RESEARCH PAPER

Methodological Insights into Measuring Mental Workload in Radiological Reporting Using Applied Psychology Tools

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Abstract
Radiological reporting represents a critical analytical stage within modern diagnostic pathways, relying on sustained visual–cognitive processing to transform complex imaging data into clinically actionable outputs. As imaging volumes and diagnostic complexity continue to increase, understanding and measuring mental workload has become essential for evaluating human-centered sources of analytical variability that may influence diagnostic reliability. This review provides a methodological synthesis of applied psychology tools used to assess mental workload in radiological reporting, with particular emphasis on their relevance to applied bioanalysis. The article examines the conceptual foundations of mental workload, distinguishing it from cognitive load and situating it within established theoretical frameworks, including Multiple Resource Theory and Human Information Processing models. It systematically evaluates subjective self-report instruments, performance-based and behavioral measures, physiological and neuropsychological indicators, and multimodal assessment approaches, highlighting their respective analytical strengths, limitations, and contextual dependencies. Special attention is given to how these methods capture different dimensions of workload, including temporal, cognitive, emotional, and visual–perceptual demand. By framing radiological interpretation as an analytical output influenced by human cognitive state, this review positions mental workload as a measurable analytical variable analogous to sources of variability in laboratory bioanalysis. The synthesis underscores the importance of multimodal assessment strategies and methodological standardization to support robust evaluation of diagnostic performance. Overall, the review contributes a bioanalytically grounded framework for integrating cognitive workload measurement into diagnostic quality assurance and analytical reliability research.

Keywords: mental workload; radiological reporting; applied bioanalysis; cognitive performance variability; diagnostic quality assurance; multimodal workload assessment

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Introduction

Radiological reporting is a process that can be described as cognitively intensive part of modern clinical diagnostics that involves anti-cyclic visual data and aids radiologists to translate such data into analytical results which directly impact clinical decision-making. With the current developments in imaging technologies, such as multidetector computed tomography, high-field magnetic resonance imaging, and hybrid imaging systems, the volume, resolution, and dimensionality of imaging datasets have increased significantly. Consequently, radiologists regularly have to read hundreds to thousands of images per scan, combine the image information with clinical and laboratory data, and make accurate diagnostic reports with significant time constraints (Roser *et al.*, 2018; Krupinski *et al.*, 2020).

The high growth in imaging usage has exacerbated diagnostic workloads in healthcare systems especially in high throughput imaging in emergency radiology, oncology imaging, and population-based screening programs. These are environments that require short turnaround time without reducing the analytical accuracy and consistency. The sustained constraints of such conditions of operations to visual perception, allocations of attention, working memory and decision making are usually compounded by interruptions and switching of tasks. Medical imaging and cognitive science evidence constantly proves that radiological interpretation is a delicate visual-cognitive process that is extremely sensitive to changes in mental load and fatigue (Krupinski, 2014; Waite *et al.*, 2017).
Mental workload is usually defined as a ratio between task requirements and mental resources possessed by an

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operator at a particular time. Cognitive overload can happen when there are task demands that surpass the resources available to them and this results in decreased attentional control, slower processing of information and higher error rates. On the contrary, small workload may lead to cognitive underload, which is defined by a lack of vigilance and attentional disengagement, and can deteriorate the reliability of performance as well (Young and Stanton, 2015). Overload and underload have been linked to perceptual and interpretive error in radiological practice and supporting an optimal cognitive operating range through which diagnostic accuracy and consistency is ensured (Waite *et al.*, 2017). Healthcare and human factors research also show empirical evidence that there is a strong correlation between sustained mental workload, fatigue and degradation of performance. The systematic reviews revealed that chronic cognitive load is a contributing factor to attentional lapses, impaired working memory, and lower quality of decisions made by medical workers, which have a direct effect on the diagnostic safety and well-being of clinical workers (Golubic *et al.*, 2020). In addition to the behavioral indicators, complementary physiological studies prove that fatigue-related fluctuations in visual attention and eye-motions patterns indicate cognitive effort escalation in full-term visual tasks, which are objective evidence of workload-related vulnerability of diagnostic performance (Marandi *et al.*, 2018).

In terms of applied bioanalysis, radiology is a very important endpoint of analysis in a diagnosis pathway. Although bioanalysis has traditionally focused on measuring things with help of molecules, using analytical instrumentation, and validating assays, diagnostic accuracy is eventually displaced on the dependability of human understanding of complicated data streams. It is possible to therefore conceptualize radiological reports as analytical deliverables that are analogous to laboratory test results where the variability of cognitive state can bring about an interpretive disparity similar to the analytical variance in bioassays (Krupinski *et al.*, 2020). Mental workload therefore, is a human-focused analytical variable which may affect the reliability of diagnosis, reproducibility, and consequential clinical decisions.

In recent interdisciplinary studies, it has become important to incorporate cognitive and behavioral aspects of diagnostic quality assurance frameworks because, despite technical accuracy, the analysis will not necessarily produce strong result outcomes (Zhou *et al.*, 2022). Mental workload measurements offer a methodological means of determining cognitive bottlenecks, the optimization of diagnostic processes, and helping to create safer and more resilient systems of analysis. This view is very much consistent with the aims of applied bioanalysis, which aim at maximizing the validity, reproducibility, and strength of the processes of analyses in clinical settings.

Applied psychology provides various tested methods of measuring mental workload such as subjective rating scale, performance based measurement as well as physiological measurement. NASA Task Load Index is one of the most popular tools used in the healthcare sector to represent dimensions of perceived workload, whereas objective tools like eye-tracking or a heart rate variability may also offer a complementary perspective on attentional demands and cognitive effort (Buchanan and Short, 2021; Longo, 2018). Nevertheless, the use of these tools in radiological reporting is still highly diverse methodologically with significant differences in the study design, ecological validity and interpretation of the results.

This is required because of the growing complexity of radiological workflow and the growing focus on the quality of diagnoses and patient safety, a methodological synthesis of mental workload measurement strategies is justified. The paper is a critical review of the applied psychology instruments that were applied to measure mental workload in radiological reporting, focusing especially on theoretical backgrounds, methodological advantages and limitations. This review will offer methodological advice to the researchers and clinicians as well as establish future directions of integrating cognitive workload assessment into diagnostic quality assurance systems by synthesizing insights of applied psychology, human factors engineering, and bioanalysis.

Conceptual Foundations of Mental Workload

Mental workload is a fundamental concept of human factors and applied psychology since it defines the mental effort involved in executing a task under certain operational circumstances. Mental workload is especially applicable to applied diagnostic environments as it is the measure of the relationship between task demands, environmental constraints, and the available cognitive resources accessible to the human operator at one point. Even though the term is commonly used interchangeably with that of cognitive load, the two concepts have different sources of theories and are used to analyse different issues. The concept of cognitive load is one area of educational psychology, which mainly deals with the influence of information-processing load on the working and learning memory capacity (Sweller *et al.*, 2019). Conversely, mental workload involves instantaneous cognitive tasks on task performance and thus more directly relatable to complicated clinical and analytical work procedures where performance dependability is highly important (Young and Stanton, 2015).

This difference is particularly relevant in the case of radiological reporting, where visual perceptions and integrative reasoning and time-conscious decision-making are maintained but not learning processes. Although cognitive load theory focuses on intrinsic, extraneous, and germane cognitive processing loads, mental workload also focuses on temporal pressure, emotional load, and complexity. These dimensions are inherent to the real-life diagnostic setting where the complexity of the data can be affected by the workflow design, the organization limitations, and operational conditions (Buchanan and Short, 2021). In turn, the mental workload offers a more holistic and operationally important conceptual framework of operating variability in diagnostic performance and analytical reliability.

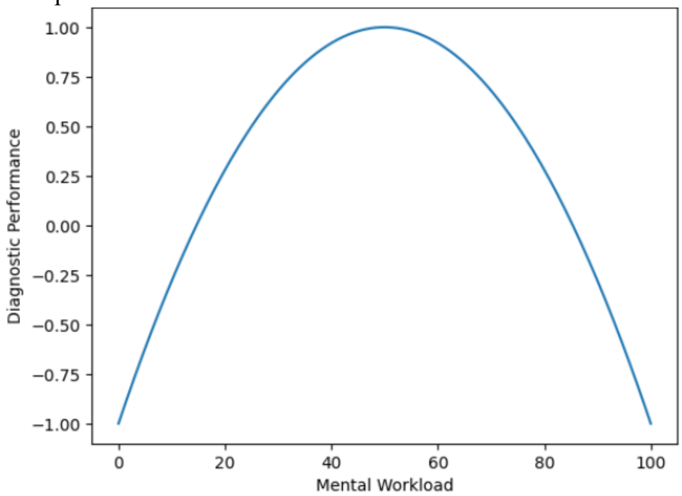

Figure 1. Conceptual inverted-U relationship between mental workload and diagnostic performance.

Figure 1 illustrates the conceptual inverted-U relationship between mental workload and diagnostic performance in radiological reporting. When workload is increased between low to moderate levels, diagnostic performance is improved because of the increased engagement and sustained attention, and resourceful use of cognitive resources. Nevertheless, under overload or when workload surpasses cognitive capacity, the performance becomes poor due to overload, fatigue, and the perception and interpretative error vulnerability.

The majority of mental workload models are based on the relationship between task demands and capacity of operators. Task demands refer to features that relate to objective tasks like the amount of information, the diagnosis, and the pace of the work that one can perform at a specific moment, whereas the operator capacity is the reference to the cognitive resources that a person can assign at a particular moment. The operators capacity is influenced by expertise, fatigue, stress, and inter-individual discrepancies, which are all of great importance in clinical diagnostic practice (Wickens, 2017). Mental workload grows when the demands of the tasks are on or surpass the cognitive resources available, and thus, the risk of low processing efficiency and lack of analytical reliability.

What is important is that this is a non-linear relationship. Too many task demands may cause cognitive overload, which is an upsurge in the number of attentional lapses and interpretive mistakes, just as too few may cause cognitive underload and less vigilance and disengagement (Young and Stanton, 2015). In applied bioanalysis terms, such theoretical bases warrant the view of mental workload as an analytical variable (human-based) that is measurable and contributes to the variability of diagnosis and results in quality assurance.

Table 1. Conceptual foundations of mental workload relevant to radiological reporting and applied bioanalysis

Dimension	Mental Workload	Cognitive Load	Relevance to Radiological Reporting	Implications for Applied Bioanalysis	Key References
Theoretical origin	Human factors and applied psychology	Educational and cognitive psychology	Mental workload reflects real-time cognitive demands during image interpretation and reporting	Supports treating human cognition as an analytical variable influencing diagnostic outputs	Young & Stanton (2015); Sweller *et al.* (2019)
Core definition	Dynamic relationship between task demands and available cognitive resources	Load imposed on working memory by information processing requirements	Captures fluctuating demands during continuous visual analysis and decision-making	Enables assessment of cognitive variability affecting analytical reliability	Wickens (2017); Young & Stanton (2015)
Primary focus	Task execution under	Learning, comprehension,	More suitable for evaluating clinical	Aligns with bioanalytical	Sweller *et al.* (2019);

	operational constraints	and schema acquisition	performance rather than learning processes	emphasis on process reliability rather than training outcomes	Buchanan & Short (2021)
Key components	Mental, temporal, emotional, perceptual, and stress-related demands	Intrinsic, extraneous, and germane load	Reflects combined impact of image complexity, time pressure, and workflow design	Facilitates multidimensional assessment of diagnostic variability	Wickens (2017); Paas & van Merriënboer (2020)
Sensitivity to environment	Highly sensitive to workflow, interruptions, fatigue, and system design	Less sensitive to operational and environmental factors	Suitable for real-world radiology environments with high contextual variability	Supports ecological validity in applied diagnostic bioanalysis	Buchanan & Short (2021); Young & Stanton (2015)
Analytical utility	Measurable using subjective, behavioral, and physiological tools	Primarily inferred from task design and learning outcomes	Enables continuous or task-level workload assessment during reporting	Enhances diagnostic quality control frameworks	Longo (2018); Wickens (2017)

The major differences in the conceptual differences that form the basis of mental workload are summarized in Table 1 which includes the relationship between mental workload and cognitive load, task demands and operator capacity. These constructs are put into context in the table by radiological reporting, which shows the relevance of these constructs as human-based analytical variables in diagnostic reliability.

Key Theoretical Frameworks

The measurement and interpretation of mental workload in a complicated clinical setting is based on several theoretical frameworks of applied psychology and cognitive science. These frameworks are useful in radiological reporting not due to their theoretical abstraction but due to their structured models of how cognitive demands may affect the results of analytical performance and diagnostic reliability. Some of the most influential include Multiple Resource Theory, Cognitive Load Theory, and Human Information Processing models, each of which provides a complementary viewpoint, which is applicable to the workload assessment.

Multiple Resource Theory views human cognition as depending on a variety of partially independent pools of processing resources in terms of sensory modality, representational form and processing level. Based on this framework, performance degradation takes place more in situations where component elements of a task compete to share the same pool of resources as opposed to being a factor of the total task demand. This view is very applicable to the radiological reporting where visual perception, spatial thinking, memory retrieval, and decision-making are usually simultaneous. As an illustration, concurrent interpretation of several series of images as they are produced and reports are generated may result in intra-modal competition that proportionately excessively loads the mental processing resources and decreases efficiency at the expense of analytical processing. Measurement wise, this framework justifies the application of multidimensional workload measures that can measure modality-specific cognitive demand.

Cognitive Load Theory offers an additional framework by focusing on the impact of task organization and the presentation of information on the working memory capacity. It differentiates intrinsic load, which is related to task complexity; extraneous load, which is presented by inefficient system or interface design; and germane load, which is linked to schema development and gaining of expertise (Paas and van Merriënboer, 2020). In radiological processes, intrinsic load indicates the complexity of images and uncertainty in diagnosis, whereas extraneous load can be because of a badly designed workstation, incomplete displays, or ineffective navigation. This framework comes in handy especially when defining workload measures in connection to the quality of the system design and the sources of analytical strain that can be avoided.

The Human Information Processing models also play a role of conceptualizing thinking as a series of processing stages encompassing perception, memory and choice of response. These models underline the constraints in time and processing bottlenecks and focus on the fact that congestion in any of the stages can be harmful to the overall performance of the tasks. Through radiological reporting, these bottlenecks can be in the form of perceptual oversights or slow decision making. All of these frameworks together underpin the use of mental workload as a quantifiable predictor of analytical performance in order to inform the choice and analysis of workload measures in applied bioanalytical settings.

Dimensions of Mental Workload

Mental workload is a construct of multiple dimensions with interconnected dimensions that together contribute to the level of performance in the intricate analytical settings. These dimensions are dynamically interrelated in clinical diagnostics, and especially in radiology reporting where they can variously influence the analytical accuracy, efficiency and reproducibility. Workload dimensions should be well characterized thus playing an imperative role in choosing the right measurement metrics and their interpretation in relation to quality of diagnostic outcome.

Temporal demand is the time pressure created by task pacing, task deadlines and task interruptions. The temporal demand is high limits the amount of time that can be allocated to process, verify and recover information and in most cases under the circumstances; quick decisions have to be made. High time demand may impose a greater cognitive load and less potential error check in diagnostic imaging settings, where turnaround time is a key operational indicator. Regarding the applied bioanalytical field, too much time pressure can cause variability in interpretive results similar to time-varying variability in analytical assays.

Cognitive demand is the mental load involved in information processing, retrieval of information, problem solving and decision making. High information density, diagnostic ambiguity, or complex reasoning tasks are very demanding in terms of cognitive requirements. In radiological reporting, it is due to the interpretation of huge volumes of images and the combination of multimodal clinical information and the synthesis of results into a diagnostic conclusion. Once cognitive demand becomes equal or even greater than the available cognitive resources, processing efficiency reduces, making one more vulnerable to interpretive error and inconsistent analysis.

The mental workload is also comprised of emotional and stress elements, which involve the affective reaction of anxiety, frustration, and long-term mental stress. The given reasons are especially applicable to the health care context where the diagnostic responsibility and possible outcomes of error cause psychological stress. Stress-related work load on chronic basis has been associated with fatigue, burnout and diminished cognitive resilience, which indirectly undermines attentional control and decision consistency.

Visual-perceptual workload is a unique and critical aspect of radiology, which occurs due to prolonged searching of the visual field, identification of the pattern, and space interpretation of images. Image complexity, subtle findings, and long viewing times are associated with a higher visual workload. Medical image perception studies have shown that high visual workload places a strain on attentional resources and predisposes perceptual oversights especially in cases of fatigue (Krupinski *et al.*, 2017).

A combination of these aspects highlights the importance of multidimensional workload evaluation plans. To apply bioanalysis, the measurement of these elements helps to gain a more detailed vision of what human cognitive factors are behind the differences in diagnostic results and strengthen mental work as a measurable variable of the quality of analysis.

Methodological Approaches to Measuring Mental Workload

Table 2. Overview of Major Methodological Approaches for Measuring Mental Workload in Radiological Reporting

Measurement Category	**Method / Tool**	**Primary Workload Dimensions Assessed**	**Analytical Strengths**	**Key Limitations**	**Representative References**
Subjective Measures	NASA Task Load Index (NASA-TLX)	Mental, temporal demand; effort; frustration; perceived performance	Easy to administer; multidimensional; sensitive to task and system changes	Retrospective bias; inter-individual variability; limited temporal resolution	Hart & Staveland (2019); Buchanan & Short (2021); Longo & Orru (2021)
Subjective Measures	SWAT	Time load; mental effort; psychological stress	Sensitive to time pressure and stress; structured scaling	Complex setup; less commonly used in radiology	Grier (2015); Longo & Orru (2021)
Subjective Measures	RSME / VAS	Perceived mental effort or stress	Rapid assessment; low burden; suitable for repeated measures	Unidimensional; limited diagnostic specificity	Ayres (2020); Lesage *et al.* (2019)
Performance-Based Measures	Reporting time; diagnostic accuracy; error rates	Cognitive demand; efficiency; performance degradation	Directly linked to diagnostic outcomes; high clinical relevance	Influenced by case complexity and experience	Roser *et al.* (2018); Waite *et al.* (2017); Krupinski *et al.* (2020)
Behavioral Measures	Eye-tracking (fixations,	Visual–perceptual workload;	High temporal resolution; insight into perceptual-	Requires specialized equipment;	Holmqvist *et al.* (2017);

	saccades, scan paths)	attentional allocation	cognitive processes	complex data interpretation	Krupinski *et al.* (2017)
Dual-Task Methods	Secondary task paradigms	Cognitive interference; spare attentional capacity	Captures real-time workload fluctuations	Reduced ecological validity; task interference risk	Longo & Orru (2021)
Physiological Measures	HRV; pupillometry	Autonomic arousal; sustained mental effort	Continuous, objective workload indicators	Susceptible to noise; inter-individual variability	Forte *et al.* (2019); Alshanskaia *et al.* (2018)
Neurophysiological Measures	EEG; fNIRS	Neural correlates of cognitive load	High sensitivity to workload changes; objective	Intrusiveness; signal complexity	Herff *et al.* (2014); Pušić *et al.* (2021)
Multimodal Approaches	Integrated subjective, behavioral, physiological models	Multidimensional workload states	Improved validity through triangulation; adaptive system potential	High analytical and implementation complexity	Hogervorst *et al.* (2014); Putze *et al.* (2019); Rojas *et al.* (2021)

Table 2 provides a structured overview of major methodological approaches used to measure mental workload in radiological reporting, spanning subjective, behavioral, physiological, and multimodal techniques. The table highlights the analytical strengths, limitations, and diagnostic relevance of each method, supporting informed selection of workload metrics in applied bioanalytical research.

Subjective Assessment Tools

The instruments that are commonly applied in the measurement of mental workload are subjective assessment tools because they are easy to administer, require little resources, and are capable of directly measuring perceived cognitive demand by the person undertaking a task. These tools are based on the structured self-report to measure mental effort, stress, and task difficulty, which gives an idea about the cognitive experience of the operator when carrying out the task.

Subjective measures are especially useful in clinical diagnostic settings like radiological reporting, where they can be implemented without disrupting the workflow and do not need other equipment or massive data processing. They are highly applicable to measuring experiential aspects of workload, like perceived effort or frustration, that are likely to affect diagnostic consistency but cannot be readily predicted using a behavioral or physiological marker (Longo, 2018). Regarding the applied bioanalysis aspect, these tools may be considered as the complementary tools of analytical measures that define the human cognitive contribution towards diagnostic variability. Although subjective measures are inherently vulnerable to the bias of the individual perception and response, systematic use means that they may be used to assist the larger workload evaluation and diagnostic quality assessment.

NASA Task Load Index (NASA-TLX)

One of the most widely approved and used subjective human factors research evaluation tools in applied human factors research is the NASA Task Load Index (NASA-TLX). It measures work load in six dimensions-mental demand, physical demand, temporal demand, perceived performance, effort and frustration-on a continuous scale. The dimension scores can be summed up to a workload index through a weighted or unweighted procedure (Hart and Staveland, 2019).

NASA-TLX has been applied to perceived workload in radiological and more broadly clinical diagnostic settings related to image complexity, reporting quantity, workflow disruptions, and incorporation of decision support or artificial intelligence-powered tools. Empirical evidence suggests that the tool is responsive to task difficulty and system architecture change in a medical imaging context and can be used in workflow assessment and technology acceptance (Buchanan and Short, 2021). Nevertheless, being a retrospective self-report scale, NASA-TLX is prone to recall bias and inter-rater difference in the interpretation of scales. It is also restricted in its capacity of detecting job-related changes in workload that are temporal in nature when interpreting images and is best used in conjunction with objective behavioral or physiological data (Longo & Orru, 2021).

Subjective Workload Assessment Technique (SWAT)

Subjective Workload Assessment Technique (SWAT) is another multi-dimensional method of assessing mental workload. It assesses workload in three basic elements, that is, time load, mental effort load, and psychological stress load. The procedure usually involves a scaling process to determine individual participant-specific values on workload category, which can enhance internal consistency, but complicates the methodology (Grier, 2015).

SWAT has been implemented primarily in safety-critical and time-sensitive operational sectors, such as in a healthcare environment in which temporal pressure and stress are major sources of workload. According to comparative studies, although the two SWAT and

NASA-TLX are largely correlated, SWAT might be more responsive to changes in time pressure and stress-related demand than NASA-TLX, which has a wider range of cognitive and affective workload dimensions. NASA-TLX is still more prevalent in radiological reporting, but SWAT can be used as a complement to it in high-pressure diagnostic cases where time is a chief source of cognitive load (Longo & Orru, 2021).

Other Self-Report Scales

Besides multidimensional scale, simple self-report scale is also employed to measure mental workload. The Rating Scale Mental Effort (RSME) is a unidimensional scale that is used to measure effort of the mind based on a continuous numerical scale. It has been shown that RSME is sensitive to variations in task difficulty, and is especially appropriate in the case of experimental and repeated-measures designs involving low-burden workload (low-energy and quick) (Ayres, 2020).

Another effective method is Visual Analogue Scales (VAS) whereby individuals are able to use a continuous line on which they can point out perceived workload or stress with one extreme being the lowest and the other extreme the highest. In spite of the fact that VAS do not have the multidimensional design of such instruments as NASA-TLX, their simplicity and non-complicated administration allows their use in rapid assessment as well as comparative evaluation in clinical research context. In practice, the scales prove to be most applicable in capturing the impressions of global workloads as opposed to focusing on the detailed diagnostic elements (Lesage *et al.*, 2019).

Performance-Based and Behavioral Measures

Performance-based and behavioral indicators can offer objective signs of mental workload by quantifying the relationship between task requirements and observable behavior as well as diagnosing results. These methods, in contrast to subjective ones, assume workload based on quantifiable alterations in efficiency, accuracy and execution patterns and are especially applicable to applied bioanalysis when objectivity and reproducibility are essential. Such measures are highly connected to diagnostic quality in radiological reporting, and they provide first-hand information about the influence of cognitive demand on interpretive performance in the real world (Longo, 2018).

Task Performance Metrics

The most proximate behavioral measures of mental workload are task performance measures. Cognitive demand is often represented as reporting time so that the greater the workload, the longer the interpretation and reporting time. Diagnostic imaging empirically proves that higher image complexity, case volume, and time pressure considerably prolong reporting times, which is an indicator of increased mental load, and large load (Roser *et al.*, 2018).

The performance measures that are of particular importance in clinical settings are diagnostic accuracy and error rates. Overworking and burnout of the mind has been continuously associated with the heightened perceptual and interpretation error rates, such as omitting findings and misclassification, and the direct effect on patient safety (Waite *et al.*, 2017). On the other hand, extremely low workload can make a person less vigilant, and it is essential to keep the range of workload optimal. The case complexity also makes performance measures vulnerable to the workload effect, which can be used to distinguish the workload effect on diagnostic cases with either subtle or ambiguous findings (Krupinski *et al.*, 2020).

Eye-Tracking Metrics

Eye-tracking has become a strong behavioral measure in evaluation of mental workload in tasks that involve a lot of visual work like radiological interpretation. Measurements of fixation period, frequency of saccades, and organization of scan-path can give a clue of the attentional distribution and cognitive processing requirements. More systematic scanning patterns and longer fixations are often identified with more workload, uncertainty, or tiredness, and efficient scan strategies are related to cognitive expertise (Holmqvist *et al.*, 2017; Krupinski *et al.*, 2017). Combination of gaze measurements with diagnostic results also allows making inferences about latent cognitive states, such as the confidence and cognitive load (Krupinski *et al.*, 2020).

Secondary Task Techniques

Secondary task methods evaluate workload by adding a secondary task whilst assuming a limited set of resources. Reductions in performance in the secondary task are assumed to be due to an increment of workload in the primary diagnostic task. Such paradigms can be applied in order to record the actual workload changes that cannot be indicated by retrospective ratings (Longo and Orru, 2021). Their use in clinical practice is, however, limited by their possible interference with the diagnostic performance and low ecological validity.

Physiological and Neuropsychological Measures

Physiological and neuropsychological measures give continuous objective measures of mental workload through measuring autonomic and neural responses to cognitive work. The cardiovascular parameters and especially heart rate variability are constantly reduced when cognitive demand is high and the attentional load is maintained, independent of performance per se (Forte *et al.*, 2019; Thielmann *et al.*, 2021). The complementary information on the workload-related neural activity is provided by the neurophysiological method like electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS), and the moment-to-moment changes in the cognitive effort are observed through the oculometric method of measurements, such as pupillometry (Herff *et al.*, 2014; Pušica *et al.*, 2021; Alshanskaia *et al.*, 2018).

Even though they are characterized by both high temporal resolution and analytical sensitivity, the methods have drawbacks concerning the signal noise, inter-individual variability, and dependence on the context, limiting their interpretability in a single application. Physiological and neuropsychological indicators should therefore be viewed as complementary analytical indicators that add value to the workload characterization when used with behavioral and subjective measures in the context of multimodal assessment that is applicable in applied bioanalysis.

Multimodal and Hybrid Measurement Approaches

Multimodal and hybrid methods of measurement have been becoming more popular in mental workload studies as a way of describing the dynamic and complex nature of cognitive demand in real-life tasks. These methods combine the subjective self-reports, behavioral performance measures and physiological or neurophysiological indicators which will give a more holistic picture of the mental work load than any one of them individually. Multimodal assessment is especially beneficial in areas with a high level of cognitive demands, including radiological reporting, as perceptual, cognitive, and affective processes are all involved in these processes, and they interact (Hogervorst *et al.*, 2014).

The combination of complementary modalities makes it possible to capture different aspects of workload simultaneously. Subjective measures give an understanding of perceived effort and stress, behavioral measures give an indication of task efficiency and diagnostic accuracy, and physiological signals give an indication of continuous objective indices of cognitive strain. Empirical research shows that joint modeling of these data streams are more sensitive to changes in workload and that they can better differentiate workload conditions, creating a higher level of construct validity and reducing bias related to each individual method of measurement (Muhll *et al.*, 2014; Rojas *et al.*, 2021).

Adaptive diagnostic systems are especially well served by hybrid methods, in which workload estimation in real-time can be used to dynamically change task allocation, interface complexity, or decision-support devices. The latest studies indicate that multimodal models utilizing eye-tracking and cardiovascular markers and neural activity are more effective in the task of predicting cognitive workload, particularly in more complex visual tasks (Putze *et al.*, 2019). The results can be directly applied to radiology in which workload-conscious systems can be used to reduce the errors associated with fatigue, as well as improve diagnostic accuracy.

In spite of these benefits, multimodal assessment has methodological issues, such as synchronization of signals with different time resolutions, noise and artifact control, and interpretation of potentially discordant signals. The complexity of the system and the requirements of the data-processing might be also restricting the routine clinical implementation (Alimardani *et al.*, 2020). These issues are critical in order to convert multimodal workload assessment into scalable applications in radiological and applied bioanalytical settings.

Applications of Mental Workload Measurement in Radiological Reporting

The practical importance of measurement of mental workload in radiological reporting can be seen to be beyond the theoretical knowledge, and to give practical knowledge on the best way to enhance the workflow, design of technology, training and patient safety. With the ever-growing imaging volumes and the increasing complexity of diagnostic tasks, workload evaluation provides an evidence-based solution to the optimal use of human human resources and achieving the reliability and repeatability of diagnostic results.

Workflow Design and Optimization

A workflow design is one of the most straightforward uses of workload measurement. The radiological workload differs significantly based on the complexity of the cases, modality, urgency and reporting environment. The measurements of workloads can also be used to shape case sequencing plans which can be used to ensure that there is a more balanced distribution of cognitively demanding cases as opposed to having them concentrated during reporting sessions. It is indicated that, with long-term exposure to complex cases and a lack of recovery, there is an increase in cognitive burden and risk of error, but balanced sequencing facilitates long-term diagnostic performance (Roser *et al.*, 2018; Krupinski *et al.*, 2017).

Another application of high importance is break scheduling. Both physiological and subjective measures of workloads reveal that cognitive fatigue is cumulative with long term reporting durations even when obvious performance seems normal. Micro-breaks informed by workload have the potential to replenish the resources of attention, decrease mental load, and lead to a successful diagnosis (Forte *et al.*, 2019). In contrast to the fixed schedules, break policies based on workload could be dynamically adjusted to real-time cognitive need.

The workload assessment can also be used to perform adaptive allocation of work in a multi-reader or team-based work environment. Cognitive load monitoring enables tasks to be shifted to times with low demand to enhance system resilience and to reduce the personal load of more complex radiology processes.

Technology Assessment

The role of mental workload measurement in the assessment of radiological technologies (mainly PACS and reporting interfaces) cannot be overestimated. Unresponsive navigation, disjointed information presentation, as well as visual noise may provide an extraneous load, which adversely influences faster and more accurate reporting (Longo, 2018). The combination of the workload measures with the usability tests is useful in designing the human-centered diagnostic system.

The use of AI-enabled reporting systems also helps to emphasise the significance of workload evaluation. Although artificial intelligence can help to decrease the workload with simple cases, it can cause more cognitive loads, as it is necessary to verify and calibrate trust on cases of higher complexity (Krupinski *et al.*, 2020). Workload measures allow assessing objectively whether AI systems are truly helpful in improving cognitive efficiency or reallocating cognitive resources.

Training, Quality Assurance, and Bioanalysis

Workload measurement offers an important point of training and competency assessment, and it has always been seen that experts have lower workload and a more efficient visual strategy compared to their novice counterparts (Krupinski, 2014). Monitoring workload in learning the skill would enable training to be adapted to cognitive ability in order to facilitate the long-term learning.

Regarding quality assurance, high workload has a close relationship with diagnostic errors and clinician burnout (Waite *et al.*, 2017; Golubic *et al.*, 2020). Notably, radiological interpretations are analytical products in the pathways of diagnosis. Cognitive overload can cause variability in its turn, thus analytical error can be conceptualized, which makes the workload measurement consistent with the principles and aims of applied bioanalysis.

Table 3. Applications of Mental Workload Measurement in Radiological Reporting and Their Relevance to Diagnostic Bioanalysis

Application Domain	**Use of Mental Workload Measurement**	**Primary Outcomes Assessed**	**Implications for Diagnostic Quality**	**Relevance to Applied Bioanalysis**	**Representative References**
Workflow Design	Case sequencing and workload balancing	Cognitive strain; reporting efficiency	Reduced fatigue-related errors; sustained performance	Supports consistency and reproducibility of diagnostic outputs	Roser *et al.* (2018); Krupinski *et al.* (2017)
Work Scheduling	Workload-informed break scheduling	Fatigue accumulation; attentional recovery	Improved vigilance and error prevention	Analogous to controlling analytical drift over time	Forte *et al.* (2019); Golubic *et al.* (2020)
Adaptive Work Allocation	Dynamic task redistribution based on workload	Operator capacity utilization	Enhanced system resilience; reduced overload	Treats human cognition as a controllable analytical variable	Wickens (2017); Young & Stanton (2015)
Technology Assessment	Evaluation of PACS and reporting interfaces	Extraneous cognitive load	Improved usability; faster and more accurate reporting	Optimizes analytical interfaces to reduce human-induced variability	Longo (2018)
AI-Assisted Reporting	Assessment of cognitive impact of AI tools	Verification effort; trust calibration	Identification of automation bias and vigilance loss	Ensures AI integration improves, rather than degrades, analytical reliability	Krupinski *et al.* (2020); Young & Stanton (2015)
Training and Education	Monitoring novice–expert workload differences	Cognitive efficiency; skill acquisition	Targeted training; reduced trainee overload	Aligns competency development with analytical robustness	Krupinski (2014)
Competency Evaluation	Longitudinal workload profiling	Cognitive resilience under complexity	Early identification of performance vulnerability	Complements accuracy metrics with cognitive stability indicators	Longo & Orru (2021)
Quality Assurance	Identification of workload-related error thresholds	Diagnostic error rates	Preventive workload management	Treats cognitive overload as a source of analytical error	Waite *et al.* (2017)
Burnout Mitigation	Long-term workload monitoring	Chronic stress and fatigue	Improved clinician well-being and safety	Supports sustainability of analytical systems	Golubic *et al.* (2020)
Diagnostic Bioanalysis	Integration of workload into QA frameworks	Interpretive variability	Holistic diagnostic quality control	Expands bioanalysis beyond molecular measurements	Zhou *et al.* (2022)

Table 3 provides an overview of the most important uses of mental workload measurement in radiological reporting and indicates its implication in the quality of diagnosis and reliability of the analysis. It shows that workload evaluation is one of the human-centered analytical control variables of applied bioanalysis, which connects cognitive demand to workflow optimization, technology analysis, and quality assurance.

Methodological Challenges and Limitations

Although there is an increasing trend in the measurement of the mental workload in radiological reporting, there are serious methodological limitations that impair the strength and external validity of the existing research results. One of the problems is related to the validity and reliability of subjective measures of workload. Self reporting instruments have a tendency to be affected by recall bias, social desirability, and personal interpretation of rating scales. There may also be transient effects of mood, motivation, or task results on reported workload, undermining the predictive validity of perceived workload and actual cognitive demand (Longo, 2018).

There is also inter-individual variability that also makes interpretation difficult. Variations in knowledge base, cognitive processes, tolerance to fatigue and stress, result in significant differences in workload responses to the same task situation. Even in cases of more complex cases, expert radiologists usually report reduced perceived workload and more efficient visual search strategies than novices (Krupinski, 2014). This variance requires close design of experiments and stratification of expertise and suitable statistical controls.

Another limitation that persists is the ecological validity. Most of the studies are based on laboratory-based or simplified task that does not reflect the complexity of actual clinical workflow as it contains interruptions, multi-tasking, time constraint and organizational limitation. Consequently, the clinical workload could be underestimated (Roser *et al.*, 2018).

Lastly, ethical, practical and standardization issues-especially that physiological measures have not yet been adopted universally and no standardized assessment protocols exist-are still present as obstacles to large-scale use and cross-study comparisons (Charles and Nixon, 2019).

Future Directions and Emerging Trends

The use of artificial intelligence, the development of digital health technologies, and precision diagnostics are closely connected to the development of mental workload assessment in radiological reporting in the future. With more and more complex and data-driven radiology workflows, workload-aware systems will likely be at the core of diagnostic performance, without compromising clinician well-being.

One of the emerging directions is the combination of the mental workload measurement with artificial intelligence systems. Adaptive platforms can dynamically react to the current workload situation by simplifying or complicating the interface, emphasizing case presentation or by tuning decision support output. Instead of substituting humans, these systems will be more likely to promote human-AI collaboration paradigms, where the cognitive responsibility is divided and AI tools are supposed to be utilized to complement human judgment. These practices can be used to alleviate the risks related to automation bias, dependency on algorithms, and attentional disengagement.

One more trend that is worth being mentioned is the creation of digital biomarkers of cognitive load. Passive and continuous observation of physiological and behavioral indicators has the possibility to determine workload in real-time without interrupting clinical activities. These computerized markers may advance conventional bioanalytical models because they may capture cognitive variability which in turn has a direct impact on diagnostic interpretation. Jackson and Frame (2002) suggest that the evidence of cognitive load measures in conjunction with molecular, imaging and analytical data could improve the overall strength and explainability of diagnostic results.

The workload management strategies will also tend to become more personal. It is possible that the level of workload balance is not consistent because of individual differences in levels of expertise, cognitive capacity, and stress resilience. Individualized cognitive profiling may be used to drive adaptive schedules, focused training, and individualized decision-support systems, and supports the ultimate objectives of precision diagnostics.

On a larger scale, these advancements have some major implications to bioanalytical and clinical research. The introduction of human operator as a part of the diagnostic system is seen by expanding bioanalysis beyond measurement of molecules to consider a cognitive and behavioral component of the system. Cognitive analytics can also be a useful part of the diagnostic quality control and can contribute to more reliable, sustainable, and human-centered healthcare delivery.

Conclusion

This review discussed methodological strategies of measuring radiological reporting mental workload with the focus on the significant cognitive workload of contemporary diagnostic imaging. The radiological interpretation involves long-term attention, high visual-perceptual processing, working memory and time-pressured decision-making. The discussed methods such as self-report instruments (subjective), performance-based and behavioral measurements, physiological and neuropsychological measurements, and multimodal approaches prove that mental workload is a multidimensional construct that cannot possibly be fully reflected with the help of one measure. Both methods have their contrasting advantages and disadvantages, and the need to match complementary interventions in order to achieve more balanced and valid insight on the cognitive demand in a clinical practice. The tools of applied psychology are instrumental in the development of workload evaluation in the radiology field. Both subjective and objective measures of cognitive strain and performance efficiency are offered by subjective measures, indicators of perceived effort and stress, and behavioral indicators and physiological indicators respectively. When properly implemented, the tools assist in detecting workload risks, directing workflow optimization, as well as facilitate the creation of human-oriented

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technologies. It is especially topical when the field of radiology is becoming more and more automated and artificial intelligent, and the human-system cognitive interaction is the key to safe and effective implementation. The mental workload measurement is a critical issue in radiology, but it also is relevant to clinical diagnostics and bioanalytical science in general. Radiology reports are the analytical products that affect clinical practice and cognitive overload corresponds to the variability like that caused by analytical error in laboratory measurements. The introduction of the workload evaluation into the current diagnostic qualitative models is consistent with the principles of applied bioanalysis because the human cognition is identified as a factor of analytic reliability. The further way forward will be interdisciplinary collaboration and the design of standardized methodologies, common protocols, and consensus-based guidelines to assist in translation into daily clinical practice and sustainable and high-quality diagnostic systems.

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