Mental Workload: Assessment, Prediction and Consequences

Christopher D. Wickens[1,2(✉)]

[1] University of Illinois at Urbana-Champaign, Chicago, USA
Wickens@colostate.edu
[2] Colorado State University, Fort Collins, USA

Abstract. I describe below the manner in which workload measurement can be used to validate models that predict workload. These models in turn can be employed to predict the decisions that are made, which select a course of action that is of lower effort or workload, but may also be of lower expected value (or higher expected cost). We then elaborate on four different contexts in which these decisions are made, with non-trivial consequences to performance and learning: switching attention, accessing information, studying material, and behaving safety. Each of these four is illustrated by a series of examples.

Keywords: Mental workload · Human performance · Effort

1 Introduction

A fatigued motorist, driving at night, along a 4-lane motorway decides to change lanes while half of his resources are diverted to a fascinating story about Brexit on BBC. A quick glance at the side view mirror suggests clear passage, but he does not rotate his head and body far enough to “check the blindspot” behind, an implicit decision, or choice of non-action, that throws his car directly into the path of the overtaking car in the next lane. It simply required too much effort to turn his head, and the accident resulted. The concept of effort or mental workload can be examined from three perspectives, those of measurement, of prediction and of consequences. We describe each of these perspectives in turn, show how they are interrelated and then focus our greatest attention on the consequences of high mental workload (MWL), particularly to decision making, as this has, I believe, been an under-represented field of research. To preview, our argument is that an underappreciated value of research on measurement of MWL is has been to provide objective criteria against which to validate predictive metrics of MWL. And the greatest value of such predictive metrics, is to be able to predict the consequences of high mental workload to performance, and particularly the decision to engage in one type of behavior (e.g., risky behavior) over another (e.g., safe behavior). There are of course a multitude of other factors that influence such choices; but the impact of effort is profound, and represents one of the most important ramifications of the MWL field of study. In the following, I will use the term “effort” and “mental workload” interchangeably.

L. Longo and M.C. Leva (Eds.): H-WORKLOAD 2017, CCIS 726, pp. 18–29, 2017.
DOI: 10.1007/978-3-319-61061-0_2

2 Measurement of Workload

In the last half century, there have been hundreds of studies of the measurement of mental workload; and of the four major categories of techniques that can be used to assess the relative demands of tasks on the limited information processing capabilities of the human operator: performance of primary and secondary tasks, subjective measures and physiological measures (e.g., [1, 2]). Many of these were triggered by the foundational book edited by Moray [3]; and Fig. 1 indicates the growth of MWL studies over the last half century with the arrow signaling the acceleration of research. Certainly the recent development of new brain imaging technologies and the neuro-ergonomics approach to MWL have added to this continued growth, which shows little sign of leveling off.

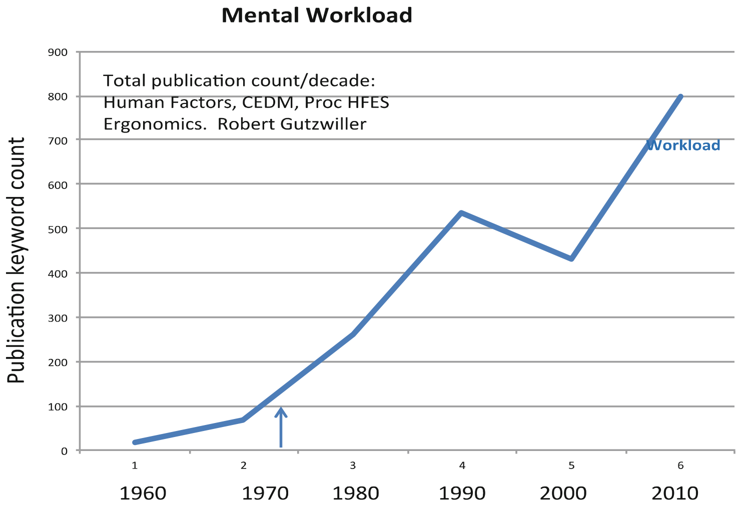

Fig. 1. Growth of the number of workload studies, as published in human factors and ergonomics journals

While I applaud this continued line of research, I cannot help but think that there may be some diminishing returns as progressively more papers appear, often repeatedly examining the same techniques (e.g., NASA-TLX). The workload research community has done a pretty good job of assessments, and it is now time to shift our efforts more toward the most critical application of assessment: the validation of models and metrics of MWL.

3 Predictive Models of Mental Workload

The value of predictive models of human performance and cognition in complex systems is realized because of the problems with systems that are fielded and then may be found out, in human-in-the-loop simulation testing or real world operations to impose excessive demands on the human operator, leading to their disuse or to workload-overload accidents. To prevent such loss of money and more tragically, the loss of life or limb, the problems above can potentially be avoided by harnessing predictive models of workload and multi-tasking capability (See Wickens and Sebok, [4] for a review of such models in aviation). Such models can be of two types: models of how multiple tasks interfere, and their performance breaksdown, such as Threaded Cognition [5] or Multiple Resources [6], and models of how the demands of individual tasks, impose on the limited resources of the performer, such as models of relational complexity [7], of working memory capacity [8], or imposed information processing bandwidth [9].

These metrics have great value because a careful tasks analysis, can reveal properties of task demand that may push performance over "the red line" of MWL where performance begins to suffer, as there is no more spare capacity remaining: the supply of cognitive effort is exhausted. Here again, as with predictive models of workload metrics, they can be implemented before complex systems are built, fielded and then found to be wanting. Their value then is to predict performance breakdowns. Naturally the models of individual task MWL can then feed directly into models of multiple task interference because such models as multiple resources have joint inputs of demand level and competition for common resources as predictors of dual task interference [6].

4 Consequences of High Mental Workload

When workload becomes excessive, three things can happen. First, over the long run, high workload can exert a toll on health and well being; thus workload is often classified, along with such factors as sleep disruption and anxiety as a stressor [10]. Second, when workload is driven over the "red line", performance can start to fail: errors begin to appear when time stress is excessive, or when digital phone numbers exceed the classic 7 ± 2 capacity limits. Third, and the focus of the remainder of this paper, because people are typically effort conserving, often wishing to avoid the stress of high MWL, they often make decisions to avoid high workload; and many of these decisions have major negative consequences to performance.

The underlying framework adopted in the following pages is the decisions that people make to choose between one of two alternatives; one of **higher value**, and the other of **lower effort**. At its most elementary level, we can think of a choice between engaging in a task, for example submitting a job application, which requires a lot of effort, or not doing so, which allows us to relax. Both options have utility. The former clearly leading to the expectancy of income (but not guaranteed, it is risky and may be wasted effort if we are not offered the job). The latter conforms to an inherent effort-conserving tendency exhibited by all species [11, 12]. Indeed this latter option should not be given the pejorative label of "laziness", because in many instances, particularly when resources are scarce, it is adaptive to conserve those resources (avoid effort). The critical influence of the metrics of mental workload, is to help predict the degree of influence of effort conservation on this choice; particularly the extent to which a high-valued option is discarded. That is, to the extent that we can predict both value (or expected value) of one option, versus the effort (saved) by the other, the choice tendency or degree of preference itself can be predicted. In the following, we consider four classes or contexts of choice, and show how they can be driven by effort conservation. These "4 Ss" are the choice:

- To **Switch** attention between tasks.
- To **Seek** information.
- To **Study** material.
- To **Safely** behave.

We consider these diverse applications in order to demonstrate the ubiquity of the concept of effort and mental workload, and the vital role that its prediction and measurement play in all aspects of human endeavor.

4.1 Switching Tasks

Two recent domains of human factors interest – interruption management [13–15] and voluntary task switching (e.g., [16, 17]) have been integrated into a multi-tasking model called STOM (Strategic Task Overload Management; [18, 19]. This is essentially a multi-attribute decision model that predicts, based on four task attributes, which task a person will choose to switch attention to (and hence, by default, which ones they will neglect or avoid), amongst a multi-task ensemble in overload situations. Such might describe the management of an off-shore oil rig disaster [20] or the aircraft pilot trying to handle an in-flight emergency in which troubleshooting, maintaining stability, navigation and emergency communications must all compete for attention. In the STOM model, the attributes of the tasks which are competing for the operators limited attentional capacity are priority, interest, salience and, most important for the current paper, task difficulty.

Two aspects of the STOM model cry out for valid predictive models of task difficulty, MWL or effort demands. First, within the four attributes, difficulty or effort demand has been found to produce a fairly robust influence on task switching: people are inclined to choose the easier of a set of tasks to switch to (assuming that all other attributes are roughly equivalent; [17, 19]. But how much of an influence does difficulty exert relative to other attributes? To determine this, it is necessary to establish a reliable metric of task difficulty, a commodity offered by a well validated predictive model of task load. Second, a fundamental component of the model is that human's have an inherent "switch resistance", or bias to keep doing what they are doing. In extreme, this can evolve into undesirable cognitive tunneling. [21] Such a bias results from the effort costs imposed by the executive functioning that underlies the very decision to switch [18]. When resources are more scarce, as when an ongoing task is more effortful, or when the operator is fatigued, the central executive is less likely to decide to switch at all. Thus the effort, or MWL of a component task in a multi-task ensemble can negatively influence the decision to switch, and if a switch is in fact chosen, what task to switch to.

4.2 Seeking and Accessing Information

As we described above, the STOM model describes the movement of *mental attention* around the "*task space*" in the brain. A model called SEEV (Salience, Effort, Expectancy, Value) is closely related to STOM because it describes the movement of *visual attention* (via some combination of scanning, head movement and body rotation) around the *visual space* in order to acquire information necessary to accomplish a specific task. That is, SEEV is a model of visual scanning [22]. As the second term in the model indicates, this too involves the role of effort in the decision of where and whether to look, in a very vital way.

These two terms, where and whether define different classes of decisions. In the first case, "where", describes an effort function, shown in Fig. 2, that approximates, roughly, the amount of effort required to move the fixation of the eyeballs from straight ahead, to various angles to the side. The function consists of three segments [23, 24] (1) an eye-field, within which there is little effort cost to move the eyes, and minimal increased costs for longer movements up to about 20°. The fact that eye movements are cheap (but not free) is because the eyeball has minimal inertia in rotation. (2) a head field, in which typical neck rotation is required, extending from 20 to about 90°. Here, because of the greater inertia of the head, and the increasing resistance to progressively larger neck rotations, there is a growing cost with increasing eccentricity relative to the forward orientation of the torso. (3) a body field, typically requiring torso rotation, and still greater muscular effort. As these effort costs grow, so does the effort conserving resistance to expending them in seeking information. Hence we can account for the

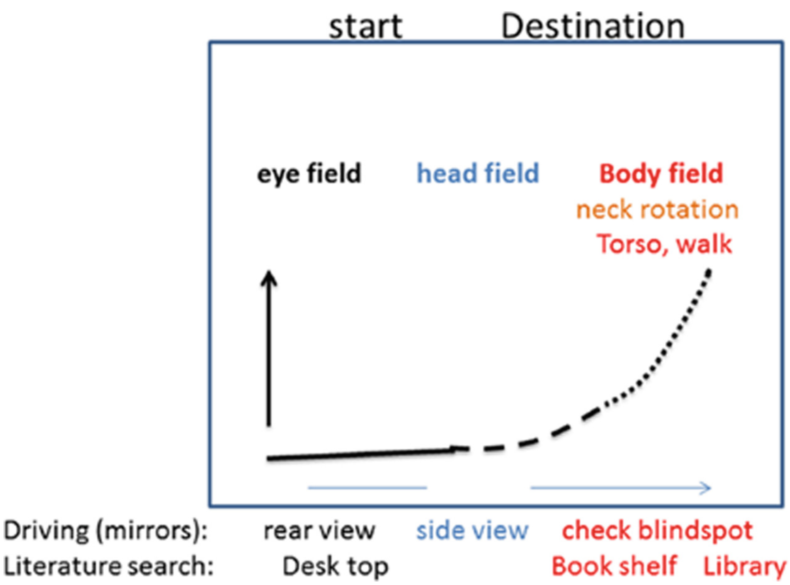

Fig. 2. Information access effort as a function of distance from the forward view: the legends on the X-axis represent the access of two different kinds of information: a view behind a vehicle (top row) and a reference citation (bottom row). From [22].

unfortunate driver's failure to decide to check the blind spot in our opening example, amplified by the added inhibition on this choice imposed when resources for peripheral information seeking were scarce (allocated to listening to BBC, and diminished by fatigue). Thus, in this case, the "where" (looking behind) influences the "whether" (the decision not to scan).

In the above example, the effort-driven decision was whether or not to seek information at all. This decision is also manifest in whether to seek information in the world, or to rely in information "in the head" (i.e., memory; [25]). As an example, I have often decided to trust my memory for the accurate date or spelling of a reference citation in a text that I am typing, rather than to take the effort to look it up, and particularly walk to the book shelf and locate the right book where I know that reference appeared in print. (Clearly the internet and computer are designed to make access to information in the world less effortful). The consequences of effort avoidance in the example of finding the book reference citation are relatively minor, a wrong citation in my text. However sometimes this effort-avoidance choice can have serious safety consequences.

As an example Yang and her colleagues [26] examined a health care professional's important decision, when communicating patient information from a departing to an arriving professional at the medical handover between shifts; this is the decision of whether to consult their memory of patient condition, or to access this information in printed medical records. The former option (knowledge in the head) is less effortful; the latter (knowledge in the world) is more valuable (i.e., more likely to be accurate). While both options were sometimes chosen by participants, a point critical to the argument here is that seeking information in the world (medical records) was significantly (4 times) less likely when those records were 5 m distant from the handover point, than when they were directly in front of the worker. This difference could have serious safety implications given that memory information was also observed to be 23% less accurate. In a second finding of the study, this tendency to sacrifice accuracy over effort conservation was further exacerbated to the extent that participants were overconfident in the accuracy of their memory, thus under-estimating the cost of the effort-reducing reliance on memory. The phenomenon of overconfidence, in biasing toward the low-effort option, will be addressed again in the following section. An important issue illustrated by the above example is the linkage it illustrates between ergonomics above the neck (decision) and below the neck (the effort of walking) [27].

4.3 Studying and Learning

Many of the choices that students make in study strategies result, in part, from the false belief that easier (less effortful) study and learning strategies signal better retention or transfer of learning; that is, higher value [28–32]. In other words, learners have a belief that cognitive ease [12] is a proxy for quality of learning. In the previous two contexts when a user decides on a low effort option, such a decision is arrived at knowing that value or accuracy may be sacrificed as a consequence. However in the case of studying, if it is believed (falsely) that the low effort option is also of higher value, the effort-avoidance tendency is likely to be particularly pernicious. In particular, Table 1

Table 1. Tradeoff of effort and value in study strategies

Lower effort and value (to retention and transfer)	Higher effort and higher value
Massed practice	Spaced practice (contextual interference)
Listening	Note taking (active response generation)
Note taking	Self quizzing (active retrieval practice)
Part task training	Whole task training

provides four examples of contrasting learning or training strategies, listed in each row. On the left is a low effort strategy that mistakenly signals better retention or transfer to the learner. On the right is a contrasting higher effort strategy that has been empirically shown to produce higher retention of studied material or transfer of training of a learned skill.

- Massed practice involves studying a given type of material (or practicing a given task) repeatedly, and doing no studying of alternative material in between trials, or periods of study of this target material. Massed practice does indeed often produce faster learning which makes it seem to the learner like retention should be better. However for longer term retention and transfer, the alternative strategy of interspersing the study/practice of other material proves superior, even though (and perhaps because) this other material provides some contextual interference with the target of study and practice [30] Learning to filter out that interference is a useful skill that can transfer beyond the learning environment.
- Pure listening or reading, even when a lecture or text is engaging and interesting, is easier than taking notes about it, which requires effort; both the physical effort of writing and the cognitive effort of deciding what to write about. Yet it is found that the active generation of responses about something lead to better retention of that material than passively experiencing it, a phenomenon known as “the generation effect” [33]. This generation effect too describes the better retention of a route followed by a driver making active navigational decisions, than that viewed passively by a passenger.
- While note taking comes out better than passive listening; it is also a poorer study strategy when compared to actively quizzing one’s self about the material, following exposure to that material [34–36]. The former can be accomplished through a relatively (mental) effort-lite process of just writing down verbatim what is heard; the latter typically requires the active process of retrieving the material, a skill that will be essential when the material is used in a later context (e.g., in transfer).
- Many complex skills, such as flying an aircraft, translating speech to a different language, or playing an instrument with two hands (e.g., guitar, piano) require concurrent task performance. The easier training strategy, part task training, is to practice each task at a time, a strategy in which capacity is never overloaded. Yet empirical data indicate that despite its greater effort demands, whole task training is more effective for transfer [37, 38].

All of these examples and many more, can be characterized both by the general tendency to reduce effort (choosing the strategy on the left of Table 1), and inflating its subjective value by the simple heuristic: “if its easier to learn, I must be learning it

Table 2. Risky but low effort options (left column) versus safer but high effort options (right column)

Lower effort	Cost of compliance
No seat belt or safety helmet	Time to fasten/discomfort of helmet
Ignore safety instructions	Read safety instructions
Mind wandering while driving	Concentrate on the road
Exploit high degree of automation (of actions)	Perform manually: stay in the loop

better" [27, 28]. The role of effort here, and its measurement, is at the fundamental core of the cognitive load theory of instruction [39, 40]. This theory elaborates the single concept of effort to distinguish between three sources of effort demands (MWL) imposed in the learning environment. (1) more complex tasks intrinsically demand more effort to be performed (intrinsic load). (2) More effort can be invested into the more physically and cognitively challenging but effective strategies on the right side of Table 2: it is productive or "germane" for learning, known as germane load. (3) effort can be demanded in the learning environment that has little effectiveness, it is "extraneous load". Extraneous load might include a clunky interface in computer-based instruction; but could also include features of the learning environment that invite the investment of resources, but have little proven effectiveness in training. Examples include entertaining lecturers who tell several irrelevant jokes or anecdotes, or the introduction of distracting animation [41]. Extraneous load will always consume scarce resources in the learning environment, and hence amplify the undesirable tendency to choose the reduced-effort strategies on the left of Table 2.

4.4 Safe Behavior

We in the human factors community we are advocates for safety, and as psychologists, want to encourage or "nudge" people to make the decision to behave safely [42]. Such decisions often weight the value of safe behavior (and reducing risk) against the utility of effort reduction, or avoiding the "cost of compliance". Four examples of these, expressed in the same framework as in Table 1, are shown in Table 2.

In all of these examples, some effort cost can be attributed to the actions on the right side of the table, although these may be manifest in different ways. In the first example the "discomfort" of wearing a safety helmet is not truly a source of effort demands, but imposes the same sort of negative or unpleasant valence as expending effort, particularly if the driver is experiencing other sources of stress. In the second example, reading long safety instructions on equipment or drug labels is clearly effortful, particularly if they are not well worded and excessive in number. Safety researchers have concluded that the best technique to induce safer behavior is to reduce the cost of compliance. Like the bias to overestimate the benefits (value) of some training strategies discussed above, so also the overconfidence bias to underestimate the expected costs or risks of unsafe behavior ("it can't happen to me" [43], can further amplify the effort-reduction tendencies.

Regarding the third example of safe (or unsafe) behavior, in many boring tasks, such as driving on a straight motorway late at night, and when fatigue diminishes the capacity to mobilize effort, it is quite pleasurable, and we might say subjectively valuable, to engage in mind wandering at the expense of mobilizing effort to stay in the loop, continue to concentrate on the roadway and be vigilant for unexpected hazards; this low effort preference is clearly one factor accountable for the higher per vehicle accident risk exposure in night driving. The fourth contrast in Table 2 is directly related to the third. Higher degrees of automation facilitate the ability to engage in effort-light pleasure like mind wandering. Here "degree of automation" is defined with reference to the taxonomy of automation proposed by Parasuraman and colleagues [44], by which automation can support, and indeed replace progressively later stages of information processing, and at each stage, higher levels of automation can carry out progressively more cognitive work for the human (see also [45]). The combination of later stages and higher levels within stages defines the higher degree of automation. In particular we call attention to the distinction between earlier stage automation, that can integrate information and provide an estimate of the state of the world (supporting situation assessment), and later stage automation, that can recommend, and sometimes execute actions based on that state, supporting or replacing decision making. Since automation decision support must generally be based also on an automated assessment of the state, the lower cognitive effort availed by later stage, than by earlier stage automation is apparent. But here, explicitly, choosing to rely upon automation at all, and choosing to rely on higher rather than lower degrees of automation, is a decision that incurs progressively greater risks (lower expected value) if the automation should unexpectedly fail [46].

5 Conclusions

In all four domains above, effort or MWL imposed by a decision option is seen to negatively influence the degree of preference for, and hence the decision to avoid that option. Generally it is assumed that more effort imposes a negative weight, when balanced against the perceived or actual value of the option; and this is particularly likely when the resources are otherwise scare: depleted by fatigue, or demanded by concurrent tasks. (Of course this is not always the case, and sometimes we do gain intrinsic pleasure and value by investing more effort: the feeling of "flow" in working hard at an engaging interesting task).

Naturally there are also other factors at play to influence the decision of what tasks to attend to, where to look, what to study and whether to behave safely. Prominent among these is a miscalibrated (and often overconfident) estimation of the value of the low effort option (or under-estimation of its expected cost). We saw its operation in both the choice to access information, to study and (not) to be safe. Nonetheless effort is a vital component of all of these decisions, and if we wish to predict such choices accurately in the workplace, in the vehicle and in the schoolhouse, then validated (via assessment) and predictive quantitative metrics and models of mental workload remain of enduring importance [47, 48].

References

1. Young, M., Brookhuis, K., Wickens, C., Hancock, P.: State of science: mental workload in ergonomics. Ergonomics **58**(1), 1–17 (2015). doi:10.1080/00140139.2014.956151
2. Wickens, C.D., Tsang, P.: Workload. In: Boehm-Davis, D., Durso, F., Lee, J. (eds.) Handbook of Human-Systems Integration. American Psychological Association
3. Moray, N.: (ed.): Human Workload: Its Theory and Measurement. Plenum Press
4. Wickens, C., Sebok, A.: Flight deck models of workload and multi-tasking: an overview of validation. In: Vidulich, M., Tsang, P., Flach, J. (eds.) Advances in Aviation Psychology, vol. 1, pp. 69–84. Dorset Press, Dorset (2014)
5. Salvucci, D.D., Taatgen, N.A.: The Multi-tasking Mind. Oxford University Press, Oxford (2011)
6. Wickens, C.D.: Multiple resources and mental workload. Hum. Factors Golden Anniv. Spec. Issue **3**, 449–455 (2008)
7. Halford, G.S., Wilson, W.H., Phillips, S.: Processing capacity defined by relational complexity: implications for comparative, developmental, and cognitive psychology. Behav. Brain Sci. **21**, 803–831 (1998)
8. Engle, R.W.: Working memory capacity as executive attention. Curr. Dir. Psychol. Sci. **11** (1), 19–23 (2002)
9. Hart, S.G., Wickens, C.D.: Cognitive workload. In: NASA Human Systems Integration Handbook, chap. 6 (2010). Workload. Ergonomics **58**, 1–17
10. Hancock, P.A., Desmond, P.: Stress, Workload and Fatigue. Erlbaum, Mahwah (2001)
11. Shugan, S.M.: The cost of thinking. J. Consum. Res. **7**, 99–111 (1980)
12. Kahneman, D.: Thinking, Fast and Slow. Farrar, Straus, Giroux, New York (2011)
13. Trafton, J.G., Monk, C.: Task interruptions. Rev. Hum. Factors Ergon. **3** 111–126 (2007). http://rev.sagepub.com/content/3/1/111.short
14. Salvucci, D.: Multitasking. In: Lee, J., Kirlik, A. (eds.) The Oxford Handbook of Cognitive Engineering. Press, Oxford U (2013)
15. Dismukes, R.K.: Remembrance of things future: prospective memory in the laboratory, workplace and everyday settings. In: Harris, D. (ed.) Reviews of Human factors and Ergonomics, vol. 6. Human Factors and Ergonomics Society, Santa Monica (2010)
16. Janssen, C.P., Brumby, D.P.: Strategic adaptation to performance objectives in a dual-task setting. Cogn. Sci. **34**, 1548–1560 (2010)
17. Kool, W., McGuire, J.T., Rosen, Z.B., Botvinick, M.M.: Decision making and the avoidance of cognitive demand. J. Exp. Psychol. Gen. **139**(4), 665–682 (2010)
18. Wickens, C.D., Gutzwiller, R., Santamaria, A.: Discrete task switching in overload: a meta-analyses and a model. Int. J. Hum.-Comput. Stud. **79**, 79–84 (2015). http://doi.org/10.1016/j.ijhcs.2015.01.002
19. Wickens, C.D., Gutzwiller, R.S., Vieane, A.Z., Clegg, B.A., Sebok, A., Janes, J.: Time sharing between robotics and process control: validating a model of attention switching. Hum. Factors **58**, 322–343 (2016)
20. Flin, R., Slaven, G., Stewart, K.: Emergency dcision makig in the offshore oild and gas industry. Hum. Factors **38**, 262–277 (1996)
21. Wickens, C.D., Alexander, A.L.: Attentional tunneling and task management in synthetic vision displays. Int. J. Aviat. Psychol. **19**, 182–189 (2009)
22. Wickens, C.D.: Noticing events in the visual workplace: the SEEV and NSEEV models. In: Hoffman, R., Parasuraman, R. (eds.) Handbook of Applied Perception. Cambridge University Press, Cambridge (2014)

23. Sanders, A.F., Houtmans, M.J.M.: Perceptual processing models in the functional visual field. Acta Physiol. **58**, 251–261 (1985)
24. Wickens, C.D.: Cognitive factors in display design. J. Wash. Acad. Sci. **83**(4), 179–201 (1993)
25. Norman, D.A.: The Psychology of Everyday Things. Basic, New York (1988)
26. Yang, J., Wickens, C., Park, T., Siah, K., Fong, L.: Effects of information access cost and accountability on medical residents' information retrieval strategy and performance during prehandover preparation: evidence from interview and simulation study. Hum. Factors **57**, 1459–1471 (2015)
27. Mehta, R., Parasuraman, R.: Effects of mental fatigue on the development of physical fatigue: a neurorergonomics approach. Hum. Factors **56**, 645–656 (2014)
28. Koriat, A., Bjork, R.A.: Illusions of competence in monitoring ones own knowledge during study. J. Exp. Psychol.: Learn. Mem. Cogn. **31**, 187–194 (2005)
29. Dunlosky, J., Rawson, K., Marsh, E., Nathan, M., Willingham, D.: Improving students' learning with effective lerning techniques. Psychol. Sci. Public Interest **14**, 4–58 (2013)
30. Putnam, A., Sungkhasettee, V., Roediger, H.: Optimizing learning in college: tips from cognitive psychology. Psychol. Sci. **11**, 652–660 (2016)
31. Healy, H., Bourne, L. (eds.): Training Cognition: Optimizing Efficiency, Durability, and Generalizability. CRC Press, Boco Ratan (2012)
32. Kornell, N., Rhodes, M., Castel, A., Tasuber, S.: The ease-of-processing heuristic and stability bias. Psychol. Sci. **22**, 787 (2011)
33. Slamecka, N.J., Graf, P.: The generation effect: delineation of a phenomenon. J. Exp. Psychol.: Hum. Learn. Mem. **4**, 592–604 (1978)
34. Callender, A., McDaniel, M.: The limited benefits of rereading educational texts. Contemp. Educ. Psychol. **34**, 30–41 (2009)
35. Karpicke, J.: Retrieval based learning: active retrieval promotes meaningful learning. Curr. Dir. Psychol. Sci. **21**, 157–163 (2012)
36. Karpicke, J., Roediger, H.L.: The critical importance of retrieval for learning. Science **319**, 996–998 (2008)
37. Wickens, C.D., Hutchins, S., Carolan, T., Cummings, J.: Effectiveness of part task training and increasing difficulty training strategies: a meta-analysis approach. Hum. Factors **55**(2), 461–470 (2013)
38. Wightman, D., Lintern, G.: Part task training for tracking and manual control. Hum. Factors **27**, 267–284 (1985)
39. Paas, F., Renkl, A., Sweller, J.: Cognitive load theory and instructional design: recent developments. Educ. Psychol. **38**, 1–4 (2003)
40. Paas, F., van Gog, T.: Principles for designing effective and efficient training for complex cognitive skills. In: Durso, F. (ed.) Reviews of Human Factors and Ergonomics, vol. 5, pp. 166–194. Human Factors and Ergonomics Society, Santa Monica (2009)
41. Mayer, R.E., Griffith, I., Jurkowitz, N., Rothman, D.: Increased interestingness of extraneous details in a multimedia science presentation leads to decreased learning. J. Exp. Psychol.: Appl. **14**, 329–339 (2008)
42. Thaler, R., Sunstein, C.: Nudge: Improving Decision Making About Health, Wealth and Happiness. Yale University Press, New Haven (2012)
43. Hertwig, R., Erev, I.: The description-experience gap in risky choice. Trends Cogn. Sci. **9**, 1–7 (2009)
44. Parasuraman, R., Sheridan, T.B., Wickens, C.D.: A model for types and levels of human interaction with automation. IEEE Trans. Syst. Man Cybern. Part A Syst. Hum. **30**(3), 286–297 (2000)

45. Onnasch, L., Wickens, C., Li, H., Manzey, D.: Human performance consequences of stages and levels of automation: an integrated meta-analysis. Hum. Factors **56**(3), 476–488 (2014)
46. Sebok, A., Wickens, C.D.: Implementing lumberjacks and black swans into model-based tools to support human-automation interaction. Hum. Factors **59**, 189–202 (2017)
47. Longo, L.: A defeasible reasoning framework for human mental workload representation and assessment. Behav. Inf. Technol. **34**(8), 758–786 (2015)
48. Longo, L.: Formalising human mental workload as a defeasible computational concept. Ph. D. thesis, Trinity College Dublin (2014)

http://www.springer.com/978-3-319-61060-3

Human Mental Workload: Models and Applications
First International Symposium, H-WORKLOAD 2017,
Dublin, Ireland, June 28-30, 2017, Revised Selected
Papers
Longo, L.; Leva, M.C. (Eds.)
2017, X, 265 p. 70 illus., Softcover
ISBN: 978-3-319-61060-3