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New Paradigm for Task Switching Strategies While Performing Multiple Tasks: Entropy and Symbolic Dynamics Analysis of Voluntary Patterns

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Abstract: *It has become well established in laboratory experiments that switching tasks, perhaps due to interruptions at work, incur costs in response time to complete the next task. Conditions are also known that exaggerate or lessen the switching costs. Although switching costs can contribute to fatigue, task switching can also be an adaptive response to fatigue. The present study introduces a new research paradigm for studying the emergence of voluntary task switching regimes, self-organizing processes therein, and the possibly conflicting roles of switching costs and minimum entropy. Fifty-four undergraduates performed 7 different computer-based cognitive tasks producing sets of 49 responses under instructional conditions requiring task quotas or no quotas. The sequences of task choices were analyzed using orbital decomposition to extract pattern types and lengths, which were then classified and compared with regard to Shannon entropy, topological entropy, number of task switches involved, and overall performance. Results indicated that similar but different patterns were generated under the two instructional conditions, and better performance was associated with lower topological entropy. Both entropy metrics were associated with the amount of voluntary task switching. Future research should explore conditions affecting the trade-off between switching costs and entropy, levels of automaticity between task elements, and the role of voluntary switching regimes on fatigue.*

Key Words: topological entropy, Shannon entropy, orbital decomposition, task switching, fatigue, performance

THE COMPLEXITIES OF COGNITIVE WORKLOAD AND FATIGUE

Contemporary research on cognitive workload and fatigue has encountered numerous entangled problems. Work load demands are often confounded

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with work speed demands (Hendy, Liao, & Milgram, 1997), and after prolonged work on the task it is often difficult to separate the effect of work load per se from fatigue or from sources of stress that are external to the task itself (Ackerman, 2011; Hancock & Desmond, 2001). Prolonged time on task can produce the performance decrements that are usually associated with fatigue, but it can also produce improvements in performance that could result from practice and automaticity (Guastello, 1995).

Furthermore, low-demand and high-demand tasks can both produce fatigue, possibly for different reasons, and it is sometimes possible to quell fatigue by switching from a low-demand task to a higher-demand task (Alves & Kelsey, 2010; Lorist & Faber, 2011). On the other hand, switching tasks could be mentally costly (Andreadis & Quinlan, 2010; Lorist et al., 2000; Rubinstein, Meyer, & Evans, 2001). Concomitantly, it has not been clear how much of cognitive fatigue results from the total time of demanding cognitive work and how much of it results from time on a specific task. In the case of performance decrements related to time on a specific task, there is another question as to how much of the decrement is fatigue per se, in the sense of what happens when physical exertion is prolonged, and performance decrement related to a dissipation of intrinsic motivation (Hockey, 2007, 2011; Kanfer, 2011).

Principles of nonlinear dynamical systems (NDS) theory have become useful for untangling some portions of the web of performance phenomena associated with cognitive workload and fatigue (Guastello, 2003, in press; Guastello, Boeh, Shumaker, & Schimmels, 2012; Guastello, Boeh, Gorin, in press; Guastello, Boeh, Schimmels, in press; Hong, 2010; Thompson, 2010). The present study investigates voluntary task switching strategies from the NDS perspective with the intent of accounting for the processes that people would naturally use to maintain their performance and minimize the experience of fatigue. The principle of minimum entropy is investigated here using a form of time series analysis that computes entropy levels literally. The empirical study that follows considers the role of situational constraints on task sequence choices and the relationship between task switching patterns, entropy, and performance.

TASK SWITCHING

Numerous studies, summarized in Andreadis and Quinlan (2010) and Rubinstein et al. (2001), have shown that switching tasks incurs a *switching cost* in the form of lower response time. The time loss was traced to the activation of rule groups when anticipating the next task. Rule complexity adds to the switching cost, such that a switch from Task A to Task B might not be the same as vice versa. Some of the cost is attentional, and some of it is computational (Lorist et al., 2000).

Andreadis and Quinlan (2010) noted that experimental paradigms for task switching typically relied on predictable sequences of tasks, e.g., blocks of trials that are all repeated tasks or alternating tasks. They found that predictable patterns incurred lower switching costs as did cuing the impending task and lengthening the lag time between the cue and the task. Ambiguous task cues increased switching costs, because both rule sets remained activated when the cue was presented. Such "crosstalk" between tasks was equivalent for both predictable and unpredictable sequences. Under conditions of ambiguous cues, switching costs were actually less during the unpredictable conditions than under predictable conditions (p. 1788).

In the foregoing studies, task switching regimes were planned by the experimenter. They might mimic conditions where task selection is controlled by automation reasonably well. The present study investigated a different class of situations, however, that does not appear to have been given much attention in the literature yet, which is the case of voluntary task switching. Often people have several tasks to choose from and many of each to do in their work queues. Although involuntary task switching can induce fatigue (Hancock, 2007; Lorist et al., 2000), there is evidence that task switching can be a means for alleviating fatigue or boredom (Alves & Kelsey, 2010; Lorist & Faber, 2011). What are the rules and patterns that people naturally engage for voluntary task switching? How similar are they to the rules governing the stability or instability of psychomotor schemata for individual tasks? How do task switching schemata shift in response to externally induced constraints on the task goals, such as task performance quotas?

NDS PRINCIPLES FOR COGNITIVE WORKLOAD AND FATIGUE

Degrees of Freedom and Minimum Entropy

The intertwined nature of cognitive workload, fatigue, and practice effects appeared to be addressed successfully by the use of two separate catastrophe models, one assesses the effect of load on performance, and one assesses fatigue (Guastello, 1995, 2003; Guastello, Boeh,Gorin et al., in press; Guastello, Boeh, Schimmels et al., in press). In both cases there are two stable states of performance with discontinuous changes occurring between them. The load model is based on the buckling of an elastic beam; one control parameter is the load level, and the second control parameter is made up of variables that govern the elasticity or resilience of the person or system. The fatigue model allows for both increases and decreases in performance or work capacity; one of its two control parameters are the time on task or the amount of work done within a fixed period of time.

Some researchers have reported three stable states of work performance, rather than two, however (Guastello, 1981, 1987, 1995; Kanfer, 2011). Three-state systems can result from substantial individual differences in ability, motivation, and the surrounding organizational context that affects motivation within the organization, and are often (but not always) associated with jobs rather than tasks and longer time horizons than what is usually the case in contemporary experimental analyses of fatigue.

In the experiment that was conducted in parallel with the present one (Guastello, Boeh, Gorin et al., in press), 105 undergraduates completed the same seven computer-based tasks that were used in the present study seven times. They worked under one of four experimental conditions: tasks fully alternated, tasks aggregated with the multitask module performed first, aggregated with the multitask module performed last, and where the participants chose the task order themselves; the latter condition was part of the present study. Results supported both the cusp models for fatigue and workload. Fatigue effects were stronger for tasks with higher memory or attentional demand, and were often counteracted by practice effects. Figure 1 shows the performance trends over time for all seven tasks performed under all experimental conditions. The trend analysis showed that all visible bends in the curve were statistically significant. Performance improved up to Trial 3 (learning effect), was followed by a downturn (fatigue effect), followed by a further increase in performance through Trial 6, and a second downturn on Trial 7. The performance improvement from Trials 4 to 6 strongly suggested a strategy change of some sort. At present the range of possible strategies that a person could deploy is not apparent in any experimental literature. An analysis of the degrees of freedom associated with task organization would be the place to look, however. Although the data captured in Fig. 1 were not organized to separate strategy changes associated with automaticity in cognitive processes (an aspect of learning) from those adopted to counteract fatigue, it was apparent that some type of strategy was taking place fairly consistently. Because mental processes are only indirectly visible, the present study was designed to study strategy change *between* tasks rather than within tasks to develop the experimental paradigm for capturing strategy choices and changes.

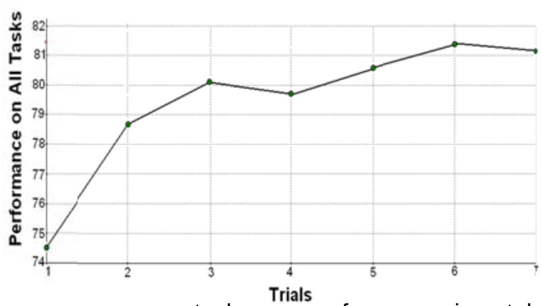

Fig. 1. Performance on seven tasks across four experimental conditions (from Guastello, Boeh, Gorin et al., in press).

The principles of degrees of freedom and minimum entropy are part of the explanation for how the discontinuities in performance occur. The concept of *degrees of freedom* was first introduced in conjunction with physical movements (Bernstein, 1967; Marken, 1991; Rosenbaum, Slotta, Vaughn, & Plandon, 1991; Turvey, 1990). In any particular complex movement, each limb of the body is capable of moving in a limited number of ways, and the movements made by one limb restrict or facilitate movement by other limbs. The degrees of freedom are the number of component parts, such as muscles or neural networks that could function differently to produce the final performance result. The notion of internally connected nodes of movement is substantially simpler and more efficient than assuming that all elements of movement are controlled by a central executive function. When a movement is in its earliest stages of being learned for the first time, several optional combinations are explored by the individual; but once learning sets in, the movement combinations gravitate towards conserving degrees of freedom, which is in essence a path of least resistance (Hong, 2010). The gravitation process is essentially a self-organization dynamic. Some variability in the movement still persists, however, which facilitates new adaptive responses. Sufficiently large changes in goals or demands produce a phase shift in the motor movements, which are observed as discontinuous changes in the sense of catastrophe models. Cognitive behaviors are thought to operate on more or less the same principle with regard to the early and later stages of schematic development, the role of executive functions and the principle of conserving degrees of freedom (Hollis, Kloos, & Van Orden, 2009).

A shift in potential energy is thought to underlie the discontinuous shifts in performance associated with cognitive workload and fatigue. Figure 2 is a graph of the potential energy function that associated with a phase shift between two stable states. The well at the left is a relative minimum that the system could occupy for a while until it finds the lower entropy state at the right. Although it requires some energy to get out of the first well, the energy expenditure is more favorable in the second well. Systems in a high state of entropy seek lower entropy conditions; thus the system self-organizes as necessary to make such a shift.

Fig. 2. Phase shift between two attractor wells.

The principle of *minimum entropy* (Hong, 2010) governs the self-organizing phase shifts in performance. Given that there are multiple ways of performing or organizing a task, the approach that typically prevails is one that consumes the least amount of energy or exudes the least amount of entropy. It is possible that the individual does not find the optimal solution at first and might be content with any solution that works well enough, but eventually a better solution will be adopted if it is found. Sometimes the better solution is simply one that involves using a different sequence of neural networks when one sequence has been fatigued.

In a well-learned and unambiguously cued task, psychomotor schemata are less variable, more predictable and automatized, and place less demand on the executive function than otherwise. Ambiguity and unpredictability require greater readiness and thus more degrees of freedom would be allocated accordingly. Ashby's (1956) law of requisite variety would apply here: The complexity of a controller needs to be at least as complex as the system it is meant to control. A certain amount of residual readiness for the unexpected would actually reduce switching costs when the unexpected occurs. Inevitably a balance between stability and change is adopted somehow, and that we expect to be evident in patterns of voluntary task switching.

It would be useful to consider here what is being controlled by whom or what else. Complex external events and the potential end states of the system, e.g. a guided missile system or an electrical power plant, are controlled by complex combinations of people and machines. It is fairly standard in these circumstances to consider the allocation of function between the person and the machine, where the former should control the latter. Numerous issues in person-machine interaction could play a role in the efficiency of the system. *Smart displays* can reduce the complexity and demand levels of the human contributions and greatly enhance their speed and accuracy, however, by conveying information about the system's critical behaviors in a form that facilities the decisions that the person is expected to make when confronted with the information.

In the case of fatigue, the system is actually seeking alternative schemata as a means of protecting the performance level of the system overall. Switching tasks affords this opportunity. In addition, it now appears that there are two logical pathways leading to a task switch – one is boredom or fatigue, and the other is adaptability. The next task is to identify task patterns and measure entropy levels inherent in them.

Entropy and Orbital Decomposition

The construct of entropy has undergone some important changes since it was introduced in the late 19th century. Hong (2010) framed the minimum entropy construct for psychomotor schemata around Boltzman entropy, which formed the basis of Shannon entropy, which in turn is probably the most widely used version today. Imagine that a system can take on any of a number of discrete states over time. It takes information to predict those states, and any variability for which information is not available to predict is considered entropy. The NDS perspective on entropy, however, is that entropy is generated *by* a system as it changes behavior over time, and thus it has become commonplace to treat Shannon information and Shannon entropy as the same thing and to use the same formula:

$$H_s = \Sigma_i\, [p_i \log_2(1/p_i)] \tag{1}$$

(Shannon 1948; Guastello, 2011a).

Other measures of entropy have become useful for NDS problems, however. Topological entropy is metric of choice here because it is the end result of the pattern detection algorithm in the orbital decomposition procedure, which accommodates a single time series of events. Kolmogorov-Sinai entropy was also designed as a form of topological entropy, but it requires ordered sets of categories along two or more pre-defined axes. The single- and double-axis cases of Kolmogorov-Sinai entropy reduce to Shannon entropy again (Ott, Sauer, & Yorke, 2004). In the orbital decomposition procedure, there is a limiting relationship between topological entropy and the largest Lyapunov exponent, which is in turn a measure of turbulence in a system. The computational method of orbital decomposition is considered next, which measures both types of entropy in context.

Orbital decomposition is a symbolic dynamics analysis that identifies recurring patterns of events in nominally-coded data. The concept for the analysis (Guastello, Hyde, & Odak, 1998) originated with the assumption that a chaotic sequence of observations originates with coupled oscillators (orbits) and thus the goal is to decouple the contributing oscillators (Lathrop & Kostellich, 1989). The analysis finds the optimal length of patterns (string length, or *C*), and the recurring patterns at that string length. The search for optimal string length is based on whether any patterns proximally recur, i.e., a particular pattern appears immediately after itself:

$$H_t = \lim_{C \to \infty} (1/C)\log_2(\mathbf{trM}) \quad (2)$$

where **trM** is the number of patterns that proximally recur. It is actually the trace of a matrix **M** of all patterns followed by any other pattern. The limit is taken by calculating Eq. 2 for values of *C* as *C* increases. Once **trM** goes to 0, the analysis backs up to the last step where **trM** >0, and the corresponding value of *C* is taken as the optimal string length for the time series.

Once the length has been determined, the patterns that appear at least twice – proximally or distally – are identified. The final statistics include string length, topological entropy, *Ht*, in the form of the (largest) Lyapunov exponent; fractal dimension, D_L; Shannon entropy, *Hs*; and a maximum likelihood chi-square test for goodness of fit. The χ^2 test compares the observed frequency of a pattern again the number of examples of that pattern that would be expected based on the combinatorial odds for each of the elements. Because some patterns occur only rarely and some possibilities might not materialize at all during a finite time series, the observed and expected frequencies associated with patterns that appear exactly once are lumped into one category for purposes of the χ^2 calculation. In the case of $C = 1$ where there are no combinations, the χ^2 test compares the distribution of codes or objects to the hypothesis of equal probability. A computer program for orbital decomposition analysis, ORBDE v1.2 (Peressini & Guastello, 2010) is freely available.

Orbital decomposition output also includes a ϕ^2 calculation. ϕ^2 was initially intended as an estimate of variance in the actual time series accounted for by the extracted patterns, but it soon became apparent that the upper bound of ϕ^2 exceeded 1.0. It was remains a useful gauge of the strength of the χ^2 relationship corrected by the number of observations (N^*) in the time series.

For further theoretical background, the computations, and applications to creative problem solving discussions, see Guastello (2000, 2011b; Guastello et al., 1998). See Pincus, Ortega, and Metten (2011) for extensions involving the comparison of multiple time series in research. For other interesting applications, see Pincus (2001) for family dynamics, Pincus and Guastello (2005) and Pincus et al. (2011) concerning group therapy dynamics, Spohn (2008) concerning political violence, Katerndahl, Ferrer, Burge, Becho, and Wood (2010) for intimate partner violence, and Katerndahl and Parchman (2010) for an analysis of medical interviews.

Application to Task Analysis and Task Sequencing

The next theoretical step is to link the concepts of entropy and degrees of freedom to observables in the task situation. Although minimum degrees of freedom and minimum entropy appear to be consistent and interchangeable concepts, they are not necessarily so. Within the phases of completing a particular task, the organization of cognitive and psychomotor schemata is not so observable. Minimizing degrees of freedom would take the form of minimizing the variety of schemata used to execute the task or task stages. Some variability should remain because the residual variability permits a response to fatigue. Switching schemata will occur insofar as doing so permits the system to maintain stable output as long as possible (Kelso, 2003).

The locations of the degrees of freedom become more obvious if the task can be parsed into subtasks, submovements, or cognitive stages. If there are *N* stages, there are *N*-1 opportunities to change a subtask in some way, and there may be more than options at any choice point, making more than *N*-1 degrees of freedom overall. The number of degrees of freedom reduces during the automaticity process where the stages congeal into intact cognitive-motor combinations and sequences. Minimization would occur here.

A similar process occurs and is probably more observable when the individual sequences consist of discrete tasks in the context of a longer work period, and possibly varying priorities. Task sequencing is essentially rule-governed, although not completely so. Again if there are *N* tasks there are *N*-1 opportunities for a task selection with possibly multiple options at each switch point. The use of rules for task selection, nonetheless, reduces the number of degrees of freedom as a task sequence become more automatic. A simulation study by Walker and Dooley (1999) showed that a system is more stable in the sense of consistently high performance to the extent that the system does not have to respond to error corrections, interruptions, or disruptions of input flows. A complex adaptive system would be successful at responding to such events, but would have a few other rules (schemata) in place to do so. The finding concerning stability resonates well with an observation by van der Linden (2011) that cognitive fatigue is related to the amount of involvement of the executive function.

Whereas the degrees of freedom occur between cognitive-motor schemata, entropy is found in the pattern of schemata or the patterns of task sequences. Entropy is minimized to the extent that the patterns remain constant or are fewer in number. The orbital decomposition algorithm searches for progressively longer patterns; topological entropy decreases as string length increases. If the set of sequences that make up a solution does a good job of covering all the sequences in the time series, as characterized by the χ^2 test, there are fewer opportunities for degrees of freedom that are not covered by any implicit rule. Degrees of freedom *within* a pattern could still remain, however. Repeating patterns of tasks suggest that a switching rule is possibly active too.

In many cases the tasks that one wishes to analyze are distinct and thus lend themselves to a simple set of codes for entropy computation through orbital decomposition. There could be situations, however, in which the tasks or subtasks could be defined according to more than one scheme. If so, the entropy and final string lengths would depend on the coding scheme used (Guastello, 2000).

Interruptions can make an impact on overall work performance by slowing down the progress on a pre-determined schedule of tasks and loss of momentum when the original schedule is resumed. Interruptions could contribute to fatigue because of the added demands on the executive function. If the interruptions come from tasks that are not part of the original task set, the interrupting sequences would be visible in the final patterns produced by orbital decomposition. If the interruptions take the form of tasks that are already in the original task, however, perhaps because of changing priorities, "rush jobs" and so on, it might not be so easy to detect an interruption sequence from a normal sequence (Guastello, Peressini & Bond, 2011). One would look, however, to the minimum entropy and minimum degrees of freedom criteria to detect an overall level of interruption taking place, with more interruptions raising the value of both indicators.

Task sequences occur in time ecologies such that one pattern might exist at a weekly level of analysis, and others on a daily basis, an hourly basis, and yet another on a scale of minutes (Koehler, 1999). Sometimes the scales can interact. Zaheer, Albert, and Zaheer (1999) observed that different interpretations of events can be possible if the problem is reframed on a different time horizon. Guastello et al. (2011) showed an example of an orbital decomposition analysis that simplified to a clearer interpretation when events were observed in two-week time intervals instead of one-week intervals. Another experimental design choice that could affect entropy, degrees of freedom, and pattern calculations is whether tasks are defined in events, regardless of the duration of those events, versus time intervals in which events occur (or not) or occupy different numbers of successive intervals.

Hypotheses for Task Sequencing

The following experiment compared the array of task sequences that were generated by experimental subjects under two conditions. In the task quota condition, the subjects were required to perform a total of 49 short tasks (totaling about one hour of work time) with the requirement that they complete seven examples of each of seven tasks; they could perform the tasks in any order they wanted. In the no-quota condition, they were required to perform a total of 49 tasks, but could do any number of the seven possibilities so long as they did a total of 49. The quota condition contained a boundary condition that the second did not contain. Because self-organizing systems are very responsive to boundary conditions (Goldstein, 2011; Prigogine & Stengers, 1984), the following hypotheses were framed:

Hypothesis 1: There would be more structure displayed in the sequences chosen by the participants in the quota condition.

Hypothesis 2: There would be lower entropy and degrees of freedom used in task switching in the quota condition.

Hypothesis 3: There would be more examples of minimum entropy in the quota condition than in the no-quota condition. The differences in entropy could be evident in the distribution of types of task performance patterns that were generated by the participants or in the structure of the patterns themselves.

Hypothesis 4: There would be significant correlations between the number of task *switches* contained in the subjects' pattern choices and entropy levels.

Hypothesis 5: There would be significant correlations between pattern entropy and task switching with overall performance. For Hypotheses 4 and 5, the relative merits of topological versus Shannon entropy were also of interest.

Hypothesis 6: Basic mental abilities, such as measured by simple tests for quantitative ability, spelling, and spatial visualization, would be correlated with performance. Thus it was hypothesized that such abilities would be correlated with performance here and with the entropy and switching measures.

METHOD

Participants

The participants were 54 undergraduates aged 18-22 (mean = 19.44 years) who were enrolled in psychological classes. Of that number 25 were male and 29 were female. The ethnicity distribution in the population is 84.5% white, 4.6% Hispanic, 1.1% Black, and 9.8% other or declined to report. Participants received class credits for their participation time.

Measurements

Mental Abilities

Participants completed three tests of arithmetic ability, spelling ability, and spatial ability, prior to the task sequences. All three tests were speeded with the total score based on the number of items correct in a 5 minute period.

The arithmetic test consisted of 19 items requiring addition, subtraction, multiplication, or division. The alpha value for internal consistency was .72 (Form A, M = 11.12, $SD = 3.06$, $N = 151$) based on a previous study (Guastello et al., 2011b).

The spelling test consisted of 50 items in which the responded was required to identify a misspelled word in a sentence and write the correct spelling on the answer line; some items did not contain a misspelling. The alpha value for internal consistency was .88 (Form A, M = 28.26, *SD* = 8.38, *N* = 151) based on a previous study (Guastello et al., 2011b).

The Employee Aptitude Survey (EAS) Spatial Visualization test consisted of 20 items in which the respondent is shown a diagram of a pile of blocks and asked to report the number of blocks that touches the block that is marked. The reliability value of the test was reported as .89 using the method of parallel test forms (Ruch & Stang, 2005). Spatial Visualization showed an average correlation of .26 with other mental abilities in the EAS battery.

Cognitive Tasks

The seven tasks that were the focus of the investigation were available on a computer game, Brain Waves (Armor Games, 2011): memory, accuracy, coordination, reaction, speed, perception, and multitask. For all tasks, the background screen created an illusion of moving through a tunnel-like setting. In all tasks, participants were provided feedback throughout the task (with each click, the participant viewed "oops," "good," "great," "ok," etc. on the screen). Each task was scored as the percentage of items correct. For purposes of the experiment, the percentage scores were used as an indication of performance.

In the memory task, black circles of varying sizes were displayed asymmetrically on the screen. Participants were instructed to remember the order that the circles were displayed on the screen. After all circles appeared, participants attempted to click on the circles in the order they appeared. When an incorrect circle was selected or after the participant correctly remembered the sequence, a new circle sequence was provided.

The accuracy task involved correctly clicking on the middle of circles and rectangles of various sizes and angled positions. After participants clicked on the middle of each shape as accurately as possible, another shape appeared. In the coordination task, participants attempted to keep the mouse arrow in a moving sphere. A green circle bounced around a shifting square labeled with "This Side Up." The square flipped and turned in a circular, horizontal, and vertical fashion and participants had to track the bouncing circle in the midst of the moving square structure.

The reaction task entailed targeting circles by moving the mouse cursor over moving black circles of varying sizes. The circles appeared randomly across the screen. The reaction speed score was the amount of time the participant spent successfully tracking the circles.

In the speed task, a keyboard (with normal key positioning) appeared on the screen. Participants had to type the highlighted letter, as quickly and accurately as possible. In the perception task, participants were instructed to click on the last flashing light in a set of squares. The squares exponentially increased at most levels and a light quickly flickered randomly from square to square. Participants had to attentively watch for the final flashing light and hence, were scored according to accurate perception.

The multitask involved performing a spatial orientation task and a simple arithmetic problem simultaneously. On the left side of the screen, a three dimensional object was displayed. Four similar objects (of varying colors) were displayed above the target object. On the right side of the screen, an arithmetic problem with four potential answers was presented. The participant had to match the objects (by clicking on the correct match), while calculating the simple arithmetic problems (by clicking on the correct sum) as quickly as possible. Each level was timed, as indicated by two dropping bars on each side of the computer screen. If participants failed to click before time ran out or incorrectly answered, a new object and arithmetic problem set was generated.

The total performance score for each participant was the sum of 49 performance results.

Procedure

Research activities took place in a university laboratory that was equipped with a work table and a desktop computer. Participants completed the arithmetic, spelling, and spatial ability tests then proceeded to the main activity, having been assigned to one of two experimental conditions. In the quota condition, the participants were required to perform a total of 49 short tasks with the requirement that they complete seven examples of each of seven tasks; they could perform the tasks in any order they wanted. The experimenter informed them when they completed the quota for a task type. In the no-quota condition, they were required to perform a total of 49 tasks, but could do any number of the seven possible tasks so long as they did a total of 49.

Analyses

Orbital decomposition (ORBDE v1.2; Peressini & Guastello, 2010) was performed on each of the task sequences that were generated by the 52 participants. ORBDE determined the lengths of the sequences, the content of the sequences, and the topological and Shannon entropy associated with each of those sequences.

Sequences for the quota condition were then classified according to four expected prototypes: (a) “task-first” in which the participant completed the quota on one task, (b) “set-first” in which the participant completed a set of seven different tasks then repeated the cycle, (c) random, and (d) “mixed strategies.” Random sequences were identified if the χ^2 text on the final string length in the ORBDE analysis was not significant; such as result would indicate that the apparent patterns could have occurred by chance given the combinatorial odds associated with the individual tasks. “Mixed strategies” were any non-random patterns that did not resemble a task-first or set-first strategy; they were thought to be the result from participants using more than one rule for task switching during the course of the experimental session.

Sequences for the non-quota condition were expected to resemble the foregoing prototypes. (a) The favorite task strategy was thought to be similar to the task-first strategy. Inasmuch as there was no quota, participants might lock on to a favorite task for a while before switching to another one. (b) Set-first: A certain amount of exploration of tasks was expected, which some participants might do systematically using a set-first strategy part of the time. If the pattern displayed set-first throughout the session or for the majority of the session, the pattern was classified as set-first. (c) Random strategies and (d) mixed strategies were defined here as they were for the quota condition. A χ^2 test was used to determine if the two experimental conditions produced different distributions of sequence types.

Further statistical tests were used to determine the extent to which the entropy levels of two groups of participants reached a minimum. Correlations and multiple regression were used to determine the extent of relationships among entropy indicators, task switching, and total performance. Total performance was the sum of the 49 task performance scores.

Two way analysis of variance (ANOVA) was used on all the foregoing indicators to determine the extent to which they were affected by the quota rule and the task sequence type.

RESULTS

Quota Condition

The orbital decomposition results are shown in Table 1. Of the 26 participants in this condition, 10 displayed the pattern of *C* and *Ht* values that were consistent with prototypes for task- first sequences (Guastello, Peressini, & Bond, 2011); the nature of the sequences was verified by inspecting the contents of the patterns at the critical (final) value of *C* = 3. There were no variations in the topological (*Ht* = 0.936) or Shannon entropy (*Hs* = 2.549) results within this subset.

Table 1. Orbital Decomposition Results for Task-first and Set-first Strategies, Task Quota Condition

C	*trM*	*Ht*	D_L	χ^2	*df*	*N**	$\phi 2$	*Hs*
Task-first Strategy (10 subjects)								
1	7	2.807	16.566	0.000	6	49	0.000	1.946
2	7	1.404	4.07	129.136	7	48	2.69	2.303
3	7	0.936	2.549	219.521	7	47	4.671	2.652
Set-first Strategy (4 subjects)								
7	7	0.401	1.493	1004.224	7	43	23.354	1.944
14	7	0.201	1.222	1821.531	7	36	50.598	1.944
21	7	0.134	1.143	2257.452	7	29	77.843	1.943
Random Strategy (1 example of 4 subjects)								
1	5	2.322	10.195	0.000	6	49	0.000	1.946

The set-first strategy was adopted by 4 participants. The final value of *C* was 21, indicated that a maximum of 3 sets of 7 tasks immediately repeated themselves. Again were no variations in the topological (*Ht* = 0.134) or Shannon entropy (*Hs* = 1.943) results within this subset. Topological entropy was lower for the task-first strategy compared to set-first, but the opposite was true for Shannon entropy.

The random strategy was adopted by 4 participants. The final value of *C* was 1. The average topological entropy was 2.704. There were no variations in Shannon entropy (*Hs* = 1.944). An example appears in Table 1.

The orbital decomposition results for 8 mixed strategies are shown in Table 2. The final C values ranged from 2 to 18 (mean *Ht* = 0.365, mean *Hs* = 3.054). A final *C* value of 2, for instance, means that the subject did tasks in pairs, which could be seen to repeat proximately, and the rest of the sequences were of length 2. Subject #21 started with the task-first strategy then switched to set-first. Subject #24 started with a set-first strategy and then switched to task-first; see Table 3. The low-C solution suggested a lot of task switching with only very short detectable patterns.

Table 2. Orbital Decomposition Results for Mixed Strategies, Task Quota Condition

C	*trM*	*Ht*	D_L	χ^2	*df*	*N**	$\phi 2$	*Hs*
S19								
1	7	2.807	16.566	0.130	6	48	0.003	1.945
2	2	0.500	1.649	32.333	11	47	0.688	3.275
S20								
1	2	1.000	2.718	0.000	6	49	0.000	1.946
2	1	0.000	1.000	26.665	11	48	0.556	3.355
S21								
1	1	0.000	1.000	0.000	6	49	0.000	1.946
2	1	0.000	1.000	173.720	7	48	3.619	2.004
3	1	0.000	1.000	334.405	7	47	7.115	2.062
6	6	0.431	1.539	731.293	7	44	16.620	2.221
12	6	0.215	1.240	1300.516	6	38	34.224	2.296
18	6	0.144	1.154	1628.301	6	32	50.884	2.348
S22								
1	7	2.807	16.566	0.000	6	49	0.000	1.946
2	7	1.404	4.070	124.109	13	48	2.586	2.524
S23								
1	3	1.585	4.879	0.000	6	49	0.000	1.946
7	7	0.401	1.493	526.301	7	43	12.240	3.010
8	1	0.000	1.000	542.145	7	42	12.908	3.127
S24								
1	7	2.807	16.566	0.000	6	49	0.000	1.946
2	7	1.404	4.070	96.739	15	48	2.015	2.766
7	2	0.143	1.154	76.811	2	43	1.786	3.697
S25								
1	7	2.807	16.566	0.000	6	49	0.000	1.946
2	6	1.292	3.642	78.875	7	48	1.643	2.750
S26								
1	7	2.807	16.566	0.000	6	49	0.000	1.946
2	7	1.404	4.070	106.358	13	48	2.216	2.629
3	5	0.774	2.168	139.019	7	47	2.958	3.120

Table 3. Patterns extracted from Orbital Decomposition Analysis for Two Subjects, Quota Condition

Code	*repeat?*	*Freq*	*Ex Freq*
S19			
TT	yes	4	1.000
SS	-	3	1.000
RR	-	3	1.000
AA	-	3	0.734
CR	yes	3	1.000
CC	-	2	1.000
PP	-	2	1.000
PM	-	2	1.000
MA	-	2	0.857
AC	-	2	0.857
PT	-	2	1.000
(followed by 19 examples of doublets that appeared only once)			
S24			
MACRSPT	yes	2	0.000
ACRSPTM	yes	2	0.000

A = accuracy, C = coordination, M= memory, P = perception, R= reaction time, S = speed, T = Multitask

Table 3 shows the patterns that were identified by orbital decomposition analysis for two of the participants who used mixed strategies. Subject #19 gravitated to short sequences of 2 tasks. The second column shows whether the pattern repeated itself immediately. The frequency column shows the number of times the pattern appeared. Expected frequency is the number of times the pattern would be expected on the basis of combinatorial probabilities, and is part of the computation for the χ^2 test. There were also 19 patterns that only appeared once, and are thus not interpreted or shown here. The χ^2 test lumps all patterns that appear only once into a default category. Subject #24 started by using a set-first strategy, but changed to a task-first strategy, and is also included in Table 3 for illustrative purposes.

Non-quota Condition

The 28 participants showed 8 examples of task-first strategy, 4 examples of set-first strategy, 5 examples of random strategy and 11 examples of mixed strategies. A likelihood χ^2 test showed that distribution of four strategy types was not significant between the two experimental conditions ($\chi^2 = 0.742$, $df = 3$, $p > .05$).

On the other hand, if one wanted to be strictly consistent about the category definitions across the two experimental conditions, there would be a fifth category whereby favorite-task was distinct from task-first. No examples of favorite-task were possible for the quota condition, and all cases of task-first in the non-quota condition would be re-classified as favorite-task. Furthermore, there would be only 2 exact examples of set-first in the quota condition; the other 3 were close approximations that would be re-classified as mixed. When considered in this fashion, the likelihood χ^2 test showed that distribution of the five strategy types was indeed significant between the two experimental conditions ($\chi^2 = 26.868$, $df = 4$, $p < .01$).

The orbital decomposition results for three subjects are shown in Table 4. Subject #29 was an example of a favorite-task strategy. Subject #27 was a mixed strategy that looked similar to the set-first strategy. Subject #28 was a mixed strategy that was similar to the other mixed strategies found in the quota condition.

Table 4. Orbital Decomposition Results for Favorite-Task and Mixed Strategies, Non-quota Condition

C	***trM***	*Ht*	D_L	χ^2	*df*	*N**	$\phi 2$	*Hs*
S27 (Mixed strategy, modified set-first, 1 example of 2)								
1	6	2.585	13.263	7.013	6	49	0.143	1.874
2	1	0.000	1.000	47.171	12	48	0.983	2.952
7	2	0.143	1.154	80.739	2	43	1.878	3.697
S28 (Mixed strategy, other types, 1 example of 11)								
1	3	1.585	4.879	19.364	6	49	0.395	1.748
3	1	0.000	1.000	19.469	5	47	0.414	3.703
S29 (Favorite-task strategy, 1 example of 8)								
1	3	1.585	4.879	24.186	6	49	0.494	1.699
2	1	0.000	1.000	17.491	11	48	0.364	2.888
3	1	0.000	1.000	30.287	4	47	0.644	3.272
4	1	0.000	1.000	21.570	2	46	0.469	3.502
5	1	0.000	1.000	25.270	1	45	0.562	3.568

Entropy, Switching, and Performance

The correlations among the entropy metrics, performance, and task switching appear in Table 5. There was significant correlation between topological entropy and performance, although the effect was small ($r = -.19$, $p < .10$). The relationship, nonetheless, supported the notion that performance is better when entropy is minimized.

Table 5. Bivariate Correlations among Entropy Metrics, Switching, and Performance

Variable	*2*	*3*	*4*	*5*	*6*
1. Performance	0.15	-.19*	-.19*	-0.04	-0.03
2. Final C		.21*	-.46***	-.29**	.42***
3. Final **trM**			.44***	-.56***	-.24**
4. Topological Entropy				-.42***	-.25**
5. Shannon Entropy					-0.14
6. Switches					

**p* < .10, ***p*<.05, ****p*<.01, *****p*<.001

There was a negative relationship between the number of switches in the individual task patterns and topological entropy (r = -.25, p < .05). The most pronounced examples were task-first and set-first strategies. In task-first, topological entropy is larger, but the number of switches is less. In set-first the two indicators are reversed: long pattern lengths result in low entropy, but the total number of switches in the protocol is a maximum. Shannon entropy, however, was not related to either the number of switches or total performance.

The associations between final string length (C), **trM**, and topological entropy were expected because the computations are connected. Topological entropy was inversely related to Shannon entropy, which was also expected because the definitions of the two entities are actually the inverse of each other (Guastello et al., 1998).

Multiple regression with task switching as the dependent measured identified three significant predictors. The first two were C and **trM**, which contribute to the calculation of topological entropy. The third was Shannon entropy, which apparently demonstrated a suppressor effect; its significance only became apparent when it was tested in conjunction with the other entropy variables. The R^2 for the three-variable model was .34.

Entropy and Switching by Conditions and Patterns

The mean differences in entropy, switching, and performance between the quota and non-quota conditions appear in Table 7. The ANOVA results for the two-way analyses appear in Table 8. For these analyses, the designation of pattern categories was based on the schema of 4 patterns where favorite task in the non-quota condition was treated as equivalent to the task-first strategy in the quota condition, and the closely similar examples of set-first strategy in the non-quota conditions were treated as set-first rather than mixed. Because the multiple regression results with performance (Table 6) showed an advantage to decoupling the final C and **trM** from the entropy metrics, C and **trM** were tested as separate dependent measures.

Table 6. Multiple Regression Analysis for Task Switching

Variable	R^2	ΔR^2	β	F
Final C	.17	.17	.439	10.95***
Final **trM**	.29	.11	-.494	8.05***
Shannon Entropy	.34	.06	-.289	4.16**

**p<.05, ***p<.01, ****p<.001

The two conditions produced differences in topological entropy and Shannon entropy, but in different directions. Topological entropy was higher in the quota condition, but Shannon entropy was lower in the same condition. Task switching was not significantly different between the two conditions in spite of the lower number of switches in the quota condition. Performance was higher in the non-quota condition.

The four patterns produced different levels of entropy and switching, but not for performance. Mean differences for topological entropy and its two component variables, C and **trM** are shown in Figs. 3-5. For C, all means were different from each other at $p < .05$ or beyond using Tukey's LSD tests, with the exception of task-first with random strategies. For **trM**, all means we were different from each other at $p < .01$ or beyond, except that random versus mixed was not as strong ($p < .10$), and the difference between task-first with random strategies was not significant. For topological entropy, all the differences between means resided between the random strategy and the three other strategies ($p < .001$).

Means for Shannon entropy were all different from each other at $p < .001$ except that the difference between task-first and mixed was not as strong ($p < .05$), and the difference between set-first and random was not significant (Fig. 6). Means for task switching were all difference from each other at $p < .001$ except that the difference between set-first and random was not as strong ($p < .05$), and the difference between random and mixed was not significant (Fig. 7).

A significant interaction between patterns and conditions was obtained for C, **trM**, and switches. The interaction effect did not hold up when C and **trM** were combined into topological entropy, however, so they were not considered further. The interaction effect for switching is shown in Fig. 7.

Table 7. Means Entropy, Switching, and Performance for Quota and Non-Quota Conditions

Variable		*Quota*	*Non-Quota*
Final C	M	6.23	6.46
	SD	7.24	5.94
Final **trM**	M	5.69	2.52
	SD	2.15	2.34
Topological Entropy	M	0.86	0.50
	SD	0.70	0.96
Shannon Entropy	M	2.55	2.91
	SD	0.50	0.64
Switches	M	24.58	32.21
	SD	18.18	11.94
Performance	M	3946.31	4098.64
	SD	162.39	227.42

Table 8. ANOVA Results for Task Patterns and Quota vs. Non-Quota Conditions

		F		R^2
Variable	*Conditions*	*Patterns*	*Interaction*	
Final C	0.00	542.76****	35.13**	.95
Final **trM**	25.20****	8.24****	7.14****	.69
Topological Entropy	3.79*	8.71****	2.07	.43
Shannon Entropy	9.31***	20.00****	0.33	.61
Switches	1.62	30.37****	3.80**	.71
Performance	8.21***	0.82	1.60	.24

**p* < .10, ***p*<.05, ****p*<.01, *****p*<.001

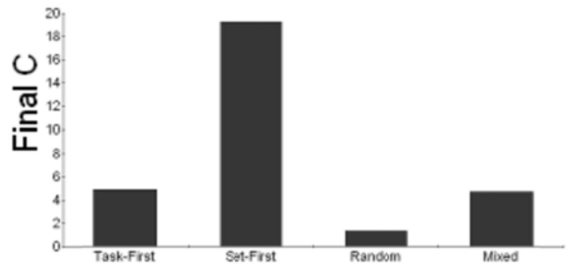

Fig. 3. Means for final string lengths across pattern categories.

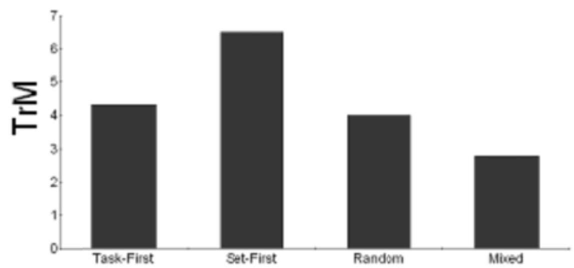

Fig. 4. Means for immediately repeating patterns across pattern categories.

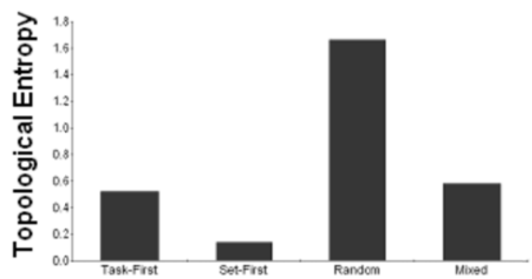

Fig. 5. Means for topological entropy across pattern categories.

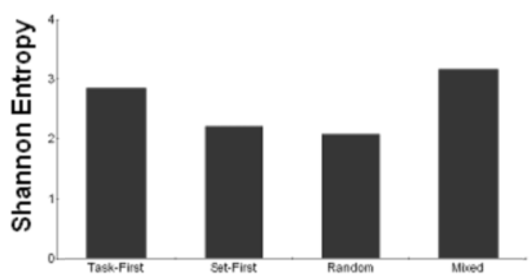

Fig. 6. Means for Shannon entropy across pattern categories.

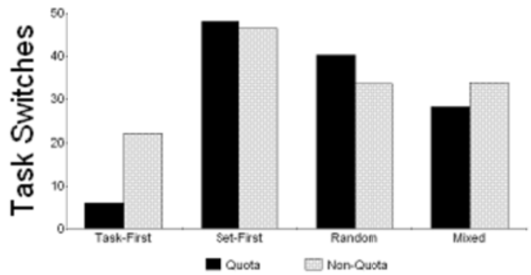

Fig. 7. Mean task switches across pattern categories and quota conditions.

Ability and Performance

Arithmetic ability was significantly correlated with total performance (r = .29, p < .05), but spelling (r = .11) and spatial visualization (r = .09) were not. Arithmetic was significantly correlated with spelling (r = .44, p < .001) and spatial visualization (r = .33, p < .01), however. Spelling was not correlated (r = .06) with spatial visualization. None of the ability variables were significantly correlated with the measures of entropy or task switching.

DISCUSSION

The mainstay of cognitive research on task switching showed that task switching induces a negative impact on performance by increasing response time when the switch occurs. The typical experimental design involved planned or forced switching similar to what happens when someone is interrupted in their work, or task sequences are driven by automation. Some researchers thought, furthermore, that switching contributes to fatigue because of the additional demands placed on the executive function.

The minimum entropy principle, however, holds that the stability of a cognitive or psychomotor strategy serves to maintain task performance, and in so doing minimizes the demand on the executive function as the task is learned and practiced. It also prescribes, however, that switching will occur under conditions of fatigue as a means of protecting performance results. Thus the voluntary instances of task switching become another matter entirely. Thus the present study offered a new experimental paradigm to assess entropy measures and their effects on task switching and performance, where voluntary task switching can be observed. It also offered an opportunity to manipulate rules that could affect the emergence of task performance patterns.

Behavior Patterns and Boundary Conditions

There was a clear set of task patterns that emerged from both the quota and non-quota conditions. In the quota condition, subjects who used the task-first pattern did as many examples of one task as possible before switching to the next task. The task-first pattern did not occur in the non-quota condition, although there was a closely related pattern in the non-quota condition whereby subjects focused on a favorite task of the possible seven tasks. In the quota condition there was also a set-first pattern whereby subjects did a complete set of tasks before repeating the set; this strategy produced lower topological entropy than task-first, but more task switching. The set-first strategy was observed in the non-quota condition, perhaps reflecting an exploration schema, but not as often. There were two less structured or consistent categories of response, which were the random and mixed patterns. In any case, the first hypothesis, that there would be more structure displayed in the sequences chosen by the participants in the quota condition, was upheld because the strictly-defined task-first and set-first strategies were more prevalent in the quota condition.

The second hypothesis that there would be lower entropy and degrees of freedom used in task switching in the quota condition was true in two out of three tests. Switching and Shannon entropy were lower in the quota condition, but topological entropy was higher. Two important findings are evident here. First, Shannon entropy and topological entropy can be expected to behave in opposite directions because of the differences in their definitions. Second, the raw quantity of switching is not synonymous with either form of entropy. Instead the switching *patterns* contribute to the entropy levels.

The third hypothesis that there would be more examples of minimum entropy in the quota condition than in the no-quota condition was predicated on the assumption that not all participants in either condition would identify and adopt the most efficient task pattern, that there would be some variation, but the most efficient patterns would be more frequently found in the quota condition. Topological entropy was lower for task-first and set-first strategies, compared to random or mixed strategies (Fig. 5), and strictly defined cases of both were more prevalent in the quota condition. Task switching was lowest in the task-first pattern, which was in turn more prevalent in the quota condition. A similar relationship for Shannon entropy was not apparent, however. Thus the third hypothesis held for two out of three indicators.

The fourth hypothesis that there would be significant correlations between the numbers of task *switches* contained in the subjects' pattern choices and entropy levels held true. The multiple regression analysis showed that C, **trM**, and Shannon entropy correlated with switching relatively well. The components of topological entropy and Shannon entropy displayed complimentary effects when predicting task switching: More switching was positively associated with longer string lengths, a smaller number of final strings that immediately repeated, and *lower* Shannon entropy.

The fifth hypothesis, that there would be significant correlations between pattern entropy and task switching with overall performance, produced an interesting result. Lower topological entropy was the only pattern metric that was correlated with total performance. In many circumstances, the performance outcome is the criterion that has the most practical importance. Regarding the sixth hypothesis concerning abilities, the arithmetic pre-test was significantly correlated with total performance also, but the abilities were unrelated to the pattern metrics.

What Did We Learn?

Perhaps the most singular contribution of the present study is that it defined a new paradigm for studying task switching phenomena where voluntary switching is prominent. In doing so it explored relationships between entropy, task switching, and performance that are critical to the understanding of cognitive fatigue phenomena. Furthermore, it produced new information about task switching that can be organized into the three initial questions plus one more concerning the implications for studying entropy principles on a continuing basis.

Regarding the rules of task switching, the first rule was that one or more meta-rules can develop that are induced by the external demands placed on performance the tasks. Second, and more specifically, there were four strategies in the quota condition: task-first, set-first, random, and mixed. There was a very similar set of strategies in the non-quota condition: favorite task, set-first, random, and mixed. The favorite-task pattern was similar to the task-first pattern in that tasks were aggregated for a while before switching. The mixed strategies were relatively similar in principle, and both versions of it permitted explorations of the tasks that were available. The set-first and random strategies were the same in both conditions.

The third rule was that strategy adoptions were not equally frequent, and thus not random in that sense. Task-first (or favorite) and set-first involved lowest total switching costs and entropy respectively, but the two patterns (26 instances) were preferred about as often as the mixed and random strategies together across both quota and non-quota conditions (28 instances).

There were three important points regarding the efficacy of the minimum entropy hypothesis. First, lower topological entropy was associated with better performance overall. The second point was that about half of the subjects favored strategies with both lower entropy and lower task switching overall. The third point was that the subjects were making a trade-off between lower entropy and lower switching costs.

There were two important points regarding the boundary condition hypothesis. First, the boundary conditions produced the differences between experimental conditions already discussed. The second is that the quota condition produced less task switching overall, which was another feature of the system self-organizing.

Regarding the role of entropy in task organization, it appeared that topological entropy was more informative than Shannon entropy for most purposes here. Both were useful, however, for making connections between entropy and the number of switches used. The results for entropy hypotheses were predicated on patterns rather than the frequencies of single tasks. Had the analyses been confined to frequencies of single tasks, Shannon entropy would have been the same number for all subjects in the quota condition and thus not informative at all.

The point was made at the outset that switching strategies are expected to occur in response to fatigue, and that the formation and choice of strategies were dynamic. An alternative interpretation would be that strategies were simply fixed at the outset. The pattern analysis did show some consistent set-first or task-first strategies that persisted for the entire work period; these were more prominent in the quota condition. A task-first sequence of codes would be AAAAAAA (A = accuracy task), which would eventually be followed by CCCCCCC (C = coordination task) and so on. A set-first sequence of codes would be ACMPRST representing a sequence containing all tasks, usually in the order in which they were arranged clockwise on the game menu. Mixed and random strategies were clearly dynamic, however, and some of the participants' sequences never actually stabilized. Sets of examples of mixed or random patterns from two participants appear in Table 3. If the experiment was designed to last a lot longer, some of the initially-fixed strategies might be seen to shift more often.

The participants in the no-quota were asked why they chose their sequences. Many could not give an answer. Some reported that they were exploring the tasks at the start, found one that they liked or that they felt they were doing well on, and continued until they got tired of it. The tasks had built-in feedback that told the participants when they got a response correct or missed the item. Several participants reported that they liked that feature and that it kept them sustained on a task. Thus immediacy of performance feedback could be a variable that affects task switching.

A practical implication from this line of research at it presently stands is that there is a trade-off between minimizing entropy with respect to task switching and fatigue induced by prolonged time on task. The full set of rules for optimizing task sequences is not yet known, but there are some popular strategies that are known already. Once is to minimize unnecessary interruptions. Another is to batch tasks of a given type in order to gain some momentum and minimize task switching costs. Strategies for organizing component within a task have yet to be defined, but present results indicate that standard operating procedures should permit some variation in the sequencing of task elements in order help workers find the balance they need; individual differences appear to be operating. Eventually it should be possible to distinguish strategies that result from fatigue from those that are adaptive for other reasons.

Limitations and Future Research

Several questions that derive from some of the limitations of the present study should be explored. To begin, the type of task should be more challenging. Although the tasks used in the present study were more transitive than picking out a letter in a box or doing simple addition and subtraction as in many conventional studies on task switching, the tasks could have been more deeply challenging and representative of real-world tasks and demands. Similarly, work periods should probably be longer in order to produce the fatigue effect that is thought to trigger switching according to the minimum entropy theory.

The set-first pattern was the strategy with the lowest topological entropy, but it was the least preferred. It is possible that it would only be preferred for tasks where the potential for automaticity between stages is possible. For instance, martial arts students who progress through the early stages of training learn elementary moves first then combine them into more complex forms that could consist of 20 elementary moves. The goal is to execute the complex form in a seamless fashion. To do so would reflect a set-first strategy.

The calculation of entropy for any given situation is predicated on the schema one uses to define the (elementary) system states. In this study the tasks were the system states, but Hong's (2010) principle of minimum entropy was predicated on performance variability within a single task, and the switch in schemata were associated with the movements required to do the one task. It is possible that a study where the calculations of entropy are predicated on performance levels could shed some new light on the contrast between within-task performance variability and between task variability.

Although there were significant relationships between entropy metrics and behavior, the relationships were relatively small, with only about 4% of the performance variance and 12% of the task switching variance actually accounted for. Future research should explore additional sources of variance. For instance, individual differences in non-verbal mental abilities could account for some of the variance; spatial ability and measurements of working memory capacity could be candidate variables.

Another scenario is that the level of noise in behavior is moderated by variables inherent in the task situation. For instance the present task might be a high noise situation, but lower noise might be observed in tasks that are more complex in the sense of channels and stages required, greater cognitive workload demands, and longer time on task. Noise would also be less in situations where the task patterns are more saturated relative to random task choices. Situations that promote greater differences between novices and experts should show greater pattern saturation among the experts.

Finally, the propositions regarding task switching were directed toward a further understanding of fatigue and how fatigue is observed within the cusp catastrophe model. One can then ask if the task switching patterns act as control variables in the fatigue process. Additional research is in progress on this particular point.

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