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Is Variability a Window to Understanding Transfer?

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In the domain of skill learning, transfer refers to the influence of a learned task—the transfer task—on the acquisition of a new task—the criterion task. Three experiments examined transfer using a virtual implementation of the pub game skittles. The primary focus was on whether the structure of variability during learning determines the nature of transfer. The structure of variability was quantified by the TNC-Cost Method (for tolerance, noise, and covariation), an analytic method that shows how the variability of execution (i.e., movement) relates to the variability of a result (i.e., error). A secondary focus was on the amount of practice of the transfer task, namely, just until stabilization or extending well beyond stabilization. Experiment 1 established the amount of practice needed to stabilize three skittles tasks: hitting a stationary target at one position, a stationary target at different position, and a moving target. Using this baseline, Experiment 2 compared a stabilization group and an extensive practice group using one stationary target as the transfer task and the other stationary target as the criterion task. Although performance suffered with the introduction of the criterion task, positive transfer was observed equally for both practice groups. Furthermore, variability profiles did not differ for the two groups. Experiment 3 again compared a stabilization and an extensive practice group, each within two transfer groups, stationary target to a moving target, and moving target to a stationary target. Once again, the amount of practice did not matter. However, while performance suffered with the transfer from a stationary target to a moving target, performance improved with the transfer from a moving target to a stationary target. Interestingly, the variability profile for one measure, the covariation cost, resembled the error profile of performance. Results were discussed in terms of the relevance of synergistic regulation for transfer among these tasks, in particular, and their implications for the ecological approach to perception-action and learning in general.

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Chapter I: Introduction

Don't practice till you get it right; practice till you don't get it wrong.

The c ontribution of practice to learning and performance has been a subject of considerable scrutiny by scholars and practitioners alike. The opening admonition is commonplace in music, theater, and sports. Although it has the flavor of advocating that a specific skill should simply be drilled, in sports, in particular, it has been used to suggest that practice can establish a foundation that generalizes to novel situations. The contribution of practice to learning and transfer, as well as the modifications in variability associated with it, provide the focus for the proposed dissertation.

Variability and Transfer

In the literature on perception and action, learning is related to the persistence of performance improvement in a task after a period of practice. More specifically, learning is understood as relatively permanent changes in task performance due to practice and feedback (Magill, 2007; Schmidt & Lee, 2005). Orthodox models assume that learning is a process that ends at movement automation, characterized by the consistent achievement of a task's goal (e.g., Adams, 1971; Fitts & Posner, 1967). These models are centered on a description of learning of a single task; they are not clear about how one perceptual-motor skill affects another. In the complex contexts of daily activities, learning is not only about stabilizing a given behavior, but also modifying potentials for engaging in new situations. The emergence of a new skill modifies the interaction among different potentials for action (Zanone & Kelso, 1992) by re-organizing internal constraints (Iberall, 2016).

Transfer is the term used to conceptualize the mutual influence among perceptual-motor skills (Schmidt & Young, 1987). Transfer can be positive (skill A facilitates learning skill B),

negative (skill A disrupts learning skill B), or neutral (skill A does not affect learning skill B). Studies of transfer have shown that the effects (positive or negative) of performing one skill on learning another depend on the organization of the perceptual-motor system when it faces a new task (Coull, Tremblay, & Elliott, 2001; Mackrous & Proteau, 2007; Proteau, 1992).

The importance of the organization of perceptual-motor systems for learning has been promoted by proponents of the *Adaptive Process Approach* (Tani, 2005; Ugrinowitsch, Benda, Corrêa, & Tani, 2014). Tani and colleagues assume that learning is a process of constant adaptation of skills to environmental changes. Adaptation is characterized by stabilization of performance. Stabilization is a term that encompasses both accuracy (reduction of error) and precision (reduction of the variability of error), which means that a stable system is one that consistently reaches the goal of a task.

The general strategy for investigating how stabilization affects transfer consists of two phases: (1) Individuals are assigned to different groups defined by different amounts of practice of a given perceptual-motor task; and (2) either a variation of the same task or a new task is introduced. Tani and colleagues have proposed that in the first phase, individuals can manifest three qualitatively distinct levels of stabilization of performance based on the amount of practice they have received: pre-stabilization, stabilization, and super-stabilization. As noted above, stabilization refers to a state in which an individual has practiced enough to consistently reach the goal of a task. During pre-stabilization, the amount of practice has been insufficient to stabilize performance; any improvement that occurs is transitory. During super-stabilization, practice continues in excess of what is necessary to stabilize performance; that is, the appropriate level of accuracy and precision has already been achieved.

Although levels of stabilization are defined with respect to results of movement execution, proponents of the Adaptive Process Approach argue that levels of performance stabilization reflect levels of organization of systems' internal constraints (Tani, 2005; Ugrinowitsch, dos Santos-Naves, Carbinatto, Benda, & Tani, 2011). In particular, they suggest that different levels of stabilization are characterized by different variability profiles of variables that describe movement execution. In an experiment directed at this interpretation, participants were assigned to two practice conditions, stabilization and super-stabilization (Fonseca, Benda, Profeta, & Ugrinowitsch, 2012). They performed a sequential movement pattern in which the last component of the sequence was timed to coincide with a moving visual stimulus. When the speed of the visual stimulus was predictable, the amount of variability in movement execution and the averaged result of movement sequences (i.e., error) were similar between groups. With the sequence of movement kept constant but with unpredictable variation in the speed of the visual stimulus, the super-stabilization group outperformed the stabilization group. Interestingly, this superior performance was accompanied by larger variability of the last component of the executed sequence, a feature that is critical for fine timing adjustments in sequencing tasks. This result suggests that variability of movement execution is functional (cf. Manoel & Connelly, 1995).

One limitation of the preceding study is that execution variability of the required sequence was indexed by standard deviation for each component (Fonseca et al., 2012). That is to say, variability of the organization of the skill (i.e., variability of execution) was obtained independently of the variability of the result. Although the organization of the movement sequence led to a specific result, the variability of organization and result were treated independently. Consequently, the interpretation of execution variability's having a possible

functional role was not inherently linked to the result of the action. In order to advance understanding of how this variability changes with practice and how it can affect transfer, different tools are required.

Extracting Structural Variability

One of the oldest issues in the study of perception-action cycles is how to relate results of an action to movement execution. One reason it is challenging is that the space of execution variables has dimensions different from the space of result variables. Müller and Sternad (2004) suggested that reconciling result with execution requires formalizing a given perceptual-motor task by explicitly defining a function f that relates a set of execution variables, E, and a result variable, R: $R = f(E)$. This function maps all combinations of execution variables in a redundant system onto the result variable. Importantly, even in a simple redundant system composed of a single result variable, r, and a vector of E containing two execution variables, e_1 and e_2, infinite combinations of the variables composing E can lead to the same values of r. Establishing this functional relationship, one can tease apart the variability in the execution space in a set of trials of a given perceptual-motor task and directly relate it to its counterpart in the result space.

To evaluate this idea, Müller and Sternad (2004) developed a two-dimensional, virtual version of Table Skittles, a British pub game in which a small ball tethered to a pole is swung around in an attempt to knock down a wooden pin or “skittle” on the other side of the pole. In the virtual task, the tethered ball is “held” by a paddle on a fixed axle and released by a contact switch. When released, the ball follows an elliptical trajectory defined by two orthogonal and nonlinear springs (see *Appendix A*). The minimal distance between the trajectory of the ball and the coordinates of the target provides the error measure d which is completely defined by the angle α and the angular velocity ω of the paddle-ball complex at the instant of releasing. That is,

$d = f(\alpha, \omega)$. All possible combinations of α and ω and their corresponding *d*s form the action space of the task (Figure 1). Among all α-ω combinations, a small number forms a manifold that solves the task, leading to hitting the target. This solution manifold (the red region in Figure 1) has two important properties. First, it is nonlinear; hitting the target is not a matter of scaling combinations of α and ω. Second, its width is not constant; some areas are more tolerant of a large range of combinations of α and ω than others.

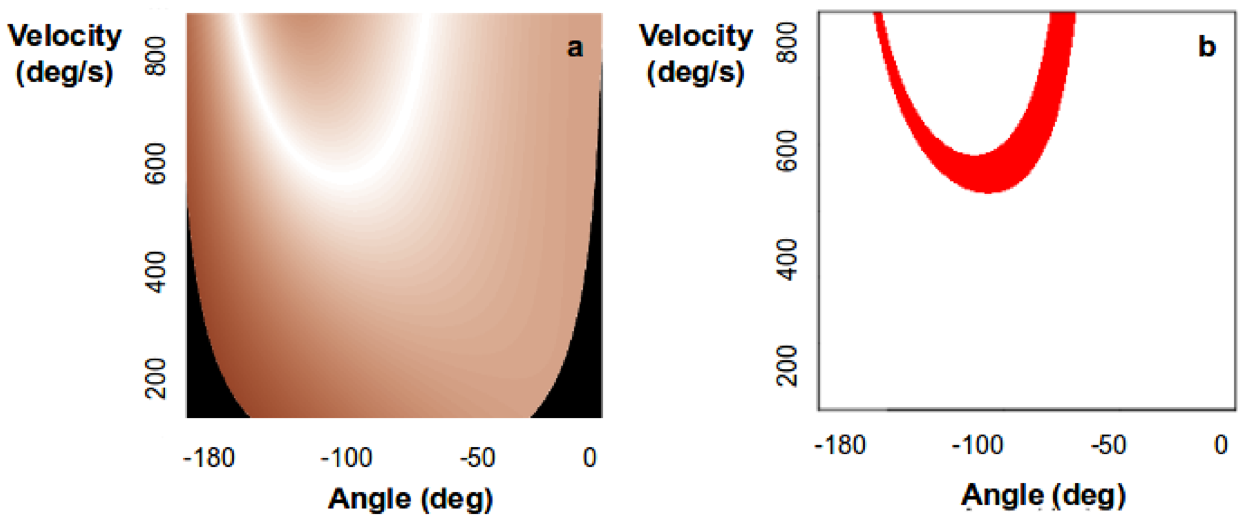

Figure 1. (a) An example of task space with a gradient of colors defined by the distance from the center of the target. Black areas indicate combinations of α and ω in which the ball hits the center post. [This graph was made using a customized version of the TNC Analysis Package (Matlab) available at www.northeastern.edu/actionlab/research/] (b) The same task space as in (a) highlighting the solution manifold (i.e., combinations of α and ω that allow for hitting the target) in red. The target was placed at coordinates [20, 50].

Once the solution manifold is known, the amount of variability in *R* over a number of trials can be decomposed into three sources of influence from *E*: tolerance or *T-Cost*; noise or *N-Cost*; and covariation or *C-Cost*. Each represents how the actual combination of execution variables contributes to non-optimal performance. And more broadly, specific calculations involving the execution variables from a set of trials can be used to generate the optimal result that this very same set of trials could provide. Each calculation generates an optimal result in

terms of one specific component of the variability, while the others remain unchanged, generating an optimal version of the data set with regard to that specific component of variability. That is, the actual data set is optimized three times, once for each component of variability. The mean of the optimized data sets is calculated and subtracted from the mean of the original and the difference is taken as the cost for not optimizing the specific component (Cohen & Sternad, 2009). All three costs mentioned above are defined in terms of the units of the result variable, that is, they represent how much *d* increases due to the data not being optimal.

Following Cohen and Sternad (2009), *T-Cost* expresses the cost of an averaged result of a given data set not being centered at the tolerance area of the solution manifold. *T-Cost* is calculated by translating the cloud of data over the execution space to the location where it generates the lowest *d* (Figure 2, left). The difference between the means of the result variable generated from the original data and the translated data set is taken as the *T-Cost. N-Cost* refers to the deleterious consequence for performance due to noise in the execution variables. To calculate *N-Cost*, the original data set is shrunk at constant steps until all data points collapse into the mean (Figure 2, center). At each step the mean of the result variable is calculated. The algebraic difference between the data set with the lowest result mean and the original one is the *N-Cost*. *C-Cost* measures the cost to performance of a given data set not fully exploiting the redundancy in the execution space, that is, the best combination of α and ω in the current data set that would produce minimum *d* (Figure 2, right). The best exploitation of the redundancy is obtained by recombining pairs of execution variables to achieve the best possible performance. The algebraic difference between the mean of the result variable of the original data set and the transformed data set is taken as *C-Cost*.

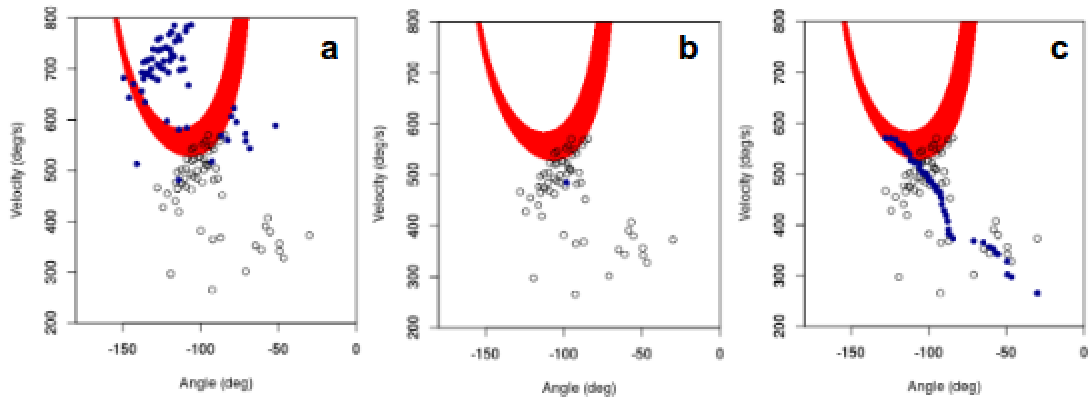

Figure 2. Example of *TNC-Cost* analysis applied to a data set. The original data distribution is in black; the ideal data for each particular transformation is in blue. (a) *T-Cost*. (b) *N-Cost*. (c) *C-Cost*.

An advantage of the *TNC-Cost* method is that it allows one to track how different execution variability components contribute to average performance over the learning process. For example, an analysis of the evolution of the variability profile for the non-experts in Cohen and Sternad (2009) performing 1080 trials evenly distributed over six days revealed not only that *d* decreased, but so did the standard deviation of both result (*d*) and execution variables (α and ω). With respect to individual components, *T-Cost* decreased and stabilized early in practice, *N-Cost* and *C-Cost* decreased more slowly, with the latter stabilizing only near the end of the period of practice. Thus, in early stages of learning, *T-Cost* seems to be the main component of execution variability that contributes to stabilization of performance. Furthermore, later stabilization of *C-Cost* did not lead to additional error reduction.

The method developed by Cohen and Sternad (2009) has proved to be a useful tool to characterize the structure of variability in the execution space and how it relates to averaged performance measured in the result space. In addition, it allows tracking the contribution of each source of variability with practice. The structure of variability is informative about the state of organization of perceptual-motor systems which, in turn, is related to the ability of such systems

to deal with new tasks. In what follows, we present the motivation of the application of this method to the study of transfer.

Research Problem and Objective

Learning can be understood as modification of the inner constraints of a system or of its intrinsic dynamics (Tallet, Kostrubiec, & Zanone, 2008; Zanone & Kelso, 1992). However, learning is a relative rather than an absolute concept. It does not make sense to say that "someone learned more than someone else" without providing the context of the test of learning. The notion of transfer makes this point clear. Transferring what was learned in one task to another does not refer to how good the performance in the first task was, but how beneficial it is to the learning of a new task. The benefit is the potential to learn, which is defined by the state of organization relative to a new task. Roughly, two qualitatively distinct states of organization are expected to respond differently when exposed to similar environmental constraints.

As described in the preceding section, the *TNC-Cost* method provides a description of the structure of the variability of execution variables that are functionally related to a task's result variable. The method allows the structure of the variability of execution variables of two versions of the same task to be compared. Moreover, *TNC-Cost* allows for direct comparison between the structure of variability and its effect on performance of two different tasks. The only requirement is that, in both tasks, the relationship between execution and result variables can be expressed by a function. The present study is intended to investigate whether different variability structures obtained by different levels of stabilization change with the opportunity to transfer to either a new version of the same task or to a new task. Different changes in variability structure, would mean different functional requirements for systems at different levels of stabilization.

Chapter II: Experiment 1

As discussed previously, studying transfer requires the understanding of task constraints, which in the current study are examined via a task space that describes all possible relations among execution variables. Having a task space for different tasks, one can investigate how novices exploit the task space in order to improve their performance. To achieve this goal, in Experiment 1 we investigated similarities and difference among three versions of the skittle task to be used in subsequent experiments: T1 was a stationary target at one location, T2 was a stationary target at a different location, and T3 was a moving target that oscillated between the aforementioned locations.

Method

Participants. Undergraduates were recruited from the participant pool of the Department of Psychological Sciences at the University of Connecticut in accordance with procedures approved by the Institutional Review Board. Thirty participants (*M* = 20, *SD* = 5.5 years) were assigned randomly to three groups corresponding to T1, T2, and T3. Five participants (two attempting T1, one attempting T2, and two attempting T3) did not learn during their practice, hitting on fewer than 2% of the trials. Consequently, 25 participants were included in the analyses.

Design and Procedures. The first experiment addresses the amount of practice necessary to reach stabilization of performance in the tasks to be used in Experiments 2 and 3. In T1, a target was positioned 20 cm to the right and 50 cm above the post. In T2, the target was placed 30 cm to the right and 35 cm above the post. Finally, in T3, the target moved back and forth between the two foregoing locations—(20 cm, 50 cm) and (60 cm, 50 cm)—at a velocity

following a sinusoidal wave with a cycle of 2.09 s. Figure 3 shows examples of solution manifolds for each target.

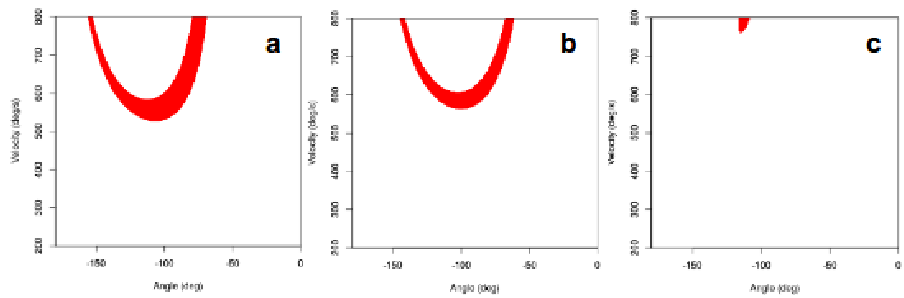

Figure 3. Action space of the execution variables angle and angular velocity (α and ω) at ball release. The red region represents the solution manifold (SM) of all combinations that lead to successfully hitting a target. (a) SM of T1. (b) SM of T2. (c) SM of T3 when the ball is released at 68% of the moving target cycle, illustrating an instant close to the border between being possible and not possible to hit the target.

Participants in each group performed nine blocks of 60 trials of their version of the task, allocated evenly over three sequential days of practice. Participants were instructed to stand sideways to the screen, laying their forearms on a manipulandum that rotated around a fixed axle attached to a wooden platform mounted on the top of a table. The manipulandum was fitted at the tip with a switch that, when released, threw the ball along the simulated physical trajectory. At the end of the participation of each individual, they were asked “Which strategy did you apply to solve/learn this task?” Participants were asked to describe what they considered that was important to improve their performance.

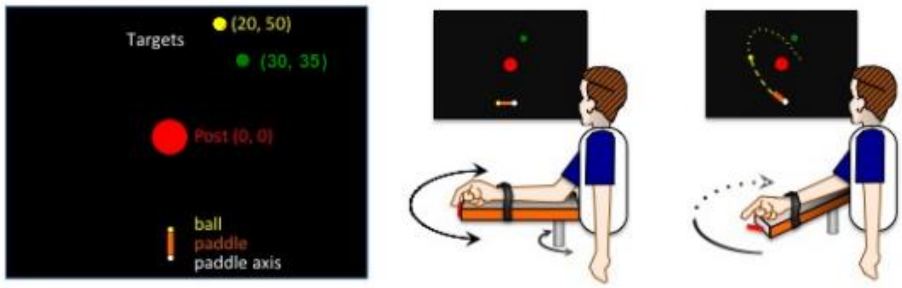

Figure 4. (left) The task layout is shown in top view on a computer screen. The ball is attached to a paddle, which rotates around a fixed axis. The ball is tethered (invisibly) to a post at the center of the image at coordinates designated (0, 0). Target positions are defined relative to that origin. (middle) The participant controls a manipulandum that rotates around a fixed axle; its position is reflected in the display. (right) When a finger-switch on the tip of the manipulandum is released, the ball is released, following a trajectory dictated by Equation (1) in Appendix A.

Dependent Measures for TNC Analysis. Following previous studies using the skittles task, we designated variables as execution, result, and costs.

Execution variables. α and ω velocity at the instant of release.

Result variables. The error measure *d* was the primary result variable. The angle of the ball in relation to the target at that point of minimal distance was also obtained (by treating the coordinates of the target at this point as the origin of a polar coordinate system). However, this measure did not reveal any interesting results and was not pursued.

Cost variables. A 600-point action space for each static target was generated by varying α coordinate from -180 to 0 deg in steps of .3 deg and ω coordinate from 201 to 800 deg/s in steps of 1 deg/s. The action space for the moving target also required taking time into consideration, varying from 0 to 2.09 s in steps of .012 s. *T-Cost* was calculated by translating the entire data set of a block of trials (without changing its dispersion) across the entire action space for a given version of the task, and subtracting the minimal averaged error of the translated data from the averaged error in the original data set. *N-Cost* was calculated by shrinking the data cloud until it collapsed into the mean in 500 steps, and subtracting the minimal error from the original. Finally,

C-cost was calculated by recombining all tuples of a data set until all possible combinations of α, ω, and timing were obtained and, then, subtracting the averaged minimal distance from the averaged distance in the original data set. For details see Cohen and Sternad (2009).

Data Reduction and Analysis. Changes in the trajectory of each dependent variable were modeled with Growth Curve Analysis (GCA). We averaged the value of each dependent variable in each block of trials and applied GCA to analyze trajectories of the mean of each dependent variable of the skittle task over nine blocks. Time was coded in terms of *blocks* and *days* of practice. Days and blocks were both centered at zero. Given the nature of the design, blocks were nested within days. A taxonomy of models was built, starting by adding the fixed effects (see Cheng, Edwards, Maldonado-Molina, Komro, & Muller, 2010). Estimates were added in the following order: *intercept*, *blocks*, *days*, interaction *blocks-days*, *group,* interaction *group-blocks,* interaction *group-days,* and interaction *group-days-blocks*. Following the standard practice in the literature of GCA (Mirman, 2014), a fitting improvement was evaluated using -2 times the changes in log-likelihood, which follows a χ^2 distribution with the number of degrees of freedom equal to the number of parameters added to a model (see Singer & Willet, 2003). Below we present the final model for each dependent variable, in turn; refer to *Appendix B* for details of how each final model was obtained. Comparisons between estimates were done using normal approximation (see Mirman, 2014). Importantly, although GCA fits and reproduces learning trajectories, it does not inform about the underlying mechanism that generates such trajectories. Instead, it provides a description of the functional form of a trajectory's probability distribution (Mirman, Dixon, & Magnuson, 2008). In what follows, the analysis of each dependent variable is presented separately.

Results

The first column of Table 1 shows the estimates that were evaluate in building the models. Subsequent columns indicate, for each variable, the final model and its associated deviance. Mean data for each group, with their respective fits, are presented in Figure 4.

Table 1

Estimates and Standard Error (SE) of the Final Growth Curve Model of Each Dependent Variable and Their Deviances (Degrees of Freedom)

	Error		**Velocity**		**Angle**		**T-Cost**		**N-Cost**		**C-Cost**	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	**2.443***	0.188	**406.213***	17.678	**-76.352***	3.2	**1.986***	0.356	**1.027***	0.298	1.348*	0.262
Blocks	**-0.853***	0.080	**60.227***	5.845	**-2.26**	0.924	**-0.660***	0.134	**-0.505***	0.138	-0.707*	0.094
Days	**-0.457***	0.051	**90.205***	8.303	**-6.902***	1.517	**-1.349***	0.201	**-0.558***	0.146	-0.969*	0.120
T2	0.308	0.239					-0.003	0.453	**1.312***	0.267	0.324	0.345
T3	0.605	0.260					0.167	0.495	0.571	0.290	0.359	0.376
Blocks-Days	**0.214***	0.038	**-29.901***	4.51			**0.376***	0.099	0.2359	0.103	0.278*	0.052
T2-Blocks											0.241	0.106
T3-Blocks											0.204	0.115
T2-Days	0.247^	0.094					**0.742**	0.234			0.577*	0.146
T3-Days	0.027	0.102					0.270	0.255			0.122	0.159
Deviance (dfs)	276.180 (15)		2434.400 (11)		1769.600 (10)		683.880 (15)		687.010 (13)		415.910 (17)	

bold: $p < .05$; *: $p < .01$; ^: $p < .10$. Shaded rows show blocks of estimates that significantly improved model fit.

Error. The final model of error included blocks, days, blocks-days, groups, and groups-days. Pairwise comparisons between estimates of groups and groups-days did not reveal any

significant difference despite a marginal difference between estimates of the groups-days of T1 and T2 [.247 (.094), $p = .065$][1]. Therefore, the groups' curves did not differ.

Velocity. The final model of velocity included blocks, days, and blocks-days; no difference between groups was identified.

Angle. The final model of angle included blocks and days; no difference between groups was identified.

T-Cost. The final model of *T-Cost* included blocks, days, blocks-days, groups, and groups-days. The interaction groups-days indicates significant differences between the estimates between of T1 and T2 [.742 (.234), $p < .05$]. In particular, T2 had more capacity to improve performance by translating all data points without affecting their relative positions than T1.

N-Cost. The final model of *N-Cost* blocks, days, blocks-days, and groups. The effect of groups indicates significant differences between the estimates of T1 and T2 [1.312 (.266), $p < .001$] and T2 and T3 [-.741 (.277), $p < .05$]. Thus, T2 had more capacity to improve performance—by shrinking the data distribution—than either T1 or T3.

C-Cost. The final model of *C-Cost* included blocks, days, blocks-days, groups, groups-blocks, and groups-days. Pairwise comparisons indicated significant differences between the estimates of T1 and T2 [.575 (.146), $p < .01$] and T2 and T3 [-.453 (.152), $p < .05$]. Again, T2 had more capacity to improve performance—this time, by re-arranging pairs of α and ω values in the task space—than both T1 and T3.

[1] Following the common practice of how to report GCA results, we provide the estimate value, followed by its standard error in parentheses.

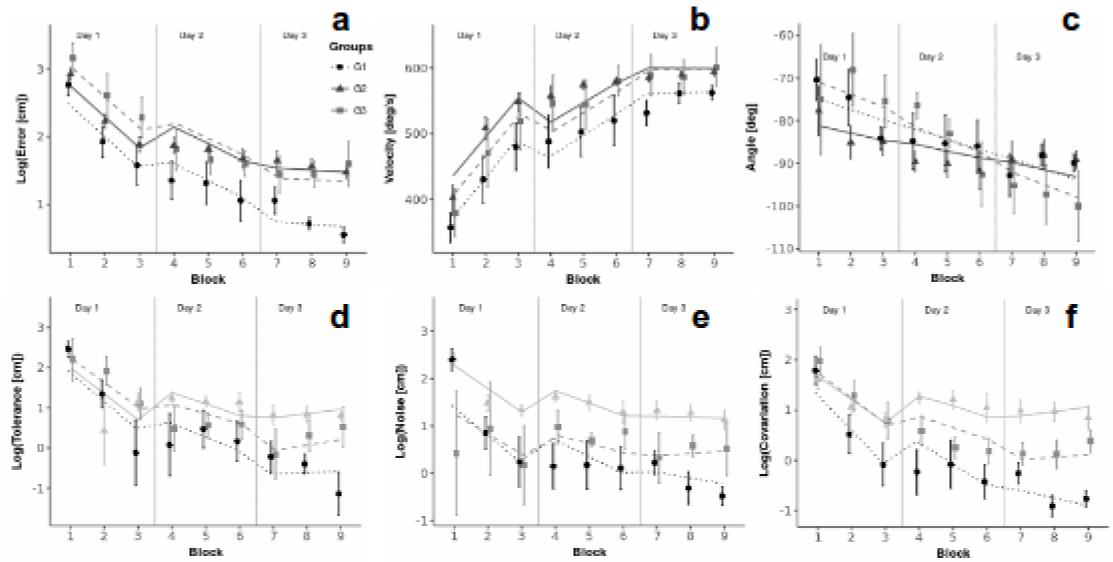

Figure 5. Means (with standard error bars), and their respective growth model fit (lines), for (a) error, (b) velocity, (c) angle, (d) *T-Cost*, (e) *N-Cost*, and (f) *C-Cost*, as a function of block for each group in Experiment 1.

Discussion

Experiment 1 assessed how individuals practicing different versions of the virtual skittle game improved and stabilized their performance. As noted earlier, stabilization refers to circumstances in which individuals reach a task goal consistently. That is, a given performance has been acquired and does not return to early (high error) levels after a period without practice or under the presence of perturbations. Stabilization of performance also refers to the relation between execution variables (in this case α and ω) that results in successful performance. That is why understanding how their relation changes as learning progresses is important.

In particular, we used an analytic method that allows variability in the task space to be expressed in terms of variability in the result space. Such method overcomes limitations of previous studies in which variability in execution variables do not have clear connection to error (e.g., Fonseca et al., 2012). To reiterate, the *TNC-Cost* method (cf. Cohen & Sternad, 2009)

allows one to interpret execution variability in terms of its functional role inherently linked to the result of the action, breaking down variability of execution variables over the period of practice into three different sources of error in performance, namely, tolerance (*T-Cost*), noise (*N-Cost*), and covariation (*C-Cost*).

Results suggest that individuals in all three conditions stabilized their performance by Block 6. As previously mentioned, stabilization is a term that encompasses both accuracy (reduction of error) and precision (reduction of the variability of error), which means that a stable system is one that consistently reaches the goal of a task. It is important to consider, however, that how accurate and precise one can be is also related to task's difficulty (Day, 1956). Although one might expect that T3—where the motion requires regulating time in addition to α and ω—would evoke larger error, that was not the case; GCA did not reveal any differences among group trajectories. The apparent performance advantage that T1 seems to hold over T2 and T3 at the end of practice is not addressed by GCA.

To better understand how these differences might affect behavior beyond error performance, it is useful to study the solution manifold of each task. A solution manifold represents a set of relations among the execution variables that lead to achieving the task's goal. In the current study, a solution manifold is interpreted as a proxy for the affordance of the skittle task; that is, it sets the boundaries between target that is "hit-able" and target that that is not "hit-able" (for a similar idea see Wilson, Weightman, Bingham, & Zhu, 2016)[2].

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[2] The current approach differs slightly from the one presented by Wilson et al. (2016). The latter assumes the solution manifold as an expression of affordance. In the current work, we understand the solution manifold as a proxy for an affordance since it sets the necessary physical constraints to achieve the goal of a task but it does inform whether or not an individual possesses the effectivities to bring about an intended result. In other words, because we follow the concept of affordance defined in Turvey (1992), to fully characterize an affordance provided by the environment one also needs to define the effectivities of the organism that inhabits that environment. Refer to

The analysis of the solution manifolds of T1 and T2 shows that they were always available to individuals who practiced the skittle task with either of these stationary targets. It means that all participants possessed the potential to hit the target (i.e., in principle, they could generate the right combination of α and ω). In contrast, the solution manifold of T3 is dynamic. At one extreme, it approximates to the solution manifold of T1; at the other extreme, it vanishes (i.e., no individual possesses the ability to generate a release velocity high enough to hit the target, independently of the release angle). While individuals attempting T1 and T2 had to be sensitive to better locations of their solution manifolds to optimize their solutions, individuals attempting T3 had an extra requirement: They had to be sensitive to when it was or was not possible to hit the target. The problem posed by T3 is similar to the one faced by proponents of the affordance-based control approach (Fajen, 2007; Harrison, Turvey, & Frank, 2016).

In discussing the outfielder problem, Fajen (2007) pointed out that the main problem confronting the outfielder is to know when it is (not) possible to reach the landing location of the ball on time, considering the limits of outfielder's capabilities. That is, prospectivity (E. Gibson, 1994; Reed, 1996) is necessary to deal with dynamic boundaries. Individuals' sensitivity to the dynamic boundary condition has been demonstrated in studies of catching balls in interceptive tasks (Oudejans, Michaels, Bakker, & Dolné, 1996) and braking in driving simulators (Fajen, 2005). Our participants seemed to be sensitive to the dynamic boundaries that characterize T3. By the sixth block of practice (the last block of the second day), they reduced their number of throws to virtually zero in a condition where it was impossible to hit the moving target.

Fajen (2007), Harrison, Turvey, and Frank (2016), Turvey (1992), and Warren (1984) for a more complete discussion of this matter.

Groups did not differ in their average velocity. This non-difference was unexpected because getting into the solution manifold of T1 required a minimal release velocity of 526 deg/s, getting into the solution manifold of T2 required a minimal release velocity of 563 deg/s, and the minimal release velocity for T3 varied according to release time. Importantly, its minimal value happened when the solution manifold of T3 overlapped with the solution manifold of T1. That is, its minimal release velocity was also 526 deg/s.

Interestingly, participants of all groups stabilized their performance with velocity values above the minimal necessary and did not show a trend to move towards the minimal values (see also Abe & Sternad, 2013). Considered in isolation, this is a counter-intuitive result since stochastic white noise is expected to increase with larger velocities (Harris & Wolpert, 1998; Schmidt, Zelaznik, Hawkins, Frank, & Quinn, 1979). However, when taking into consideration the type of constraints imposed by the solution manifold of each task and how individuals seem to solve throwing tasks in general, this seems to be a good solution. It has been shown that, in throwing tasks in general (Smeets, Frens, & Brenner, 2002) and in the virtual skittles in particular (Cohen & Sternad, 2012), individuals release the ball close to the peak velocity. In the current experiment, participants attempting T1 and T2 released the ball on average 2 ms before peak velocity, while participants attempting T3 released the ball on average 4 ms ahead of peak velocity. That means that a solution that emphasizes low velocities would barely get into the solution manifold; it would require a near-zero level of error in release timing. Although it has been suggested that throwing tasks require a precision of the order of 2 ms (Smeets et al., 2002), this suggestion has been challenged. As one alternative, the effects of timing error in releasing the ball can be decreased by staying longer inside the solution manifold, which necessarily implies releasing the ball with values above the minimal necessary (Cohen & Sternad, 2012).

Such a solution counters the amount of intrinsic neural noise generated by high velocity and its consequences for performance (see also Sternad, Abe, Hu, & Müller, 2011).

As noted above, T1 and T2 did not elicit differences in performance. Of importance, their solution manifolds overlap. Considering the last day of practice only, about 15% of the throws in T1 happened inside this common zone, representing 30% of the total of hits in this group. In contrast, about 25% of the throws performed for T2 occurred in the same zone, representing 82% of the hits for this group on the last day. These indicate that the solutions applied by participants executing T1 and T2 were similar, partly rationalizing the non-difference observed. A representative example is presented in Figure 6.

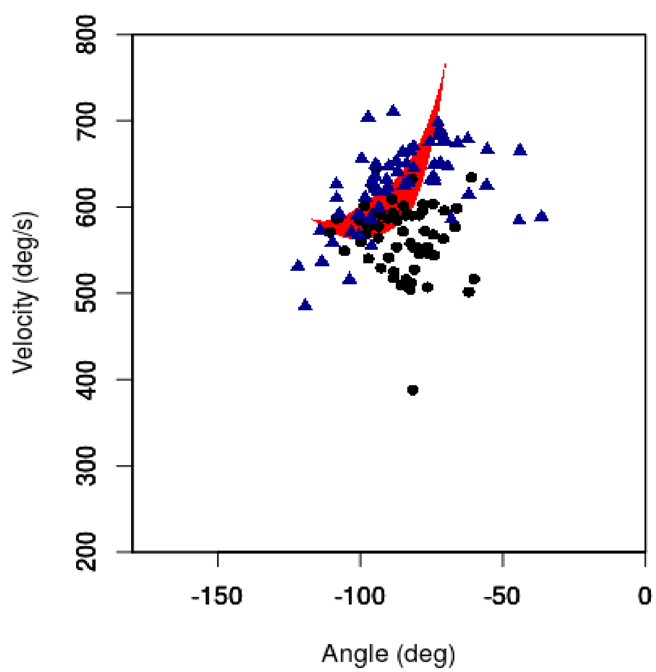

Figure 6. Sample data distributions for two representative participants in the last block of practice for T1 (circles) and T2 (triangles). The red band shows the overlap of the solution manifolds for those two tasks.

Analyzing variability using the *TNC-Cost* method is informative about the capacity to improve performance in light of what was done; the potential improvement is calculated independently for each source. Interestingly, even though *T*-, *N*-, and *C-Cost* are calculated independently, what each quantifies can affect the others (Cohen & Sternad, 2009).

T2 elicited a larger *N-Cost* than both T1 and T3. *N-Cos*t gives an index of how much performance could be improved if the spread of data was reduced to an optimal value. Given the fact that T3 has a task space with three-dimensions, while T1 and T2 have task spaces with only two dimensions, it was expected that variations in data dispersion would have a larger impact in T3 than T1 or T2. However, that was not the case. The difference between the groups executing T2 and T3 indicates that it is not only the dimension of the task space that matters, but also how the solution manifold constrains action. This idea is reinforced by the fact that all costs values (*T*-, *N*-, and *C-Cost*) were larger for T2 than for T1, despite the fact that both were stationary targets with a one-dimensional solution manifold embedded in a two-dimensional task space.

To recapitulate, the *T-Cost* curve refers to individuals searching for a better locus in the task space such that the dispersion of the data cloud of execution variables in an ensemble of trials has a small impact on performance. A larger *T-Cost* for T2 indicates that individuals in this group kept themselves farther from their optimal region than individuals in attempting T1. *N-Cost* has been understood as fine tuning, by reducing the consequences of stochastic white noise for performance (Abe & Sternad, 2013; Cohen & Sternad, 2009). Although velocity differences between groups were not significant, in absolute terms, T2 resulted in the largest velocity values. Since stochastic white noise is expected to increase with larger velocities (Harris & Wolpert, 1998; Schmidt et al., 1979), it is possible that the small difference in velocity still influenced *N-Cost*. Notice that this suggestion does not contradict the idea of individuals staying longer in the

solution manifold d increase performance. Finally, a larger *C-Cost* (how much more execution variables could have compensated for one another so as to maintain a good level of performance) for T2 can indicate less flexibility to deal with a more constraining solution manifold.

Examination of averaged group data and individual data suggests that the contribution of each cost to error changes with practice. More specifically, *T-Cost* contributed the most to error at the beginning of practice while *N-Cost* contributed the most to error by the end of practice. Although not unique, this trend was strong in all three groups.

In short, Experiment 1 showed that individuals in all conditions stabilized their performance with relatively limited practice (about six blocks of 60 trials each). Performance trajectories were relatively similar despite different constraints imposed by each task. However, only the constraints of T2 affected cost values.

Chapter III: Experiment 2

The main goal of this study is to examine the hypothesized relationship between transfer and structural variability. We will follow terminology from Schmidt and Young (1987): A *transfer task* is the first task, the one that is learned so that its skills can be applied in a new context; a *criterion task* is the task in the new context, the one that is used to evaluate transfer. T1 and T2 from Experiment 1 were designated as the transfer task and the criterion task, respectively, and the amount of practice devoted to learning the transfer task was manipulated. In particular, the stabilization group (SG) practiced the transfer task until stabilization; the extensive practice group (EG) engaged in practice beyond stabilization.

Given the overlap between the solution manifolds for T1 and T2, the stationary targets defined as in Experiment 1, transfer from one to the other demands a relatively small modification in the values of the execution variables. We developed the following hypotheses:

1. Immediately before being exposed to the criterion task, SG and EG will not differ in their performance (i.e., error), but their structural variability will differ. In particular, we expect lower values of *N-Cost* and *C-Cost* in EG.
2. Error in the criterion task will be lower for EG than SG.
3. The correlation between each cost in the last practice block and performance in the criterion task will differ SG and EG.

Method

Participants. Sixteen participants (18-24 years-old) at the University of Connecticut were recruited in accordance with procedures approved by the Institutional Review Board. Fifteen were undergraduate students from the participant pool of the Department of

Psychological Sciences; one was a lab member. Participants were assigned randomly to the two practice groups. Two participants in SG did not learn during their practice (hitting the target on fewer than 2% of the trials). Consequently, only 14 participants were included in the analyses (8 in EG and 6 in SG).

Design and procedures. In Experiment 1, stabilization was found to occur by block 6. Consequently, participants in SG performed six blocks of 60 trials of T1, distributed over two days (for a total of 360 trials). On the third day (the day of transfer) they first performed one block of 60 trials with T1. In blocks 2 and 3 the criterion task was introduced. Finally, in block 4, participants performed the transfer task again. Participants in EG practiced the transfer task for four days, with three blocks of 60 trials per day (for a total of 720 trials). Their transfer day was the same as that for SG: one block with T1, two with T2, one final block with T1.

General procedures were the same as those applied in Experiment 1.

Dependent measures for TNC analysis. Similar to Experiment 1.

Execution variables. Similar to Experiment 1.

Result variables. Similar to Experiment 1.

Cost variables. Similar to Experiment 1.

Data Reduction and analysis. In addition to the analyses conducted in Experiment 1, we performed correlations between *T*-, *N*-, and *C-Cost* from the first block of the last day of practice and performance in the first block of the criterion task. These were conducted separately for SG and EG.

Results

Once again, we were interested in characterizing the trajectories of the dependent variables as learning progressed, and assessing how each group of participants (EG and SG) performed in the criterion task. Since SG and EG differed in the amount of practice, the analysis was divided in two parts, one directed at assessing group differences at the beginning of practice (i.e., simply to see if people randomly assigned to the groups differed) and the other assessing group differences during performance of the criterion task (i.e., evaluating the influence of the amount of practice).

Analysis of the beginning of practice. Initial analysis was limited to the first two days (i.e., blocks 1-6), corresponding to the period during which conditions were the same for SG and EG. Using the procedures described earlier, we present the final model for each dependent variable in turn; refer to *Appendix B* for details of how each was obtained. The first column of Table 2 shows the estimates that were evaluated in building the models. Subsequent columns indicate, for each variable, the final model and its deviance. Mean data for each group, with their respective fits, are presented in Figure 7.

Table 2

Estimates and Standard Error (SE) of the Final Growth Curve Model of Each Dependent Variable and their Deviances (Degrees of Freedom)

	Error		Velocity		Angle		T-Cost		N-Cost		C-Cost	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	**2.250***	0.192	**466.929***	23.380	**-87.32***	7.774	**9.354***	2.155	**9.384***	1.634	**3.843***	0.934
Blocks	**-0.617***	0.082	**64.394***	7.617	0.15	2.939	**-4.339***	0.844	**-4.146***	0.711	**-1.521***	0.369
Days	**-1.046***	0.169	**130.161***	17.491	2.706	6.031	**-7.127***	1.461	**-6.594***	1.152	**-2.154***	0.598
Groups					11.071	11.875						
Blocks-Days	**0.510***	0.112	**-65.694***	9.046	-3.374	3.034	**3.846***	0.744	**3.682***	0.698	**1.204***	0.361
Groups-Days					-21.651	9.213						
Groups-Blocks					-6.648	4.489						
Groups-Days-Blocks					**13.817**	4.635						
Deviance (dfs)	134.574 (10)		894.451 (11)		659.340 (15)		197.412 (11)		197.249 (11)		158.604 (11)	

bold: $p < .05$; *: $p < .01$.

Error. The final model of error included blocks, days, and blocks-days. No difference between groups was uncovered.

Velocity. The final model of velocity included blocks, days, and blocks-days. Again, no difference between groups was identified. However, removing the correlation between random effects from the modeling (see Appendix B) made the difference suggested by visual examination of the graph evident. Nonetheless, for the sake of consistency, the standard stochastic structure will be maintained.

Angle. The final model of angle included blocks, days, days-blocks, groups, groups-days, groups-blocks, and groups-days-blocks. The influence of group within groups-days-blocks [13.817 (4.635), $p < .05$] revealed that, relative to EG, SG increased the value of angle during blocks on the second day of practice

T-Cost. The final model of *T-Cost* included blocks, days, and blocks-days. No difference between groups was apparent.

N-Cost. The final model of *N-Cost* included blocks, days, and blocks-days. No difference between groups was apparent.

C-Cost. The final model of C-Cost included blocks, days, and blocks-days. No difference between groups was apparent.

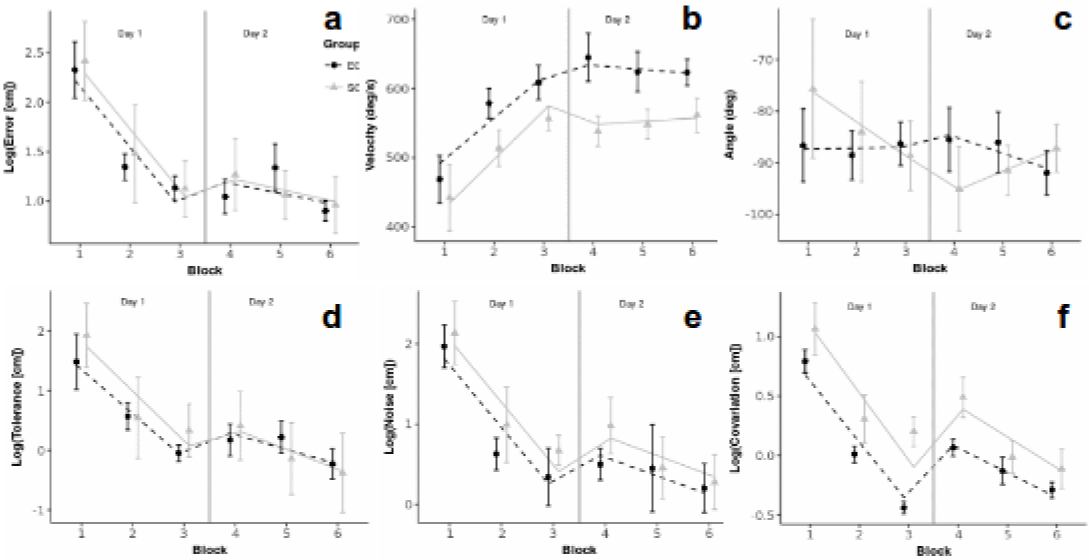

Figure 7. Means (and standard errors), with their respective model fits, for (a) error, (b) velocity, (c) angle, (d) *T-Cost*, (e) *N-Cost*, and (f) *C-Cost*, as a function of day and the first six blocks for each group in Experiment 2.

Analysis of the end of practice. The final four blocks of practice on the last day (whether that was Day 3 for SG or Day 5 for EG) were analyzed. Once again, we present the final model for each dependent variable, in turn, with details of how each was obtained provided in *Appendix B*. The first column of Table 3 shows the estimates that were evaluated in building the models. Here, target refers to T1 (encountered in Blocks 1 and 4) and T2 (encountered in Blocks 2 and 3). Subsequent columns indicate, for each variable, the final model and its deviance. Mean data for each group, with their respective fits, are presented in Figure 8.

Table 3

Estimates and Standard Error (SE) of the Final Growth Curve Model of Each Dependent Variable and Their Deviances (Degrees of Freedom)

	Error		Velocity		Angle		T-Cost		N-Cost		C-Cost	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	**0.607***	0.17524	**593.157***	10.402	**-96.891***	3.986	0.982	0.524	**1.5017***	0.561	**1.078**	0.396
Blocks	-0.090	0.0452	**6.152**	2.267	1.383	0.986	-0.156	0.183	-0.184	0.215	-0.106	0.159
Targets	**0.851***	0.09474			**6.351***	1.781	**1.766**	0.577	**2.571**	0.583	**2.261***	0.479
Groups	0.428^	0.19271			14.679^	6.089	0.704	0.483	0.741	0.475		
Groups-T2					**-9.031***	2.72	0.195	0.807				
Groups-Blocks					-2.776	1.506						
Deviance (dfs)	52.543 (11)		526.454 (4)		371.230 (13)		145.724 (8)		89.654 (11)		73.802 (10)	

bold: $p < .05$; *: $p < .01$; ^: $p < .10$.

Error. The final model of error included blocks, targets, and groups. Only the difference between the estimates of targets was significant [.851 (.095), p < .001], indicating that error increased for both groups when performing T2.

Velocity. The final model of velocity included only blocks. Release velocity increased across blocks. No group difference was identified.

Angle. The final model of angle included blocks, targets, groups, groups-blocks, and groups-targets. Significant effects were observed in targets [6.351 (1.781), p < .01] and groups-targets [-9.031 (2.720), p < .01]. The introduction of a new target location led to angles that were less negative for EG, but angles that were more negative for SG.

T-Cost. The final model of T-Cost included blocks, targets, groups, and groups-targets. Only the difference between the estimates of targets was significant [1.766 (.577), p < .05], indicating that both groups could reduce their error by translating all data points without affecting their relative positions in the task space.

N-Cost. The final model of *N-Cost* included the effect of blocks, targets, and groups. Only the difference between the estimates of targets was significant [2.571 (.853), $p < .05$], indicating that both groups could reduce their error by shrinking the distribution of data points in the task space. No difference between groups was identified.

C-Cost. The final model of *C-Cost* included blocks, targets, and groups. Only the difference between the estimates of targets was significant [2.261 (.479), $p < .01$], indicating that both groups could reduce their error by re-arranging pairs of α and ω values in the task space.

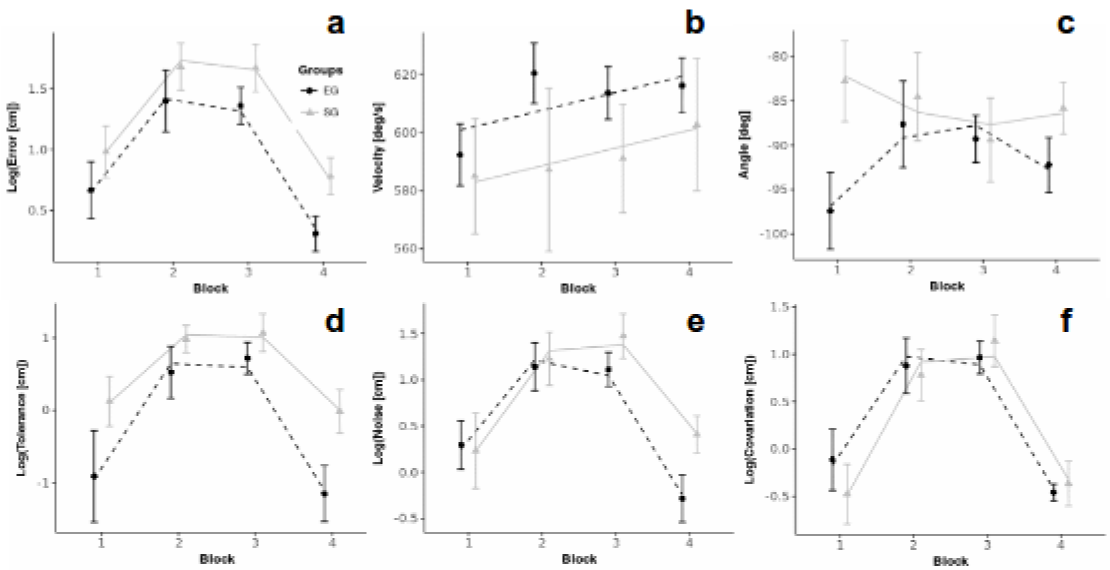

Figure 8. Means (and standard errors), with their respective model fits, for (a) error, (b) velocity, (c) angle, (d) *T-Cost*, (e) *N-Cost*, and (f) *C-Cost*, as a function of the last four blocks for each group in Experiment 2.

Correlations. We conducted a linear correlation between *T-*, *N-*, and *C-Cost* in the first block of the transfer task and the error in the first block of the criterion task. For SG, no correlation was significant: error and *T-Cost*, .030, $p = .954$; error and *N-Cost*, .492, $p = .321$; and error and *C-Cost*, .617, $p = .192$. For EG, the correlation between error and *T-Cost* was not

significant, .497, $p = .210$. However, the correlations between error and *N-Cost*, .770, $p < .05$, and error and *C-Cost*, .812, $p < .05$, were significant.

Discussion

The main goal of Experiment 2 was to evaluate whether different amounts of practice, implemented in the groups SG and EG, affected transfer from one virtual skittles task to another, implemented in terms of switching from one stationary target location to another. As expected, groups did not differ in any dependent variable in the first two days of practice, when their conditions of practice were the same. Contrary to our expectations, however, groups did not differ when the criterion task was introduced either.

In regards to the effect of practice on transfer, two theoretical perspectives have been proposed, namely, the Adaptive Process Approach (APA) and the Specificity of Practice Hypothesis (SPH). APA assets that transfer (or adaptation in their language) requires stabilization of performance (Tani, 2005). A common practice in this framework is to contrast a group that practices enough to stabilize its performance with a group that practices beyond stabilization or super-stabilization[3]. In the framework of APA, extensive practice has been shown to lead to better transfer than practice just until stabilization (Fonseca et al., 2012). The superiority of extensive practice over stabilization has been attributed to a broader exploration of the task space and a type of functional variability resulting from this process (Manoel & Connolly, 1995). This suggests that there ought to be differences in structural variability or costs

[3] A strategy applied to investigate super-stabilization is to provide participants with enough practice such that after reaching a plateau in the performance, they increase their variability of execution variables without affecting performance. In the current study, super-stabilization and extensive practice are treated interchangeably.

between groups in the block before transfer. However, we did not find differences between SG and EG in performance in the criterion task nor in the structural variability.

SPH claims that those who practice for too long in a given condition will perform worse when submitted to a new condition (Proteau et al., 1987). SPH has two main assumptions (Proteau, 1992): (1) Learning relies on contextual information,[4] altering it by either adding or removing sources of information leads to disruption of performance; (2) as learning progresses, the dependence of performance on contextual information available during practice of the transfer task is stronger. Therefore, modifications of practice, such as introducing a criterion task, should lead to a deterioration of performance, as we observed. However, SPH also predicts that this deterioration should be larger after extensive practice, which we did not observe. Therefore, neither APA nor SPH were supported by the current findings.

The question remains: *Was learning of T1 minimally transferred to T2?* In the absence of a control group that only practiced T2, we used the first block of practice of T2 from Experiment 1. We conducted a t-test for unequal variances between the pooled data of SG and EG with the data from Experiment 1. This comparison indicated that practice with T1 promoted gain in performance in the criterion task [$t(19.069) = 7.499$, $p < .001$, $g = 2.764$]. Therefore, participants obtained some benefit from their previous practice with T1.

Of importance, SG and EG practiced 120 trials with T2, which is equivalent to the first two blocks of practice with T1. Unlike the first two blocks of T1, they seem not to have improved their performance from the first to the second block of practice with the criterion task. Visual inspection of the average values in these two blocks with the values obtained in T2 of

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[4] Proteau (1992) does not use information in ecological sense.

Experiment 1 on the second and third days of practice (when their performance was already stabilized) indicates that error did not decrease from the first block of practice with the criterion task to the second, presumably because individuals started out at the plateau level reached in the Experiment 1.

Contrary to our predictions, SG and EG did not differ in their cost values when exposed to the criterion task. Interestingly, all cost values increased. What is not clear yet is whether this increment was due to the target per se (in Experiment 1, T2 presented larger *T*-, *N*-, and *C-Cost* values than T1) or if it is an effect of a new condition. Since we were interested in a possible relation between variability (costs) and transfer and how this effect would be moderated by amount of practice, correlations between each cost and error were conducted in each group separately. Interestingly, for both groups *C-Cost* and *N-Cost* presented larger correlation values with error than *T-Cost*, although these correlations were significant only in EG, indicating that practice may have an effect on how structural variability relates to transfer.

In sum, the amount of practice did not affect transfer. Furthermore, *T*-, *N*-, and *C-Cost* did not differ between groups during the transfer, although all costs increased by placing the target at a new location, that is, by introducing a criterion task. In addition, SG and EG qualitatively differed in their correlations between costs before the transfer and error during the transfer.

Chapter IV: Experiment 3

In Experiment 2, transfer simply demanded a re-parameterization of an already learned task. In Experiment 3, we examined transfer between tasks with a different number of execution variables and investigated whether it is affected by different amounts of practice. More specifically, we were interested in understanding how practice of the skittles task with a stationary target transfers to a moving target and vice-versa. We hypothesized that:

1. Error would be higher for groups whose transfer task was a moving target than for groups whose transfer task was a stationary target.
2. During transfer, changing from a stationary to a moving target will increase error while changing from a moving to a stationary target will decrease error.
3. During transfer, costs will increase or decrease according to the value of error.

Method

Participants. Thirty-two participants (18-24 years-old) at the University of Connecticut were recruited in accordance with procedures approved by the Institutional Review Board. Twenty-eight undergraduate students from the participant pool of the Department of Psychological Sciences; four were lab members. Participants were assigned randomly to four groups.

Design and Procedures. The four experimental groups were characterized by the combination of amount of practice and type of target: (1) extensive practice with a moving target and transfer to a stationary target (Ex:M-S), (2) extensive practice with a stationary target and transfer to a moving target (Ex:S-M), (3) practice until stabilization of performance with a moving target and transfer to a stationary target (St:M-S), and (4) practice until stabilization of

performance with a stationary target and transfer to a moving target (St:S-M). The targets were T1 (stationary) and T3 (moving) from Experiment 1.

Participants in the S- groups, performed with their respective transfer tasks for two days (three blocks of 60 trials per day for 360 trials), while participants in the Ex- groups practiced with their respective targets for four days (three blocks of 60 trials per day for 720 trials). The last day of practice for each group resembled the design of Experiment 2: In the first block, participants performed the transfer task; in the second and third blocks the criterion task was introduced; finally, in the fourth block, participants performed the transfer task again.

General procedures were the same as those used in Experiment 1.

Dependent Measures for TNC Analysis

Execution variables. Similar to Experiment 1.

Result variables. Similar to Experiment 1.

Cost variables. Similar to Experiment 1.

Data Reduction and Analysis. Similar to Experiment 2.

Results

The data analysis in Experiment 3 followed the same rationale of Experiment 2. Since groups differed in the amount of practice until the transfer test, two separate analyses were conducted, one directed at assessing group differences at the beginning of practice (i.e., simply to see if people randomly assigned to the four groups differed) and the other assessing group differences during performance of the criterion task (i.e., evaluating the influence of the amount of practice and whether transfer was stationary to moving or moving to stationary).

Analysis of the beginning of practice

Initial analysis was limited to the first two days of practice (i.e., blocks 1-6) of each group, corresponding to the longest period in which all groups were practicing the transfer task. The taxonomy of models for each dependent variable consisted of block, days, and group and predictors (see *Appendix B*). The first column of Table 4 shows the estimates that were evaluated in building the models. Subsequent columns indicate, for each variable, the final model and its deviance. Mean data for each group, with their respective fits, are presented in Figure 9.

Table 4

Estimates and Standard Error (SE) of the Final Growth Curve Model of Each Dependent Variable and Their Deviances (Degrees of Freedom)

	Error		Velocity		Angle		T-Cost		N-Cost		C-Cost	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	**2.227***	0.132	**443.695***	16.624	**-84.594***	5.797	**1.135**	0.395	**1.650***	0.180	**1.028***	0.150
Blocks	**-0.577***	0.045	**52.192***	6.531	-2.241	1.146	-0.434	0.165	**-0.618***	0.149	**-0.596***	0.059
Days	**-1.320***	0.104	**120.860***	16.406	-1.243	4.416	**-1.185***	0.335	**-1.005***	0.180	**-1.327***	0.124
Ex:M-S	**0.905***	0.163			5.696	7.744	0.551	0.439			**0.845***	0.177
St:S-M	**0.154***	0.164			7.717	7.781	0.440	0.441			0.076	0.178
St:M-S	0.937	0.163			3.454	7.744	0.294	0.439			**0.868***	0.177
Blocks-Days	**0.437***	0.060	**-37.038***	8.793			0.080	0.213			**0.419***	0.082
Ex:M-S-Days					-2.336	5.964						
St:SM-Days					-14.658	5.994						
St:M-S-Days					**6.262***	5.964						
Deviance (dfs)	218.919 (14)		2131.541 (11)		1524.200 (16)		676.087 (14)		639.093 (10)		301.221 (14)	

bold: $p < .05$; *: $p < .01$. Shaded rows represent blocks of estimates that significantly improved model fit.

Error. The final model of error included blocks, days, blocks-days, and groups. Pairwise comparisons between levels of groups indicate significant differences between Ex:S-M and Ex:M-S [.905 (.163), $p < .001$], Ex:S-M and St:M-S [.937 (.163), $p < .001$], St:S-M and Ex:M-S [.751 (.164), $p < .001$], and St:S-M and St:M-S [.783 (.164), $p < .001$]. Thus, practicing with the

moving target led to larger error than practicing with the stationary target independently of group (keep in mind that the practice condition has not yet been implemented in these first six blocks).

Velocity. The final model of velocity included blocks, days, and blocks-days.

Angle. The final model of angle included blocks, days, groups, and groups-days. Pairwise comparisons of the interaction groups-days indicated that the difference between the estimates of St:S-M and St:M-S was significant [20.960 (5.994), $p < .01$].

T-Cost. The final model of *T-Cost* included blocks and days. Therefore, no difference between groups was identified.

N-Cost. The final model of *N-Cost* included blocks and days. Therefore, no difference between groups was identified.

C-Cost. The final model of *C-Cost* included blocks, days, blocks-days, and groups. Pairwise comparisons between levels of groups indicate significant differences between the estimates of Ex:S-M and Ex:M-S [.845 (.177), $p < .001$], Ex:S-M and St:M-S [.868 (.177), $p < .001$], St:S-M and Ex:M-S [.770 (.178), $p < .001$], and St:S-M and St:M-S [.793 (.178), $p < .001$]. Thus, both groups that practiced with the moving target could reduce their error by re-arranging pairs of α and ω values in the task space more than the groups that practiced with the stationary target.

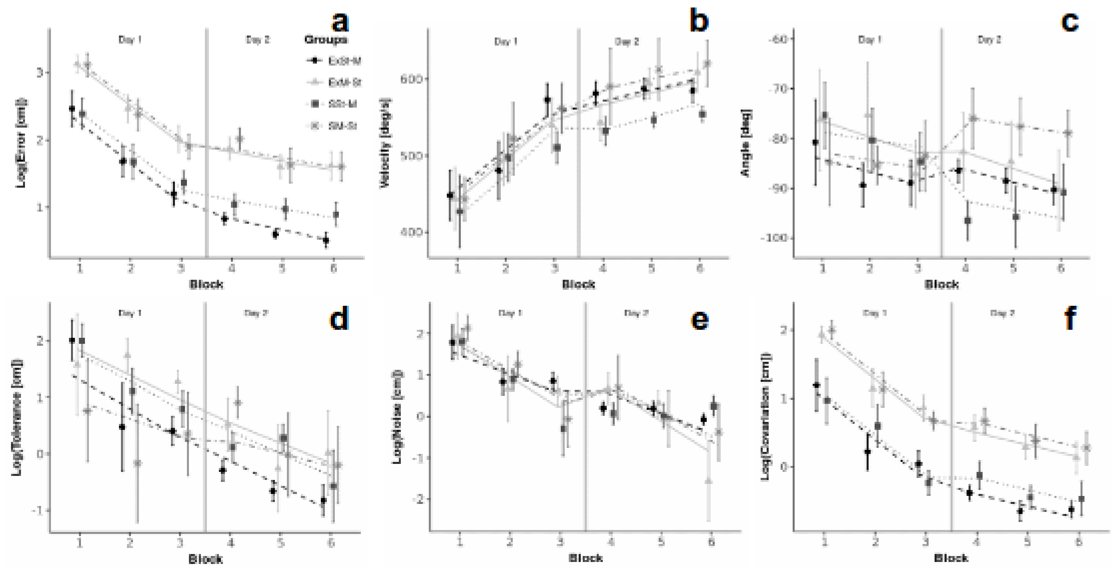

Figure 9. Means (and standard errors), with their respective model fits, for (a) error, (b) velocity, (c) angle, (d) *T-Cost*, (e) *N-Cost*, and (f) *C-Cost*, as a function of day and the first six blocks for each group in Experiment 3.

Analysis of the end of practice

The final four blocks of practice on the last day (whether that was Day 3 for the stabilization groups or Day 5 for the extended practice groups) were analyzed. Once again, we present the final model for each dependent variable, in turn, with details of how each was obtained provided in *Appendix B*. The first column of Table 5 shows the estimates that were evaluated in building the models. Here, target refers to the type of target (i.e., stationary or moving). Subsequent columns indicate, for each variable, the final model and its deviance. Mean data for each group, with their respective fits, are presented in Figure 10.

Table 5

Estimates and Standard Error (SE) of the Final Growth Curve Model of Each Dependent Variable and Their Deviances (Degrees of Freedom)

	Error		Velocity		Angle		T-Cost		N-Cost		C-Cost	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Intercept	**0.532**	0.157	**580.080***	11.219	**-91.183***	1.684	**-0.553**	0.222	-0.113	0.365	-0.420	0.174
Blocks	0.017	0.049	8.373	4.066			0.050	0.090	0.088	0.188	-0.064	0.033
Targets	**1.534***	0.246	**71.222***	10.748			-0.605^	0.290	1.697	0.764	**1.201***	0.164
Ex:M-S	0.390	0.287							0.846	0.748	0.282	0.233
St:S-M	0.433	0.222							-0.239	0.517	0.013	0.233
St:M-S	0.596	0.287							0.777	0.748	0.140	0.233
Blocks-Targets	-0.346	0.136	-11.946	5.746					-0.688	0.403		
Ex:M-S-Blocks	-0.233	0.140							-0.460	0.448		
St:S-M-Blocks	-0.096	0.070							-0.094	0.266		
St:M-S-Blocks	-0.305	0.140							-0.454	0.448		
Ex:M-S-Targets	**-1.415***	0.348							-1.748	1.081	**-0.694***	0.230
St:S-M-Targets	0.092	0.348							-2.453	1.081	0.099	0.230
St:M-S-Targets	**-1.272***	0.348							**-3.227**	1.081	**-0.697**	0.230
Ex:M-S-Targets-Blc	0.559^	0.192							0.608	0.571		
St:S-M-Targets-Blc	0.055^	0.192							1.614^	0.571		
St:M-S-Targets-Blc	0.527	0.192							1.383	0.571		
Deviance (dfs)	123.902 (23)		1309.414 (10)		960.587 (3)		428.809 (10)		386.459 (23)		198.995 (10)	

bold: $p < .05$; *: $p < .01$; ^: $p < .10$. Shaded rows represent blocks of estimates that significantly improved model fit.

Error. The final model of error included blocks, type of target, amount of practice, blocks-type of target, blocks-amount of practice, type of target-amount of practice, and blocks-type of target-amount of practice. Pairwise comparisons indicate that groups did not differ in error when performing with the stationary target. In contrast, the analysis indicated significant differences between the estimates of Ex:S-M and Ex:M-S [-1.415 (.348), $p < .01$], Ex:S-M and St:M-S [-1.272 (.348), $p < .01$], St:S-M and Ex:S-M [-1.507 (.348), $p < .001$], and St:S-M and St:M-S [-1.364(.348), $p < .01$] when performing with the moving target. Thus, an asymmetry in transfer was observed, with transfer from the stationary to the moving target being more difficult than the other way around.

Velocity. The final model of velocity included blocks, targets, and blocks-targets. Therefore, no difference between groups was identified.

Angle. The final model of angle did not include any effect, that is, the best model fit was obtained with the unconditioned mean model.

T-Cost. The final model of *T-Cost* included blocks and type of target. A pairwise comparison between the estimates of the stationary and the moving target did not reveal a difference [-.606 (.290), $p = .094$].

N-Cost. The final model of *N-Cost* included blocks, type of target, amount of practice, blocks-type of target, blocks-amount of practice, type of target-amount of practice, and blocks-type of target-amount of practice. Pairwise comparisons indicate a difference between the estimates of the interaction of blocks-type of target-amount of practice. The difference in the estimates of Ex:S-M and St:S-M was significant [-3.227 (1.081), $p < .05$]. That is, St:S-M could reduce its error more than Ex:S-M could by shrinking the data distribution in the task space.

C-Cost. The final model of *C-Cost* included blocks, type of target, amount of practice, and type of target-amount of practice. Pairwise comparisons indicate that groups did not differ in *C-Cost* when the transfer task used the stationary target. In contrast, the analysis indicated significant differences between the estimates of Ex:S-M and Ex:M-S [-.694 (.230), $p < .05$], Ex:S-M and St:M-S [-.697 (.230), $p < .05$], St:S-M and Ex:M-S [-.792 (.230), $p < .01$], and St:S-M and St:M-S [-.796 (.230), $p < .01$]. Thus, the error obtained when transferring to the moving target could have been reduced more by re-arranging pairs of α and ω values in the task space.

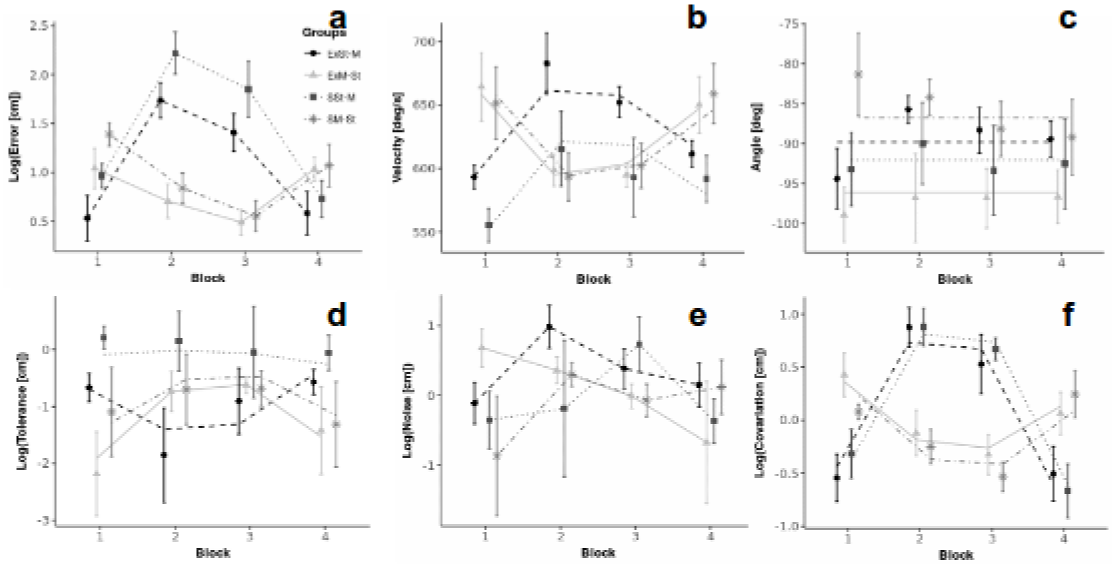

Figure 10. Means (and standard errors), with their respective model fits, for (a) error, (b) velocity, (c) angle, (d) *T-Cost*, (e) *N-Cost*, and (f) *C-Cost*, as a function of the last four blocks for each group in Experiment 3.

Correlations. We conducted a linear correlation between each cost value in the first block of the last day and the performance in the first block of the criterion task. We tested the correlation between *T*-, *N*-, and *C-Cost* in the transfer task and the error in the criterion task. The correlations were not significant for either extensive practice group. However, St:S-M showed a moderate correlation between *T-Cost* and error (.775, $p < .05$) and St:M-S demonstrated moderate correlations between error and both *T-Cost* (.742, $p < .05$) and *N-Cost* (.707, $p < .05$).

Discussion

The main goal of Experiment 3 was to examine transfer between tasks with different functional relations between execution and result variables, and to evaluate whether different amounts of practice affected this transfer. Using a moving target version of the skittle game, which required the regulation of an extra degree of freedom (release time) meant that the functional form that defines the minimal distance between the ball's trajectory and the target's

position was different between the stationary and moving target conditions. Of particular interest is whether transfer is asymmetric in going from a transfer task with a moving target to a criterion task with a stationary target and vice versa.

With respect to error, results indicated an asymmetry. Consider performance on a given task during the last block when it served as the transfer task and the first block when it served as the criterion task. When the task in question used the stationary target, performance in these two settings was equivalent regardless of the amount of practice. However, when the task in question used the moving target, performance in these two settings differed: Performance with a moving target after switching from a stationary target was worse than performance with a moving target before the switch, again regardless of the amount of practice. Importantly, the profile for *C-Cost* echoed this (compare Figures 10a and 10f).

Similar to Experiment 2, the amount of practice before the introduction of the criterion task did not affect transfer. Therefore, neither APA nor SPH can account for the results of the present experiment. Furthermore, the results of Experiment 3 impose an additional challenge to SPH. A fundamental assumption of SPH is that changing information in the context of practice, either adding new sources of information (Proteau, Marteniuk, Girouard, & Dugas, 1987) or removing sources of information (Proteau, 1992) should lead to a decrement in performance. This was the case for transfer from the stationary target to the moving target—adding information (although a different dimension of task space can also have an effect; see below). However, an improvement in performance was observed in the transfer from the moving to the stationary target—removing information. These results are clearly contrary to SPH's assumption.

Although performance with the moving target in Ex:S-M and St:S-M was worse than in Ex:M-S and St:M-S, it remains to be seen whether or not their previous practice contributed to their performance with the moving target. To assess that possibility, an independent t-test with unequal variances was conducted between the pooled mean of the first block of the Ex:S-M and St:S-M (M = 24.56, SD = 10.86) and the pooled mean of the first block of transfer of the Ex:M-S and St:M-S (M = 8.67, SD = 6.10). The t-test revealed a significant difference between the means of the two situations [$t(23.601) = 5.107$, $p < .001$, $g = 1.582$]. Therefore, despite poor performance of Ex:S-M and St:S-M during the switch to the moving target, previous practice still contributed to their performance.

Analysis of the correlation between costs in the block immediately before transfer and error in the criterion task (when transfer happened) showed that *T-Cost* presented the largest (and positive) correlation with error in conditions of practice until stabilization (St:S-M and St:M-S). The lack of the same correlation in conditions of extensive practice (Ex:S-M and Ex:M-S) indicates that the amount of practice has an effect on the relation between costs and error. The functional meaning of this relation is not clear though.

In sum, we did not observe an effect of the amount of practice on transfer. We observed, however, an asymmetric transfer in practicing with the moving target first transferred better than practicing with the stationary target first. *C-Cost* curves resemble the behavior observed in error curves, indicating a possible relevance of flexibility for transfer.

Chapter V: General Discussion

In the literature on perception and action, learning is related to persistence of performance improvement after a period of practice. More specifically, learning is understood as relatively permanent change in the performance of a task due to practice and feedback (Magill, 2007; Schmidt & Lee, 2005). In addition, learning also refers to how acquiring one skill affects the learning process of another skill (Adams, 1987). That is, learning is not only about obtaining more accurate and consistent behavior through practice, but also modifying potentials for engaging in new situations, that is, transfer.

Transfer has been defined in terms of how practicing in one condition influences performance in another condition (Adams, 1987) or how performance of a criterion task is improved due to experience with another so-called transfer task (Schmidt & Young, 1987). It has been a subject of study in psychology and motor control for a long time. Arguably, transfer is the most important feature of learning since humans and animals constantly face new perceptual-motor problems and their solutions are influenced by individuals' previous experiences. Since the seminal works of Thorndike and Woodworth (1901) and Woodworth and Thorndike (1901), researchers have tried to understand which factors affect transfer and to find optimal ways of promoting it.

Theoretical approaches to transfer have emphasized the similarity between the transfer and the criterion tasks (Thorndike & Woodworth, 1901; Woodworth & Thorndike, 1901), ~~the~~ differentiation in information processing (Lee, 1988), or the similarity between sub-actions performed by the learner (see Rosalie & Müller, 2012). Within these approaches, studies have emphasized differences in performance between the transfer and the criterion tasks. Their emphasis is consistent with the concept of transfer since learning is ultimately defined with

respect to performance. In other words, the emphasis on the performance of a criterion task considers the accomplishment of a potential generated, among other things, by the practice of the transfer task.

Although transfer is manifested in performance, until one is exposed to a new task it is a latent condition. That is, transfer has a prospective meaning, referring to a potential to contribute to do something new. At the behavioral level, this potential should be expressed in terms of execution variables relative to environmental variables because together they define the result of an action. With this assumption in mind, we investigated transfer across different conditions using the paradigm of the virtual skittles task (cf. Müller & Sternad, 2004). Our focus was on the structure of the variability of execution variables in terms of ~~its~~ consequence for performance. More specifically, we applied the *TNC-Cost* analysis (Cohen & Sternad, 2009), which assesses the influence of three sources of non-optimal data distributions on the average result of an ensemble of trials. In brief, the analysis consists of applying iteratively three different operations ~~up~~on a data set in the task space and relating the outcome of each operation to the solution manifold of the task (i.e., the particular combination of execution variables that leads to achieving the task's goal) in order to obtain an index of how much a given performance could be improved considering the same set of data points.

In addition to approaching transfer by considering the structure of variability of different tasks, we investigated the influence of different amounts of practice on transfer and structural variability. Studies with experts (Chow, Davids, Button, & Koh, 2007) and in laboratory settings (Pew, 1966) have shown that different amounts of practice lead to different movement organization. In short, we investigated how different amounts of practice affect structural

variability and whether structural variability is related to transfer. Three experiments were conducted against this backdrop.

In Experiment 1, participants were assigned randomly to three different groups, each corresponding to a different version of the virtual skittles task, namely: a stationary target that required lower velocity to be hit (T1), a stationary target that required higher velocity to be hit (T2), and a moving target (T3) whose solution manifold at one extreme of its trajectory collapses onto the solution manifold of T1. This experiment was developed to characterize similarities and differences among the three tasks and to establish the amount of practice with these tasks that is needed for stabilization of performance. Its results indicated that the structure of variability in the learning process of T2 is different from T1 and T3 but that all tasks stabilized by the sixth block of 60 trials.

In Experiment 2, we tested the transfer of T1 to T2 considering different amounts of practice and how structural variability would be affected. Results indicated that performance suffered in both practice groups by introducing T2—error increased after the switch—but not to the level of T2 *de novo* (i.e., compared to T2 in Experiment 1). However, linear correlations between structural variability in the transfer task and error in the criterion task were significant only in the groups of individuals with extended practice.

In Experiment 3, we tested transfer between stationary (T1) and moving (T3) targets again in the context of different amounts of practice. Results indicated an asymmetry in transfer. Whereas performance suffered when T1 was the transfer task and T3 was the criterion task (but again not to the level of T3 *de novo),* performance did not suffer when T3 was the transfer task and T1 was the criterion task. Indeed, performance on $T1_{criterion}$ was equivalent to the stabilized

level of $T1_{transfer}$. The trajectory for *C-Cost* resembled the trajectory for error, perhaps indicating the relevance of synergistic regulation for transfer among these tasks. Finally, a significant correlation between a component of structural variability in the transfer task and error in the criterion task was only apparent in the groups with the lesser amount of practice.

In what follows, we consider some questions that arise considering the three experiments together.

Can information-for-learning contribute to the reduction in values of *T-Cost*?

The time unit of practice is a trial; thus, practice is a process defined in a discrete time domain. For instance, in the virtual skittles task, the width of the solution manifolds of different tasks are not constant over the task space. Wider regions of a solution manifold indicate that a larger number of adjacent values of the execution variables lead to achieving the goal, namely, hitting the target. This implies that such regions are less sensitive to variation in execution variable values or, put in another way, they are more tolerant of perturbations or disturbances. Due to this feature, tolerance areas have been related to attractor stability in continuous processes (Sternad & Abe, 2010). For instance, in bimanual coordination, a process represented in a time-continuous domain, the relative phase between limbs tends to stay in the more stable attractor (Haken, Kelso, & Bunz, 1985). The average of an ensemble of cycles, however, never sits at the bottom of the attractor well due to intrinsic noise (Schöner, Haken, & Kelso, 1986).

Returning to the discussion about tolerance region and learning, a similar inability to stay at the center of the most stable region was also observed in the present study. That is, the average of an ensemble of trials is not located at the center of the tolerance region. Despite the role played by intrinsic noise in this deviation from the bottom of an “attractor”, other sources of constraints seem to be important. For example, one may argue that the amount of practice was

not enough for the distribution of execution variables in a block of trials to sit at the center of the tolerance region. This argument assumes that all individuals should end at the same location of the task space.

To rule out the preceding argument, it is useful to revisit Wilson et al. (2016). In their study, college athletes in baseball, cricket, and softball were asked to throw a ball to a target at different locations in different orientations. The three groups of athletes performed equally well in the task. Importantly, besides the fact that the solution manifold was roughly the same for all participants, the distribution of their execution variables occupied different locations of the solution manifold. For instance, baseball players occupied regions where high release velocities are required to stay within the solution manifold compared to cricket players. Wilson et al. argued that this was the case because of the specificity of each sport/practice. Therefore, a long period of practice does not necessarily imply a persistent move toward the most tolerant area.

Another factor that could affect individuals' data distribution location in a task space is information. In the mainstream of Ecological Psychology, information refers to a specific relation between structure of the ambient energy array and an environmental property (Gibson, 1979). In a structured ambient energy distribution, the gradient of energy surrounding an organism differs in different directions. The gradient distribution is a consequence of environment organization and it is unique at each point that an organism can occupy. Specification characterizes a 1:1 relationship between the structure of the ambient array and the environmental property that generates it. This sense of information seems to face difficulties when brought into the context of learning studies, which have shown that learners are not always attuned to specifying information (Michaels & Vries, 1998) and which variable they attune to can change with practice (Jacobs, Runeson, & Michaels, 2001).

In their direct learning theory, Jacobs and Michaels (2007) discussed two types of information: information for perception and information for learning. Information for perception refers to the mapping between a (sub) structure in the ambient array and an environment property. At the behavioral scale, it regulates action (Gibson, 1979). In the current study, information for perception would be a variable that participants used to define when to release the ball. Information for learning, in contrast, refers to the mapping between a result and a structure in the ambient array. In analytical terms, information for learning has been defined in terms of the covariance between result/error and a perceptual variable (e.g., Jacobs, Silva, & Calvo, 2009; Michaels & Romaniak-Gross, 2012). In short, it is expected that one learns which variable(s) co-vary(ies) with error in order to reduce the latter. In the current study, information for learning would be a perceptual variable that a participant used to stabilize the value of an execution variable. The rate of change due to learning varies among execution variables and it is expected that the variables for which small variations significantly affect the result of an action will stabilize and covary with error first, since they are more salient to the perceptual systems (van de Langenberg, Kingma, & Beek, 2006). Thus, we suggest that information for learning is relevant to defining which areas of the task space one visits during the learning process.

Did participants attune to the same information?

One of the procedures employed in each experiment was to ask participants how they managed to hit the target. Participants were asked to describe where they were fixing their gaze during a throw and, in (Experiment 1 and 2, whether or not they kept the same strategy when transfer was required. In addition, the experimenter also took notes on where participants seemed to direct their gaze.

Experimenter observation and participants' self-report indicated that all participants whose transfer task was the moving target payed attention to the target at the instant of release. Most of the participants started focusing on the paddle-ball complex, but considered this strategy inefficient and shifted their gaze towards the target. In contrast, participants whose transfer task was a stationary target seemed to have payed attention to the complex paddle-ball during the entire period of practice. When participants were performing their criterion task (i.e., after the switch), those who started out with a stationary target shifted their gaze to the target. In contrast, participants who started out with the moving target kept their gaze directed at the target even when it was stationary.

The foregoing discussion suggests the strategy of focusing gaze on the target is transferable to different contexts, while focusing on the complex paddle-ball is limited to situations with stationary targets. Different experiments are required to identify optic variables that individuals attune~~d~~ to in each situation and how these variables might be related to the critical parameters that define success in the task.

Does the amount of practice matter?

In Experiments 2 and 3, the comparison between groups that practiced with the same transfer task indicates that different amounts of practice did not affect performance in the criterion task. It has been suggested that extensive practice indexes exploratory behavior after stabilization of performance (Corrêa, Benda, de Oliveira, Ugrinowitsch, Freudenheim, & Tani, 2015; Fonseca et al., 2012), which would lead to a complementary relation between stabilization and exploration. Such a combination of stability and exploration has been suggested as predictor of transfer (Pacheco & Newell, 2015), reinforcing the idea that those who engage in extensive practice should transfer better than those who practice until stabilization only.

If that is the case, why did we not observe differences in performance between the stabilization and extensive practice groups? One possibility is that extensive practice needs to promote changes in the internal constraints of learners that are qualitatively different from those who practice until stabilization (cf. Iberall, 2016). More specifically, this qualitative change has to be with reference to the criterion task.

We suggest that this qualitative difference would be observed in two ways, either by modifying the relation between feedback and execution variables or in the relation between execution variables themselves. In the context of perceptual learning, it has been suggested that how feedback relates to the essential variables needed to perform a task affects transfer (Wagman & Van Norman, 2011). Moreover, how the relation among execution variables changes with practice has been demonstrated to be task-specific (Latash, Yarrow, & Rothwell, 2003; Yang & Scholz, 2005). The lack of differences in *T-Cost* and *C-Cost*, respectively, between groups that practiced the same version of the task in Experiments 2 and 3 indicates that none of these relations were modified. Therefore, despite different amounts of practice, participants in each group practicing with the same transfer target were at the same level of learning and, consequently, they transferred equally. Future studies within the current paradigm should investigate the foregoing hypothesis.

Final Considerations

The current study addressed how different amounts of practice and different kinds of variability are related to transfer. Changes in their trajectories were examined in order to identify possible similarities in processes. Despite expectations from two influential approaches to skill learning, our results indicate that different amounts of practice have no effect on transfer. However, it seems that variability provides useful information about why the transfer might be

weaker or stronger under certain regimes of practice. For instance, In particular, the similarity in the trajectories of the fact that C-Cost resembled the shape observed in and error (Experiment 3) indicates that it C-Cost captures at least part of the dynamics underlying the transfer process. Of importance, the fact that variability is calculated Notably, using the TNC-Cost method to calculate variability allows us to derive ascribe a functional value to it. In short, variability seems to be is useful to the study of transfer. We anticipate that the relationship between variability and transfer will be further illuminated by although it is necessary to take into considering how it variability interacts with other factors such as individual differences and different types of perceptual-motor tasks.

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Appendix A

In what follows, all information about the physics simulated in the task is provided in terms of virtual world coordinates, which match real world coordinates. The simulation is based on a setting in which a 3 cm diameter ball is swung around a 16 cm diameter center post so as to hit a 3 cm diameter target on the other side of the post. The ball is initially attached to a paddle (12 cm diameter) that rotates around a fixed axis (on a plane 50 cm below the center post on the display). When the ball is released, it follows a trajectory determined by two orthogonal nonlinear springs:

$$x(t) = A_x \sin(\omega t + \varphi_x) e^{\frac{-t}{\tau}}$$

$$y(t) = A_y \sin(\omega t + \varphi_y) e^{\frac{-t}{\tau}} \qquad (1)$$

where A_i is the amplitude in the direction i, t stands for the time period after releasing the ball, is the frequency of oscillation, is the phase difference, and is the relaxation time (for details, see Müller & Sternad, 2004, *Appendix A*).

An optical sensor recorded angular displacement of the manipulandum and sent a signal to an analog-digital converter box (National Instruments). The manipulandum was fitted at the tip with a switch that also sent a signal to the analog-digital converter box. Optical recorder and switch signals from the A-D box were sent to a computer (Windows 8.1 64-bit operating system) to be streamed by a customized Simulink® model (Mathworks 2016a) that read the manipulandum position in order to simulate paddle and ball positions while the participant held the switch down. When the switch was released, the ball was thrown and followed the trajectory governed by equation (1).

Appendix B

The construction of the taxonomy of models followed the basic rationale to model time effects first. We started adding *blocks*, then *days* or *targets* (depending on the experiment and its phase), followed by time interactions (i.e., *days-blocks/targets-blocks*). Then, the fixed effect of *group* was added, followed by interactions, starting with the interaction with the fast time scale *blocks*, followed by *days/target*. In a few cases, these sequences needed to be modified (indicated in the text below).

Experiment 1

Error

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 20.681, $p < .001$). Similarly, an improvement was obtained by adding *days*, ($\Delta\chi^2$ (4) = 153.671, $p < .001$), the interaction *days-blocks* ($\Delta\chi^2$ (1) = 28.511, $p < .001$), and *groups* ($\Delta\chi^2$ (2) = 10.554, $p < 0.01$). In contrast, the interaction *groups-blocks* did not improve model fit ($\Delta\chi^2$ (2) = 4.092, $p = 0.129$). Adding the interaction *groups-days* improved model fit ($\Delta\chi^2$ (2) = 7.277, $p = 0.026$), but the three-level interaction *group-days-blocks* did not improve the model fit ($\Delta\chi^2$ (4) = 5.244, $p = 0.263$).

Velocity

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 22.006, $p < .001$), *days* ($\Delta\chi^2$ (4) = 147.859, $p < .001$), and the interaction *days-blocks* ($\Delta\chi^2$ (1) = 38.839, $p < .001$). In contrast, adding *groups* ($\Delta\chi^2$ (2) = 4.83, $p = 0.089$), the interactions *groups-blocks* ($\Delta\chi^2$ (4) = 4.839, $p =$

0.304), *groups-days* ($\Delta\chi^2$ (4) = 5.918, *p* = 0.205), and *group-days-blocks* did not improve the model fit ($\Delta\chi^2$ (8) = 7.075, *p* = 0.529).

Angle

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 5.575, *p* = 0.134), was improved by adding *days* ($\Delta\chi^2$ (4) = 147.859, *p* < .001), but not by adding *days-blocks* ($\Delta\chi^2$ (1) = 2.742, *p* = 0.098), *groups* ($\Delta\chi^2$ (3) = 3.196, *p* = 0.362), *groups-blocks* ($\Delta\chi^2$ (3) = 3.196, *p* = 0.362), *groups-days* ($\Delta\chi^2$ (4) = 6.825, *p* = 0.145), or *group-days-blocks* ($\Delta\chi^2$ (9) = 14.21, *p* = 0.115).

T-Cost

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 9.167, *p* = 0.027), *days* ($\Delta\chi^2$ (4) = 46.086, *p* < .001), and *days-blocks* ($\Delta\chi^2$ (1) = 13.867, *p* < .001), but not *groups* ($\Delta\chi^2$ (2) = 4.812, *p* = 0.090). Fit was improved by the interaction *groups-blocks* ($\Delta\chi^2$ (4) = 11.406, *p* = 0.022), and by *groups-days* without *groups-blocks* ($\Delta\chi^2$ (0) = 1.698, *p* < .001). Finally, *group-days-blocks* did not improve the model fit ($\Delta\chi^2$ (4) = 6.208, *p* = 0.184).

N-Cost

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 8.465, *p* = 0.037), *days* ($\Delta\chi^2$ (4) = 15.751, *p* = 0.003), *days-blocks* ($\Delta\chi^2$ (1) = 5.149, *p* = 0.023), and *groups* ($\Delta\chi^2$ (2) = 15.971, *p* < .001), but not *groups-blocks* ($\Delta\chi^2$ (2) = 2.407, *p* = 0.30), *groups-days* ($\Delta\chi^2$ (2) = 5.922, *p* = 0.052), or *group-days-blocks* ($\Delta\chi^2$ (6) = 11.071, *p* = 0.086).

C-Cost

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 21.716, *p* < .001), *days* ($\Delta\chi^2$ (4) = 79.919, *p* < .001), *days-blocks* ($\Delta\chi^2$ (1) = 26.457, *p* < .001), and *groups* ($\Delta\chi^2$ (2) = 13.255, *p* = 0.001), but not *groups-blocks* ($\Delta\chi^2$ (2) = 2.8, *p* = 0.247). Adding *groups-days* ($\Delta\chi^2$ (4) = 16.145, *p* = 0.003) improved model fit, but *group-days-blocks* did not ($\Delta\chi^2$ (2) = 3.075, *p* = 0.215).

Experiment 2 – Blocks 1-6

Error

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 18.847, *p* < .001), *days* ($\Delta\chi^2$ (4) = 21.57, *p* < .001), and *days-blocks* ($\Delta\chi^2$ (1) = 17.201, *p* < .001), but not *groups* ($\Delta\chi^2$ (1) = 1.21, *p* = 0.271), *groups-blocks* ($\Delta\chi^2$ (2) = 1.429, *p* = 0.489), *groups-days* ($\Delta\chi^2$ (2) = 1.225, *p* = 0.542), or *group-days-blocks* ($\Delta\chi^2$ (1) = 3.274, *p* = 0.07).

Velocity

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 14.592, *p* = 0.002), *days* ($\Delta\chi^2$ (4) = 21.57, *p* < .001), and *days-blocks* ($\Delta\chi^2$ (1) = 17.201, *p* < .001), but not *groups* ($\Delta\chi^2$ (1) = 3.668, *p* = 0.055), *groups-blocks* ($\Delta\chi^2$ (2) = 4.146, *p* = 0.126), *groups-days* ($\Delta\chi^2$ (2) = 5.301, *p* = 0.071), or *group-days-blocks* ($\Delta\chi^2$ (4) = 9.456, *p* = 0.051).

Angle

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 4.912, *p* = 0.178), but it was improved by adding *days* ($\Delta\chi^2$ (4) = 21.57, *p* < .001) and *days-blocks* ($\Delta\chi^2$ (1) = 17.201, *p* < .001). In contrast, adding *groups* ($\Delta\chi^2$ (1) = 3.668, *p* = 0.055), *groups-blocks* ($\Delta\chi^2$ (2) = 4.146, *p* = 0.126), *groups-days* ($\Delta\chi^2$ (2) = 5.301, *p* = 0.071), or *group-days-blocks* ($\Delta\chi^2$ (4) = 9.456, *p* = 0.051) did not improve model fit.

T-Cost

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 18.18, *p* < .001), *days* ($\Delta\chi^2$ (4) = 31.355, *p* < .001), and *days-blocks* ($\Delta\chi^2$ (1) = 10.123, *p* = 0.001), but not *groups* ($\Delta\chi^2$ (1) = 0.063, *p* = 0.801), *groups-blocks* ($\Delta\chi^2$ (2) = 0.11, *p* = 0.946), *groups-days* ($\Delta\chi^2$ (2) = 0.318, *p* = 0.853), or *group-days-blocks* ($\Delta\chi^2$ (4) = 0.944, *p* = 0.918).

N-Cost

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 19.11, *p* < .001), *days* ($\Delta\chi^2$ (4) = 15.049, *p* = 0.005), and *days-blocks* ($\Delta\chi^2$ (1) = 8.306, *p* = 0.004), but not *groups* ($\Delta\chi^2$ (1) = 0.652, *p* = 0.419), *groups-blocks* ($\Delta\chi^2$ (2) = 0.764, *p* = 0.683), *groups-days* ($\Delta\chi^2$ (2) = 0.757, *p* = 0.685), or *group-days-blocks* ($\Delta\chi^2$ (4) = 1.464, *p* = 0.833).

C-Cost

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 23.278, *p* < .001), but not *days* ($\Delta\chi^2$ (4) = 6.967, *p* = 0.138), and improved by adding *days-blocks* ($\Delta\chi^2$ (1) = 5.089, *p* = 0.024). In contrast, *groups* ($\Delta\chi^2$ (1) = 1.238, *p* = 0.266), *groups-blocks* ($\Delta\chi^2$ (2) = 1.292, *p* = 0.524),

groups-days ($\Delta\chi^2$ (2) = 1.697, *p* = 0.428), or *group-days-blocks* ($\Delta\chi^2$ (4) = 3.056, *p* = 0.548) did not improve fit.

Experiment 2 – Last day

Error

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 1.895, *p* = 0.595), but it was improved by adding *targets* ($\Delta\chi^2$ (7) = 56.015, *p* < .001) and *groups* ($\Delta\chi^2$ (1) = 4.036, *p* = 0.045). Model fit was not improved by adding *groups-blocks* ($\Delta\chi^2$ (1) = 0.491, *p* = 0.484), or *groups-targets* ($\Delta\chi^2$ (1) = 0.451, *p* = 0.502).

Velocity

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (1) = 6.786, *p* = 0.009), but not by adding *targets* ($\Delta\chi^2$ (3) = 3.892, *p* = 0.273), *groups* ($\Delta\chi^2$ (1) = 0.962, *p* = 0.327), *groups-blocks* ($\Delta\chi^2$ (2) = 0.988, *p* = 0.61), or *groups-targets* ($\Delta\chi^2$ (4) = 5.19, *p* = 0.268).

Angle

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (1) = 0.065, *p* = 0.799), *targets* ($\Delta\chi^2$ (4) = 2.485, *p* = 0.647), *groups* ($\Delta\chi^2$ (2) = 1.523, *p* = 0.467), or *groups-blocks* ($\Delta\chi^2$ (3) = 4.949, *p* = 0.176). However, adding *groups-targets* to *groups-blocks* was significant ($\Delta\chi^2$ (10) = 25.127, *p* = 0.005).

T-Cost

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 0.663, *p* = 0.882), was improved by adding *targets* ($\Delta\chi^2$ (7) = 46.963, *p* < .001), and was not improved by adding *groups* ($\Delta\chi^2$ (1) = 1.803, *p* = 0.179), *groups-targets* ($\Delta\chi^2$ (2) = 5.427, *p* = 0.066), or *groups-blocks* ($\Delta\chi^2$ (2) = 2.941, *p* = 0.23). However, adding *groups-targets* to *groups-blocks* was significant ($\Delta\chi^2$ (4) = 17.523, *p* = 0.002).

N-Cost

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 0.966, *p* = 0.809), was improved by adding *targets* ($\Delta\chi^2$ (7) = 49.72, *p* < .001), was not improved by adding *groups* ($\Delta\chi^2$ (2) = 1.523, *p* = 0.467), *groups-blocks* ($\Delta\chi^2$ (1) = 1.747, *p* = 0.186), *groups-targets* ($\Delta\chi^2$ (1) = 0.03, *p* = 0.862), or *groups-blocks* ($\Delta\chi^2$ (2) = 1.817, *p* = 0.403) did not improve model fit.

C-Cost

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 0.897, *p* = 0.826), but was improved by adding *targets* ($\Delta\chi^2$ (7) = 73.624, *p* < .001). In contrast, neither *groups* ($\Delta\chi^2$ (1) = 0.063, *p* = 0.801), *groups-blocks* ($\Delta\chi^2$ (2) = 1.04, *p* = 0.595), or *groups-targets* ($\Delta\chi^2$ (2) = 0.387, *p* = 0.824), nor *groups-blocks* was significant ($\Delta\chi^2$ (3) = 1.677, *p* = 0.642).

Experiment 3 – Blocks 1-6

Error

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 32.879, *p* < .001), *days* ($\Delta\chi^2$ (4) = 129.059, *p* < .001), *days-blocks* ($\Delta\chi^2$ (1) = 45.088, *p* < .001), and *groups* ($\Delta\chi^2$ (3) = 30.418, *p*

< .001). In contrast, adding *groups-blocks* ($\Delta\chi^2$ (3) = 2.228, *p* = 0.526), *groups-days* ($\Delta\chi^2$ (3) = 3.655, *p* = 0.301), or *group-days-blocks* ($\Delta\chi^2$ (9) = 5.934, *p* = 0.747) did not improve model fit.

Velocity

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 21.789, *p* < .001), *days* ($\Delta\chi^2$ (4) = 89.27, *p* < .001), *days-blocks* ($\Delta\chi^2$ (1) = 16.634, *p* < .001), but not *groups* ($\Delta\chi^2$ (3) = 4.617, *p* = 0.202), *groups-blocks* ($\Delta\chi^2$ (6) = 5.729, *p* = 0.454), *groups-days* ($\Delta\chi^2$ (6) = 5.15, *p* = 0.525), or *group-days-blocks* ($\Delta\chi^2$ (12) = 10.768, *p* = 0.549).

Angle

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 3.458, *p* = 0.326), was improved by adding *days* ($\Delta\chi^2$ (7) = 40.487, *p* < .001), not improved by adding *days-blocks* ($\Delta\chi^2$ (1) = 1.715, *p* = 0.19), *groups* ($\Delta\chi^2$ (3) = 2.389, *p* = 0.496), or *groups-blocks* ($\Delta\chi^2$ (6) = 7.396, *p* = 0.286), was improved by adding *groups-days* ($\Delta\chi^2$ (6) = 13.672, *p* = 0.034), but not by *group-days-blocks* ($\Delta\chi^2$ (7) = 8.445, *p* = 0.295).

T-Cost

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 8.959, *p* = 0.03), *days* ($\Delta\chi^2$ (4) = 31.355, *p* < .001), and *days-blocks* ($\Delta\chi^2$ (1) = 10.123, *p* = 0.001), but not by *groups* ($\Delta\chi^2$ (1) = 0.063, *p* = 0.801), *groups-blocks* ($\Delta\chi^2$ (2) = 0.11, *p* = 0.946), *groups-days* ($\Delta\chi^2$ (2) = 0.318, *p* = 0.853), or *group-days-blocks* ($\Delta\chi^2$ (4) = 0.944, *p* = 0.918).

N-Cost

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 19.11, p < .001), and *days* ($\Delta\chi^2$ (4) = 41.889, p < .001), but not *days-blocks* ($\Delta\chi^2$ (1) = 3.413, p = 0.065), *groups* ($\Delta\chi^2$ (3) = 0.848, p = 0.838), *groups-blocks* ($\Delta\chi^2$ (6) = 3.416, p = 0.755), *groups-days* ($\Delta\chi^2$ (6) = 2.088, p = 0.911), or *group-days-blocks* ($\Delta\chi^2$ (13) = 15.8, p = 0.260).

C-Cost

Model fit was improved by adding *blocks* ($\Delta\chi^2$ (3) = 31.427, p < .001), *days* ($\Delta\chi^2$ (4) = 100.851, p < .001), *days-blocks* ($\Delta\chi^2$ (1) = 23.834, p < .001), and *groups* ($\Delta\chi^2$ (3) = 26.987, p < .001), but not *groups-blocks* ($\Delta\chi^2$ (3) = 0.60, p = 0.896), *groups-days* ($\Delta\chi^2$ (3) = 2.048, p = 0.562), or *group-days-blocks* ($\Delta\chi^2$ (9) = 2.372, p = 0.984).

Experiment 3 – Last day

Error

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 2.108, p = 0.550), was improved by adding *targets* ($\Delta\chi^2$ (7) = 102.052, p < .001), was not improved by adding *targets-blocks* ($\Delta\chi^2$ (1) = 0.175, p = 0.675), *groups* ($\Delta\chi^2$ (3) = 4.978, p = 0.173), or *groups-blocks* ($\Delta\chi^2$ (6) = 9.104, p = 0.168), and was improved by adding *groups-targets* ($\Delta\chi^2$ (6) = 21.504, p = 0.001), and *groups-targets-blocks* ($\Delta\chi^2$ (7) = 16.462, p = 0.021).

Velocity

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 0.549, *p* = 0.908), was improved by adding *targets* ($\Delta\chi^2$ (7) = 91.757, *p* < .001), and *targets-blocks* ($\Delta\chi^2$ (2) = 36.823, *p* < .001), and was not improved by adding *groups* ($\Delta\chi^2$ (3) = 4.541, *p* = 0.209), *groups-blocks* ($\Delta\chi^2$ (6) = 7.011, *p* = 0.32), *groups-targets* ($\Delta\chi^2$ (6) = 8.984, *p* = 0.174), or *groups-targets-blocks* ($\Delta\chi^2$ (12) = 14.656, *p* = 0.261).

Angle

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 5.207, *p* = 0.157), *targets* ($\Delta\chi^2$ (7) = 11.186, *p* = 0.131), *targets-blocks* ($\Delta\chi^2$ (8) = 13.201, *p* = 0.105), *groups* ($\Delta\chi^2$ (10) = 17.175, *p* = 0.071), *groups-blocks* ($\Delta\chi^2$ (13) = 21.333, *p* = 0.067), *groups-targets* ($\Delta\chi^2$ (13) = 19.433, *p* = 0.11), or *groups-targets-blocks* ($\Delta\chi^2$ (20) = 26.886, *p* = 0.138).

T-Cost

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 1.123, *p* = 0.772), was improved by adding *targets* ($\Delta\chi^2$ (4) = 100.851, *p* < .001), and was not improved by adding *targets-blocks* ($\Delta\chi^2$ (1) = 0.386, *p* = 0.534), *groups* ($\Delta\chi^2$ (3) = 4.829, *p* = 0.185), *groups-blocks* ($\Delta\chi^2$ (6) = 7.309, *p* = 0.293), *groups-targets* ($\Delta\chi^2$ (6) = 6.768, *p* = 0.343), or *groups-targets-blocks* ($\Delta\chi^2$ (13) = 13.043, *p* = 0.444).

N-Cost

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 0.939, *p* = 0.816), was improve by adding *targets* ($\Delta\chi^2$ (4) = 100.851, *p* < .001), and was not improved by adding *targets-blocks*

($\Delta\chi^2$ (1) = 0.018, *p* = 0.894), *groups* ($\Delta\chi^2$ (3) = 3.513, *p* = 0.319), *groups-blocks* ($\Delta\chi^2$ (6) = 10.8, *p* = 0.095), *groups-targets* ($\Delta\chi^2$ (6) = 7.926, *p* = 0.244), or *groups-targets-blocks* ($\Delta\chi^2$ (12) = 18.374, *p* = 0.105).

C-Cost

Model fit was not improved by adding *blocks* ($\Delta\chi^2$ (3) = 1.357, *p* = 0.716), was improved by adding *targets* ($\Delta\chi^2$ (4) = 100.851, *p* < .001), was not improved by adding *targets-blocks* ($\Delta\chi^2$ (1) = 0.401, *p* = 0.527), *groups* ($\Delta\chi^2$ (3) = 1.376, *p* = 0.711), or *groups-blocks* ($\Delta\chi^2$ (6) = 6.406, *p* = 0.379), was improved by adding *groups-targets* ($\Delta\chi^2$ (6) = 17.512, *p* = 0.008), but not by adding *groups-targets-blocks* ($\Delta\chi^2$ (7) = 11.572, *p* = 0.116).