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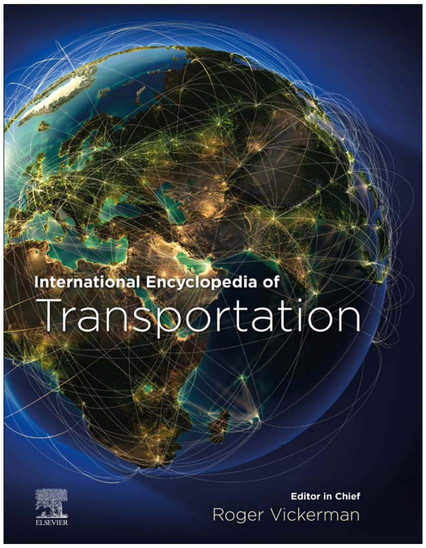

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Driver State and Mental Workload

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Mental Workload

Mental workload is a concept that people can relate to; at the same time, it is not clear whether all have the same concept in mind. For many people the difficulty of a task equals mental workload. In many ways that is not such a bad representation, as difficulty is very subjective. In fact, one of our main points is that; as with physical workload, mental workload depends not only on the task that one has to perform, but also on the person concerned. Therefore the level of mental workload is not constant between or within individuals.

The idea that mental workload can be quantified probably originates from its comparison with physical workload. For physical work, the force required to move an object can be defined in Newton, representing what is required to perform a task. However, it is more difficult to define mental workload. One could try to quantify the information-processing demands (for example, the number of calculations that are required to solve a problem). Crucial, however, is the individual capacity to perform these operations— for physical workload as well; moving 60 kg is easier for a physically fit person than for a fragile child. For physical workload, however, we tend to focus on task demands, while for mental workload we take the capacity to perform a task into account. In other words, with mental workload we must also consider the interaction between task demands (the task to perform) and the capacity to perform the task. The latter, also referred to as mental resources, provides a link to operator state, the background state of an individual. State differs not only between but also within individuals. The same task may require different mental resources for a novice and an experienced person—difficult for the first, easy for the second. Additionally, the capacity to perform a task differs within an individual; for example, after a bad night's sleep the task normally considered routine will be experienced as far more difficult to complete.

This brings us to another important concept in mental workload: effort. Effort is a voluntary process, which can best be described as trying hard. The result of effort can be that the performance is maintained at an acceptable level, that is performance is protected, but internally there are (energy) costs. There are two types of effort: *computational effort*, task-related effort (to deal with the increased demands of a task), and *compensatory effort*, state-related effort (to counteract a deteriorated state). In Fig 1 this is graphically illustrated: it shows the relation between task demands (x-axis) and the level of performance and mental workload (y-axis) (De Waard, 1996).

Above all these considerations is self-regulation: deciding how the different task demands are managed. This can mean accepting a lower level of performance or changing to a more efficient strategy to accomplish the goal.

In sum, task demand is a property of the task to be performed. Mental resources are the capacity to perform a task, and they depend on short- and long-term factors such as experience and operator state. With the investment of mental effort, performance can often be kept at an acceptable level. Investment of effort is an effective mechanism, but it incurs costs so it cannot be continued over long periods of time.

The next section focuses on car driving.

Mental Workload During Driving and Driver State

During a drive, a driver's task demand can vary substantially, for example, the drive can start in a busy city but then continue on a quiet highway. In addition, each individual driver has certain characteristics, some may be novice, some professional, or, the most likely, somewhere in between. For a novice, protecting performance (driving safely without getting into a collision) can require continuous effort investment taking up most of their mental capacity, while for the professional enough mental capacity is left over to do other things, such as operating the radio. During a journey, driver state is also likely to change. Driver state is the driver's mental and physical condition, often reflected in physiological parameters such as an electroencephalogram (EEG). The environment plays an important role here. While monotonous, quiet highways at night are ideal circumstances for driver state to deteriorate, the opposite—when roads are extremely busy—could overload drivers. Imagine being overloaded by information in an unfamiliar city and trying to find your way with an uncooperative navigation device that continues to ignore the roadwork and keeps on nagging that you should turn left when turning left is not possible. On the other hand, low task demands could stimulate drivers to do things other than driving, such as using their mobile phone. The question is: how can we ensure optimal driving performance under these very different circumstances in order to secure safety and comfort? The driver who can regulate task demands also plays a role. For example, many older drivers seek to keep task demands low by avoiding complex traffic situations, such as driving at night, or adverse weather. However, if the weather suddenly changes or the preferred familiar road is closed, task demands may become very high for them, and bring them in an uncomfortable situation. The main message, however, is that people adapt to the tasks they perform in a way that in their perception is comfortable and not stressful.

Mental Workload and Driver State in Partly Self-Driving Vehicles

We are currently transitioning towards fully automated driving (Van Nes and Duivenvoorden, 2017). In the meantime, the use of driver support systems has increased, and an increasing number of vehicles are partly self-driving (also referred to as semi-automated), meaning the automation can take over part of the driving task or even that the car can drive by itself in certain conditions (the autopilot function for the highway). New systems are constantly being introduced to support the driver in the driving task. Systems such as Advanced Cruise Control (ACC) and Lane Keeping Systems (LKS) take over parts of the driving task; the ACC removes the mental load of maintaining a certain speed and keeps a safe distance from a lead vehicle, while the LKS takes care of lateral positioning. As more systems are introduced, more tasks are being taken over by automation. The role of the driver is slowly shifting from operator of the vehicle to a supervisory role, which is extremely monotonous. As a result, even though the task demands and mental workload are reduced, supervising a (partly) automated vehicle without an active role has a negative effect on driver state. From a safety perspective, the priority is to keep driver workload in the "optimal performance" window (central area in Fig. 1). State-related efforts to maintain the performance for longer periods of time should be avoided, but drops in performance (right hand side of the graph) are even worse.

Another potential risk is introduced by the temporary increase in task demand created by these systems themselves. Each system communicates to the driver in some way, giving warnings (blind spot warning, forward distance warning, etc.) and/or indicating the status of the system (on, off, or changing). With an increased number of systems, communication demands also increase. Different signals can be confusing or contradictory, leading to increased mental workload. Another increase in workload is caused by the fact that the driver has to be continuously aware whether systems are on or off and understand the systems' limitations—and check whether these may apply. It is therefore just as important to avoid too much increase in mental workload due to task-related effort requirements (Fig. 1).

Clearly, the use of driver support systems and partly self-driving vehicles impact task demand, leading to possible overload or underload, two situations that impact driver state and task demands. Thus there is the risk of leaving the optimal performance window, resulting in degraded driving performance. In the transition towards higher levels of vehicle automation, it is crucial to mitigate this risk and ensure drivers stay within the optimal performance window. Every level of automation should be designed in such a way that the optimal performance window is respected, which would require settings that can be changed.

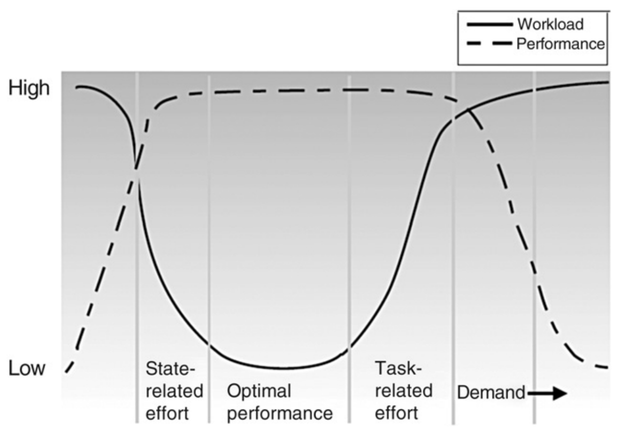

Figure 1 Increasing task demands (*x*-axis); task performance, and mental workload (*y*-axis). *Source: From De Waard (1996).*

Clearly, higher levels of automation offer the opportunity to mitigate driver workload. An interesting way to manage this effect would be to continuously monitor driver state during a trip to determine if it stays within the optimal performance window, and take measures if needed.

Assessment of Mental Workload and Driver State

Given the potential negative effects of mental underload/overload on driving behavior and safety, correct assessment of the driver's mental workload and state are crucial. There are three types of measures that can provide an indication of mental workload and driver state: performance, self-reporting, and psychophysiology (Paxion et al., 2014).

Performance

An assessment of mental workload and driver state should start with driving performance. In driving, primary task performance is reflected in lateral and longitudinal control. Both lateral control, that is the lateral lane position, and its variability (standard deviation of the lateral position: SDLP) have been used for a long time to reflect driver state. SDLP is sensitive to many factors, including the use of sedative drugs such as alcohol, distraction, and fatigue. Mean lateral position can reflect strategic choices: it has been shown that drivers who noticed the sedative effects of medicinal drugs drove closer to the emergency lane, where more space is available. Longitudinal control is reflected in the vehicle's speed and speed variability and distance to other vehicles (time headway). The latter measure is always in interaction with other vehicles and frequently a car following test is used where a lead car changes speed and needs to be followed at a close but safe distance. In this test, driver response time (delay in sensitivity to speed changes) can be calculated (Brookhuis et al., 1994).

In addition to primary task performance, which reflects the behavior to control the vehicle safely, there is secondary task performance. Secondary tasks are frequently used by researchers "to fill up the capacity of the driver." The idea is that with an extra task that is demanding, the driver will no longer have the spare capacity that is usually not required for normal driving. Instead, the secondary task will require this spare capacity, causing performance on either the primary driving task or the secondary task to deteriorate. In this way we are able to see, for example, which parts of a route are more demanding and resulted in higher workload. For the secondary task an artificial task is very often used. One such example is the N-back task: the driver has to remember a stimulus (a letter or a figure, the target) that was presented N stimuli back, and indicate whether it is presented again. The target has to be updated continuously. As N increases, the task can become very demanding. Another example is the peripheral detection task: drivers have to respond to a light that is presented in their peripheral vision. Both techniques are popular, but they also have major drawbacks. To start with, they are artificial. During normal driving you do not have to keep a memory set in mind and respond to it. Even though the peripheral detection task has some ecological relevance in the sense that a driver may have to respond to stimuli in the periphery, the task is still artificial because in normal traffic this need is seldom a continuous task (and the stimuli are, for example, pedestrians or other cars, not a red light). In other words, normal driving may be distorted. Moreover, we do not know which task the driver prioritizes, the secondary task or the primary task. However, there are embedded secondary tasks (that are part of normal driving): an example is mirror checking. Glancing in the rear-view mirror is a part of safe driving, but it is not a crucial task if one is not changing lanes. It has been shown in on-road experiments that the frequency and duration of mirror checks can change. For example, the frequency drops if the driver is operating a telephone or driving in a busy environment.

Thus, primary task performance (vehicle control) must be assessed when evaluating mental workload. If a secondary task is used, it should be clear that it does not affect normal driving, which in practice is difficult. An embedded secondary task is preferred.

Self-Reports, Subjective Measures

Asking how demanding a situation was for a driver has always been a popular technique to assess workload. It definitely makes sense to ask people how they experienced a situation, as this gives information that cannot be assessed in any other way. Simple, one-dimensional scales such as the Rating Scale Mental Effort can assess the experienced mental workload (and the effort invested). The popularity of self-reports may also be due to the ease and low cost of the technique. However, when assessing mental workload, self-reports are not enough (De Waard and Lewis-Evans, 2014; Matthews et al., 2019). For example, to know whether performance was protected by the investment of mental effort, one needs some objective measure of performance, in addition to the self-reported measure of workload.

Self-reports are also useful for assessing driver state: fatigue and sleepiness can be scored on a validated scale such as the Karolinska Sleepiness Scale. But again, just as with mental workload, a self-report of driver state is not enough, nor is it always accurate. Simply put, if drivers were able to evaluate their state correctly, why would accidents with drivers who fall asleep still happen? Another disadvantage of self-reports is timing: either normal behavior needs to be interrupted to obtain a rating, or ratings have to be given in retrospect after completing a (part of the) drive, which means they may be impacted by memory decay.

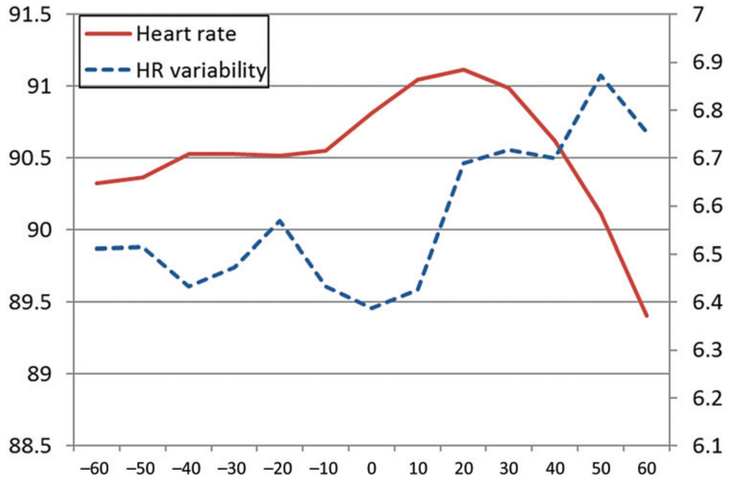

Figure 2 Example of a psychophysiological measure. Average heart rate in beats/minute (left axis) and variability of heart rate (HR Variability) in the 0.10 Hz frequency band (right axis, Ln-transformed, unit MI^2). The averaged values of 24 participants performing a merge maneuvers (at $t = 0$ s) in their own car are depicted. On the *x*-axis, time is depicted in seconds. In general heart rate increases while variability decreases with increased mental effort.

Physiology

The ability to register how the driver responds physically to certain situations makes psychophysiological measures very attractive as indicators of mental workload or driver state (Hughes et al., 2019; Mehler et al., 2012). There is a broad range of measures, some requiring more advanced equipment than others. Heart rate and heart rate variability are relatively easy to assess, even though for the latter higher measurement accuracy is required. Average heart rate alone can reflect increased effort investment and reduced driver state. For driver state, measures that reflect Central Nervous System activity, such as EEG (electroencephalogram), are more accurate, but they are also more intrusive than Peripheral Nervous System activity measures, such as electro dermal activity and heart rate.

Some of these measures give the impression that they are objective and reveal the truth. In practice, this is not the case. These measures simply reflect how we respond to situations after interpreting them, and in that sense could just as well be called subjective measures. Apart from the fact that some require almost esoteric knowledge to administer and interpret them, a major disadvantage is that their reliability can be severely impacted by artifacts (disturbances that are not part of the physiological signal of interest, occurring as a result of movement, for example). On the other hand, an advantage of these measures is that many of them can be collected and interpreted continuously, so they can potentially be used in (partly) self-driving cars for monitoring purposes.

Fig. 2 illustrates how heart rate can reflect the performance of an effortful maneuver in traffic. A relatively high heart rate from the beginning reflects mental preparation; the heart rate variability is reduced in this condition, signifying higher mental effort. After the effortful maneuver, the heart rate slows down and the variability increases—both reflect less mental effort as the driving circumstances become less demanding.

Interpretation of Measures

Different measures can reflect different processes and driver states. For several reasons, it is important not to focus on one measure only. Different measures can and will diverge, which actually helps to interpret how the driver handled the situation. For example, the previously mentioned protection of performance should, by definition, show no primary task performance deterioration, while other measures such as self-reports or physiological measures can indicate an increase in mental workload. Furthermore, not all measures are equally sensitive or sensitive to the same task demands. For example, self-reports reflect investment of extra effort in conditions of both state- and task-related effort, while a physiological measure, such as heart rate variability, is only sensitive to task-related effort.

One would expect performance in the central area of Fig. 1 to be optimal; however, there are conditions related to self-regulation which could further improve performance. For example, while driving on a wide highway lane there is no need to minimize SDLP (swerve as little as possible)—however, with increased task demands drivers may actually swerve less, improving performance as a result of being extra activated. This somewhat counter-intuitive finding should be kept in mind when interpreting data: drivers have a lot of freedom to regulate their behavior, not only with regard to performance, but also at higher levels, depending on the goals they set. Self-regulation can also lead to other changes in behavior: drivers may decide to avoid situations that increase attentional demands, deciding, for example, not to drive during adverse weather conditions or on unfamiliar roads. In terms of traffic safety this can be a positive effect for drivers with limited experience (graduated licensing) and may extend mobility for drivers who suffer from mild cognitive impairment.

Conclusion

Driver state and workload demand can both affect performance, and thus driving safety. New advanced in-car systems that support, or even take over, parts of the driving task have the potential to make driving safer, but at the same time they affect driver workload and driver state. Before fully automated driving is realized, increasing levels of partial automation will continue to transform the driving task into a monotonous supervisory task, which can lead to driver underload. This state is obviously suboptimal and can jeopardize safety. On the other hand, as vehicles become more automated, if the driver needs to monitor many systems which are not well integrated, then the opposite effect— driver overload—could occur. To avoid both undesirable conditions, automation at all levels must be designed to provide optimal task demands, and this requirement must be tested prior to its introduction on the road. One promising way to optimize task demand is to dynamically adapt the driver's tasks on the basis of driver state and adaptive automation. In conditions where demands are high and overload is possible, tasks are taken over by automation to reduce the mental workload. In conditions where demands are low and underload lurks, tasks are handed back to the driver. In this way, the driver's performance is kept at the top of the inverted U in Fig. 1.

Importantly, we should take multiple measures when we evaluate mental workload in experimental or naturalistic conditions, such as when investigating the effect of adaptive automation on mental workload (Van Gent et al., 2018). There is no single measure that reflects mental workload over the full range. Each measure is sensitive and not to all changes in task demand; the patterns that emerge from performance measures, self-reports (in experimental studies), and physiological parameters can provide a good indication of driver's mental workload and state.

See Also

Elderly driver safety issues; Human Factors in Transportation; Sleep-related Issues and fatigue; Education and Training of drivers; Drugs, illicit and prescription (Rune Elvik)

References

Brookhuis, K.A., De Waard, D., Mulder, L.J.M., 1994. Measuring driving performance by car-following in traffic. Ergonomics 37, 427–434.

De Waard, D., 1996. The measurement of drivers' mental workload. PhD thesis, University of Groningen. Haren: University of Groningen, Traffic Research Centre. Open access: https://www.rug.nl/research/portal/files/13410300/09_thesis.pdf.

De Waard, D., Lewis-Evans, B., 2014. Self-report scales alone cannot capture mental workload. A reply to De Winter, Controversy in human factors constructs and the explosive use of the NASA TLX: A measurement perspective. Cog. Technol. Work 16, 303–305, doi:10.1007/s10111-014-0277-z.

Hughes, A.M., Hancock, G.M., Marlow, S.L., Stowers, K., Salas, E., 2019. Cardiac measures of cognitive workload: a meta-analysis. Hum. Factors. DOI: 10.1177/0018720819830553.

Matthews, G., De Winter, J., Hancock, P.A., 2019. What do subjective workload scales really measure? Operational and representational solutions to divergence of workload measures, Theor. Issues Ergon. Sci. DOI: 10.1080/1463922X.2018.1547459.

Mehler, B., Reimer, B., Coughlin, J.F., 2012. Sensitivity of physiological measures for detecting systematic variations in cognitive demand from a working memory task: an on-road study across three age groups. Hum. Factors 54, 396–412, doi:10.1177/0018720812442086.

Paxion, J., Galy, E., Berthelon, C., 2014. Mental workload and driving. Front. Psychol. 5, 1344, doi:10.3389/fpsyg.2014.01344.

Van Gent, T., Melman, H., Farah, N., van Nes, B., van, Arem., 2018. Multi-level driver workload prediction using machine learning and off-the-shelf sensors. Transp. Res. Rec. 2672 (37), 141–152, doi:10.1177/0361198118790372.

Van Nes, N. van, K. Duivenvoorden, 2017. Safely towards self-driving vehicles. New opportunities, new risks and new challenges during the automation of the traffic system. R-2017-2E. SWOV, The Hague.

Further Reading

Brookhuis, K.A., De Waard, D., Fairclough, S.H., 2003. Criteria for driver impairment. Ergonomics 46, 433–445.

Schwarz, J.F., Ingre, M., Fors, C., Anund, A., Kecklund, G., Taillard, J., Philip, P., Åkerstedt, T., 2012. In-car countermeasures open window and music revisited on the real road: popular but hardly effective against driver sleepiness. J. Sleep Res. 21, 595–599.

Sparrow, A.R., LaJambe, C.M., Van Dongen, H.P.A., 2019. Drowsiness measures for commercial motor vehicle operations. Accid. Anal. Prev. 126, 146–159.