illustrate how the difficulty of the task affects the expected level of practice performance for four hypothetical levels of skilled performers. Our assumption is that with a task of a given level of nominal difficulty, an individual at any level of skill is likely to perform at a predictable level. For the beginner, performance outcome is expected to be high only under conditions of very low nominal task difficulty. That point, shown in the upper left side of the graph at which all four functions originate (representing the four different skill levels), is at the same level of predicted performance for all individuals because it represents a ceiling effect for all individuals: The task is so easy that anyone can perform it with a high level of expected success. As the task becomes more difficult, however, the expected level of performance for the beginner drops rapidly and reaches a floor level of performance at a relatively low level of task difficulty (hence, the steep negatively decelerating curve in Figure 1). Expected performance for the intermediate and skilled individuals would drop off at moderate rates as a function of increased nominal task difficulty (the moderately negative and positively decelerating curves, respectively). Only the most nominally difficult tasks would be expected to pose a problem for the expert (thus, the steep positively decelerating curve in Figure 1).

Although the functions illustrated in Figure 1 represent negatively decelerating curves for beginners and intermediate performers and positively decelerating curves for skilled and expert performers, the exact shape of those functions is less important than is the idea that performance expectations interact as a function of the difficulty of the task and the skill level of the performer. The simple, straightforward idea in Figure 1 is that with increases in nominal task difficulty comes the expectation that performance will decrease and that the rate of decline in performance will be more rapid for the lower skilled performer.

Task Difficulty and Information

A fundamental assumption in this article is that learning is a problem-solving process in which the goal of an action represents the problem to be solved and the evolution of a movement configuration represents the performer's attempt to

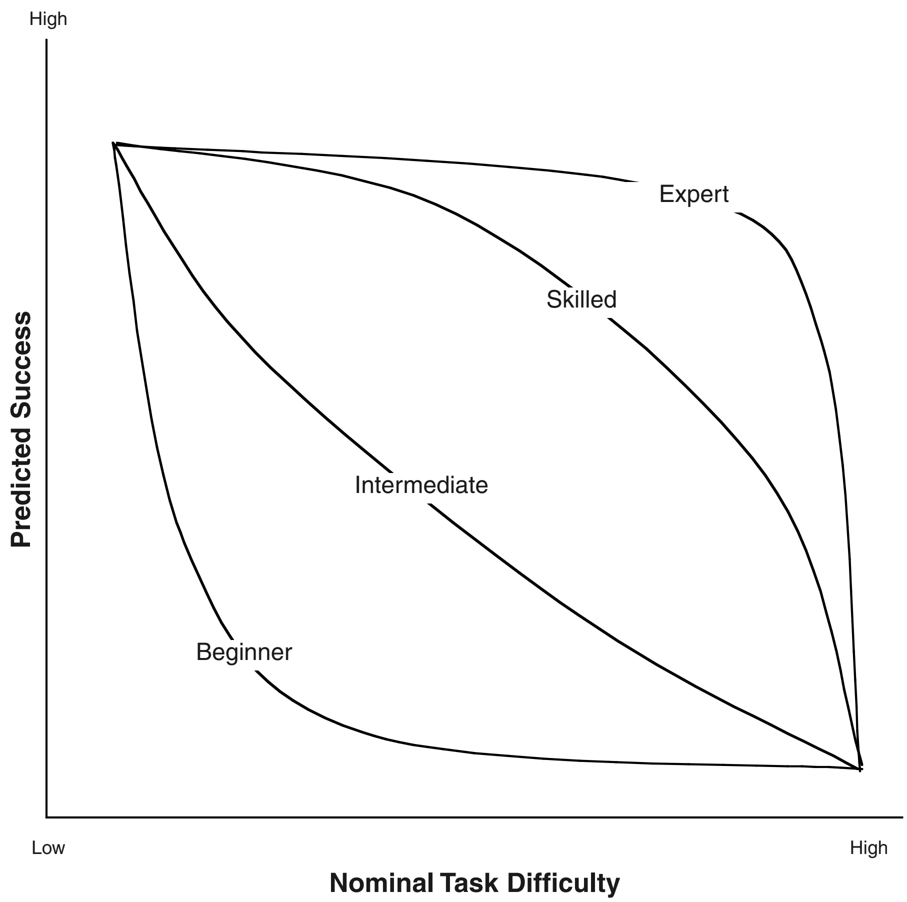

FIGURE 1. The relationship between nominal task difficulty and expected performance as a function of the individual's skill level. During practice, predicted success becomes a decreasing function of nominal task difficulty.

solve the problem (Miller, Galanter, & Pribram, 1960). Sources of information available during and after each attempt to solve a problem are remembered and form the basis for learning, which is defined as a relatively permanent improvement in skill that results from practice (Guthrie, 1952). Another fundamental assumption in this article is that two sources of information are critical for learning: (a) the action plan and (b) feedback. We borrow from Miller et al. (1960) the concept of an action plan as a construct that invokes intention and ultimately results in a specific movement configuration on a given performance. We also ascribe a predictive function to the action plan—however, one that allows for the anticipation of feedback sensations. The action plan works in a manner suggested by inverse and forward internal models of motor control and learning (Wolpert, Ghahramani, & Flanagan, 2001; Wolpert & Kawato, 1998). According to that theory, the processing system uses pairs of inverse (motor predictor) and forward (sensory predictor) internal models to generate output signals, and it uses sensory feedback as the input signal. The feedback represents information from sources (a) that are inherent to the performer and are normally available during a performance (e.g., visual and kinesthetic feedback) and (b) that might not normally be available to the performer but can be augmented to the performance experience by an extrinsic source (e.g., an instructor's comments or a video replay).

From communication theory (e.g., Shannon & Weaver, 1949), we borrow the concept that information is transmitted only when uncertainty is reduced. For example, the statement, "it is dark outside," carries little meaning if spoken during the middle of the night. One would normally expect darkness at that time, and therefore the statement reduces little uncertainty. If one were to say the same thing during the day, however, then information is being transmitted, because even though daylight usually means a certain amount of bright light, there are a number of reasons why there might be relative darkness during the day (e.g., inclement weather or a solar eclipse). Thus, information is being transmitted because the statement is reducing some uncertainty (see also Fitts, 1954; Fitts & Posner, 1967; Legge & Barber, 1976; Marteniuk, 1976; Miller, 1956).

Action plans and feedback also represent the means by which information can be transmitted. The selection of an action plan that is intended to solve a particular motor problem results in the expectation of certain outcomes at different levels of analysis. At the level of an observable outcome, one might expect, for example, that an apple core thrown at a wastepaper basket would have a certain trajectory that would result in the core's landing in the basket. The expectation would be highest when the basket is right below one's hand and substantially lower when the basket is located across the room. Visual feedback would provide results of the throw.[3] When the basket is directly below the person's hand and the expectation for success is extremely high, then vision of the apple core entering the basket would provide very little information. In that case there was little uncertainty about the outcome of the performance before the shot was taken. A miss from that short distance, however, would be considered informative, because the outcome did not match the highly anticipated expectation. The shot to a basket across the room represents a different scenario. There the expected outcome of the action plan is less assured—the level of expectation of success (or failure) is moderate—so vision of the outcome of the shot would provide information to the performer regardless of whether the apple core does or does not go into the basket.

Action plans and feedback can also be considered from another level of analysis. The action would result in a copy of the efferent signals that would be available for analysis and for comparison with the sensory feedback received from the ongoing and completed movement (Wolpert et al., 2001). In the thrown apple core example, a comparison of the expected sensations with the actual sensations arising from the movement would result in information if uncertainty were reduced. It should also be noted that the production of information may or may not be available at a conscious level of analysis.

The nominal difficulty of a task would affect expected performance and therefore the potential information arising from performance. Having the wastepaper basket close at hand would present an easier task in terms of expected success than would having the basket across the room (Woodworth, 1899; Fitts, 1954). But now let us compare the performance of an expert apple core thrower with that of a novice apple core thrower. Clearly, the lower nominally difficult (easy) task results in little available potential information for either the novice or the expert. However, if the waste paper basket was located across the room, then that situation represents a task of high functional difficulty for the novice but a less high functional difficulty task for the expert. The novice, not knowing whether the action plan will produce an accurate shot, will receive uncertainty-reducing feedback regardless of the outcome. In contrast, the action plan for the expert facing the task of low functional difficulty is expected to be correct, and confirmation by feedback would produce little or no information.

Those ideas form one key part of the challenge point framework. Tasks of identifiable nominal difficulty performed by an individual of a specific level of skill partially define functional task difficulty. We take that idea one step further to bring in the concept that conditions of practice also contribute to the functional difficulty of the task.

By their very nature, some practice conditions have the effect of making a task easier or more difficult to perform well. For example, to make a swing easier to achieve, producers of golf training devices have marketed certain physically restricting guidance aids. By definition, then, tasks of nominally high difficulty performed under a practice condition that has been designed so that the task is made easier will produce a task of lower functional difficulty. Other practice conditions (e.g., random-practice orders) contribute to making a task more difficult to perform well (Battig, 1966; J. B. Shea & Morgan, 1979). We do not wish to imply that only a performer's skill level and certain practice conditions contribute to defining the functional difficulty of a task. However, for our purposes, those two characteristics are critical in optimizing the potential information that the result of a performance might be expected to contribute during the motor learning process.

The present conceptualization of the effects of task difficulty for different skill levels shares some similarity to the ideas developed by Marteniuk (1976). Citing the work of Kay (1962, 1970), Marteniuk suggested that practice leads to redundancy, less uncertainty, and, hence, to reduced information. The more that practice leads to better expectations, the less information there will be to process. The essence of that idea is developed further in the curves illustrated in Figure 2.

The relation between task difficulty and the amount of information available to be obtained from performance of the task (i.e., learning) is represented in Figure 2. Note that Figure 2 is similar to Figure 1, except that the ordinate has been changed from Predicted Success to Potential Available Information and the abscissa from Nominal to Functional Task Difficulty. We have also inverted the scale to represent the concept that potential information increases as a positive function of increased functional task difficulty. The performance curves for the four groups of performers take on the same shape as in Figure 1 but are now inverted. Differences in the amount of absolute potential information are the focus of interest in Figure 2. Therefore, whereas Figure 1 represented practice performance, Figure 2 represents the information available for learning. As such, Figure 2 demonstrates hypothetical functions that illustrate the fact that increases in task difficulty are accompanied by increases in potential information. As functional task difficulty increases, there is less certainty about the potential success of a movement (action plan) and about the potential outcome of the movement (feedback).

Optimal Challenge Points

According to the challenge point framework, learning is

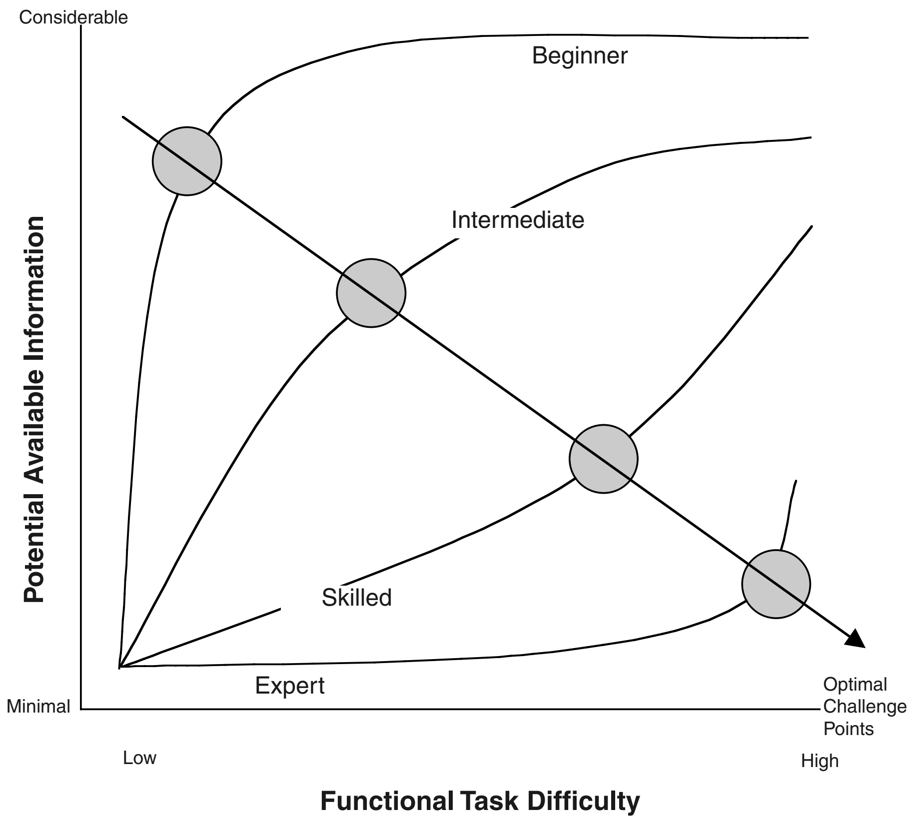

FIGURE 2. Optimal challenge points for learning (retention) related to different skill levels, functional task difficulty, and potential available information arising from action, with optimal challenge points resulting earlier (lower functional difficulty) for less experienced performers.

directly related to the information available and interpretable in a performance instance, which, in turn, is tied to the functional difficulty of the task. Our thesis is that information represents a challenge to the performer and that when information is present, there is potential to learn from it. As stated previously, the following corollaries arise from that thesis: (a) Learning cannot occur in the absence of information, (b) learning will be retarded in the presence of too much information, and (c) learning achievement depends on an optimal amount of information, which differs as a function of the skill level of the individual. Therefore, the factors contributing to functional task difficulty (including the level of the performer and practice conditions) interact to dictate the optimal amount of interpretable information and, hence, the potential for learning.

As Figure 2 illustrates, increases in task difficulty are accompanied by increases in potential information. Although potential information is dependent on nominal task difficulty, interpretable information is based on functional task difficulty. (That concept is discussed in greater detail in the following sections.) Note that if information is to serve a role, it must be interpretable. As functional task difficulty increases, so too does potential available information, as is illustrated in Figure 2. However, there is a limit to which potential information is interpretable. It is assumed that the limit is governed by one's information-processing capabilities and that those capabilities change with practice (Marteniuk, 1976). Hypothetical points for each performer's level are shown in Figure 2. Those points represent the optimal amount of potential interpretable information and are called *optimal challenge points*.

As skill improves, the expectations for performance become more challenging. Therefore, to generate a challenge for learning, one must obtain increased information; that information can arise only from an increase in the functional task difficulty.

There is one other relationship to describe. Because task difficulty is negatively associated with performance level, there is a performance–learning paradox: Depending on the skill level of the performer, increases in functional task difficulty result in decreased performance expectations but in an increase in the available interpretable information. Hence, the optimal challenge point represents the degree of functional task difficulty an individual of a specific skill level would need in order to optimize learning. The anticipated amount of performance decrement, the specific function relating performance decrement to information to be processed, and, hence, the potential for learning are determined by the individual's abilities relative to the task at hand.

In Figure 3, we illustrate how the information potential for learning relates to both the expected immediate effect on performance and the optimal challenge point. Regardless of the skill level of the individual, the concept holds that as functional task difficulty begins to reach its optimal challenge point, there is an increase in information that provides a potential learning benefit. Two functions that change simultaneously with a change in the functional task difficulty are illustrated Figure 3. The solid line in Figure 3 represents the effect of functional task difficulty on performance during practice (temporary performance effects). The dashed line in Figure 3 represents the effect of functional task difficulty on potential learning that could arise from practice (as would be seen in retention or transfer tests). The effect on performance is straightforward: As the task becomes more functionally difficult, one would expect to observe a point at which performance would falter dramatically (note also that the curve in Figure 3 is a positively decelerating function—which would correspond to a skilled performer, as is illustrated in Figure 1; one would expect the shapes of the performance functions for individuals of other skill levels to resemble the curves illustrated in Figure 1).

The effect of task difficulty on the potential benefit for learning is illustrated as an inverted-U function in Figure 3 for individuals of all skill levels. The concept is that increased functional task difficulty will result in more information generated in the performance of the task (more uncertainty reduced). That information represents greater useful information in terms of potential learning benefit, but only to a point (i.e., the optimal challenge point). As suggested by Marteniuk (1976), one would anticipate that after that point there will be too much information to be used effectively—the amount of information would exceed the capacity of the individual to process the information efficiently, thereby diminishing the potential benefit to learning. In other words, even though the amount of information available increases, the amount of interpretable information does not. In that case, the learner cannot sufficiently process enough of the available information in the performance context to improve upon the skill level. Thus, the information-processing system becomes overwhelmed and both performance and learning begin to suffer.

Finally, whereas in Figure 3 the effect of task difficulty on the potential learning benefit for individuals of all skill levels can be seen, in Figure 4 one can see the effect of task difficulty on the potential learning benefit for a single indi-

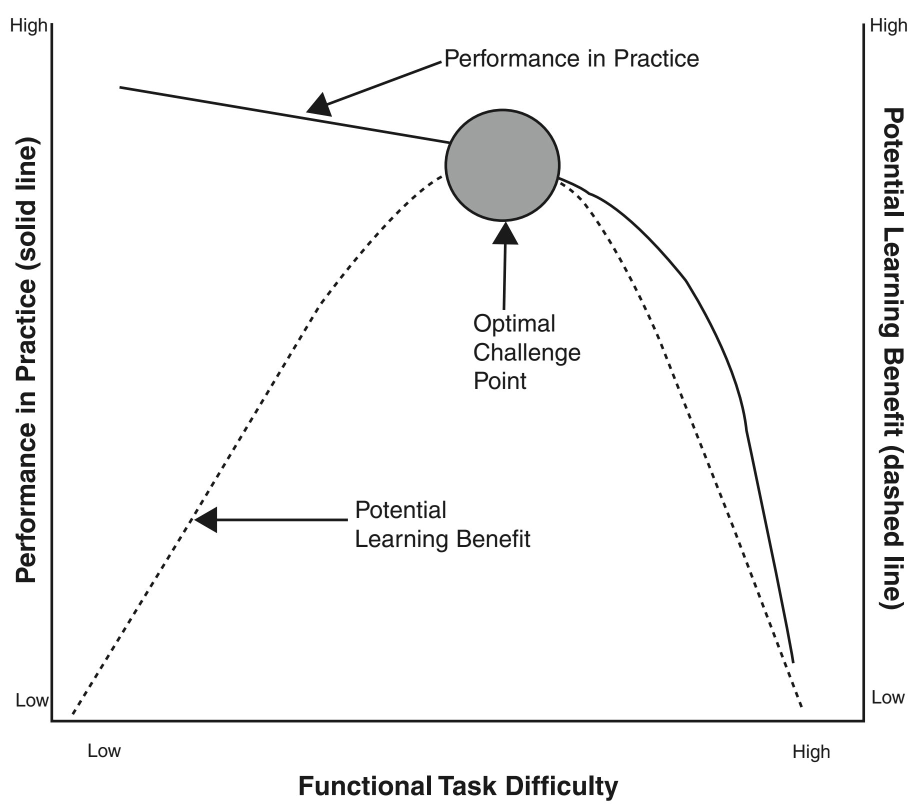

FIGURE 3. The relation between learning and performance curves and the optimal challenge point related to tasks of different levels of functional complexity. The point of functional task difficulty where learning is optimized is not the point at which practice performance is optimized.

vidual who is increasing skill level through practice. An implication of Figure 4 is that as a performer's information-processing capabilities increase, so too should the functional difficulty of the task. That is, because the learner's information-processing abilities change and his or her ability to use information changes, the optimal challenge point should change as well. Figure 4 is an extension of Figure 3. By increasing the functional task difficulty as the performer's ability increases, one maintains an optimal challenge for the performer. As such, an appropriate functional difficulty for a beginning performer would be an inappropriate (too low) functional difficulty for an expert performer. Most interesting, it is likely that even though the functional task difficulty increases as expertise increases, the perceived difficulty of the task (i.e., performer's rating of difficulty) remains

Manipulating Practice Variables to Create Optimal Challenge Points

Optimal challenge points are similar in concept to what Bjork (1998) has termed *desirable difficulties in performance*. For our purposes, one of the most important roles of practice variables is to influence performance and, therefore, the potential for learning. To recall an earlier discussion, we assume that for any given individual with a known level of skill, each task holds a nominal level of difficulty and, therefore, a potential amount of information available for learning. The conditions under which the task is practiced will make the task either more or less difficult to perform, thereby defining its functional level of difficulty on that practice trial. Depending on the skill level of the individual, the functional task difficulty will be either optimal or more or less challenging in terms of its influence on both performance and learning. Therefore, with regard to the effects of various practice variables, it is predicted in the framework that learning will be a function of the skill level of the learner and the functional task difficulty and, thus, the challenge of the task in terms of its information potential. In the next section, we survey some studies with respect to various predictions arising from the framework.

Practice Variables That Influence Action Planning Information

It has been demonstrated in many studies that various practice conditions (i.e., CI and KR) influence the amount of information available for acquisition and, hence, learning. In the following sections, we review those studies as empirical evidence to support the challenge point framework.

Contextual Interference

The most common finding in the extensive literature comparing blocked- versus random-practice schedules is

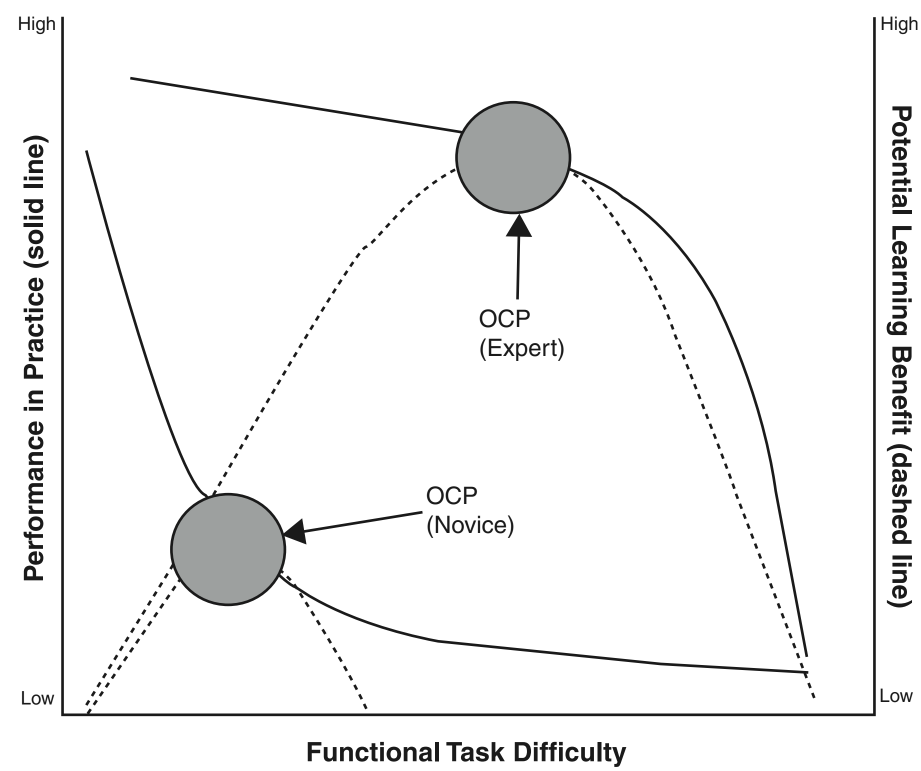

FIGURE 4. The relation between learning curves, performance curves, and the optimal challenge point (OCP) related to 2 performers of different skill levels.

that blocked practice produces better performance than does random practice during acquisition trials but that random practice results in better retention performance than blocked practice does (e.g., Magill & Hall, 1990). By far, the majority of those studies have involved participants who have had no previous experience with a relatively simple task. In terms of the challenge point framework, it seems straightforward that in comparison with blocked practice, random practice will increase the functional difficulty of a task. Other schedules of practice (e.g., small, randomized blocks of trials) are predicted to produce intermediate levels of contextual interference. Therefore, on basis of the framework, we make the following predictions:

1. *For tasks with differing levels of nominal difficulty, the advantage of random practice (vs. blocked practice) for learning will be largest for tasks of lowest nominal difficulty and smallest for tasks of highest nominal difficulty.*

Albaret and Thon (1998) reported on research that is relevant to that prediction. In their study, participants practiced a drawing task in which the patterns to be learned differed in terms of the number of individual segments. Six groups of learners practiced three variations of the drawing task: Two groups practiced patterns involving only two segments, one in a random order and the other in a blocked order; two groups (random and blocked) practiced three-segment patterns; and the remaining two groups practiced four-segment patterns. CI effects did not interact with task complexity in tests of retention: For patterns of all complexities, the random-practice groups performed better in retention than did the blocked groups. There was, however, a CI × Task Complexity interaction for tests of transfer in which the drawing tasks were reduced or enlarged in size or rotated in orientation. The random-practice groups were better than the blocked-practice groups for those transfer tests but only for the two simplest task-complexity groups (two- and three-segment task complexities). No CI differences in transfer were found between the most complex (four segments) blocked- and random-practice groups.

From a challenge point framework view, one could argue that the four-segment pattern was complex enough in terms of nominal task difficulty so that action-planning processes were being sufficiently challenged, regardless of the functional difficulty introduced by the practice schedules. In contrast, action planning in the two- and three-segment task was easy. Learning was enhanced only when the random-practice schedule introduced an additional level of functional difficulty to the task (relative to blocked practice).

2. *For individuals with differing skill levels, low levels of CI will be better for beginning skill levels and higher levels of CI will be better for more highly skilled individuals*.

In an early study, Del Rey, Wughalter, and Whitehurst (1982) demonstrated that finding well. Participants who had either very little experience or considerable expertise in open sport skills performed a coincident anticipation-timing task under random, blocked, or constant practice conditions (variations in runway speeds during practice). Performance on a novel transfer task revealed that the open-skill novices were better following constant practice conditions than after either blocked- or random-practice orders. In contrast, the open-skill experts performed the transfer test better following random practice than after either blocked- or constant-practice conditions.

C. H. Shea, Kohl, and Indermill (1990) investigated the relationship between CI and the amount of practice completed on the task. Presumably, if skill level is related positively to the development of skill at the task, then larger amounts of practice will produce learners of higher skill. Following a blocked- or a random-practice order, learners received either 50, 200, or 400 practice trials on a force-production task. After completing 50 trials, the group that received a blocked-practice schedule performed better in a retention test than did a random-practice group. However, after extended practice (400 trials), the group that received the random-practice schedule was superior to the blocked-practice group. Those findings are consistent with the challenge point framework because, early in practice, an easier functional task difficulty condition (blocked practice) was more effective for learning than a harder functional task difficulty condition (random practice). However, following either 200 or 400 practice trials (presumably taking the learner to a more proficient skill level), the harder functional task difficulty condition was more beneficial for learning.

In a more recent study, Guadagnoli, Holcomb, and Weber (1999) manipulated CI and performer level (novice or experienced) on a task that was considered to be relatively complex in nominal difficulty (golf putting). Following an acquisition period in which both novice and experienced golfers followed either a random- or blocked-practice schedule, retention performance was found to depend on both the skill level of the golfer and the acquisition practice schedule. In retention, the performance of novices who had practiced under a blocked protocol was superior to that of the novices who had practiced under a random protocol. In contrast, the experienced participants who had practiced in a random protocol performed better than the experienced participants who had practiced in a blocked protocol. Those findings are also consistent with predictions of challenge point framework.

Recall that in the original demonstration of the CI effect, J. B. Shea and Morgan (1979) compared blocked and random practice of a spatial learning task for beginning learners. Using a similar task, Al-Ameer and Toole (1993) replicated those blocked versus random retention differences and also found that groups of learners who followed a schedule in which they received randomized blocks of two or three trials also performed the retention test as well as the random group. Thus, for the beginning-level learners, a functional task difficulty that was much easier than that experienced in random practice might have been equivalent for learning. Those findings must also be considered in light of the fact that acquisition performance was better in those randomized-block groups than in the random-practice group. Thus, those moderate levels of functional task difficulty seemed to have facilitated (or optimized) both short-term and more long-lasting gains in performance.

Modeled Information in Practice

Lee, Wishart, Cunningham, and Carnahan (1997), Richardson (1997), and Simon and Bjork (2001) investigated a practice variable that appears to work in a manner opposite to that described in the previous discussion. Participants in those studies were asked to use the keypad of the computer keyboard to learn three different patterns. The task goal was to time the pattern of key presses—the patterns were not to be tapped out as rapidly as possible, but instead were to be completed in a movement time that was specific for each pattern. An important difference between the studies was the nature of those timing goals. In the studies of Lee et al. and Simon and Bjork, each of the three patterns to be learned had associated with it a single, overall goal movement time (900, 1,200, or 1,500 ms). There was no requirement of a specific timing relation between each of the five key presses that made up the patterns. The timing goals for the Richardson study were more specific. For all three patterns (each pattern represented by four key presses), the overall movement time goal was 1,200 ms. However, each pattern differed in terms of the between-key movement time goals. For example, one pattern consisted of the keypad sequence 1-4-8-9, and movement time goals between key presses were 1–4 = 600 ms, 4–8 = 400 ms, and 8–9 = 200 ms. The other two patterns had a similar composition of overall movement times and between-key times but a temporal pattern different from the previously mentioned segment timings (200, 600, and 400 ms; and 400, 200, and 600 ms).

Three groups of participants learned those patterns in all of the studies (Lee et al., 1997; Richardson, 1997; Simon & Bjork, 2001). Two groups represented the typical CI manipulation of blocked- and random-practice sequences. The third group also received a random-practice schedule. However, for that group (random+model), the computer provided three modeled demonstrations of the spatial and temporal requirements of the next pattern to be performed, with auditory sounds to help augment the temporal information of the demonstration. In addition, in the Lee et al. and the Simon and Bjork studies, the augmented feedback that followed each trial presented information about the timing errors relative to the overall movement time goal, and in the Richardson study, augmented information was provided with respect to each of the segment timing goals. The functional task difficulties in Lee and his colleagues' and in Simon and Bjork's studies were easier than they were in Richardson's.

In all experiments, the blocked group performed better in acquisition than the random group, and the random group performed immediate and delayed retention tests better than the blocked groups did. The interesting difference between the studies was the effect of the random+model conditions. In all studies, that group performed better than the other two groups during acquisition, which demonstrated the powerful, positive effect that the modeled demonstrations had on the reduction of timing error. For retention, however, the influence of the random+model manipulation depended on the nature of the task. In the overall timing goal task (Lee et al., 1997; Simon & Bjork, 2001), the random+model group's retention performance was as poor as that of the blocked group in immediate retention and was worse than that of the blocked group in delayed retention. In contrast, for the more complex timing task (Richardson, 1997), the random+model group had the lowest error overall, outperforming the random group in both the immediate and delayed retention tests.

Together, the results of those experiments indicated that providing modeled timing information via computer just before the execution of a practice trial made the task much easier to perform than did withholding that augmented information. When the nominal difficulty of the task was easy (overall MT), the addition of that augmented information was detrimental to learning, even though the acquisition sequence involved a random order. We argue that the reason for the detriment in learning is that the modeled information reduced the action planning that was required of the learner before the initiation of a practice trial. The reduced planning requirement degraded learning despite the augmented functional difficulty introduced by the random-practice schedule. In contrast, when the more difficult nominal task (segment goal times) was combined with a random-practice order, the augmentation of the modeled timing information facilitated both performance and learning of the task. We believe that the explanation for that result is that planning operations involved in performing the task, although facilitated by the modeled information, were still required of the learner because of the combination of the nominal difficulty of the task (complex timing) and the additional functional difficulty introduced by the random-practice schedule.

We now turn to a more frequently examined use of augmented information, in which the information is provided about an action either during movement or after its completion. What we find most commonly, however, is similar to the outcomes of the studies just described: Learning is affected when augmented information (as feedback) is presented in such a way that it influences the overall functional difficulty of the task.

Practice Variables That Influence Feedback Information

The most common finding in the extensive literature comparing feedback frequencies, schedules, or both, has been that high KR frequencies or more immediate presentation of KR during acquisition trials produces better performance than do lower KR frequencies or less immediate presentation of KR. That trend is reversed for retention performance (see Salmoni, Schmidt, & Walter, 1984). By far, the majority of those studies have involved participants who had no previous experience with a nominally easy task. In terms of the challenge point framework, it seems straightforward to argue that relative to immediate KR, frequent KR, lower KR frequencies, or less immediate presentation of KR will increase the functional difficulty of a task (Guadagnoli, Dornier, & Tandy, 1996). Therefore, we make the following predictions:

3. *For tasks of high nominal difficulty, more frequent or immediate presentation of KR, or both, will yield the largest learning effect. For tasks of low nominal difficulty, less frequent or immediate presentation of KR, or both, will yield the largest learning effect.*

In the summary KR method, the learner performs a series of practice trials before augmented feedback about those trials is provided. When information is provided, the feedback includes all of the trials since the previous delivery of feedback. Therefore, as the number of trials to be summarized increases, more information will be presented in the augmented feedback, and the average delay in presenting feedback about each trial will increase. As compared with KR given immediately after each trial, summary feedback has been shown to be strongly detrimental to short-term performance gains. However, like the random-practice effect discussed previously, summary feedback is also positively related to learning (Guadagnoli et al., 1996; Lavery, 1962; Schmidt, Young, Swinnen, & Shapiro, 1989). A number of studies have shown that for the learning of nominally easy tasks, learning is positively related to the size of the KR summary: Larger summaries produce better learning effects (see reviews of that literature in Salmoni et al., 1984; Schmidt & Lee, 1999, chap. 12).

Schmidt, Lange, and Young (1990) attempted to discover the optimal length of summary KR; they predicted that the optimal length was task dependent (i.e., related to the nominal task difficulty). To test that prediction, they used a task presumed to have high nominal difficulty and provided augmented feedback to a group of participants after every trial (essentially a 1-trial summary), after every 5th trial (a summary of the previous 5 trials), or after every 15th trial (a summary of the previous 15 trials). The results supported their prediction that for a relatively difficult task, a medium summary length (5-trial summary) was more effective for learning than were the short and long summary lengths.

In a more recent study, Guadagnoli et al. (1996, Experiment 2) examined the relationship between optimal summary level and task complexity. Rather than using a single task and presuming its level of complexity, Guadagnoli and his colleagues used two versions of a force-production task that differed in complexity. (Pilot studies had revealed that one version, a single force production, was less difficult than another version, a dual force-production task). Guadagnoli et al. used the same summary conditions that were used by Schmidt et al. (1990; 1-, 5-, and 15-trial summaries). For the simple version of the task, the 15-trial summary yielded better retention results than did 5-trial and 1-trial summaries. For the complex version of the task, the retention results for the 1-trial summary group was superior to those of the 5-trial and 15-trial summary groups. Therefore, Guadagnoli et al. confirmed the work of Schmidt et al., suggesting that an optimal summary size was task dependent. Taken together, those findings support the prediction that for efficient learning, differing levels of nominal difficulty require differing levels of KR. The challenge point framework provides a possible reason for that requirement. Learning is intimately related to the information available and interpretable in a performance instance. A novice performer might have the information available but be incapable of interpreting it efficiently. As such, more frequent or immediate information, or both, would be needed for learning.[4]

4. *For tasks about which multiple sources of augmented information can be provided, the schedule of presenting the information will influence learning. For tasks of low nominal difficulty, a random schedule of augmented feedback presentation will facilitate learning as compared with a blocked presentation. For tasks high in nominal difficulty, a blocked presentation will produce better learning than a random schedule.*

Teaching golf is a good example of a task for which augmented feedback can be provided about many aspects of a learner's performance. The instructor might be interested in pointing out to the learner, for example, something about the grip, the stance, the body position relative to the ball, or aspects of the swing plane. It is generally acknowledged, however, that providing augmented information about one aspect of the swing following a performance is preferable to distributing attention to multiple aspects of the swing. A very practical question is: When instructing a learner, should the same aspect of performance (e.g., the swing plane) be the focus of repeated instances of augmented feedback or should aspects of performance be the focus of attention?

Lee and Carnahan (1990) and Swanson and Lee (1992) have provided a laboratory task analog of the golf example. Their task involved multisegment timing, requiring participants to move to three target locations in preestablished time requirements (to the first location in 160 ms, from the first to the second in 380 ms, and from the second to the third location in 250 ms). Groups differed in terms of which segment was the focus of augmented feedback (KR) on subsequent trials. For the blocked group, one segment was the repeated focus of KR for 20 consecutive trials, followed by a different segment for 20 trials and the final segment for the last 20 trials. For the random group, a different segment was the focus of each consecutive trial. The finding for that task was a clear learning advantage for the random group (Lee & Carnahan, 1990; Swanson & Lee, 1992).

In contrast to the above finding were the results of a study by Wulf, Hörger, and Shea (1999). Groups of participants learned a complex ski-simulation task, for which whole-body, slalom-type movements were practiced on 4 consecutive days. Previous research had shown that augmented feedback about the downward force motion of the feet was beneficial for learning. Groups in Wulf et al. were provided force-onset feedback about either the left or right foot during practice. For the blocked group, feedback relative to only one of the feet was presented during an entire session of practice per day (e.g., left foot feedback on Days 1 and 3 and right foot feedback on Days 2 and 4). For the random group, the foot for which force-onset feedback was presented was switched on every consecutive trial over the 4 days. In direct contrast to the findings reported by Lee and Carnahan (1990) and by Swanson and Lee (1992), the results for that more complex task (and more complex feedback provided) favored the blocked schedule over the alternating schedule.

Challenge Points and the Performance–Learning Relationship

In this article, we have developed a framework that suggests that task difficulties create a learning potential whose function differs according to the level of the performer, the complexity of the task, and the training environment. Because increased task and environment complexity are differentially associated with performance levels, there is a performance–learning paradox. As a result, the optimal challenge point for learning does not coincide with the optimal challenge schedule for immediate (practice) performance.

For relatively simple skills, a rudimentary action plan might be developed within a few practice trials, and further refinement of the skill is dependent on the extent to which the learner is challenged by the practice conditions. The development of a movement representation for a more complex skill that requires, for example, the coordination of many degrees of freedom, might initially be stored as a series of relatively independent subcomponents. Such a movement would typically take considerably longer to learn and would inherently require more effort and information-processing activities on the part of the learner. It is conceivable that introducing additional demands for the learner during this process is actually detrimental, rather than beneficial, because the additional demands compete for a limited amount of processing capacity with the essential processing activities during learning. Instead, it is predicted that providing the learner with practice conditions that facilitate performance (at least until a relatively stable movement presentation is acquired) will enhance complex skill learning. In addition to possible differential effects that some variables might have on simple versus complex skill learning, it is also predicted that this type of relationship may exist for experienced versus novice performers.

According to classic learning theory, when the performer is in an early stage of learning the processing system is too inefficient to deal with multiple task elements (e.g., Adams, 1971; Fitts & Posner, 1967; Miller, 1956). Therefore, the information should be presented in more appropriate units for efficient processing. Situations such as a shorter summary KR length or less practice variability might serve to provide information in more suitably organized units. Therefore, those schedules should lead to more efficient skill acquisition for an early learner. When a performer is in a later stage of learning, however, the system's ability to process information improves, and thus the performer can and should handle more demanding acquisition protocols. The overall efficiency of processing information is dependent on functional task difficulty, which is determined by the ability of the performer, the complexity of the task, and the conditions of practice. As stated earlier in this article, the expectations for performance also become more stringent as skill improves. Therefore, to generate an equivalent amount of information in the performance of a task, one must increase the functional task difficulty, which paradoxically should enhance learning while hindering acquisition performance.

Concluding Comments

As stated in the introduction, many of the ideas expressed in this article have been suggested before, either implicitly or explicitly. Indeed, the concepts of information theory and information processing as they relate to motor performance and motor learning have a long history (e.g., Fitts & Posner, 1967; Welford, 1968) and are certainly not unique to the present framework. The concept of adapted training as a strategy that progressively increases task difficulty as an individual acquires skill (Lintern & Gopher, 1978; Mané, Adams, & Donchin, 1989; Walter & Swinnen, 1992) shares many similarities with the present framework. K. M. Newell, et al.'s (1991) delineation of the perceptual-motor workspace, which describes task, organism, and environmental constraints on action, also shares some similar themes. We believe that the unique contribution of the present article is that we make explicit some ideas relating the role of practice variables in the context of skill levels, task difficulty, and information theory concepts. In doing so, we have bypassed some tricky concepts (e.g., defining task difficulty) and have asked the reader to accept a few leaps of faith (e.g., the specific shapes of the curves seen in the figures).

Quoting Crick and Koch (2003) once again, "A good framework is one that sounds reasonably plausible relative to available scientific data and that turns out to be largely correct. It is unlikely to be correct in all the details" (p. 119). Whether or not the present framework turns out to be largely correct or mostly incorrect, we will consider it a success if research is conducted that advances our knowledge regarding the role of practice variables in motor learning.

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NOTES

1. We have attempted to acknowledge as many of those sources as possible at various points in this article. Some sources might have been missed, however, and we apologize in advance for any oversights.

2. Although each of the continua is relatively effective in describing task difficulty, no one continuum is satisfactory in quantifying the complexity of the wide variety of motor tasks. In the larger context, one must consider in the determination of task difficulty where a task fits on a number of continua, how the continua interact to fully define difficulty, and ultimately the demands placed on the memory and processing capacity of the learner.

3. We do not distinguish here between inherent and augmented sources of feedback in terms of the quality of information they provide to the learner. In the given example, vision of the apple core going into the basket provided uncertainty-reducing feedback that could also have been provided by augmented sources if, for example, the room lights had been extinguished.

4. Along with the notion that the specific shape of the curve is of less consequence than the general trend is, it should be noted that the issue of continuous as opposed to discontinuous (nonlinearities) aspects of the curve is also of less consequence than is the general trend for the purpose of the present framework.

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