

# Mental effort: One construct, many faces?

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## Introduction

We can all feel exhausted after a day of work, even if we have spent it sitting at a desk. The intuitive concept of mental effort pervades virtually all domains of human information processing and has become an indispensable ingredient for general theories of cognition (Anderson, 2007; Shenhav et al., 2017; Lieder & Griffiths, 2015). However, inconsistent use of the term across cognitive sciences, including cognitive psychology, education, human-factors engineering and artificial intelligence, makes it one of the least well-defined theoretical constructs across fields. A number of recent approaches lay the foundation for a consensus by offering formal accounts of mental effort. Yet, reaching a multifield-wide consensus on the operationalization of mental effort will require cross-talk between different empirical and computational approaches, including symbolic architectures, non-parametric Bayesian statistics and neural networks. The purpose of this full-day workshop is to review and integrate these emerging perspectives.

Mental effort can be defined as a construct that “mediates between (a) the characteristics of a target task and the subject’s available information-processing capacity and (b) the fidelity of the information-processing operations actually performed” (Shenhav et al., 2017, p. 100). One of the prime examples of mental effort in cognitive psychology concerns cognitive control: our ability to bias information processing toward relevant task goals. Recent theories suggest that exerting cognitive control is associated with a cost, and that agents consider this cost when making decisions about how to allocate mental effort (Shenhav, Botvinick, & Cohen, 2013; Verguts, Vassena, & Silvetti, 2015). These theories have become increasingly attractive as they can explain irrationalities and/or idiosyncracies of human performance in terms of rational adaptation to the cost of mental effort, e.g., in tasks that require cognitive control (Musslick, Shenhav, Botvinick, & Cohen, 2015), the selection between cognitive heuristics (Lieder & Griffiths, 2015) or model-based planning (Kool, Gershman, & Cushman, 2017). Furthermore, this view has influenced the understanding of cognitive impairments in mental disorders, adding the possibility that deficits in task performance stem from changes in the decision-making

process about effort allocation rather than or in addition to one’s limitation to exert mental effort (Grahek, Shenhav, Musslick, Krebs, & Koster, 2019).

The concept of mental effort has also played a significant role for theory development in human factors and educational research. In human factors research, mental effort manifests itself as mental workload in domains such as driving, supervisory control, or mobile interaction (Wickens, 2014). Recent frameworks, building on the modular cognitive architecture ACT-R (Anderson, 2007), quantify mental workload of a given task in terms of the duration over which processing modules need to be active (Jo, Myung, & Yoon, 2012). Educational research relates mental effort to invested working memory resources in learning situations, building on the Cognitive Load Theory (Sweller, Van Merriënboer, & Paas, 1998). In this context, production-based cognitive modeling approaches have been used to connect the conceptual framework directly to mechanisms of human learning (Wirzberger, Borst, Krems, & Rey, 2019) and problem solving (Sweller, 1988). Paralleling modeling efforts in cognitive control, they leverage metrics such as the number of elements in working memory, the number of productions to fire, or processing module activity over time.

## Goal and Scope

The goal of the workshop is to compare how the construct of mental effort is defined and treated across different research domains, such as cognitive control, decision-making, human-factors engineering, education, and artificial intelligence, and how it is operationalized across various modeling efforts, including symbolic architectures, non-parametric Bayesian statistics, connectionist models, reinforcement learning, as well as quantum mechanic accounts. To achieve this goal, we invited experts in these fields to present an accessible summary of their research, and allocate ample time for dialogue and audience participation across two panel discussions (see Table 1). Key questions of discussion will include (but are not limited to):

- What are the experimental phenomena that lay a foundation for theories of mental effort?
- What is the common ground in operationalizing mental effort across different domains of cognitive science?
- Which modeling approach(es) is (are) best suited to answer which questions regarding mental effort?

Table 1: Full-day workshop structure and confirmed presenters.

<b>Morning session: measurement and operationalization of mental effort</b>				
<b>Time</b>	<b>Presenter</b>	<b>Topic</b>	<b>Position</b>	<b>Institution</b>
9:00-9:15	Sebastian Musslick	<i>Introductory Remarks</i>	PhD Candidate	Princeton University
9:15-9:40	Wouter Kool	<i>Neural and computational signatures of cost-benefit decision making</i>	Assist. Prof.	Washington University in St. Luis
9:40-10:05	Eliana Vassena	<i>Meta-control as the neurobiological solution to the effort allocation problem</i>	Assist. Prof.	Radboud University
10:05-10:30	Tom Verguts	<i>Cognitive effort via neural synchronisation</i>	Professor	Ghent University
10:45-11:10	Amitai Shenhav	<i>Empirical and theoretical applications of the Expected Value of Control model</i>	Assist. Prof.	Brown University
11:10-11:35	Jonathan D. Cohen	<i>On the rational boundedness of cognitive control</i>	Co-Director, Professor	Princeton Neuroscience Institute
11:35-12:00	All session presenters	<i>Panel Discussion (moderator: Maria Wirzberger)</i>		
12:00-13:00	Poster presenters	<i>Poster session (organizer: Laura Bustamante)</i>		
<b>Afternoon session: the role of mental effort across cognitive science</b>				
13:00-13:25	Thomas L. Griffiths	<i>Modeling the rational use of mental effort</i>	Professor	Princeton University
13:25-13:50	Matthew M. Botvinick	<i>Why is mental effort costly? Some ideas inspired by recent AI research</i>	Director, Professor	Google Deepmind, UCL
13:50-14:15	Lena Rosendhal	<i>Using quantum mechanical potential wells to model task sets and its implications for mental effort</i>	PhD Candidate	Princeton University
14:15-14:40	Ivan Grahek	<i>Individual differences in the allocation of mental effort</i>	Post-Doc	Brown University
14:45-15:10	Nele Russwinkel	<i>Workload-over-time modeling in a cognitive architecture</i>	Assist. Prof.	TU Berlin
15:10-15:35	Maria Wirzberger	<i>Cognitive load in instructional design &amp; closing remarks</i>	Assist. Prof.	University of Stuttgart
15:35-16:00	All session presenters	<i>Panel discussion (moderator: Laura Bustamante)</i>		

In this way, we want to foster collaborations across different domains. We also want to give early career researchers the opportunity to present their work in a dedicated poster session (for more information, see our [workshop website](#)). Finally, we plan to invite the participants to collaborate on a review article aimed at outlining the points of consensus and divergence in understanding mental effort.

## Target Audience

The interdisciplinary character of the workshop will appeal to a broad audience, including researchers from psychology, artificial intelligence, economics, clinical science, education and philosophy. Furthermore, the topic of this workshop is paradigmatic for multi-methodical approaches in cognitive science to the same concept, and is designed to attract scholars with expertise in different modeling frameworks who seek to expand their interest to other methodologies.

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