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Mental workload assessment and prediction for train operators

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ABSTRACT

Train protection and control systems are crucial for improving railway safety by reducing operator-related accidents. However, they shift operators from manual control to monitoring, presenting both advantages and challenges. This change requires rapid assimilation of vast information, risking mental overload and performance degradation. Therefore, assessment and prediction of the workload associated with train systems is essential.
This paper examines mental workload studies in train operator settings, categorizing them by their approaches (subjective-objective, analytical-empirical), methods, metrics, and the types of train cab systems studied. It also analyzes how train technology affects operator workload, emphasizing the importance of addressing workload during system design for safe and efficient railway operations. Our analysis highlighted a preference for the subjective-empirical approach for analyzing train operators' workload, often applied after system prototypes and simulator experiments are available. Early workload analysis is recommended for user-centred design, preventing operator errors and costly redesigns. Furthermore, the literature presented diverse findings on the effects of in-cab systems and automation on train operators' workload. These disparities may arise from system characteristics, individual differences, environmental factors, operational conditions, and infrastructure variations. Additionally, differences in the stages of information processing studied can contribute to varying workload outcomes for the same system.

1 INTRODUCTION

The concept of workload, as defined by Wickens and Tsang (2015), is the balance between the resources required for a task and those available to the operator. This balance includes various elements such as physical, visual, auditory, and cognitive aspects (Halliday et al., 2005). Mental workload, distinct from physical tasks, focuses on the cognitive demands on individuals (Hamilton and Clarke, 2005), and is the interplay between a task's demands and the operator's mental capacity (Kruger, 2008).

The impact of workload on operator performance is crucial and is illustrated in Figure 1.

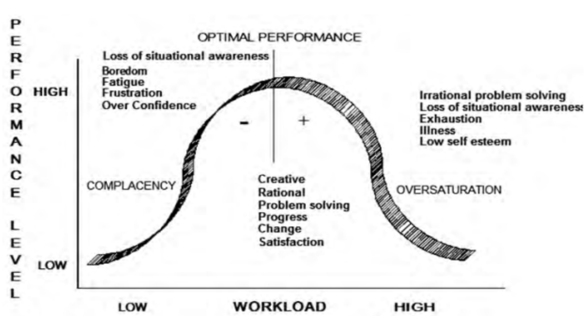

Figure 1. Workload versus performance (FRA, 2014).

Figure 1 highlights how both under-load and over-load can detrimentally affect performance. Specifically, under-load can lead to fatigue, boredom, and a decline in situational awareness, while over-load might result in exhaustion and compromised problem-solving abilities (FRA, 2014; Robinson et al., 2015).

Despite the importance of workload in system design and operator performance, there is no unifying approach for defining, quantifying, and measuring mental workload (Foulkes, 2004; Jex, 1988). This gap is particularly evident in the context of train operations, where workload intricacies are critical for safety and efficiency. Current methodologies include time-based assessments, which compute workload as a ratio of time spent on tasks to available time, and task-based evaluations, which contrast mental effort against individual capacity (Hamilton and Clarke, 2005; Parasuraman et al., 2008; Wang et al., 2016). Furthermore, various methodologies and tools exist for measuring mental workload. To gain a comprehensive understanding of mental workload, several scholars — Xie and Salvendy (2000), Miller (2001), Cain (2007), Kruger (2008), Young et al. (2015), Wilson et al. (2017), and Heard et al. (2018) — have reviewed and categorized different approaches for defining, quantifying, and measuring mental workload.

These techniques fall into two primary categories: objective-subjective and empirical-analytical (Nneji, 2019; Rusnock et al., 2015). Objective methods rely on real-world facts, such as task performance metrics and physiological indicators, whereas subjective methods depend on personal perceptions of workload (Heard et al., 2018). Empirical and analytical classifications offer another perspective. Empirical techniques are based on observed evidence, often from laboratory or field studies, while analytical methods hinge on theoretical reasoning, frequently employed in early system design stages (Rusnock et al., 2015; Xie and Salvendy, 2000).

While many studies on train operators' workload exist, there is a lack of a comprehensive review that unifies these diverse approaches for a specific focus on train operators. Such a review is vital for enhancing system design and rail transportation efficiency. This paper fills this gap by analyzing the existing literature on this topic.

The paper is structured as follows: Section 2 presents the background, and Section 3 categorizes workload studies into subjective-empirical, subjective-analytical, objective-empirical, and objective-analytical. Section 4 summarizes these studies, and Section 5 concludes with key insights and implications of the review.

2 BACKGROUND

The measurement of mental workload, a pivotal aspect in the field of human factors and ergonomics can be dissected into two primary dimensions: objective versus subjective and empirical versus analytical. This categorization leads to four distinct categories of workload measurement approaches, each with its unique methods and metrics (see Figure 2) (Rusnock et al., 2015).

a. Subjective-Empirical Measures: This category comprises methods that gather subjective opinions, typically via self-report questionnaires following simulator experiments. Such methods aim to estimate workload as experienced by the individual directly. Prominent examples include the NASA-TLX (Hart and Staveland, 1988), SWAT (Reid and Nygren, 1988), Cooper-Harper (Cooper and Harper, 1969), MRQ (Boles and Adair, 2001), Overall Workload (Jung and Jung, 2001), and Workload Profile (Tsang and Velazquez, 1996). These tools are crucial in capturing the operator's perceived effort and stress, offering insights into their subjective experience of workload.

b. Subjective-Analytical Measures: In this approach, workload estimation relies on the expertise of subject matter experts or experienced users (Xie and Salvendy, 2000). These assessments are based on comparisons with similar systems or previous experiences. Techniques in this category, such as checklists and walkthrough methods (Evans, 2017), are particularly useful at the early design stages of systems, where empirical data from prototypes might not yet be available (Rusnock et al., 2015). They provide a preliminary understanding of the expected workload in new or modified systems.

c. Objective-Empirical Measures: This category involves the direct assessment of objective workload metrics. These metrics can include task performance indicators (like error frequency or response time) and physiological measurements (such as heart rate or eye movement). Such assessments are typically conducted in controlled environments like laboratories or simulators (Rusnock et al., 2015; Wilson et al., 2017; Xie and Salvendy, 2000). These methods are valuable for quantitatively assessing workload in scenarios that closely mimic real-world conditions.

d. Objective-Analytical Measures: These methods integrate task, environmental, and personal knowledge into mathematical models for workload assessment. They often involve detailed task analysis and understanding the system, operator, task, context, and modelling approaches. Techniques in this category are essential during the early design stages when empirical data are unattainable. Examples include Control Theory, Information Theory, Queuing Theory, Timeline Analysis and Prediction (TLAP), Visual Auditory Cognitive Psychomotor (VACP), W/INDEX, and various simulation models and human performance modelling tools like ATLAS, IMPRINT, and IPME (Rusnock et al., 2015; Wilson et al., 2017; Xie and Salvendy, 2000).

	Analytical	Empirical
Subjective	Comparison Expert opinion	Operator opinion-rating scales or questionnaire/ interview
Objective	Mathematical models Task analysis models Simulation models	Performance measures Psychophysiological measures

Figure 2. Workload measurement approaches and methods.

3 TRAIN OPERATORS' WORKLOAD ASSESSMENT STUDIES

Several studies have been conducted in the railway sector to explore the mental workload of train operators, examining both existing operational conditions and the impact of newly implemented train control systems. This section provides a comprehensive review of the diverse approaches employed in these studies to assess workload, offering a detailed insight into the methodologies and findings within this important area of research.

3.1 Subjective-empirical studies on train operators' workload

The study of subjective-empirical approaches to assess train operators' workload has been a focus of numerous researchers, including Gibson et al. (2007), Spring et al. (2009), Dunn and Williamson (2012), Scott and Gibson (2012), Large et al. (2014), Robinson et al. (2015), Basacik et al. (2015), Hely et al. (2015), Van Der Weide et al. (2017), Brandenburger et al. (2018), Brandenburger et al. (2019), Huang et al. (2019), and Verstappen et al. (2022). This section reviews key findings from these studies, emphasizing their methodologies and contributions to understanding the workload in train operations.

Gibson et al. (2007) examined the impact of Train Protection Warning Systems (TPWS) on operators. Using simulator experiments, they collected subjective responses on workload through the Driver IWS rating, particularly for two improved TPWS driver machine interface (DMI) variants. Their findings underscored the potential benefits of these design modifications. Scott and Gibson (2012) also investigated the TPWS DMIs, employing the NASA-TLX method. Their results showed generally low workload measures, offering limited differentiation between the performances of the DMIs. Robinson et al. (2015) and Basacik et al. (2015) both utilized simulator experiments and the NASA-TLX for subjective workload measurement. Robinson et al. (2015) focused on the Automatic Warning System (AWS), uncovering that various factors influence workload. Notably, they found that AWS could lead to underloading in less demanding driving scenarios, and that increasing workload in such cases positively impacts self-reported measures of workload, arousal, and fatigue. Large et al. (2014) and Verstappen et al. (2022) conducted comprehensive studies on the Driver Advisory System (DAS) using subjective-empirical workload assessments. While Large et al. (2014) applied NASA-TLX, Verstappen et al. (2022) used the Rating Scale Mental Effort (RSME). Their research indicated that although DAS systems support efficient operation, they require operators to process considerable information, potentially leading to mental overload, especially in scenarios demanding rapid interpretation of prompts. Spring et al. (2009) explored the workload associated with the Automatic Monitoring Aid (AMA) system in Australia. Their methodology involved simulator experiments, assessing subjective workload perceptions using NASA-TLX and the Subjective Work Underload Checklist (SWUC). Their findings suggested that increased automation in train driving could reduce mental workload to suboptimal levels. Dunn and Williamson (2012) also used NASA-TLX to assess Australian train operators' perceived workload, discovering that task complexity significantly impacts mental workload. Hely et al. (2015) compared the workload under Automatic Train Protection (ATP) and non-ATP conditions, noting that ATP, while enhancing safety, also increases attentional demands.

Studies by Van Der Weide et al. (2017), Brandenburger et al. (2018), and Brandenburger et al. (2019) focused on the European Train Control System (ETCS). Using subjective workload metrics like NASA-TLX and DLR-WAT, these studies generally found that ETCS tends to reduce mental workload compared to traditional systems. Huang et al. (2019) conducted an analysis combining both objective and subjective-empirical approaches. Their subjective analysis, based on the NASA-TLX metric and real-world observations, concluded that the workload in manual driving mode is significantly higher than in automatic mode.

3.2 Subjective-analytical studies on train operators' workload

Research conducted by Wreathall et al. (2003), Foulkes (2004), Halliday et al. (2005), Wreathall et al. (2007a), Wreathall et al. (2007b), Roth et al. (2013), Simoes et al. (2016), and Van Der Weide (2017) represents pivotal subjective-analytical approaches in understanding train operators' workload.

Halliday et al. (2005) examined the In-cab Signal Reminder Device (ICSRD), noting its potential to enhance safety by reducing dependency on trackside signals. However, they identified an increase in cognitive demands, especially in interpreting semaphore signals. Wreathall et al. (2003) and Roth et al. (2013) delved into the implications of Positive Train Control (PTC) systems. Their research, leaning on expert opinions and subjective evaluations, suggested that PTC systems might reduce workload in simpler operations but increase it in complex or emergency scenarios. Further studies by (Wreathall et al., 2007a; 2007b) also highlighted the impact of PTC systems, finding an increased workload due to non-informative alarms and manual data input requirements. Foulkes (2004) and Van Der Weide (2017) explored the workload associated with the European Train Control System (ETCS). Based on Subject Matter Experts (SMEs), Foulkes's study indicated that ETCS Level 2, which eliminates lineside signals, could decrease mental workload relative to traditional systems but also flagged potential workload increases during transitions into and out of ETCS areas. Van Der Weide (2017) observed a generally lower workload for operators using ETCS compared to the legacy ATB system, with highly experienced operators even reporting instances of boredom. Simoes et al. (2016) undertook a subjective analysis using DALI (Driving Activity Load Index), an adaptation of the NASA-TLX. Their study leveraged expert insights to evaluate the workload impact of different train operation tasks. This approach offered a detailed understanding of how various operational aspects influence the mental workload of train operators.

3.3 Objective-empirical studies on train operators' workload

This section highlights studies employing objective-empirical methods, including works by Robinson et al. (2015), Basacik et al. (2015), Hely et al. (2015), Gillis (2016), Balfe et al. (2017), Sebok et al. (2017), Huang et al. (2019), and Nneji et al. (2019).

In the realm of train operators' workload studies, a substantial focus has been placed on objective-empirical approaches, with some researchers also integrating subjective metrics for a more comprehensive analysis. For instance, Robinson et al. (2015) focused on objective measures like heart rate and response times to study the workload effects of the Automatic

Warning System (AWS), supplementing these with subjective assessments such as the NASA-TLX. Basacik et al. (2015) combined reaction time and error rate analysis with physiological data (skin conductance, heart rate) and subjective feedback to explore cognitive underload in train driving. Hely et al. (2015) assessed workload in Automatic Train Protection (ATP) using objective metrics like speed, acceleration, and response times, alongside eye-tracking and subjective evaluations. Similarly, Huang et al. (2019) emphasized objective measures, particularly reaction times across shifts, and included subjective assessments to enrich their analysis.

Later studies, such as those by Gillis (2016), Balfe et al. (2017), Sebok et al. (2017), Huang et al. (2019), and Nneji et al. (2019), predominantly focused on objective-empirical methods. Gillis (2016) focused on Cognitive Task Analysis (CTA) of train operation tasks, combining simulator experiments with direct observations of train operators to scrutinize their responses in different scenarios. Balfe et al. (2017) extracted task load data from on-train-data-recorders (OTDR), analyzing task times and calculating task time pressures. Sebok et al. (2017) investigated the impact of Trip Optimizer (TO) and PTC systems on operator workload, assessing human error rates in different workload-level scenarios. Nneji et al. (2019) conducted a study on the workload effects of PTC systems, utilizing real-world observations. They applied Task Analysis (TA) and assessed time pressure to understand the system's impact. The study revealed that in heavy traffic conditions, automation provided by PTC systems could be more effective than a freight conductor in managing the workload of locomotive engineers. However, in contrast, this automation might negatively affect operator performance in typical short-haul freight rail scenarios.

3.4 Objective-analytical studies on train operators' workload

This section reviews the application of objective-analytical methods by researchers such as Foulkes (2004), Hamilton and Clarke (2005), Blanchard (2013), Groshong (2016), Verstappen et al. (2017), and Wang et al. (2021), highlighting their contributions to understanding the workload in train operations.

Foulkes (2004) investigated the mental workload in the European Train Control System (ETCS), employing Task Analysis (TA) and the Workload Assessment Tool (WAT) to focus on task duration and cognitive demands. Hamilton and Clarke (2005) used cognitive theory and Visual, Auditory, Cognitive, and Psychomotor (VACP) measures to model train operators' workload under ETCS, validating their model by comparing VACP predictions with observed NASA-TLX values. Blanchard (2013) performed a detailed analysis of Cambrian train operations, evaluating workload using VACP metrics. The study highlighted that while automation reduces manual task frequency, it increases the complexity and cognitive demands associated with in-cab tasks. Groshong (2016) explored how different train control systems affect cognitive aspects of train operation, particularly decision-making and information processing. Verstappen et al. (2017) assessed the workload in the Netherlands Railways' in-cab systems using the PARRC model, task analysis, and VACP analysis. They found that monitoring new devices while driving elevates workload due to increased visual and cognitive demands. Wang et al. (2021) developed a Timed Petri Net-based mental workload evaluation model, conducting a driving simulator experiment to validate their approach for system task optimization.

4 AN OVERVIEW OF THE TRAIN OPERATORS' WORKLOAD STUDIES

This section presents a consolidated overview of various studies on train operators' workload, as detailed in Table 1. This table methodically outlines the methodologies, metrics, and systems each study examined. The majority of the 30 studies reviewed, predominantly from the US and UK, varied in their approach – some analyzed workload under existing train systems, while others assessed the effects of new in-cab systems and automation.

Particularly in Europe and America, studies focusing on the European Train Control System (ETCS) and the Positive Train Control (PTC) system form a significant part of this research area. A marked trend in these studies is the preference for subjective-empirical methods, with the NASA-TLX tool being commonly used. Furthermore, the analysis indicates a preference for empirical workload assessment methods, combining subjective and objective metrics to validate findings, as shown in Figure 3. This preference suggests a tendency among railway companies to delay comprehensive workload analysis until the development of system prototypes or the availability of simulator experiments. While beneficial for testing in realistic or simulated environments, this strategy might overlook the advantages of early-stage analysis, which is crucial for optimizing operator interfaces, automation, and information presentation (Eggemeier et al., 1985; Endsley, 1995).

The findings from the train operators' workload studies reveal diverse and sometimes contrasting effects of in-cab systems and automation on train operators' workload. Such variability in outcomes emphasizes the intricate nature of workload assessment, which is affected by a multitude of factors, including system features, individual operator characteristics, environmental conditions, and operational dynamics.

Table 1. A review of the train operators' workload assessment and prediction studies.

ID	Authors	Country	Subjectiv/ Objective	Empirical/ Analytical	Data sources	Methods and Metrics	System
1	Wreathall et al. (2003)	US	Subjective	Analytical	SMEs	-	PTC
2	Foulkes (2004)	UK	Subjective, Objective	Analytical	SMEs	TA, Task time, WAT	ETCS
3	Hamilton and Clarke (2005)	UK	Objective	Analytical	Documents review	CTA, Task time, Time pressure, VACP analysis	ETCS
4	Halliday et al. (2005)	UK	Subjective	Analytical	SMEs	-	ICSRD
5	Wreathall et al. (2007a)	US	Subjective	Analytical	SMEs	-	PTC
6	Wreathall et al. (2007b)	US	Subjective	Analytical	Documents review, SMEs	-	PTC
7	Gibson et al. (2007)	UK	Subjective	Empirical	Simulator experiments	IWS	TPWS
8	Spring et al. (2009)	Australia	Subjective	Empirical	Simulator experiments	NASA-TLX, SWUC	AMA
9	Dunn and Williamson (2012)	Australia	Subjective	Empirical	Simulator experiments	NASA-TLX	-
10	Scott and Gibson (2012)	UK	Subjective	Empirical	Simulator experiments	NASA-TLX	TPWS
11	Roth et al. (2013)	US	Subjective	Analytical	SME, Observations	-	PTC
12	Blanchard (2013)	UK	Objective	Analytical	Documents review, Observations	TA, VACP, Frequency of driving tasks	-
13	Large et al. (2014)	UK	Subjective	Empirical	Simulator experiments	NASA-TLX	DAS
14	Robinson et al. (2015)	UK	Subjective, Objective	Empirical	Simulator experiments	NASA-TLX, Physiological & Performance measures	AWS
15	Basacik et al. (2015)	UK	Subjective, Objective	Empirical	Simulator experiments	NASA-TLX, Physiological & Performance measures	-
16	Hely et al. (2015)	Australia	Subjective, Objective	Empirical	Simulator experiments	NASA-TLX, Performance measures, & Eye-tracking	ATP
17	Groshong (2016)	US	Objective	Analytical	Documents review, SMEs	CTA, Number of actions	-
18	Simoes et al. (2016)	Portugal	Subjective	Analytical	SMEs	DALI (adapted the NASA-TLX)	-
19	Gillis (2016)	Belgium	Objective	Empirical	Simulator experiments Observations	CTA	-
20	Balfe et al. (2017)	Ireland	Objective	Empirical	OTDR	TA, Task time, Time pressure	-
21	Sebok et al. (2017)	US	Objective	Empirical	Simulator experiments	Performance measures	TO, PTC
22	Van Der Weide et al. (2017)	Netherlands	Subjective	Empirical	Simulator experiments	RSMI	ETCS
23	Van Der Weide (2017)	Netherlands	Subjective	Analytical	SMEs	-	ETCS
24	Verstappen et al. (2017)	Netherlands	Objective	Analytical	SMEs	TA, PARRC, VACP analysis	In-cab systems
25	Brandenburger et al. (2018)	Germany	Subjective	Empirical	Simulator experiments	NASA-TLX, DLR-WAT	ETCS
26	Brandenburger et al. (2019)	Germany	Subjective	Empirical	Simulator experiments	NASA-TLX	ETCS
27	Nneji et al. (2019)	US	Objective	Empirical	Observations	TA, Task time, Simulation, Time pressure	PTC
28	Huang et al. (2019)	China	Subjective, Objective	Empirical	Observations	TA, Task time, NASA-TLX, Physiological measures	-
29	Wang et al. (2021)	China	Objective	Analytical	Documents review	TPN	-
30	Verstappen et al. (2022)	Netherlands	Subjective	Empirical	Simulator experiments	Physiological measures and Rating Scale Mental Effort	DAS

This complexity necessitates a detailed and careful interpretation of workload study results within the context of train operations.

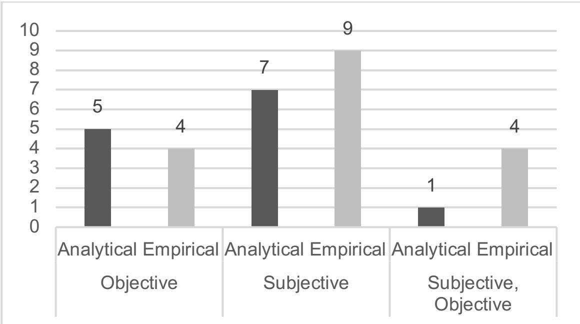

Figure 3. The applied approaches in train operators' workload studies.

5 CONCLUSIONS

This paper provided a review of studies focused on the mental workload of train operators, especially in the context of evolving train protection and control systems. Our analysis categorized these studies based on their methodologies—subjective vs. objective and analytical vs. empirical—while also considering the methods, metrics, and types of train cab systems examined.

This review highlighted the prevalent use of subjective-empirical methods in train operators' workload studies, with a focus on evaluations conducted post-prototype development or through simulator experiments. However, this approach sometimes overlooks the benefits of early workload analysis, which is essential for user-centric design and error prevention. Furthermore, the review revealed diverse impacts of in-cab systems and automation on workload, influenced by factors like system characteristics, operator individuality, and environmental conditions. This variability underscores the complexity of workload assessment in railway operations and the need for comprehensive evaluation methodologies.

For future research, there are two critical directions: Firstly, analyzing the workload of train operators in Canadian railways, particularly post-implementation of the Enhanced Train Control (ETC) system, would provide valuable insights into the effects of advanced control systems in different national contexts. Secondly, future studies should address the lack of consideration for contextual factors in analytical workload models. This would enhance understanding of how environmental and situational variables impact operator workload, leading to more effective and adaptive system designs.

Overall, a balanced approach is recommended to integrate both subjective and objective methods as well as analytical and empirical methods in the early and later stages of system development. Such a strategy will contribute significantly to ensuring railway operations' safety and efficiency while improving train operators' overall well-being and performance.

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