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Discrete task switching in overload: A meta-analyses and a model ☆

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ABSTRACT

We describe a computational multi-attribute decision model that predicts the decision aspect of sequential multitasking. We investigate how people choose to switch tasks or continue performing an ongoing task when they are in overload conditions where concurrent performance of tasks is impossible. The model is based on a meta-analytic integration of 31 experiments from the literature on applied task switching. Consistent trends from the meta-analysis, to avoid switching, and to switch to tasks lower difficulty, along with greater salience, priority and interest are used to set polarity parameters in the mathematical model.

1. Sequential multi-tasking

Human multitasking can be divided into two different modes (Wickens and McCarley, 2008). One mode involves concurrent performance, where two tasks, like driving and talking, are carried on at the same time. Attention is divided by sharing limited, multiple resources in the brain (Navon and Gopher, 1979; Meyer and Kieras, 1997, Wickens, 2002, 2008). The other mode involves sequential task performance, when the operator must choose to do one task or the other because concurrent task performance is impossible in overload situations.

Human experience provides many examples of the high workload breakdown of such multi-tasking (Dismukes, 2010; Loukopoulos et al., 2009; Wickens and McCarley, 2008). Some of these breakdowns result in tragedy: when texting diverts the eyes from the roadway leading to a collision; when the operators at Three Mile Island nuclear power plant became so engaged in fault diagnosis, that they failed to perceive a critical indicator (Rubenstein and Mason, 1979); when the pilots of an L1011 became so focused on a potential landing gear failure, that they stopped monitoring altitude and crashed into the Everglades (Wiener, 1977); and when an air traffic controller became overloaded with traffic management, and forgot to move a waiting aircraft off of an active runway (NTSB 1991).

Indeed aviation in particular is populated by several cases when tasks that should have been of the highest priority have been shed or neglected in favor of others of lower importance (Chou et al., 1996; Damos, 1997; Loukopoulos et al., 2009; Raby and Wickens, 1994). Often situations like these represent the failure to switch attention, a form of cognitive tunneling or task fixation (Dehais et al., 2011; Wickens and Alexander, 2009).

What then causes certain tasks to be performed and others neglected or "shed" within the high workload environment, when concurrent task performance is difficult or impossible? Can this choice or implicit decision of task switching or task shedding be modeled?

Numerous models of sequential operations in multi-task performance can be found, and these can be positioned along a time-scale continuum (Salvucci and Taatgen, 2011). The majority of such models appear to lie toward the "micro" end of the continuum, modeling task switching time in the order of milliseconds (e.g., QN-MHP, Liu, 1996; EPIC, Meyer and Kieras, 1997, or models of the psychological refractory period, Pashler, 1998, Salvucci and Bogunovich, 2010). Often, their focus is exclusively on time, and on accounting for variance in multi-task performance time required to carry out relatively simple cognitive activities.

Some sequential model predictions do focus on task switching performance at a courser grain size involving more complex real world tasks, such as driving and cell phone use (Brumby et al., 2009; Janssen and Brumby, 2010); but here the unit of model analysis is often on the sequential allocation of non-sharable cognitive/motor operations between tasks. Furthermore, the decision to perform one task over (prior to) another is typically based on time of arrival, or the availability of certain processors. Such models are extremely useful in predicting multi-task performance, but do not fully account for the array of real world multi-tasking. First, they do not account for additional factors, such as interest, difficulty or time-on-task that may influence decisions to switch (Kurzban et al., 2013); and second

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they do not generally extend beyond dual task interleaving to the choice between *multiple* (> 2) tasks.

The Strategic Task Overload Management (STOM) model we present here addresses those multi-task situations on the long time end of the multi-task switching time continuum, and focuses exclusively on the decision of what task to perform (or to keep performing), rather than the time, or quality of the switching performance, as these are well addressed by other models. As such, it is more closely aligned with multi-attribute decision models (Dawes, 1979); and as we describe below, some of its parameters are based on the results of a meta-analysis.

2. The STOM model

The STOM model addresses multi-tasking performance of an overloaded operator, already performing an *ongoing task* (OT), who may *decide* to keep performing it or, because concurrence is impossible, may switch to one of several possible *alternative tasks* (AT) that are "waiting in the wings". Alternative tasks vary in their "attractiveness", based on their task *attributes* (e.g., interest, priority), and the OT itself will vary in its "stickiness" (switch resistance) based on many of the same attributes. Collectively these integrated attribute values influence whether to switch from the OT, and, if a switch is chosen, which AT to switch to.

The basis of the five STOM attributes lies in the well validated SEEV model of visual scanning (Wickens, 2014, 2015; Wickens et al., 2003), which in turn is derived from fundamental models of optimal information sampling (Moray, 1986; Sheridan, 1970), and queuing (Barabasi, 2005; Moray et al., 1991, Waldon and Rouse, 1978). Both SEEV and STOM are based on the idea of attraction: "attractiveness" of visual areas for SEEV modeling scanning of the eyeball, and "attractiveness" of tasks for STOM modeling switching of the "mindball". SEEV contains four parameters that determine visual attractiveness: the Salience of an area of interest (AOI), the Effort required of a scan to access an AOI from the current location of fixation, the Expectancy that new information will be obtained there (related to bandwidth) and the Value of that information for the task(s) at hand, the latter based on the importance of the task, multiplied by the relevance of the information source to the task. As a discrete event simulation model, each calculation of the attractiveness of all visual areas is made at the maximum frequency of eye movements (about 3/sec), and the eye moves to AOIs or stays put in proportion to the degree of attractiveness of all competing areas. Importantly, SEEV can be expressed as a normative expected value model of where one should look, to maximize the acquisition of important information, and has been evaluated to show higher conformance with optimal scanning for experts than for less skilled operators (Koh et al., 2011; Wickens et al., 2008).

The STOM model borrows heavily from the four SEEV *AOI* attributes to generate its five *task* attributes. As we elaborate below, in STOM, the Salience of a task is defined by its sensory properties; the Effort corresponds to the effort of task switching, and the Value of a task is decomposed into two components: task priority, where this can be objectively established via instructions or job-related guidance (Schutte and Trujillo, 1996), and task interest, or engagement, which may be decoupled from Priority. The Difficulty of a task attribute (in STOM) has no current counterpart in SEEV, and the Expectancy attribute (in SEEV) has no counterpart in STOM. However, emerging versions of STOM incorporate a time-on-task influence (Kurzban et al., 2013; Gutzwiller, 2014) that is related in part to expectancy.

The architecture of the STOM model is shown in Fig. 1. On the upper left, the operator is performing some ongoing task, in high workload such that there are alternate tasks waiting in the queue to be performed. At each iteration a decision is made to continue performing the OT, or switch to an AT. As we see (and will justify below) this decision weight favors staying and avoids switching with a roughly 60–40 or 3–2 "preference ratio". If a switch is made, then the new AT becomes the OT. This switch decision tendency is modified by a number of task attributes, creating a multi-attribute decision making task. On the right are four attributes of the alternative task(s) that determine its attractiveness, and can either offset or amplify this tendency to avoid switching to it. We speak of the polarity of these attributes: that is, if the AT is easy, interesting, of high priority and salient, it becomes more attractive. If it is hard, boring, low priority and non salient, these weights reverse accordingly. The specific weights in the top left box for the AT (0.63) indicates the strength of attractiveness of an easier task, as we discuss further below.

Just as these attributes influence the relative attractiveness of different ATs, so three of them can also be attached to the OT to determine its "stickiness", or switch resistance, as shown in the left half of the figure. The three attributes of engagement, priority and

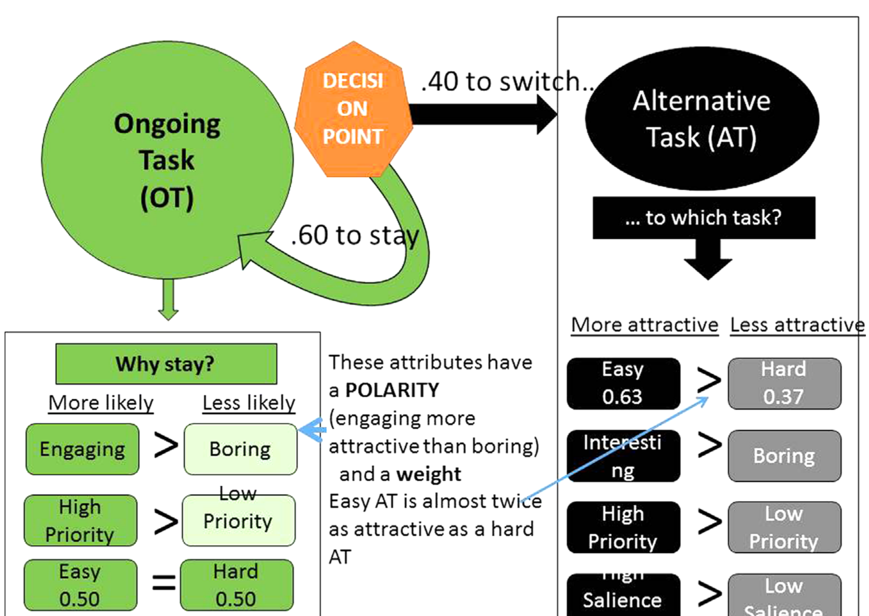

Fig. 1. Strategic task overload management (STOM) model.

difficulty are the same as with the AT, though their weights may vary. Task salience however cannot be a property of a task one is already doing, since salience refers to the task's external stimulus properties that call attention to it.

The model runs as an iterative discrete event simulation (Laughery et al., 2012) such that, on each iteration, it makes a probabilistic decision whose outcome – to stay or trigger a switch, and where to switch if there is more than one AT – has probabilities associated with the net sum of weights for all tasks over all attributes. A critical feature in the model is how long each iteration should be. For visual scanning models such as SEEV, this can simply be the minimum dwell time in operational environments (i.e., about 0.4 s). But what is the minimum time on task? While there is no clear answer to this, a naturalistic flight simulation study in high workload by Raby and Wickens (1994) provided a reasonable estimate of approximately 0.70 s, the shortest time on task of the six tasks assessed.

3. Meta-analytic review of the literature

In order to go beyond the model architecture, and begin to attach weights that are the hallmark of multi-attribute decision models, four classes of literature were considered for our evaluation of task switching preferences. First, there is a large literature on interruption management (see Wickens et al., 2013 for a meta-analytic review). In general this literature was not relevant to the current model, because (a) it only dealt with a pair of tasks – an ongoing and interrupting task, in a single cycle of OT-IT-OT, and (b) the overwhelming approach is to assess time, rather than choice. That is, how long does it take to react to the interruption, and how long to resume the ongoing task. Whether or not a switch took place at all (e.g., choice) is rarely addressed.

Second, there is a large literature on task switching (e.g., Monsell, 2003; Kiesel et al., 2010) that characterizes the speed and fluency with which people switch between two different “tasks”, such as classifying digits by their magnitude (high-low) or type (odd–even). However these are better characterized as *rule switching* (e.g., between classification rules), and again, they examine the time and fluency of required switching, rather than the choice of whether or not to switch.

The third class was study that examines switching among heterogeneous tasks, such as between two different forms of games. This third class is heavily populated by a paradigm developed by Arrington and Logan, that we describe as “constrained task switching”, in that participants are asked to perform an equal number of the two tasks (constraining overall switching between them to be 50%) and to switch between them “randomly”. However the paradigm does allow them to choose to perform a given task repeatedly for any time before switching to the other, so long as the 50% constraints were satisfied by the end of the trial (e.g., Arrington and Logan, 2004). We used such studies exclusively to evaluate the magnitude of the switch avoidance preference.

The fourth class was only sparsely populated, and contained heterogeneous tasks while also allowing voluntary, unconstrained switching. Such data provide a basis for establishing or confirming the task characteristics or attributes that drive the “attractiveness” of one task over another, the heart of the STOM model.

3.1. Switch avoidance

The model parameter with the greatest confidence in its estimate is the fundamental switch avoidance tendency, which we estimated at 60%. Fifteen studies entered into this estimate, including multiple experiments in some studies, and availed 25 independent switch probability estimates (Table 1). This produced a fairly small 95% confidence interval around the value (58–62%). Studies included both the constrained switching studies of class 3 and the unconstrained studies of class 4. Collectively, they confirmed this “cost of switching” well known from the basic psychology literature (class 1), as well as from an earlier generation of information sampling models (Sheridan, 1970). Such a finding is entirely consistent with the resource costs of “executive functioning” in task switching (Banich, 2009), when coupled with assumptions of an inherent cognitive effort avoidance or resource-conservation tendency (Kahneman, 2011; Kurzban et al., 2013; Kool et al., 2010; Shugan, 1980). Individual differences in working memory capacity hence may be related to differences in switch propensity.

Table 1
Overall switch avoidance estimates.

Study	P (switch)	N
Arrington and Logan (2005) – Exp 4	0.43	16
Arrington and Logan (2005) – Exp 5	0.45	16
Arrington and Logan (2005) – Exp 6	0.43	16
Arrington and Yates (2009)	0.38	57
Arrington et al. (2010) – Exp 1	0.43	24
Arrington et al. (2010) – Exp 2	0.39	24
Butler et al. (2011) – Exp 1	0.38	82
Butler et al. (2011) – Exp 2	0.45	74
Demanet and Liefooghe (2013) – Exp 1	0.42	25
Demanet and Liefooghe (2013) – Exp 2	0.42	26
Demanet and Liefooghe (2013) – Exp 3	0.47	29
Demanet et al. (2013)	0.42	25
Demanet et al. (2010) – Exp 1	0.47	24
Demanet et al. (2010) – Exp 2	0.45	24
Demanet et al. (2010) – Exp 3	0.48	32
Gollan and Ferreira (2009) – Exp 1	0.3	73
Gollan and Ferreira (2009) – Exp 3	0.28	56
Kool et al. (2010): Expt 1	0.32	43
Liefooghe et al. (2009)	0.37	27
Liefooghe et al. (2010)	0.36	50
Mayr and Bell (2006) – Exp 1	0.34	72
Orr and Weissman (2011)	0.43	54
Vandamme et al. (2010)	0.46	10
Weywadt and Butler (2013)	0.29	48
Yeung (2010) – Exps 1a and 1b	0.38	16 and 16

The interpretation that there are effort costs of switching is also consistent with the empirical finding that switching frequency is reduced in the context of more difficult tasks (Gutzwiller et al., 2014). In addition to this difficulty finding, we have also noted in Gollan and Ferreira (2009) that fluent bi-lingual participants were more likely to switch between different languages (35% switch rate) than English-dominant (but Spanish knowledgeable) participants (24%). Assuming the latter are more “resource-challenged” (finding the task overall more difficult), such a finding is consistent with this view that switching itself is resource-limited, and less likely as the tasks involved become more difficult. An extension here is that under high cognitive load, switching may sometimes diminish to the point of cognitive tunneling, one cause of the Three Mile Island disaster referred to at the outset.

3.2. Task attributes

Given the fundamental inertia to stay with, rather than switch to another task, we then looked to the literature, as well as borrowing from the SEEV model, to inform us regarding the four task attributes that modulated this tendency.

3.2.1. Task difficulty

To the extent that people are “cognitive misers”, avoiding difficult tasks, particularly under high cognitive load when resources are already heavily taxed, we might also anticipate that switching to effortful tasks would be less likely than switching to easier tasks. Eleven experiments, listed in Table 2 availed a comparative estimate of the preference to perform and easier versus a more difficult task (all from class 3 articles above), and these yielded a mean of 63% easy preference, with a confidence interval of $+/-5\%$.

Unfortunately, studies that examine the effect of OT difficulty on switch resistance were sufficiently scarce that no estimates of this tendency to avoid switching from a more difficult (or easier) OT were available. However, one might conclude from the null effect of OT difficulty observed in interruption management studies (Wickens et al., 2013) that this does not play a role in task management. This is reflected in the equality polarity for OT difficulty depicted in Fig. 1.

Beyond the difficulty of the AT, the remaining parameters, like OT difficulty, were not sufficiently supported by empirical studies to reliably estimate weights, but only the polarity of the factors, so that weights are not included in the figure.

3.2.2. Priority

Three studies examined the influence of priority on task choice. Janssen and Brumby (2010) examined the effect of priority instructions for manual phone dialing versus driving (steering). They observed what can be interpreted as a preference ratio of 0.67 to steer rather than dial when driving was emphasized. This priority was supported by steering events and lane-keeping error, observed at the break point between chunks of dialing. Raby and Wickens (1994) found that priority influenced the time stayed on a task once it was switched to, but not necessarily the probability of switching to it in the first place. Gutzwiller et al. (2014) found a small influence of priority on task switching choices between four tasks, supporting its polarity, but also suggesting that this weight might be fairly low under multi-task situations.

3.2.3. Interest

One study explicitly examined a tradeoff of difficulty against other variables. Spink et al. (2006) examined users' choice between search databases. They found that those rated by the user as easier (while still more preferred than the more difficult, as above), were less preferred to those rated as more interesting or *engaging*. Such a tendency is backed by findings of cell phone engagement, which sometimes “trumps” the greater priority of attention to the task of safe driving and hazard avoidance (Horrey et al., 2009).

3.2.4. AT salience

Salience refers to the salience of a reminder to perform the task. From the interruption management literature (see Wickens et al., 2013; Lu et al., 2013), we concluded that the salience of an auditory interruption is 12% greater than that of a visual one (inferred from switching time). And from the study of prospective memory in task management (Dismukes, 2010), we concluded that a visual reminder is more salient than no reminder at all. Such a conclusion was documented in a naturalistic interruption management study by Grundgeiger et al. (2010) as creating a 28% advantage for a visually reminded over a non-reminded task.

Table 2
Meta analysis of difficulty effects.

Study	Ratio (preference for easy)	N
Kessler et al. (2009) – Exp 2	0.53	20
Kushleyeva et al. (2005)	0.45	10
Kool et al. (2010) – Exp 1	0.68	43
Kool et al. (2010) – Exp 2	0.64	24
Kool et al. (2010) – Exp 3	0.64	37
Kool et al. (2010) – Exp 4	0.73	16
Kool et al. (2010) – Exp 5	0.67	19
Metcalfe (2002) – Exp 5	0.67	12
Jin and Dabbish (2009)	0.67	13
Payne et al. (2007) – Exp 2	0.6	72
Payne et al. (2007) – Exp 4	0.66	24

3.3. Attribute weights and trade-offs

While the above studies have established the polarity of the STOM attributes, and in one case (AT difficulty) the weight, reliable weight estimates are missing from the others. Such weight estimates become necessary to predict the tradeoffs in task switching between for example an easy but boring task, and a hard engaging one. Studies of such tradeoffs in high workload multi-task environments were absent. However one recent investigation in our laboratory (Gutzwiller, 2014) avails some such data. Across three experiments, four tasks in the Multi-Attribute Task Battery II were evaluated for overload switching choice dominance. Furthermore, each task was subjectively rated on the three STOM attributes of priority, difficulty, and interest or engagement, and was objectively coded for task salience. While the data are presented elsewhere, one prominent finding was that a task of high salience and low difficulty trumped a task of higher interest and higher perceived priority, thereby suggesting the collectively greater weights of the former two attributes. Furthermore, the polarity of all attributes was confirmed in this research.

4. Conclusions and implications

While all of the above provide some evidence on the switch tendencies, another important variable is “time on task”. Are people more likely to abandon a task as time goes on, as they lose interest in the task? Is this tendency reversed as the operator expects the end of the task (“I'm almost finished, so I'll stay until I am”)? Again, data are lacking here, but such effects and their interactions with other effects can be simulated in our STOM discrete event simulation model.

One clear problem that modeling such interactions will help to address is the ambiguity of the time frame for time-on-task switching effects. For example, Kurzban et al. (2013) postulates a general switch resistance decline over time. However, what span of time must be observed before a decline would emerge? The issue of time scale arose earlier, in establishing what the current model addresses: a time frame beyond the millisecond range, for switch choice iterations since the informative meta-analysis tended to include data that are primarily within the range of one second or less.

Second, many of the studies in task management did not involve true workload overload paradigms. However they imposed a choice between tasks that clearly could not be done concurrently because of their high workload and common resource demand, no opportunity was actually provided to allow time sharing if they could.

Finally, we note the need for more studies to be run that evaluate tradeoffs between attributes on task switching, such as the design of Gutzwiller et al. (2014) discussed above. Such studies are necessary to establish at least the relative ordering or dominance of attribute weights, if not the specific value of those weights.

In conclusion, we are optimistic that, with additional data, the courser grained STOM model can complement finer grained hybrid models of concurrent/sequential multi-tasking (Liu, 1996; Salvucci and Taatgen, 2011), as well as models of concurrent performance to achieve global predictions of multi-tasking.

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[1] TS indicates task-switching paper, others cited in the text but not employed in the meta-analysis have no designation.

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