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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 "mind-ball". 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

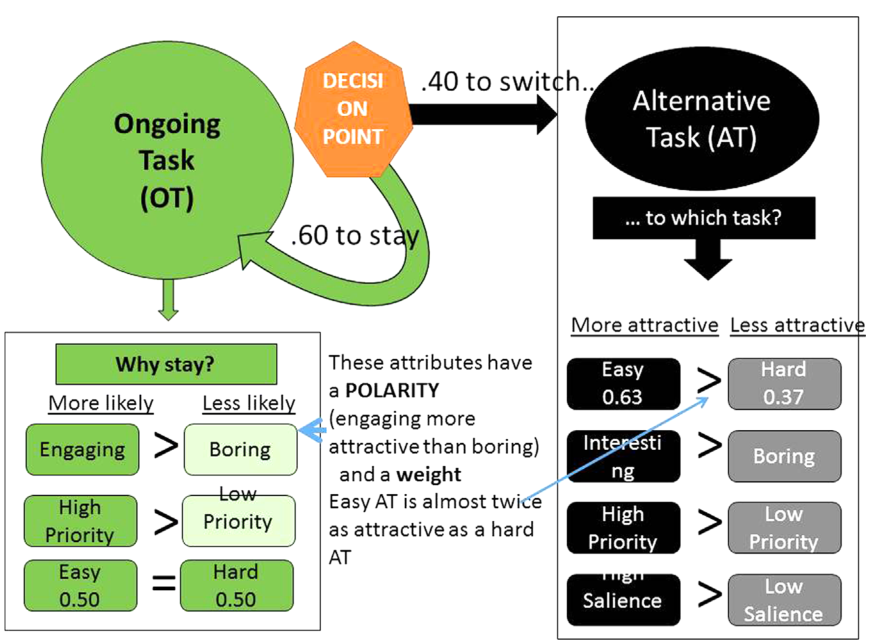

Fig. 1. Strategic task overload management (STOM) model.