Computational models for the dynamic assessment of operator’s mental fatigue and the human error probability in production processes

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Final Dissertation

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by

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Course n°35, 01/11/2019-31/10/2022

Politecnico di Bari

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Computational models for the dynamic assessment of operator's mental fatigue and the human error probability in production processes

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“Keep your eyes on the stars, and your feet on the ground”.

Theodore Roosevelt

Sommario

Abstract

The past decade has seen an increase in the use of technologies in everyday activities and work environments in which the need for cognitive resources seems to increase. In contrast, the level of physical exertion seems to decrease. The rapid developments of the so-called "Internet of Things" (IoT) and its new automation archetypes in cyber-physical systems, as well as the increased analytical requirements arising from the need to analyze large amounts of data, are some examples of underlying elements that mark an increased cognitive demand of individuals to perform control tasks and get an overview of the distributed systems we are required to monitor. The main reason for measuring mental or cognitive workload is to quantify mental effort in performing specific tasks and assess its implications on human performance. Human Mental Workload (MWL) modeling can be used to support the design of interfaces, technologies and information-processing activities that are better aligned with each individual's mental capabilities.

This doctoral dissertation focuses on developing computational models for the dynamic assessment of operator mental fatigue (which is identified as mental workload and/or cognitive workload) and the probability of human error in executing production process-related tasks. Mental fatigue, its measures, dimensions, models, applications and consequences are addressed. This thesis follows a multidisciplinary approach and is not only confined to the field of industrial ergonomics.

Recent developments in the context of theoretical models of MWL and practical applications aimed at business support and management of MWL in operations are presented. Therefore, the contributions have been organized into sections where mental fatigue and the probability of human error in the context of production processes are investigated; here, the models developed are based on the information theory presented by Shannon. The thesis work was organized as follows:

(a) State-of-the-art analysis of the increasing importance of the human factor in intelligent production systems, paying particular attention to the importance of human mental fatigue in performing tasks with predominantly cognitive rather than physical parts.

(b) State-of-the-art analysis of existing methodologies, applied in different fields and for different purposes, used to assess human mental workload in performing a specific task.

(c) Innovative proposals for modeling the operator's mental workload and evaluating the related performance, focusing on physiological factors and different types of tasks to be performed.

The state-of-the-art analysis of existing methodologies used for MWL assessment, addressed in Chapter 1, helps to understand the shortcomings in analysing human factors related to mental fatigue in production processes.

To overcome these limitations, the "n-back" test, a standardised tool for simulating tasks with different cognitive complexities, is presented in Chapter 2. Both objective and subjective methodologies are used here to assess mental workload during experimental sessions. The case study presented in Chapter 2 is used to simulate a real industrial setting that highlights how operators, due to the increase of cognitive tasks within their work activities, must make an increasing number of decisions.

Chapter 3 uses the n-back test and literature data to create a new formulation for quantifying operators' mental workload and performance. The formulations presented consider both subjective and objective parameters of operators; in addition, the ageing workforce in advanced market economies and the impact on the evaluation of human factors in production processes in the era of digitalisation are investigated.

Chapter 4 examines the complexity of two-dimensional (2D) object recognition tasks. The presented formulation allows modeling the difficulty of the task and the associated mental workload.

Finally, in Chapter 5, human performance in repetitive tasks is studied. Here the operator's performance in performing a manual assembly task is evaluated.

The modeling of mental workload, assessment of task difficulty and operator performance presented in this thesis can give the designer a hint about the improvement that can be achieved if the task assignment is optimised by considering different types of tasks and operators. Operator well-being will play a crucial role in task assignment. Mental workload assessment can be applied in job rotation programs to minimise mental workload. As explained in the Introduction,

the proposed model formulations can fill the gaps in the existing scientific literature related to human factors in the digital factory.

1. Introduction

In 2000, Wilson defines Human Factors (HF) as "the theoretical and fundamental understanding of human behavior and performance in purposeful interacting sociotechnical systems, and the application of that understanding to the design of interactions in the context of real settings" (Wilson, 2000). The human factor is a considerable element that has a relevant impact on the productivity in term on time and quality in industrial contexts, especially in those requiring several types of cognitive activities with a different level of experience and knowledge.

In last years, experts and practitioners have increased their research on the impact that human factors has in production environment to improve productivity and to guarantee better ergonomic conditions in the workplaces. Otto and Battaia state that workplace ergonomics depends on three main aspects: physical, cognitive and organizational factors (Otto & Battaïa, 2017). Better ergonomic workplace could guarantee a higher operators' well-being and increase performance of the global organization. On the contrary, a poor ergonomic design in the workplace can generate a large number of sick leaves. In addition to these aspects, it is necessary to consider the presence of different operators such as highly skilled not easily interchangeable with robots or automated systems.

In a recent study for the OECD, automation is perceived as a threat that will ultimately foster technological unemployment. Thus, smart digitalization and continuously progressing robotic process automation will transform jobs and but also have begun to have an impact on how work is performed and structured in the next few years (Hofmann et al., 2020). The advanced technologies are likely to enhance productivity and efficiency, but also will create new jobs in the digital world, boosting consumer demand and generating new revenue streams. According to the World Bank, the share of automatable jobs varies between 6% in Korea and 12% in Austria and the jobs with high automatability percentage will be found in Spain, Germany or Austria, while the lowest will be found in Korea and Estonia (6%) or Belgium (7%). The utilisation of digital solutions in terms of data and computer availability allow for automating a substantial share of jobs in the near future. The latest OECD Regional Outlook (2019) shows that the prevalence of jobs at risk of automation is much higher than average for example in eastern Europe (Slovakia, Slovenia, Poland) and southern Europe (Greece, Spain), while Nordic countries and the UK seem to face a lower risk (https://ec.europa.eu/jrc/en/publication/eur-scientific-and-technical-research-reports/changingnature-work-and-skills-digital-age). According to World Economic Forum 2019, smart digitalization and cognitive automation will create new jobs, and some range of roles that are set to experience increasing demand in the period up to 2022.

The economic outlook for the future of work will be different shortly and employers will require different skills from workers compared to previous decades (Ionescu, 2019). The workers are facing shifting skills demand from job opportunities in expanding businesses.

In Europe, the number of people aged 65 or older is about to grow from 85 million today to more than 151 million in 2060 (Eurofound, 2019). The EUROSTAT estimates that by 2060, 30% of the population of the 27 EU countries will be over 65 years old. This means that the ratio of productive individuals to retired people will be 2:1, versus the current ratio of 4:1. About 44 million workers in Europe suffer from occupational musculoskeletal disorders (Ilmarinen, 2001). They represent the 38% of occupational diseases with a cost up to 2% of the Gross National Product in the EU. For these reasons, the increasing of ergonomics conditions is closely linked to a general reduction of costs and to an implementation of productivity. Companies have continuously tried to reduce the ergonomic risk of jobs that are manual and repetitive such as assembly activities, however less attention has been paid to activities involving more cognitive effort in considering the impact of human factors on the performance (Grosse et al., 2015). Operators' performance can be related to the physical aspects (e.g., the posture of operators and physical fatigue), to the mental aspects (e.g., the competency of operators) and to the psychosocial aspects (e.g., stress and motivation of the operators).

Workload is determined by the interaction of task demands, the circumstances in which the task is performed, skills, behaviors, and individual perceptions. In (Hoonakker et al., 2011) workload is a design that serves to find out how much a person's physical and mental limitations are in completing a job. Workload is also influenced by external demands of a job, such as environmental factors, organizational factors, psychological, and so on. Workers feel bored because they have higher abilities than the job requirements they face. Vice versa, workers with abilities below the job requirements will experience a workload that will cause worker fatigue. There are three workloads given to employees, namely workloads that meet standards, workloads that are too high (over capacity) and workloads that are too low (under capacity). Work activities carried out involve all body organs, muscles, and brain so that an increase in work activity indicates an increase in workload (Davis et al., 2009). The workload of each job can be in the form of physical workload and mental workload.

Task demands in the form of carrying out physical actions (physical workload) and cognitive tasks (mental workload). The impact of this action depends on the ability of the individual who carries it out.

The following doctoral dissertation highlights the criticalities linked to the new technological structure of in the digital factory. In the literature the human factor is not analyzed in a global way, paying no attention to the evaluation of the mental workload of operators who perform tasks of an increasingly cognitive nature. The methodologies identified, aimed at assessing the mental workload of operators, are often linked to a specific work environment and to specific tasks. Therefore, the existing methodologies do not appear to be innovative and do not adapt well to the evaluation of the mental workload in dynamic working environments.

1.1. Physical and Cognitive Ergonomics research

The field of human factors and ergonomics (HF/E), since its inception, has been instrumental in developing methods, tools, and solutions when considering cognitive and physical systems independently. However, every human action is orchestrated by mind (and brain) and body interactions. To comprehensively understand of how humans interact with their work environments is necessary to employ approaches that effectively identify, assess, and facilitate development of controls and remedial measures that address these mind-body interactions. The study of physical ergonomics is concerned with human anatomic, anthropometric, physiological, and biomechanical characteristics as they relate to physical work systems. The study of cognitive human factors is concerned with mental processes, such as perception, memory, reasoning, and motor response, as they affect interactions among humans and other elements of a system. Many tasks involve some level of mental or cognitive processing in addition to physical efforts, so that ideally physical and cognitive demands should be considered together when examining human behaviour at work. High cognitive demands can influence physical capabilities, and physical demands can influence cognitive processing. So, while HF/E is a highly multidisciplinary field that considers humans relative to some aspect of their work environment, efforts are needed to integrate physical and cognitive subsystems during evaluation and (re)design when considering the human in the context of the work situation.

The following studies are focused on quantifying human behaviour when interacting with physical and cognitive subsystems, applied research that proposes predictive tools to assess multidimensional work demands, theoretical positions and new methodologies that challenge how these interactions are examined.

Mental workload, fatigue, and stress, stemming from an overloaded cognitive subsystem, have been shown consistently to affect several aspects of human physical capabilities. For example, cognitive distractors and social stress can alter biomechanical strategies during controlled processes such as upper extremity and low back exertions (Mehta et al., 2012) as well as automated processes such as walking (Osofundiya et al., 2016). Neuromuscular performance, such as muscular fatigue and recovery, also deteriorates with mental fatigue and workload (Mehta & Agnew, 2012). Mechanistic investigations have revealed cardiovascular, endocrinal, neuromuscular, and perceptual pathways through which “non-biomechanical” work factors affect worker functional capacity. These include, but are not limited to, recruitment of same motor units during separate physical and mental work (Lundberg, 2002). The impact of exercise on cognitive functions, based on type and duration, is also well established and documented (Tomporowski, 2003). Physical exercise influences the amount of attentional resources devoted to a given cognitive task, which follows an inverted U-shaped behavior of differences in physical intensity (Kamijo et al., 2004). Previous evidence has also demonstrated that the timing of cognitive tasks during exercise can regulate cognitive performance during dual-task scenarios (Audiffren et al., 2009).

HF/E design strategies have regularly exploited sensitizing both auditory and visual systems for signal detection and information dissemination to enhance stimulus salience. The effect of physical exertions on concurrent cognitive task performance with different modalities of information presentation are examined by (Kaber et al., 2016) . Using traditional ergonomic techniques to assess physical exertions during running, the authors reported that in occupations where workers are heavily physically challenged, presenting cognitive information through visual modality may result in faster processing of inhibition responses than through auditory channels. In (Pankok et al., 2016) is simulated physical exertions in a controlled lab environment using a treadmill, the ecological validity of physical demands may be questioned. Indeed, it is possible that cognitive processes during running differ when one runs on a treadmill (and indoors) versus on a natural outdoor terrain. This, in fact, was examined in the next article in this issue by (Blakely et al., 2016). The authors sought to understand whether differences in natural terrain characteristics impacted cognitive and/ or running performance. The study was conducted in naturalistic settings, in even and uneven natural terrains, and a tone-counting working task at two difficulty levels was employed to manipulate cognitive demands. Decrements in running performance were found as the cognitive load increased. Moreover, cognitive performance declined with increasing workload (i.e., greater cognitive difficulty and an uneven terrain).

Findings reported by (Pankok et al., 2016) and (Blakely et al., 2016) have important implications for warning signal designs in high stress scenarios. This is particularly true in scenarios that are associated with running/exercise and are extremely physically challenging, such as those experienced by law enforcement and military officers. One might inquire if the aforementioned relationships were true for physical tasks that require greater postural stability. Maintaining balance and postural stability, both seated and standing, are critical in minimizing the risk of falls in industrial settings, such as construction and oil and gas operations. The third article in this issue, by (Cullen & Agnew, 2016), investigated the effects of a multimodal dual task paradigm (seated balance and auditory discrimination tasks) on performance, physiological, and subjective measures of workload. Contrary to the authors' hypotheses, the balance task did not affect the performance of the auditory task, and the presence of the auditory task led to better balance performance with unstable seating. While performance measures remained unchanged, and physiological workload indicator was only sensitive to the auditory task, subjective workload measures showed the greatest sensitivity to changes in workload due to both balance and the auditory task difficulty levels. As such, the authors underscore the need for employing multiple metrics of workload to better evaluate how operators interact with their multitasking environment.

The fourth article in this issue, by (Murata, 2016) employed multiple metrics, both behavioral and physiological, to predict subjective drowsiness during a simulated driving task. Driver fatigue and drowsiness is a critical HF/E challenge and current research (to practice) efforts have focused on real-time monitoring systems that can accurately predict driver drowsiness to avoid accidents. In (Murata, 2016) the author integrated several behavioral measurements, such as neck bending angle, back pressure, and foot pressure, as well as physiological measurements, such as electroencephalography, heart rate variability, and blink frequency, to develop a model that offered »97% accuracy to predict subjective drowsiness. The author successfully employed an integrated approach using key information from different operator subsystems (cognitive and physical) during simulated driving tasks, through traditional ergonomics and human factors assessments as well as more recently developed neuro-ergonomic methods. The feasibility of obtaining different measurements, which vary in the level of technology requirements, intrusiveness, and precision offered, was also discussed in the context of developing real-time monitoring systems for tracking driver drowsiness. The objective of the next article in this issue, by (Ye & Pan, 2016), was to predict subjective recovery time, which can facilitate efficient physical and mental work shift schedules, using parameters that are feasible to obtain in naturalistic work environments. Their study built upon existing evidence on the interactions between physical and cognitive work demands to develop an estimation tool that utilized gender, relative body mass index, heart rate, perceived functional ability, and physical activity rating score, to predict when during the course of physical recovery workers can safely and effectively resume cognitive work. One of the common discussion points raised in the aforementioned studies presented in this issue is the need for a better understanding of the impact of physical and cognitive stressors on various human subsystems. Neuro-ergonomics, the study of brain and behavior at work, is one of the numerous scientific impacts that Raja Parasuraman made on HF/E (Parasuraman & Wilson, 2008). The two Methods, Models, & Theories articles presented in this issue expand on this new subdomain of HF/E and as such aim to contribute to Raja's legacy. In (Hancock et al., 2016) is presented an extension to Parasuraman's vigilance taxonomy (Neigel et al., 2020), in an attempt to defeat vigilance decrements, by emphasizing the need for simple design characteristics such as cuing and knowledge of results. Rather than redesigning existing poor designs, the authors recommend that the design of interfaces be informed such that real-world, operationally critical vigilance-inducing displays are never created in the first place. At the same time, displays should be designed in such a fashion that operators do not experience visual fatigue when working. In (Richter et al., 2016), the authors present the utility of unique neuro-ergonomic research in quantifying visual effort, which has the potential to advance visual fatigue research in the emerging domain of visual ergonomics. The authors provide compelling arguments and supporting evidence that both the cognitive processes of the visual system and the biomechanical functions of the neck/ shoulder area are impacted during visual fatigue development.

The study further demonstrated the utility of functional near infrared spectroscopy (fNIRS) to uncover underlying neural mechanisms of visual fatigue. Another application of fNIRS is discussed subsequently by (Cheng et al., 2016). Their study employed fNIRS to examine functional connectivity (FC) between motor-related brain regions and high-level cognitive brain regions during distal upper extremity movements. Results of this study indicate that movement intention that requires collective neural efforts from cognitive-and motor-specific regions, during the transition period between rest and hand movement, can be accurately captured through FC changes. These findings have strong implications for improving the precision and latency of anticipation-based brain-computer interfaces, for neuro-ergonomic research related to human system integration and automation, and various neurorehabilitation approaches.

However, integration of physical and cognitive ergonomics can simply be facilitated with how we design studies, analyze, and report study findings. For example, when investigating cognitive performance of different warning signal designs, studies should consider physical activity levels of the participant pool, physical environmental impact, and psychomotor requirements of the task. Similarly, in studies that focus on traditional physical ergonomic issues, such as lifting, the cognitive processes associated with the different task features (e.g., known versus unknown weights), use of visual/auditory aids for speed of work, etc., should be considered. Such integration efforts are even more critical when examining worker fatigue, operator situation awareness, and decision making, as well as understanding etiology of work-related musculoskeletal disorders.

According to the topics presented in this first chapter, the following PhD thesis aims at developing the literature focused on the consideration of human factors in the digital factory answering to the following research question:

a. In which ways can be better considered the impact of human factors in the tasks performed in the digital factory?

In relation to this general research question, this thesis is strictly focused on the modelling of the mental workload experienced by the operators in order to implement the existing research focused on the evaluation of the human performance. In fact, till now the literature has very little focused on the evaluation of the mental fatigue and how its should be manipulated in order to minimize the impact on the human performance. In relation to this, the main research question is the following:

b. How can be modelled the mental fatigue of operators involved in cognitive and physical tasks and how can be evaluated the operators' performance?

In order to reach this contribution of the literature focused on the operators' wellbeing, it should be addressed one more research question related to how the mental fatigue level of an operator can be monitored. In fact, as far as mental workload evaluation is concerned, there still lacks the kind of methodology to be used to have real-time feedback or a prediction of the mental workload conditions of the operators. Related to this, it is necessary to answer to the following research question:

c. How can be obtained an assessment of the fatigue experienced by operators?
d. Which parameters can be considered in the estimation of the mental fatigue?

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2. Human Mental Workload

One of the primary goals of building interactive technologies, from human factors perspective, has always been managing the mental workload experienced by the users. The primary motivation is the optimization of their performance, the enhancement of their engagement, and the minimization of their errors. All human activities include some amount of mental processing and thus, at least some degree of mental workload (Mitchell, 2000). Even the most rudimentary of physical or cognitive tasks involve some degree of mental processing, and consequently a resulting level of mental workload (Longo, 2012). In the last years technological advances have shaped human-computer interaction in such a way that has reduced the human operator's physical load, while altering necessary cognitive processing in terms of its nature (passive vs. active) and quantity. The main goal of these advances, from the commercialization of systems that support direct manipulation of graphical objects, to automated language translators and gesture recognition systems, has been to reduce and/or regulate the human operator's mental workload (Hancock and Chignell, 1988; Longo, 2015).

The key attention has been to regulate the associated cognitive, visual, auditory, perceptual, psychomotor, and communication contributors to workload (Miller, 1956). However, research in the fields of learning and instructional design has indicated that the use of technology not only increases performance, but also often increases users' frustration (Hove and Corcoran, 2008). A critical evaluation of our current understanding of mental workload and the identification of key areas of progress remains extremely important because it can aid in the design of interactive technologies (Jex, 1988). Mental workload measurement is vital to the development of new technologies, information-based procedures and user interfaces that maximize human performance (Longo and Rajendran, 2021). Identifying such areas wherein users experience significant levels of mental workload, and trying to regulate it by system re-design, could also minimize human error, and in turn, increase user satisfaction, learning, and other operational advantages ('The attention economy: understanding the new currency of business', 2002). The significance of mental workload measurement is frequently expressed in the desirability of optimizing human-machine interactions (Zhang *et al.*, 2015). The key reason for measuring mental workload is to quantify the mental cost of performing tasks in order to predict operator and system responses. Other reasons to measure mental workload include the acquisition of specific certifications, or compliance with certain industrial standards (Cain, 2007).

Despite the manifest reasons for developing interactive technologies that support mental workload regulation across myriad safety-critical application domains including aviation, automobile, and maritime industries to mention just a few, there is, as yet, no universally accepted definition of mental workload (Wilson, Fullenkamp and Davis, 1994)(Borghini *et al.*, 2017). This lack of a comprehensive and universally accepted definition has not prevented the proliferation of experimental research about its effects and mitigation. Surveys and reviews have been performed on mental workload, but they are either domain-specific (Pearson *et al.*, 2006), or they focus on one particular aspect of mental workload, such as a single measurement technique (Charles and Nixon, 2019).

In the next sections the present work presents:

i. the theoretical background of mental workload;
ii. its current operational definitions;
iii. and mental workload measurement methods and measures;
iv. N-back test and methods used to evaluate subject's mental workload in the experimental setting conducted.

2.1. Mental workload theoretical background

Google Scholar was used as the primary source for identifying and gathering published material, it is an excellent tool that allows to identify academic sources. The overreaching search terms used were 'mental workload' and 'cognitive workload'. Google Scholar, at the time of querying, displayed 342, 000 results for the term "mental workload" and 311, 000 results for 'cognitive workload; the overlapping documents were considered one time if considered suitable according to the criteria outlined below. The first 100 pages of results were considered ordered relevance, with each page containing 10 results. Thus, 1,000 entries for each keyword were considered. These entries were screened based on title and abstract, and a preliminary set of scientific articles was created. Works that only mentioned mental workload, but did not contribute either to its measurement, definition, or evaluation, nor applied existing assessment methods in specific application fields, were excluded. From remaining articles, bibliographic references were analyzed, and recursively identified work were considered for review. Many of these references had previously been identified via Google Scholar, but several additional sources were not. More than 500 relevant articles were consequently added to the set. At least about 1600 manuscripts were analyzed. Though many other manuscripts no doubt exist in the literature, and a systematic review is not feasible, an executive decision was taken that the selected materials were sufficiently representative to conduct an informal analysis in order to provide a robust characterization of the state of the art concerning mental workload research. The selected manuscripts were carefully evaluated, and the following attributes were extracted in order to facilitate classification and synthesis to present the collected results in an orderly manner. These attributes were: year of publication and type (journal/conference/technical report):

- category of research (by type, form, objective, reasoning)
- domain of application, underpinning theory
- proposed definition of mental workload (if existing)
- evaluation of the reliability, validity, sensitivity or diagnostic of the underlying model
- types of measures employed and details
- experimental sample size (if empirical research), and number of citations, to provide a portraiture of the breath of research on mental workload.

Mental workload is a complex, dynamic, person-specific, nonlinear construct. It is believed by many scholars to be multidimensional (Humphrey and Kramer, 1994; Cagliano *et al.*, 2019). And intimately connected both to attention (Kantowitz, 2000) and effort (Egeth and Kahneman, 1975). Many theories proposal exist that have been used to help define, explain, and measure mental workload. These efforts seek to rationalize thinking about mental workload, and are often associated with observational research studies. Theories on mental workload aim to provide a monothetic framework to explain the intrinsic mechanisms and factors that underpin. Following the salient features related to mental workload were discussed and described. However, it should be noted that not all the theories identified in the current work, address mental workload exhaustively. Nevertheless, the related and the relevant factors to the mental workload were addressed. Figure 1.1 shows these different factors divided into three core blocks: inputs, processing, and learning. In the Figure 1.1 the factors in each block do not represent any necessary sequential order in which various sub-processes take place. Instead, each block shows the relations among the different factors listed there that have been established as influencing on mental workload, such as motivation and arousal can influence together the mental workload.

BLOCK 1 – INPUTS	BLOCK 2 – PROCESSING	BLOCK 3 – LEARNING
Task static: • Intrinsic in design and instructions (4) • Intrinsically rewarding tasks • Clear task goal and sense of progress • Clear and immediate task feedback • Match of task challenge and skill (9) **Dynamic (5):** • Context **Environment (1):** • Actors • Rules • Community	**Sensory and working memory (12)** **Relevance (19)** **Appraisal (3):** • Perceived input as a threat or a challenge • Counter threats • Benefit from threats **Decision making:** • Group decisions (10) • Individual decisions (18) **Motivation:** • Factors for satisfaction and dissatisfaction (11) • Success importance (15) • Meaningfulness of task and direct effectiveness/communication (13) **Self-awareness (22)** **Distributed cognition (6)** **Arousal (2):** • Optimal levels **Dynamic attentional capacity (14)** **Anxiety (17)** **Personality (8)** • Neocriticism • Psychoticism **Age (20)**	**Long term-memory** • Hierarchical storage: declarative precedes procedural knowledge (7) • Schemata formation or alteration (21)

Figure 1. 1 Theories linked to the construct of mental workload organized in blocks. The numbers in the brackets represents the theories linked to the construct of mental workload shown in this section

The first block of Figure 1.1 concerns the inputs users perceive. The complexity of a task, its instructions, and its demands are components that, in the terms of Cognitive Load Theory (4), are intrinsic to the task itself (Kirschner *et al.*, 2018). Another model is Flow Theory (9) which focuses on circumstances wherein task demands are perceived by the operator to be met by their available resources; a state referred to as 'flow'. One core characteristic of this state is the extremely high level of operator engagement which is driven by this skill-challenge match, but also bolstered by other task characteristics, such as clarity of goals and feedback, sense of progress and, how intrinsically rewarding the task itself is (Davis and Csikszentmihalyi, 1977). In a wider way, a context is largely driven by the task itself and, could be considered as influencing the inputs a user can receive. Thus, in turn, effect their response, and experienced mental workload, as put forth by Contextual Action Theory (5) (Sestito, Flach and Harel, 2018). A context is an identifiable configuration of environmental mission-related and agent-related features that help shape behavior (Hoc, 2001). Such factors can be considered static and prior task execution, in the sense that they are thought to be immutable while information while processing task-critical information. However, there are other factors that are dynamic in that they cannot be anticipated prior to task execution and are stochastic. Examples of such factors include actors, rules, and community in a given environment (D. *et al.*, 1979) as proposed in Activity Theory (Figure 1. 1 (1)).

The second block of Figure 1.1, the Processing block, refers to the way the task-specific inputs are subsequently processed by an operator. These signals are perceived by the sensory faculties, as explained in Information Processing Theory (12) (Simon, 2014). Sensory information is then transferred to working memory. Such memory has a limited capacity and can process and hold only a limited number of bits of information at any given moment. A variety of stimuli may be gathered, experienced, and processed by an operator executing a task. However, the cognitive processing system filters these signals and considers only those that are relevant: a trend central to Relevance Theory (19) (Smolka and Pirker, 2018). The input signals are appraised and according to Cognitive Appraisal Theory (3), an input could be perceived as a risk if it threatens the operator's future behavior. In somewhat contrast, a harm/loss is a case in which an operator has already experienced damage in the past (Zajonc, 1984). If a stimulus is perceived as a threat, then working memory processes possible measures to counter it, otherwise it can benefit from it (Zajonc, 1984). Another factor that can influence information processing is motivation. On the one hand, the Herzberg's Two-factor Theory (11) presents the hygiene and the motivation attributes, also referred to as factors for satisfaction and dissatisfaction (Herzberg, 1954). Specifically, there are certain independent factors, in the workplace, that can result in job satisfaction or dissatisfaction, and thus in turn can influence mental workload (Simon, 2014). On the other hand, apart from these mechanisms considered of automated feedback, the meaningfulness of the tasks at hand, and the directness and effectiveness of the communication with other participating individuals, have all been identified by the Job Enrichment Theory (13) as key factors which influence motivation (Cook and Salvendy, 1999). Similarly, according to Motivational Intensity Theory (15), perceived task difficulty and degree of response success can contribute to a person's motivation. In fact, when the importance associated with success is low, then motivation, and consequently effort also drop at lower levels of task difficulty or complexity. Conversely, motivation levels are maintained, despite high levels of task difficulty, if the importance to success is high (Richter, Gendolla and Wright, 2016). This proposal, when combined with the ideas postulated in Cognitive Appraisal Theory (3), can serve to explain differences in the levels of mental workload experienced by participants during real-world tasks in comparison to simulated tasks (McCarthy, Mejia and Liu, 2000). In real-world tasks, operators are more likely to perceive an impending threat. In contrast, in simulated tasks, and a high degree of importance to success, might lead an individual to perceive an impeding threat more as a challenge. Comparative studies that weigh real-world tasks against simulations, such as that reported in (Veltman, 2002), illustrate that there are clear differences in the physiological responses of humans during real-time tasks. According to the Arousal Theory (2), an individual's arousal needs to be at an optimum moderate level, neither too low nor to high to facilitate peak performance. Excessively low arousal level results in sleepiness or fatigue, whereas excessively high arousal can lead to stress and anxiety (Cohen, 2011). With regards to task complexity, it was demonstrated that optimum performance was achieved for simpler tasks when the arousal levels were high, whereas for complex tasks, better performance was achieved at a lower level of arousal (Suedfeld and Landon, 1970).

Although many additional factors, such as time of day and exogenous stimulants can influence arousal level, the literature focuses on the interaction between the following four factors:

a) participant skill
b) task familiarity/past knowledge,

c) personality and
d) task difficulty/complexity

(Hancock and Chignell, 1988; Cohen, 2011).

The difference between task difficulty and task complexity is that the former is a perceived phenomenon whereas the latter is considered an inherent property to the task. A similar idea is put forth in the Malleable Attentional Resource Theory (14). According to this model, attentional capacity can vary in response to changes in task demand. Thus, the negative performance variation, associated to situations of underload, can be justified by the lack of suitable attentional resources (Basahel, Young and Ajovalasit, 2010). Performance can also be influenced by other factors, as explained in the Processing Efficiency Theory (17). This framework explains the influence of anxiety on the performance in a demanding situation is more impactful on processing efficiency than on performance effectiveness. Processing efficiency is defined as performance effectiveness divided by associated effort. Experimental analyses have demonstrated that highly skilled humans can cope with ever higher task complexity levels. However, peak performance for such individuals is also achieved at a higher task complexity in comparison to those less skilled individuals (Gellatly and Meyer, 1992). Similarly, it has also been shown that task performance improves as the degree of task familiarity increases (Peña and Quinn, 1997). Optimum performance is consequently reached at higher levels of arousal for familiar tasks in comparison to unfamiliar ones (Fontaine and Schwalm, 1979). With regards to personality, the main factor considered to influence task performance is extraversion (Revelle *et al.*, 1980). Introverts have been found to achieve their optimum performance at lower arousal levels when compared to extroverts. According to Eysenck's Personality Theory (8), there are two other attributes that comprise personality. These are the degrees of neuroticism and psychoticism (STORMS and SIGAL, 1958). There have been other models that explain personality, and studies have examined the effects of individual personality on task performance (Rose *et al.*, 2002). Others have examined the influence of the dimensions of the 'big five' or the five factor model (extraversion,17euroticcism, openness to experience, agreeableness, and conscientiousness) on task performance (Hurtz and Donovan, 2000). For example, a detailed review has been compiled presenting the impact on seven different aspects of participant personality, namely intelligence, adjustment, extroversion-introversion, dominance, masculinity/femininity, conservation, and interpersonal sensitivity, as well as their relations to human performance in small groups (Mann, 1959). Another important factor which affects mental workload is effort (Garbarino and Edell, 1997). Effort can also influence decision-making (Recarte and Nunes, 2003). Decision-making processes drive the response of an individual to tasks, and they are generally categorized into individual and group norms (Bakr *et al.*, 2008). Rasmussen's Theory of Skilled Behavior (18) identifies three levels of expertise, at which participants could act with respect to making task decisions: skill, rule, and knowledge-based categories. However, the dynamics of decision-making in group scenarios, and the differences between competitive and co-operative groups, are explained by the Game Theory (10) (Bakr *et al.*, 2008).

Another important factor influencing information processing is age. According to Salthouse's Cognitive Theory of Aging (20), information processing is affected by age (Bosma *et al.*, 2003) such that various cognitive abilities tend to decline after peaking in the 20–30 s (Park *et al.*, 2002). One such cognitive ability crucially linked with mental workload is intelligence, which is often defined as the capacity to acquire and apply knowledge, especially toward a purposeful goal. There are various types including fluid, crystallized (Diggs, 2007) and emotional intelligence. Fluid intelligence refers to that which is used for activities such as problem solving and reasoning, where the need for prior knowledge is largely minimized. Crystallized intelligence uses previously acquired education and skills (Anderson and Craik, 2017). Emotional intelligence concerns the ability to perceive, understand, integrate, and regulate emotions. This parsing of the forms of intelligence represents a theoretical basis for understanding how task performance can be enhanced, and consequently how consequently mental workload is impacted. For example, although aging leads to decline in fluid intelligence, crystallized intelligence remains stable, or can even improve with age. Empirical evidence demonstrates how a significant interaction between task performance and age exists: older adults consistently make more mistakes than younger adults across all levels of mental workload. Similarly, adults with high emotional intelligence are prone to make more errors. These categories of intelligence have been deemed too broad, and several sub-classifications that identify and group specific aspects have bene generated in (Johnson *et al.*, 2004) and (Diggs, 2007). Another aspect strictly related to mental workload is cognition. Broadly speaking, cognition can be defined as the mental faculty of knowing. Its associated processes include perceiving, recognizing, conceiving, judging, reasoning, and imagining. Cognition is also comprised of constituent components that include intellectual ability, learning, and memory. These abilities have been further divided into more specific components, measurable by various means such as the Comprehensive Ability Battery, the Hawaii Battery and the Weschler Adult Intelligence Scale (Johnson *et al.*, 2004). Abilities, such as cognition and attention are finite and limited. A critical aspect of processing information, using limited attentional resources, is postulated by the Multiple Resource Theory (16). This theory explains the behavior of an operator as he or she concurrently performs multiple tasks that rely on the expenditure of multiple resources shared among these tasks (Wickens, 2002). The theory is comprised of four divisions of resources that can be used for information processing: perception/cognition and response stages; visual and auditory perceptual modalities; analog/spatial processes codes, and categorical/symbolic (usually linguistic or verbal), tactile processes codes; focal and ambient vision visual channels. According to this theory, multiple tasks can use different pool of resources, and in case of resource sharing, overload situations can occur, which in turn can impair an operator's performance (Wickens, 2008). Operator performance, with workload optimization, in turn, may be enhanced with an increase in self-awareness levels. According to Self-Awareness Theory (22), individuals can focus their attention on the self (internal), or on the external environment, at any given moment in time (Hsu *et al.*, 2015). The process of self-evaluation is activated when a person focuses on, and compares the self, with standards of correctness that define the expectation to think, feel, and behave. In turn, this process of self-evaluation enables humans to change their behavior, and to experience pride or dissatisfaction, based on the degree to which they meet their own intrinsic standards (OLDFIELD, 1954). Another factor that affects information processing, according to the Distributed Cognition Theory (6), is that cognition and knowledge are not attributed to a participant alone. Instead, they are distributed across social groups, the environment, and the time of interaction (Hollan, Hutchins and Kirsh, 2000).

The final conceptual category illustrated in Figure 1 is learning. This process is connected to the notion of long term memory which has unlimited capacity, and this is where any acquired knowledge is stored (Van Acker *et al.*, 2018). According to Event Perception Theory (7), events are perceived and stored in terms of hierarchical structures (Johansson, Von Hofsten and Jansson, 1980). Here, declarative knowledge precedes procedural knowledge. A similar idea is advanced in Schemata Theory (21) which postulates that experience and knowledge that are acquired are stored in the form of building blocks of cognition known as schemas. Learning is thought to take place when new schemas are formed, or existing schemas are altered (Van Acker *et al.*, 2018). Schema and learning are core elements of Cognitive Load Theory (4). According to this theory, the cognitive load that a person experience can be of one of three types: intrinsic, extraneous, and germane. This theory effectively synthesizes the three blocks of Figure 1 (inputs, processing, and learning). Intrinsic load refers to the demanded effort associated with a specific task, while extraneous load is linked to the way a task is presented (inputs block). Germane load refers to the effort and cognitive processing exerted by a human (processing block), into the formation of a schema in permanent form of knowledge in long-term memory (learning block). These three types of loads proceed through a continuous evolution, and it is still not clear whether they are independent and can be aggregated toward an overall measure of cognitive load (Orru and Longo, 2019).

In summary, many theories exist to explain human behavior and in turn, contribute to the definition of those factors that can affect perceived mental workload, and that in turn, lead to variations in associated performance. As synthesized in Figure 1, a group of these theories seeks to identify various inputs that contribute to mental workload and explain how they influence cognitive processing. These inputs can be static, for instance element related to the design of specific tasks/instructions or associated with the mental state of an operator prior to task execution. These initially identified factors can be considered immutable during cognitive processing, but they can all influence it. Other inputs are dynamic, such as those related to the context in which tasks are executed. They are dynamic as they are not predefined and change during task execution. Thus, they influence human behavior and in turn, perceived levels of mental workload.

Another set of theories are related more to the way humans process information. These models are intrinsically associated to the characteristics of an operator such as past experience, ability to process information, and the internal strategies adopted for task execution and resources usage. Similarly, others reflect internal motivational factors such as effort, and the capabilities to cope with environmental influence and interaction with other humans. Another group of theories are focused on investigating the effect of information processing on how learning occurs especially in long-term memory. In synthesis, many theories have influenced the formation of the construct of Mental Workload, each promoting different aspect and influencing factors. On one hand, their aggregation and inclusion in a unified definition of Mental Workload is simply an impossible task. On the other hand, each category of theories provides different meaningful focus on the nature and mechanisms of mental workload to enhance understanding, measurement, and regulation of the construct.

2.2. Mental workload definitions

Defining mental workload has been a major challenge to both theorists and practitioners. This circumstance is especially true given the abundance of theoretical work associated with this construct, the many interpretations of the phenomena, and the contributions from different disciplines. As a result, the term 'mental workload' is often used to broadly encompassing the demands imposed on users, the effort experienced by operators to meet those demands, as well as the consequences of attempting to meet those demands (Cain, 2007). Although mental workload can be intuitively defined as the total cognitive work needed to accomplish a specific task in a finite time period, it continues to be a challenge to define precisely. Despite many years of research, it remains hard to present a universally/generalizable and acceptable definition of mental workload (Longo, 2015). This shortfall has likewise been captured in other literature reviews (Miller, 1956; Cain, 2007) . The difficulty in defining mental workload is compounded by the diverse methods of measuring it, its own multi-dimensional nature, and its widespread applicability across operational tasks and environments of interest (BOYLING, 1989) (Veltman and Gaillard, 1993). In the table 1.1 a comprehensive list of definitions of mental workload forwarded by researchers from diverse fields is shown. They have been organized based on a semantic analysis. They were grouped together when the underlying semantics of the different definitions were similar. The two basic entities that are involved in the dynamics of mental workload are specified in the first two definitions: a task and a subject. It establishes mental workload as a multidimensional construct that originates from the interaction between these two entities. It also serves to show how mental workload represents the load that a particular task imposes on a particular operator/performer (Paas *et al.*, 2003)(Hughes *et al.*, 2019). Definitions 3 to 5 elaborate on this proposition by identifying the main attributes of this interaction: task demands and operator performance (Hancock and Caird, 1993) (Byrne, 2011) (Colombi, J.M., Miller *et al.*, 2012). Similarly, definition 6 links the cost incurred by the operator to achieve a specific level of performance (Marquart and De Winter, 2015).

Definitions 7–12 specify the cost of this interaction and identifies the elicitation of the internal cognitive resources of the operator as the cost incurred during the interaction. These characteristics establish that this cost is determined by the dynamics between the internal/cognitive resources, at the operator's disposal, and those demanded by the task (Haga, Shinoda and Kokubun, 2002) (Mizobuchi, Chignell and Newton, 2005) (Leung, Yucel and Duffy, 2010) (Palinko *et al.*, 2010) (Liang *et al.*, 2014) (Lukanov, Maior and Wilson, 2016). In consequence, definitions have helped establish a number of key dimensions in defining mental workload: a task and its demands, the operator performance on said task, and the internal limited cognitive resources necessary for successful performance.

The dynamics of resource sharing, which plays a critical role in determining mental workload, are addressed in definition 13. Herein mental workload is described in terms of costs incurred by an operator while performing multiple tasks that use a common pool of resources (Wickens, 2002). Definitions 14–31 provide greater clarity and precision regarding specific additional attributes pertaining to mental workload. In detail, these are time, cognitive capacity, information processing capacity, mental effort and memory. Definitions 32–47 describe mental workload by establishing a quantifiable relationship between these attributes. In particular, they are based upon the notions of limited information processing capacity or limited cognitive resources, to meet task or system demands. Definition 48 describes mental workload in terms of the degree of the operator engagement with the task (Weinger, Reddy and Slagle, 2004). It can be argued that the degree of expenditure of internal resources can be considered a reasonable representation of operator engagement. This is further stressed in definitions 33–36 that specify mental workload in terms of the degree to which the internal resources of the operator are used while engaging with the task (Miller, 1956; Weinger, Reddy and Slagle, 2004)(Young, Zavelina and Hooper, 2008)(Lim *et al.*, 2016)(Wang, Gwizdka and Chaovalitwongse, 2016). On the one hand, definitions 37 to 41 explicates mental workload as a difference between one or more of the aforementioned resources at the operator's disposal, and those demanded by the task (Young and Stanton, 1997) (Kum, 2007) (Zülch *et al.*, 2015) (Harriott *et al.*, 2015). Similarly, definitions 42 to 44 specify mental workload as the proportion of the total mental capacity, that is used at a given moment, to meet the task demands (Borghini *et al.*, 2014) (Pierce, 2009). On the other hand, definitions 45 to 47 are based on the belief that mental workload can be represented as the ratio of the internal resources available at the operator's disposal, to those required for the task under execution (Haga, Shinoda and Kokubun, 2002) (Saleem *et al.*, 2009) (Hu *et al.*, 2016).

Another critical point of distinction is provided by definition 47. The latter describes mental workload as the ratio between the operator's processing power and the input coming from the environment (Frey *et al.*, 2014). The distinction here lies in the use of the word "environment", as opposed to "task," implying that there could be stimuli from the environment other than those originated from task itself. For example, students in a noisy classroom are likely to have a higher mental workload in comparison to students in a quiet classroom, even though the learning task for these two groups is the same (Becker *et al.*, 1995). One commonality across all the definitions of mental workload is the lack of consideration of overload circumstances. That is situations in which the resources demanded by a task are no longer a portion of the operator's mental resources, but actually exceed them. The key distinction here is that the aforementioned definitions establish a mathematical relationship (in terms of differences, proportions and ratios), as opposed to an abstract one between the operator resources and imposed task demands. The idea of expressing mental workload, in terms of differences and ratios is useful from a practical standpoint because it provides equal emphasis on the resources available at the operator's disposal and those demanded by the task. In (Haga, Shinoda and Kokubun, 2002; Saleem *et al.*, 2009) the authors make an interesting point which could help consolidate these different factors under larger umbrella conceptualization. In their definitions (49 and 50) they argue that mental/cognitive effort, memory, cognitive and information processing capacity can be grouped under one unified aspect, referred to as human attentional resources. This is because when attention is directed at any object or entity, it naturally invokes the use of memory, cognition, and internal processing, and therefore it demands some mental or cognitive effort. Definitions 51 to 57 take the dimension of time into consideration, along with the other dimensions discussed above (Brown and Boltz, 2002) (Wickens, 2002) (Carswell, Clarke and Seales, 2005) (KUM, FURUSHO and FUCHI, 2008) (Byrne, Tweed and Halligan, 2014)(Longo, 2016) (Moustafa, Luz and Longo, 2017) (Rizzo *et al.*, 2016). The criticality of time is expressed clearly in Carswell's definition which describes mental workload as the ratio of the mental resources required to the total resources available, on a moment to-moment basis (Hancock and Caird, 1993) (Carswell, Clarke and Seales, 2005). This is a key distinction because, it clearly establishes that mental workload varies over time, when the task demand fluctuates on a moment-to-moment basis (Hancock, 2017).

Definitions 58 to 61 identify further factors, other than those already discussed, that could influence the level of attentional resources used. These factors include: situation (Parasuraman, Sheridan and Wickens, 2008), task difficulty (Staal, 2004), operator skill, and operator's past experience ('Mental Workload: Theory, Measurement, and Application', 2021). Task difficulty is a factor associated with any task, and thus more than the operator's attentional resources. However, as already discussed, task difficulty can also depend on the operator's perception of the task, as much as its inherent complexity. Therefore, perceived task difficulty is associated with the operator, whereas task complexity is linked to nature of the task itself. Definition 62 alludes to this point when defining mental workload as a concept that serves as an intermediary between imposed and perceived demands (Hancock and Caird, 1993).

An additional element is the analysis of task execution across a group of individuals over a period of time (definition 63) (Xie and Salvendy, 2000). This is a clearly distinct addition to the other definitions according to Game Theory, an operator's decision-making while executing a task, within a group of people, is different than when executing it individually (Bakr *et al.*, 2008). Definitions 64 and 65 stress this aspect of decision-making from the operator's perspective (Miller, 1956). Specifically, the difficulty and rate of making decisions, along with the rate of information processing, are key factors that mediate mental workload (Smiley, 1989). Definitions 66 and 67 focus on factors that could be considered to comprise the task demands and an operator's performance. Definition 67 expands on task demands by specifying three types: physical, temporal, and environmental demands (Neill, 2011). Finally, definition 68 characterizes mental workload with attributes related to overload. It also describes the consequences that could result if the task demands exceed the operator capacity (Reid, Potter and Bressler, 1988).

Summary, the definitions of mental workload that are found in the literature, are built around a specified number of core concepts and their interaction. In details a primary task and a person are the central notions behind each definition of mental workload. A human, sometimes referred to as operator, is the performer of a primary task, whose complexity and difficulty can be defined by the concept of attributes which require different demands. Primary tasks are usually executed in the context of a specific system, which can include additional secondary tasks. Next, the mental capacity of a performer is limited and, it is composed of a finite number of resources that can be invoked to cope with task demands and, thus, to perform the primary task. Similarly, an operator has limited working memory to be used during task execution. In sequence, the interactions between a human and a task is not a stationary one, dynamically extending across time. It is influenced by the characteristics of an operator such as skills and past experience.

During cognitive processing, a person executes a number of mental operations that are influenced by relevant attention and effort. In turn, these operations are mediated by the influence of the environment in which the task is executed and, the situation in which the performer is involved in. These external mediators, along with the internal dynamics of a person, eventually lead to a certain level of performance which is the dependent variable that usually needs to be predicted. Performance, in turn, influences and is influenced by human decision-making. Definitions vary according to the field of application derived from the orientation of the proposers and their disciplines.

In general, an 'industrial operator' is defined as everyone who carries out a manual and/or intellectual labor in an industrial context. Therefore, factory workers (performing manual or industrial labor in a mill or factory) as well as supervisors (or lower level), executive (or middle level) and administrative (or top level) managers are included in this definition. Due to the factory digitalization, operators have to process an increasing amount of data leading to employ them in more cognitive than physical tasks thus increasing their mental workload, reducing the labor-intensive tasks with physical ergonomic risks.

Clearly, then a universally accepted definition of mental workload does not presently exist. However, in the current tech-oriented and digital factories, mental workload represents the interaction between the operator and an assigned task. It can be defined as the amount of cognitive effort required to perform a certain task during a given time period. Moreover, different factors can influence mental workload as shown before. Measuring mental workload in industrial context is useful to predict the operator and system performance quantifying the mental cost required to perform an assigned task.

Table 2. 1 Mental Workload definitions

#	Mental Workload (MWL) definitions
1	Mental load is the aspect of cognitive load that originates from the interaction between task and subject characteristics (Paas et al., 2003)
2	Cognitive load is defined as a multidimensional construct representing the load that a particular task imposes on the performer (Haapalainen et al., 2010)
3	Mental workload expresses the task demands placed on an operator (Colombi et al., 2012)
4	Mental workload is recognized as a multi-dimensional concept that is largely driven by the characteristics of local task demands (Hancock and Caird, 1993)
5	MWL can be seen as an interaction between the demands of the task and the performance of the operator (Byrne, 2011)
6	The cost incurred by a human operator to achieve a particular level of performance (Marquart and de Winter, 2015)
7	The concept of workload is fundamentally defined by the relationship between resource supply and task demand (Haga et al., 2002)
8	Mental workload is defined as the demanded resources of human information processing for performing a task (Liang et al., 2014)
9	Depletion of human internal resources to accomplish the presented work (Leung et al., 2010).
10	Mental workload is the relationship between primary task performance and the resources demanded by the primary task (Lukanov et al., 2016)
11	Mental workload is a related construct that refers to the amount of resources consumed by a task (Mizobuchi et al., 2005)
12	Cognitive load (also referred to as mental workload) is commonly defined as the relationship between the cognitive demands placed on a user by a task and the user's cognitive resources (Palinko et al., 2010)
13	The cost of performing a task in terms of a reduction in the capacity to perform additional tasks that use the same processing resource (Cain, 2007)
14	Workload can be defined as how the operators can do the required work (their capacities) and how they can manage the task (task demands) to satisfy the operating system demand (Basahel et al., 2010)

15	The relative capacity to respond, the emphasis is on predicting what the operator will be able to accomplish in the future (Cain, 2007)
16	MWL has been defined as the amount of cognitive capacity required to perform a given task (Di Stasi et al., 2013a)
17	Mental workload may be described as the use and temporary expenditure of a finite amount of information processing capacity (Wa¨stlund, 2007)
18	Mental workload is usually associated with information processing tasks, but any human activity includes mental processing and thus, mental workload (Mitchell, 2000)
19	...a measurable quantity of the information processing demands placed on an individual by a task (Annett, 2002)
20	The concept of mental workload is often used to describe how much of someone's information-processing capacity is needed during task performance and how this is influenced by task demands (Stuiver et al., 2014)
21	Mental workload refers to the ability of the operator to meet the information processing demands imposed by a task or system (Wilson and Eggemeier, 2006)
22	Mental workload is used to describe the amount of mental effort involved in performing any given task (Byrne et al., 2010)
23	Mental workload refers to the cognitive effort expended during a particular task (Tavares and Eva, 2013)
24	Mental workload is defined as the overall cognitive effort a person invests in his performance while carrying out a task (Baldauf et al., 2009)
25	The mental effort that the human operator devotes to control or supervision relative to his capacity to expend mental effort (Cain, 2007)
26	Mental workload is described as a noticeable relationship between the human cognitive capacity and an effort required to process a particular function (Hou et al., 2015).
27	The intensity of mental effort can be considered as an index of mental workload. It may be defined as the total amount of controlled cognitive processing in which a subject is engaged (Paas and Van Merrie¨nboer, 1993)
28	Mental workload or cognitive load refers to the total amount of human mental effort or memory that is required for the execution of a task (Chen et al., 2016)
29	Cognitive load or the mental workload is characterized by the amount of memory resources utilized to ascertain a task (Gavas et al., 2017)
30	Mental workload refers to the amount of information and/or the complexity of mental operations that are held in or processed by working memory which depends on the prefrontal cortex (Stock et al., 2016)
31	Mental workload can be described by the demand placed on user's working memory during a task (Fre´ard et al., 2007)
32	Workload is a construct used to describe the extent to which an operator has engaged the cognitive and physical resources required for task performance (Weinger et al., 2004)
33	Mental workload is commonly defined as the extent to which human mental resource is able to meet the cognitive demands of the task (Lim et al., 2015)
34	Mental workload is a hypothetical construct describing the extent to which the cognitive resources required to perform a task that has been actively engaged by the operator (Miller, 2001)
35	Mental workload describes the level of mental resources utilized when a person is performing a task (Wang et al., 2016)
36	Workload is commonly defined as the degree of processing capacity that is expended during task performance, and it reflects a relationship between resource supply and task demand (Young et al., 2008)

37	Mental workload has been generally defined as the amount of resource difference between task demands and capacity of an individual (Lin et al., 2011)

38	MWL is defined as the level of processing capacity while performing the task or the difference between the capacity to affect the usable real performance and human-information processing system (Kum et al., 2007)
39	Mental workload is related to the difference between the amount of resources available within a person and the amount of resources demanded by the task situation (Young and Stanton, 1997)
40	Mental workload can be defined as the difference between the amount of available mental processing resources and the amount required by a task (Harriott et al., 2015)
41	Mental workload is the difference between the capacities of the information processing system that are required for task performance to satisfy performance expectations and the capacity available at any given time (Omolayo and Omole, 2013)
42	Mental workload is commonly defined as the proportion of a person's total mental capacity in use at a given moment (Pierce, 2009)
43	The term workload refers to that portion of the operator's limited capacity actually required to perform a particular task (Kim et al., 2014; Alexander et al., 2000)
44	Mental workload refers to the portion of operator information processing capacity or resources that is actually required to meet system demands (Cain, 2007; Borghini et al., 2014)
45	Mental workload is usually defined as the ratio between task demands and a person's capacity (Brouwer et al., 2012)
46	Mental workload is defined more generally as the ratio of the resources required to complete a series of tasks to resources available to complete as series of tasks (Lodree Jr et al., 2009)
47	The ratio between processing power and data coming from the environment determines mental workload (Frey et al., 2013)
48	Workload is the extent to which an operator is occupied by a task (Verwey, 1990)
49	The mental workload of any given task is the ratio of mental resources required to the total resources available (Hu et al., 2016)
50	The operator's evaluation of the attentional load margin (Haga et al., 2002)
51	Mental workload is related to the difference between the amount of finite resources (attention or mental effort) available within a person and the amount of resources demanded by the tasks being performed (Saleem et al., 2009)
52	Intuitively, it can be described as the amount of cognitive work expended to a certain task during a given period of time (Rizzo et al., 2016)
53	MWL can be defined as the amount of cognitive work required for a person to complete a certain task over time (Longo, 2016; Longo and Dondio, 2015)
54	It can be intuitively described as the total cognitive load needed to accomplish a specific task under a finite period of time (Moustafa et al., 2017)
55	Workload is the amount of work that expected to be done by an operator in a specified time. In another words, it is the interaction between the operator and assigned task (Kum et al., 2008a)
56	Mental workload can be seen as the % of mental capacity in use at any time-point (Byrne et al., 2014)
57	Mental workload for a given task is the ratio of mental resources required to the total resources available, on a moment-to-moment basis (Carswell et al., 2005)

58	Workload can be defined as the ratio of the time required to perform the tasks to the time available (Wickens, 2002)
59	Mental workload would seem to be some combination of mental effort, information processing and emotion in response to task demand (Sheridan and Simpson, 1979)
60	The term workload will be used to refer to the integrated effects on the human operator of task-related, situation-related, and operator-related factors that occur during the performance of a task (Verwey, 1990)
61	Mental workload is an inferred construct that mediates between task difficulty, operator skill, and observed performance (Staal, 2004)
62	Mental load as a concept now serves as an intermediary between imposed and perceived demands (Young and Stanton, 1997)
63	Put most simply, mental workload is the amount of mental work or effort necessary for a person or a group to complete a task over a given period of time (Xie and Salvendy, 2000a)
64	Mental workload associated with a task has been described as relating to the rate at which information is processed by an operator, the rate at which decisions are made, and the difficulty of making the decisions (Smiley, 1989)
65	Mental workload is related to the amount of attention required for making decisions (Miller, 2001)
66	the level of attentional resources required to meet both objective and subjective performance criteria, which may be mediated by task demands, external support, and past experience (Young et al., 2015; Young and Stanton, 2001)
67	Mental workload can be defined as the amount of thinking, level of cognitive demand, or thought processing effort required by the worker to meet the physical, temporal, and environmental demands of the defined task (Neill, 2011)
68	When we speak of mental workload, we are referring to some sense of mental effort, The basic idea is that we have a finite capacity for performing mental work; and if we exceed this capacity, then we will begin to make a large number of errors or experience total performance breakdown (Potter and Bressler, 1989)

2.3. Mental workload measurement methods and measures

In literature there are three main classes of measures of mental workload: self-report measures, physiological (and neurophysiological) measures, and primary task performance measures (Figure 1.2).

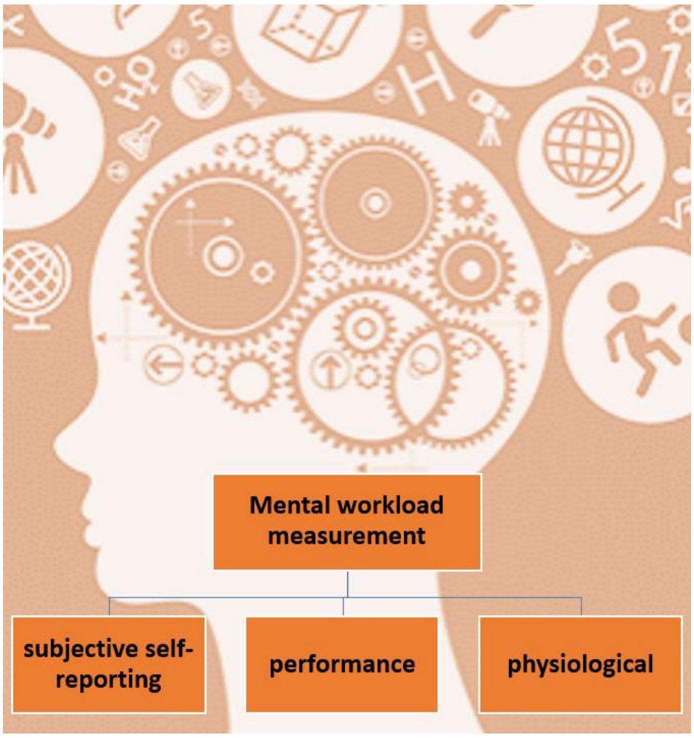

Figure 1. 2 main classes of measures of mental workload

A number of systematic reviews have been already published in this space, including (Kramer, 2020)(Cain, 2007)(Morris *et al.*, 2007)(Whelan, 2007)(Byrne, 2011)(Antonenko *et al.*, 2010)(Lean and Shan, 2012)(Marquart and De Winter, 2015)(Zülch *et al.*, 2015) (Orru and Longo, 2020)(Butmee, Lansdown and Walker, 2019)(Charles and Nixon, 2019)(Pagnotta *et al.*, 2022)(Tao *et al.*, 2019)(Marchand, De Graaf and Jarrassé, 2021). Below the state of the art in mental workload measurement is presented to develop a framework that can guide future research. For this reason, a description of each of these classes of measures, and their distribution across the identified articles considered is provided.

2.3.1. Subjective self-reporting measures

Self-report measures, often referred to as subjective measures, involve a participant or "subject" who usually provides qualitative and/or quantitative reports concerning his/her personal experience while performing either a primary, or secondary task or both (Neville, 1979)(DiDomenico and Nussbaum, 2008)(Moustafa and Longo, 2019)(Nygren, 1991)(Vidulich, 1988). In many self-report measures, a user is asked to answer a pre and/or a post-task questionnaire. This strategy aims at identifying possible biases in performance that an operator might exhibit due to their pre-task mental state. Most subjective measures are administered post-task and can be further sub-classified as: i) uni-dimensional, ii) hierarchical, and iii) multidimensional ratings. Uni-dimensional self-reports generally provide a single summary value, usually reported via a numerical/categorical scale with different ranges, provided either in written or verbal form. Although this approach is extremely simple from a data acquisition perspective, as they are non- intrusive, some believe these ratings lack structure and provide limited or sparse information at best for diagnostics purposes (Hart and Wickens, 1990). However, others have demonstrated that they may have good diagnosticity for task demands (Tsang and Velazquez, 1996)(Rubio *et al.*, 2004)(Longo and Orru, 2019). Uni-dimensional scales represent the concept of workload as one continuum, and examples include the Rating Scale Mental Effort (Zijlstra, 1993) and the Instantaneous Self-Assessment Workload (Tattersall and Foord, 1996). In hierarchical ratings, operators make a set of decisions, and each answer leads to another choice or to a final numerical rating (Hart and Wickens, 1990). Examples of hierarchical ratings include the Modified Cooper Harper Scale (Wierwille and Casali, 1983) and the Bedford Scale (Roscoe, 1987).

Multidimensional ratings operate under the assumption that component factors can be evaluated by operators more reliably than a global summary assessment. Unlike uni-dimensional ratings, these measures provide diagnostic information about the specific sources, as well as providing a global summary (Hart and Wickens, 1990). Examples of multidimensional ratings include the NASA-TLX (Hart and Staveland, 1988) (Hart, 2006), the Workload Profile

(Tsang and Velazquez, 1996) and the Subjective Workload Assessment Technique (SWAT) (Reid, Potter and Bressler, 1988). Table 2.2 lists all of the subjective measures that were used in the articles considered in our review. Although this is is not an exhaustive list, it is representative of the distribution of self-reported measures across different works. As indicated in Table 2, the NASA-TLX is the most used measure to assess mental workload, followed by the SWAT, the Rating Scale Mental Effort and the Workload Profile. Such multidimensional scales have been used across many disciplines, sectors, and domains of application. This is mainly due to their ease of use, and their obvious recognition in this field of research (Cain, 2007). Multidimensional ratings are generally considered to have high sensitivity and diagnosticity, low levels of intrusiveness and convergent validity, as well as moderate concurrent validity (Rubio *et al.*, 2004) (Fréard *et al.*, 2007). However, certain associated problems have been identified. For instance, the SWAT scale, which is supposed to operate under the assumption of conjoint analysis, violates that assumption in various places (Dey and Mann, 2010).

Table 2. 2 Subjective measures

Subjective measure	Studies that used these measures
Stress survey	(Carter et al., 2005)
Rating Scale Mental Effort	(Olsson and Burns, 2000; Brookhuis et al., 2009; Johnson and Widyanti, 2011; Tørnros and Bolling, 2005; Veltman and Gaillard, 1998; Lin et al., 2003)
Usefulness score	(Brookhuis et al., 2009)
NASA-TLX	(Athe`nes et al., 2002; Banerjee et al., 2011; Britt et al., 2015; Brouwer et al., 2012; Byrne et al., 2010; Carswell et al., 2005; Chaouachi et al., 2011; Cinaz et al., 2013; Matthews et al., 2015; Cook and Salvendy, 1999; Darvishi et al., 2016; Go´mez-Go´mez et al., 2015; Haga et al., 2002) (Hancock, 1988, 1989; Hancock and Caird, 1993; Hancock et al., 1995; Harris et al., 1995; Hoover et al., 2012; Hwang et al., 2007; Jahn et al., 2005; Johnson and Widyanti, 2011; Jones, 2009) (Jou et al., 2009; Kataoka et al., 2011; Kawakita et al., 2010; Kiselev and Loutfi, 2012; Kjeldskov and Stage, 2004; Kokini et al., 2012; Longo and Dondio, 2015; Mayes et al., 2001; Mayser et al., 2003; Mitchell, 2000) (Miyake, 2001; Miyake et al., 2009; Moroney et al., 1992; Noyes and Bruneau, 2007; Tremoulet et al., 2009; Trujillo, 1998; Vera et al., 2017; Vito´rio et al., 2012; Wiebe et al., 2010; Wu and Liu, 2007) (Piechulla et al., 2003; Riccio et al., 2011; Safari et al., 2013; Schmutz et al., 2009, 2010; Shinohara et al., 2002; Singh et al., 2009, 2010; Stefanidis et al., 2007; Svensson et al., 1997) (Wu et al., 2008; Xie and Salvendy, 2000b; Jou et al., 2009; Harbluk et al., 2007; Ikuma et al., 2014; Knaepen et al., 2015; Liang et al., 2014; Huber et al., 2006; Chen et al., 2011a; Kang et al., 2004) (Bommer, 2013; Tokunaga et al., 2001; Marquart and de Winter, 2015; Moustafa et al., 2017; Barnard et al., 2007; Haapalainen et al., 2010; Dey and Mann, 2010; Colle and Reid, 1998; Fre´ard et al., 2007; Moustafa and Longo, 2018; Harriott et al., 2015) (Lukanov et al., 2016,?; Tungare and Pe´rez-Quin˜ones, 2009; Mark et al., 2008; Schneegass et al., 2013; Basahel et al., 2010; Adamczyk and Bailey, 2004; Nielsen et al., 2006; Haapalainen et al., 2010; Fritz et al., 2014) (Fairclough et al., 2005; Newell and Mansfield, 2008; Arguel and Jamet, 2009; Wang and Dunston, 2006; France et al., 2005; Colligan et al., 2015; Rani et al., 2007; Baulk et al., 2007; Bradley and Dunlop, 2005; Byrne et al., 2014; Caggiano and Parasuraman, 2004) (Cinaz et al., 2013; Engelmann et al., 2011; Epling et al., 2016; Guznov et al., 2011; Helton et al., 2005; Hu et al., 2016; Hubert et al., 2013; Fisher and Ford, 1998; Kajiwara, 2014; Kataoka et al., 2011) (Liang et al., 2009; Lin et al., 2011, 1998; Luz et al., 2014; Rebetez et al., 2010; Rose et al., 2002; Rubio et al., 2004; Ruiz-Rabelo et al., 2015; Shinohara et al., 2002; Di Stasi et al., 2013b; Venables and Fairclough, 2009; Zheng et al., 2010, 2012; Putze et al., 2010; Lin and Wu, 2011; Zhang et al., 2014; Makhtar et al., 2011; Iwata et al., 2010; Besson et al., 2012a) (Besson et al., 2013; Gentili et al., 2014; Borghini et al., 2015; Zhang et al., 2015a; Liang et al., 2018; Entin et al., 1998; Wu et al., 2008; Won et al., 2011; Yanghua and Fansen, 2011; Besson et al., 2012b; Bodala et al., 2014) (Durkee et al., 2015; Rusnock and Geiger, 2017; Krausman, 2017; Villa and Halvey, 2013; Lan et al., 2010; Young et al., 2009; Leung et al., 2010; Stefanidis et al., 2010)
SWAT	(Baldauf et al., 2009; Carayon and Gu¨ rses, 2005; Carswell et al., 2005; Colle and Reid, 2005; Hancock et al., 1995; Luximon and Goonetilleke, 1998, 2001; Mitchell, 2000) (Pickup et al., 2005; Wittmann et al., 2006; Ikuma et al., 2014; Roscoe and Ellis, 1990; Rubio et al., 2004; Zhang et al., 2015a; Dey and Mann, 2010; Colle and Reid, 1998)
Modified RTLX for automobile apps.	(Piechulla et al., 2003)

Subjective Reports of Effort and Perceived Task Difficulty	(Pierce, 2009)
Karolinska Sleepiness Scale (KSS)	(Roy et al., 2016; Elmenhorst et al., 2009)
Standard Sleepiness Scale	(Vera et al., 2017)
Workload Profile	(Moustafa et al., 2017; Rubio et al., 2004; Fre´ard et al., 2007; Moustafa and Longo, 2018; Longo and Dondio, 2015; Tsang and Velazquez, 1996)
Scale for subjective rating of task difficulty (SRTD)	(KAKIZAKI, 1987)
Crew Awareness rating Scale	(Bommer, 2013)
Job content questionnaire (JCQ)	(Collins et al., 2005)
Situation Awareness Global Assessment Technique (SAGAT)	(Saleem et al., 2009; Ikuma et al., 2014; Luz et al., 2014)
Modified Cooper-Harper scale	(Wierwille et al., 1985)
DSTAI (STAI variation)	(Brayda et al., 2015)
Situational Awareness	(Alexander et al., 2000; Saleem et al., 2009; Trujillo, 1998; Salmon et al., 2006)
Standard Sleepiness Scale	(Vera et al., 2017)

Scale for subjective rating of task difficulty (SRTD)	(KAKIZAKI, 1987)
Crew Awareness rating Scale	(Bommer, 2013)
Nine point symmetrical category scale	(Paas and Van Merrie¨nboer, 1993)
Taylor Manifest Anxiety symptoms test	(Guastello et al., 2012)

2.3.2. Performance measures

Performance measures are used to index mental workload based on the operator's level of task completion efficiency. Although the exact relationship between operator performance and workload has not yet been unequivocally identified, it is generally accepted that the performance of an operator can be maximized by optimizing mental workload. There have been numerous experimental attempts to objectively quantify the relationship between mental workload and task performance (Van Boxtel *et al.*, 1997) (Longo and Orru, 2019). Performance measures can be classified into two broad categories, namely primary task and secondary task measures. Primary task measures represent a direct index of performance, and they have considerably high levels of accuracy in measuring long periods of mental workload (Longo, 2015). They are almost exclusively associated with an operator's capacity on the primary task. The key limitation of these measures is their inability to distinguish the source of variations in mental workload, when multiple tasks are executed simultaneously. Due to this limitation, some researchers consider primary task measures somewhat unreliable when used in isolation (Longo, 2015). Additionally, primary performance can be influenced by other non-workload factors (*Engineering Psychology and Human Performance*, 2015) . This gap can be addressed through secondary task performance measures similarly considered as a metric of an operator's spare mental capacity (Carswell, Clarke and Seales, 2005). Therefore, these measures can discriminate between the variations in mental workload due to different influences. However, the main drawbacks of secondary measures is that they are considered intrusive enough to influence the primary task performance, and they are sensitive only to large changes in mental workload (Longo, 2015). Unlike subjective and physiological measures, performance measures recorded in the selected peer-reviewed articles, varied according to the specificity of the domain and experimental tasks. Response time, task completion time, performance efficiency, task engagement, task accuracy and error rate were the most common performance measures observed.

2.3.3. Physiological measures

Physiological measures involve the assessment of mental workload through the analysis of physiological responses of an operator while executing a primary task (Hancock, Meshkati and Robertson, 1985)(Hogervorst, Brouwer and van Erp, 2014). This area of mental workload assessment has seen significant progress in recent years. A number of categories of physiological measures have been identified in the sample articles reviewed. These include electro cardiac and cardiovascular measures, respiration measures, ocular measures, neuroendocrine measures and speech measures. Also, the development of neurophysiological measures based upon brain activity, have been seen a recent growth. A brief introduction to each of these measures is provided in this section (Charles and Nixon, 2019) and comprehensive list is provided in Table 1.3.

The most commonly used electrocardiac and cardiovascular measures are heart rate (HR), hear rate variability (HRV), and blood pressure (BP)(Henelius *et al.*, 2009). This observation follows the same trend reported in this current review. It is generally understood that heart rate increases when experienced experienced mental workload increases. However, while measuring mental workload, it is critical to ensure that physical load remains more or less constant because, increments in physical load almost inevitably increase heart rate. Heart rate variability measures the variability in time between subsequent heartbeats. Blood pressure is less commonly used than other cardiac measures, mainly due to its intrusiveness. Heart rate and its variability have been proved less intrusive and more sensitive to changes in mental workload. However, they are readily influenced by factors other than just the mental workload necessary for primary task execution (Cain, 2007).

Another category includes *respiratory measures* such as the respiration rate which denotes the number of breaths per unit time. Generally, it increases as the mental workload increases (Lean and Shan, 2012). Similarly to heart rate and its variability, respiratory rate is easy to measure and can be minimally intrusive. During experimental work, the physical load should remain constant in as much as is feasible, as change in it will also have an impact on respiratory rate. An additional reported measure is oxygen consumption which also appears to have a generally positive linear relationship with mental workload (Cárdenas *et al.*, 2013).

The category of *ocular measures* is well-established and it is based on eye activities including: blink rate, blink closure rate, gaze angle, pupil size, diameter and pupillary responses (Marquart, Cabrall and de Winter, 2015). Blink rate is the frequency of eye closures in a given time period, whereas blink closure rate is the time spent while blinking. The main drawback associated with these measures is the difficulty in isolating the effects of visual workload from mental workload (Hancock et al., 2005). However, some have suggested that these measures are only effective at estimating visual workload, and they are very vulnerable to environmental changes. Pupil diameter increases with increasing mental workload, and it is sensitive to a number of demands and emotional states. However, a key drawback is that it is unresponsive after overload occurs and is highly sensitive to any changes in environmental illumination (Cain, 2007). Another prominent measure is electrooculography (EOG). This method measures the electrical potential between electrodes placed on facial muscles that contribute to the control of the eyeballs to determine eye movements. A drawback with EOG is that, in some cases, it is hard to distinguish between rapid eye movements and eye blinks. This method has the same limitations as those associated with blink rate, as it is hard to distinguish between the impact of visual workload and fatigue, from that of mental workload (Borghini *et al.*, 2014).

Neuroendocrine measures are more rare. Salivary cortisol has often been associated with mental workload measurement and has reliably been experimentally shown to reflect levels of mental workload (Fibiger, Evans and Singer, 1986). Our findings indicate that few researchers are likely to use this measure. This is probably due to its main drawback of sensitivity, only changing when the primary task demand increases. It does not show much variation, generally exhibiting low sensitivity, in the case of simple tasks (Fibiger, Evans and Singer, 1986). It is increasingly used to measure stress, which is itself often associated to the construct of mental workload (Cinaz *et al.*, 2013). Although increasingly utilized in the literature, salivary cortisol remains in its growth phase, while new ideas are being promoted in this area of research. For example, it has been proposed that salivary amylase activity can be used as an index of mental workload of a ship's navigator while in control of a ship (Hama *et al.*, 2009). Another study, based on Flow Theory, addressed the phenomenon by which users experienced an implicit addiction to the target activity leading to neglect of other significant social activities. This particular psychological state is characterized by behaviors such as intensely focused concentration, loss of reflective self-consciousness, a deep sense of control, distorted temporal experience, and most importantly, the activity feels inherently rewarding, as in the context of gaming (Keller *et al.*, 2011)(Krueger *et al.*, 2019). This phenomenon is at least partly result of the compatibility between the operator's skills and task demands, and this skills- demands-compatibility also had an influence on stress which was demonstrated by the relatively high levels of salivary cortisol recorded (Keller *et al.*, 2011).

Another category includes *skin measures*. Measuring temperature on different regions of the body is also a well-known method of assessing mental workload. Hancock asserted that auditory canal temperature can serve to reflect global changes in mental workload, and this measure could be used, despite its limitations relating to the inertia of the signal (Hancock and Chignell, 1987). Similar to salivary cortisol, the concept of measuring mental workload based on temperature has not been used as extensively as other physiological measures despite its prolonged existence. However, there are a number of experiments that have used different aspects of human body temperature and have been conducted over the last decade. For instance, it has been proposed to use the Nasal-Forehead (N-F) temperature as an effective index to evaluate a navigator's mental workload (Murai and Hayashi, 2008). The experiment that was conducted with this index concluded that the nasal temperature exhibited the broad trend of a navigator's mental workload as effectively as than heart rate variability. However, the latter was better at registering quick responses of mental workload variation (Murai and Hayashi, 2008). Itoh has experimentally showed that the temperature of the nose tip decreases when the operator engages in a secondary task (Itoh, 2009). The experiments performed by Kajiwara also showed that monitoring facial temperature, along with electrodermal activity, was effective in measuring mental workload (Kajiwara, 2014). Ohsuga observed a drop in skin temperature and an increase in heart rate when participants experienced stressful task instructions. Skin temperature reflects peripheral sympathetic nervous system activity which is activated by mental strain, and therefore, it could serve as a viable option to assess mental workload. However, a significant issue in using skin temperature is that it can also be influenced by changes in environmental temperature. Moreover, forehead skin is not as sensitive to various kinds of strain as the skin of the nose (Ohsuga, Shimono and Genno, 2001). Apart from skin temperature, several other physiological measures have been developed and identified as potential indices of mental workload. These include electrodermal activity and galvanic skin conductance response (Fritz *et al.*, 2014)(Zhang *et al.*, 2014). Electrodermal Activity (EDA) can be classified into phasic and tonic measures. The tonic element of the EDA signal is considered the baseline of skin conductance. The phasic part is the temporary increase in conductance over baseline levels across the performance of a specific task. Phasic signals could be further classified into specific and non-specific categories. Specific signals refer to those that are caused by an exposure to an identified stimulus. Non-specific EDA signals are found to have a weak link with mental workload, and there have been experiments where a correlation has been observed between these measures and operator response time (Pierce, 2009). Due to these factors, EDA has been adopted as a physiological measure only in a few situations.

As shown in Table 1. 3, the category of *neurophysiological measures* is the most utilized in mental workload assessment. The reason for this wide acceptance may be due to the fact that EEG relies on direct measurement of signals from the brain, rather than indirect measurement of other physiological responses initiated by the brain (So *et al.*, 2017). As noted earlier, Cain suggested that EEG might not be a suitable workload measure for field studies owing to the requirement of sophisticated signal processing equipment (Cain, 2007). However, it has been recently observed that, with advances in sensor-based technologies, this is no longer as impactful a limitation as once it was. For example, the field of passive brain-computer interfaces (passive- BCI) is focused on assessing and interpreting changes in the user state during Human-Computer Interaction (Zabcikova *et al.*, 2022). In particular, in the context of neurophysiological measurement, passive-BCI algorithms and biosignal acquisition procedures have allowed the identification and quantification of relevant mental and emotional states of humans. Although technically challenging, these procedures aims to function in ecological, operational, daily life settings, especially for the real-time categorization and evaluation of mental states and those brain dynamics experienced for cognition (Arico *et al.*, 2018). Passive-BCIs have been used to detect levels of mental workload in real operating environments, including real traffic conditions ('24 Improving Human Performance in a Real Operating Environment through Real-Time Mental Workload Detection', 2019). Here, mental workload is often induced through the manipulation of task difficulty, and no other aspect of an operator's state is considered. However, different human experiences can occur, even for the same task difficulty, leading to different cognitive states such as various levels of mental workload. One way of assessing these cognitive states is via EEG bands. EEG signals are usually classified into five bands, depending on their frequency: Delta waves ($0-4$ Hz), Theta waves ($4-8$ Hz), Alpha waves ($8-13$ Hz), Beta waves ($13-39$ Hz), and Gamma waves ($> 40Hz$). The ranges associated with these bands can vary slightly according to different standards and applications. Delta waves are generated during deep dreamless sleep, as well as states with loss of body awareness. Theta waves are most prominent during deep meditation and relaxation, for example in the Rapid Eye Movement (REM) phase of sleep. Alpha waves are associated with calm and relaxed, yet alert states. Beta waves are most prominent during active processing, thinking or concentration, cognition, and arousal. Eventually, Gamma waves are observed with higher mental activity, including consciousness, perception, and problem solving. In relation to mental workload, a general observation is that Beta waves increase, and Alpha waves decrease as mental workload increases. In their review, Frey and colleagues noted that the Alpha band is associated with attention, and the amplitude of these waves increases when a participant experiences fatigue, or when eyes are closed (Frey *et al.*, 2014). A work studied the impact of task demands, age, and working memory load on EEG signals (Borghini *et al.*, 2014). It was observed that younger adults experienced an increase in Theta activity in the frontal mid- line of the brain in response to increased task difficulty, whereas older adults did not experience this same increase. On the other hand, older adults showed a decrease in Alpha activity in widespread areas across the brain, whereas younger adults demonstrated decreased Alpha activity only in their parietal area. Alpha activity, in the parietal lobes, decreases with an increase in working memory load (Borghini *et al.*, 2014). Another indicator of mental workload is represented by the Theta to Alpha ratio (Di Flumeri *et al.*, 2018). This ratio is computed using the Theta band over the EEG frontal channels, and the Alpha band over the EEG parietal channels (Borghini *et al.*, 2017). A three-level N-back test was run with participants using a fully mobile self-mounted EEG device (Kutafina *et al.*, 2021). Findings demonstrated the potential of such setup for detecting changes in cognitive load, as reflected by alterations across lobes in different frequency bands. In particular, it was observed that a decrease of occipital alpha and an increase in frontal, parietal and occipital theta was associated to an increasing cognitive load. Variations in the theta EEG power spectrum was used as an index of mental workload for army drivers performing combat and non-combat scenarios in a light multi-role vehicle dynamic simulator (Diaz-Piedra, Sebastián and Di Stasi, 2020). In detail, theta EEG power spectrum in the frontal, temporal, and occipital areas was higher during the most complex task conditions. An evaluation of the alpha-to-theta and the theta-to-alpha band rations were investigated as indexes of mental workload (Guan *et al.*, 2021). In details, authors demonstrated the richness of the information in the temporal, spectral and statistical domains extracted from these indexes for the discrimination of self-reported perceptions of mental workload over two task load conditions.

Other methods to tackle the problem of mental workload modeling and assessment exist. For example, in (Qu *et al.*, 2020), Independent Component Analysis (ICA) was performed to obtain components from which energy features are extracted and used for classifying different task conditions. Another study utilized features representing intra-channel and inter- channel information to classify multiple classes of task load conditions based on EEG (Pei *et al.*, 2021). Multi-frequency power spectrum and functional connectivity (FC) were employed for the classification of two task load levels in two working- memory tasks performed by healthy participants (Kakkos *et al.*, 2021). Beside achieving good accuracy, the spectral and localization properties of designated features revealed common task-independent patterns in the neural mechanisms governing workload. A study tried to tackle the issue of cross-task mental workload generalization, and a cross-task performance-based feature selection coupled with a regression model, that was trained with data gathered from a working memory task, was developed (Ke *et al.*, 2014).

Another study employed microstates and a newly proposed dynamic brain network analysis method based on it to explore the changes in dynamic functional connectivity properties over four task load conditions (Guan et al., 2022). Six microstate topographies labeled emerged and were used to describe the task-state EEG dynamics. A dynamic brain network analysis revealed that a number of nodes and pairs of connectivity from the Frontal-Parietal region were sensitive to mental workload in all the four conditions, demonstrating how these nodal metrics can contribute to the assessment of mental workload in the cross-task scenario.

EEG is often used in conjunction with subjective measures and machine learning classifiers to predict mental workload (Arico *et al.*, 2018). For example, SWLDA (StepWise Linear Discriminant Analysis) has been used to select a low number of EEG spectral features to aid in Air Traffic Management. In a similar approach, the features selected by SWLDA were fed to a non-linear Artificial Neural Network (ANN) in order to classify different levels of mental workload (Laine *et al.*, 2002). This latter approach takes advantage of SWLDA's ability to identify features, and of the ANN to attain good predictive accuracy (Laine *et al.*, 2002). Other works have addressed the shortcomings of EEG- based mental workload estimation from the task demand perspective (Ke *et al.*, 2014). A convolutional neural network to classify EEG features across different task load conditions in a continuous performance task test was created in (Hernández-Sabaté *et al.*, 2022). The goal was to partly measures working memory and working memory capacity, as an indicator of mental workload. Existing studies that focused on estimating workload, based on EEG measures, have generally produced good results for discriminating task conditions, but only for the specific experimental selected primary tasks. Rarely, developed methods for assessing mental workload are generalisable and usable across tasks. The performance of cross-task mental workload assessment based on physiological metrics remains highly unsatisfactory.

A novel neuro-physiological method that is gaining attention in the field of mental workload modeling is functional near- infrared spectroscopy (fNIRS). This is a non-invasive, brain imaging technology that employs low levels of non-ionizing light to record variations in cerebral activity. Through the application of optical sensors placed on the scalp, similarly to electroencephalography, it records changes in blood flow that can be used to investigate the evolution of brain activation during various tasks. As a consequence, it has been deemed a promising method for the discrimination of various task conditions, each supposed to lead to different levels of experienced mental workload (Galoyan *et al.*, 2021)(Li *et al.*, 2019)(Parshi *et al.*, 2019)(Sibi *et al.*, 2016). However, as in the case of application of Electroencephalography, the performance of cross-task mental workload assessment using fNIRS remains highly unsatisfactory.

Table 2. 3 Physiological measures

Physiological measure	Studies that used these measures
Muscular Sympathetic Nerve Activity	(Carter et al., 2005)
Electroencephalography	(Arico et al., 2015; Arico` et al., 2016; Berka et al., 2007; Brookings et al., 1996; Carswell et al., 2005; Cartocci et al., 2015; Chaouachi et al., 2011; Matthews et al., 2015; Fritz et al., 2014; Haapalainen et al., 2010; Dirican and Go¨ktu¨rk, 2011; Haga et al., 2002; Hou et al., 2015; Aghajani et al., 2017; Dussault et al., 2005) (Lim et al., 2015; Ling et al., 2001; Mak et al., 2013; Mazaeva et al., 2001; Mitchell, 2000; Riccio et al., 2011; Roy et al., 2015, 2016; Ryu and Myung, 2005; Tremoulet et al., 2009; Krol et al., 2016) (Wanyan et al., 2014; Wilson and Russell, 2003a; Yin and Zhang, 2017; Zhang et al., 2015b; Zhou et al., 2008; KAKIZAKI, 1987; Kim et al., 2014; Yin and Zhang, 2014; Kang et al., 2004; Liu et al., 2017; Zhang et al., 2017a; Plechawska-Wo´jcik and Borys, 2016) (Chen and Vertegaal, 2004; Hirshfield et al., 2009; Montgomery et al., 1995; Lan et al., 2010; Fairclough et al., 2005; De Bruin et al., 2002; Sammer et al., 2007; Venables and Fairclough, 2009; Marshall, 2002; Putze et al., 2010; Mathan et al., 2010) (Besson et al., 2012a; Hwang et al., 2014a; Zhang et al., 2014; Zarjam et al., 2015; Wang et al., 2016; Rozado and Dunser, 2015; Blanco et al., 2018; Chang et al., 2016; Mallick et al., 2016; Magnusdottir et al., 2017; Almogbel et al., 2018; Kim et al., 2014) (Hwang et al., 2014b; Gentili et al., 2014; Borghini et al., 2015; Putze et al., 2015; Ke et al., 2014, 2015; Lim et al., 2016; Kraft et al., 2017; Durkee et al., 2015; Oyama et al., 2013; Walter et al., 2013; Bodala et al., 2014) (Kothe and Makeig, 2011; Kramer et al., 1987; Laine et al., 2002; Zhang et al., 2017b; Haapalainen et al., 2010; Herff et al., 2015; Bodala et al., 2015; Klosterman et al., 2016; Dimitrakopoulos et al., 2017; Liang et al., 2018; Ling et al., 2001; Wang et al., 2011) Herna´ndez-Sabate´ et al. (2022);

	Kutafina et al. (2021); Pei et al. (2020); Diaz-Piedra et al. (2020); Kakkos et al. (2021); Guan et al. (2022); Raufi and Longo (2022)
Magnetic Resonance Imaging	(Ryu and Myung, 2005; Wilson and Russell, 2003a)
Pupillary responses	(Tungare and Pe´rez-Quin˜ones, 2009; Haapalainen et al., 2010; Elkins and Hossain, 2015)
Pupil size	(Cegarra and Chevalier, 2007; Dirican and Go¨ ktu¨ rk, 2011; de Greef et al., 2009; He et al., 2012; Iqbal et al., 2004; Kawakita et al., 2010; Schultheis and Jameson, 2004; Di Stasi et al., 2013a; Wierwille et al., 1985; Zhang et al., 2004; Marquart and de Winter, 2015; Bailey and Iqbal, 2008) (Palinko et al., 2010; Iqbal et al., 2005; Chen et al., 2011b; Xu et al., 2011; Lin et al., 2003; Marshall, 2002; Mallick et al., 2016; Wang et al., 2014; Plechawska-Wo´jcik and Borys, 2016; Gavas et al., 2017)
Eye movements	(Dirican and Go¨ ktu¨ rk, 2011; Di Stasi et al., 2013a; Svensson et al., 1997; Kataoka et al., 2011; Marshall, 2002; Bodala et al., 2015; Bedziouk et al., 2006)
Blink rate	(Brookings et al., 1996; Carswell et al., 2005; Ryu and Myung, 2005; Davis, 1994; Marquart and de Winter, 2015; Elmenhorst et al., 2009; Chen et al., 2011b)
Blink closure duration	(Ryu and Myung, 2005)
Blink duration	(Hwang et al., 2007)
Interocular pressure	(Vera et al., 2017)
Respiration rate	(Brookings et al., 1996; Cegarra and Chevalier, 2007; Dirican and Go¨ktu¨rk, 2011; Haga et al., 2002; Veltman and Gaillard, 1998; Wierwille et al., 1985; Wilson and Russell, 2003a; Lin et al., 2007; Zheng et al., 2012; Putze et al., 2010; Besson et al., 2012a, 2013, 2012b; Mehler et al., 2009)
Respiratory volume	(Ohsuga et al., 2001)
Electrocardiography	(Brookhuis et al., 2009; Cinaz et al., 2010; Mahmoud et al., 2017; Matthews et al., 2015; Kumar et al., 2007; Piechulla et al., 2003; Wanyan et al., 2014; Wilson and Russell, 2003a; Zhang et al., 2015b; Liu et al., 2017; Montgomery et al., 1995; Lan et al., 2010; Fairclough et al., 2005; Heine et al., 2017) (Cinaz et al., 2013; Collins et al., 2005; Engelmann et al., 2011; Hjortskov et al., 2004; Sammer et al., 2007; Venables and Fairclough, 2009; Zhang et al., 2014; Chang et al., 2016; Besson et al., 2013; Gentili et al., 2014; Itoh, 2009; Besson et al., 2012b; Durkee et al., 2015; Zhang et al., 2017a) (Stuiver et al., 2014; Boucsein and Thum, 1997; Schellekens et al., 2000; Kraft et al., 2017; Haapalainen et al., 2010)
Pulse rate	(Liang et al., 2009)

Heart rate	(Ca´rdenas-Ve´lez et al., 2013; Davis et al., 2009; Galy et al., 2012; Murai et al., 2004; Pierce, 2009; Svensson et al., 1997; Twisk et al., 2013; Wanyan et al., 2014; Son et al., 2011; Elmenhorst et al., 2009; Ward and Marsden, 2003; Kataoka et al., 2011; Nickel and Nachreiner, 2003) (Luz et al., 2014; Son et al., 2013; Usui and Egawa, 2002; Zheng et al., 2012; Besson et al., 2012a; Reimer et al., 2008; Mehler et al., 2009)
Heart rate variability	(Brookhuis et al., 2009; Brookings et al., 1996; Hoover et al., 2012; Hwang et al., 2007; Jahn et al., 2005; Keller et al., 2011; Kum et al., 2007; Kumar et al., 2007; Mehler et al., 2011; Miyake, 2001; Murai and Hayashi, 2008,?) (Ryu and Myung, 2005; Vera et al., 2017; Davis, 1994; Knaepen et al., 2015; Green, 1994; Schneegass et al., 2013; Basahel et al., 2010; Rowe et al., 1998; Haapalainen et al., 2010)
Oxygen consumption	(Ca´rdenas-Ve´lez et al., 2013)
Salivary cortisol levels	(Keller et al., 2011; Hankins and Wilson, 1998)
Salivary amylase activity value	(Hama et al., 2009)
Saccade rate	(Brookings et al., 1996; Pierce, 2009)
Saccade distance	(de Greef et al., 2009)
Saccade speed	(de Greef et al., 2009; Chen et al., 2011b)
Head and body movements	(Twisk et al., 2013)
Fixation time	(de Greef et al., 2009; He et al., 2012; Chen et al., 2011b; Di Nocera et al., 2006)
Electrooculography	(Haga et al., 2002; Kothe and Makeig, 2011; Kramer et al., 1987; Roy et al., 2015, 2016; Ryu and Myung, 2005; Wilson and Russell, 2003a; Zhang et al., 2015b; Yin and Zhang, 2014; Elmenhorst et al., 2009; Chen and Vertegaal, 2004; Fairclough et al., 2005) (Mahmoud et al., 2017; Klosterman et al., 2016; Zhang et al., 2017a)
Core temperature variation	(Hancock, 1988)
Blood rate	(Hwang et al., 2007)
Blood volume	(Ryu and Myung, 2005; Ward and Marsden, 2003)
Blood pressure	(Ohsuga et al., 2001; Veltman and Gaillard, 1998; Elmenhorst et al., 2009; Basahel et al., 2010; Luz et al., 2014; Van Roon et al., 2004; Usui and Egawa, 2002)
Blood flow	(Wilson and Russell, 2003a)
Para/Sympathetic ratio	(Hwang et al., 2007)
Gaze angle	(Kawakita et al., 2010)
Head rotation angle	(Kawakita et al., 2010)
Finger plethysmogram amplitude	(Miyake, 2001)
Perspiration	(Miyake, 2001)

Nasal-Forehead temperature	(Murai and Hayashi, 2008)
Skin temperature	(Ohsuga et al., 2001; Trujillo, 1998; Knaepen et al., 2015; Schneegass et al., 2013)
Skin conductance	(Pierce, 2009; Knaepen et al., 2015; Son et al., 2011; Schneegass et al., 2013; Kajiwara, 2014; Venables and Fairclough, 2009; Zheng et al., 2012; Putze et al., 2010; Besson et al., 2012a, 2013, 2012b; Mehler et al., 2009)
Skin response	(Nourbakhsh et al., 2012; Zhang et al., 2014)
Electromyography	(Piechulla et al., 2003; Tanaka et al., 2000; Wilson and Russell, 2003a; Boucsein and Thum, 1997; Hubert et al., 2013; Zarjam et al., 2015; Rozado and Dunser, 2015; Besson et al., 2013, 2012b; Zhang et al., 2016)
Electrodermal activity	(Baldauf et al., 2009; Tanaka et al., 2000; Wilson and Russell, 2003a; Fritz et al., 2014; Boucsein and Thum, 1997; Rani et al., 2006; Chang et al., 2016)
Actigraphy	(Wilson and Russell, 2003a)
Oxymetry	(Wilson and Russell, 2003a)
Body temperature	(Lin et al., 2007)
Functional near-infrared spectroscopy	(Unni et al., 2015; Ung et al., 2017; Herff et al., 2015; Berivanlou et al., 2016) Durantin et al. (2014); Sibi et al. (2016); Karim et al. (2012); Sassaroli et al. (2008); Li et al. (2019); Parshi et al. (2019); Galoyan et al. (2021)
Purdue Pegboard test	(Zhang et al., 2016)
Urinary adrenaline	(Hankins and Wilson, 1998)

2.4. Mental workload evaluation in the experimental setting conducted

N-back tasks test, originally introduced by Kirchner (Kirchner, 1958) and by Mackworth (Mackworth, 1959), has become a standardized tool to simulate tasks with different cognitive complexities; it consists of standardized working memory and attention tasks with four incremental levels of difficulty.

In the *n*-back task, users have to continuously remember the last *n* of a series of rapidly flashing letters. The *n*-back task requires subjects to react when a stimulus is the same as the *n*-th letter before the stimulus letter (Figure 1.3).

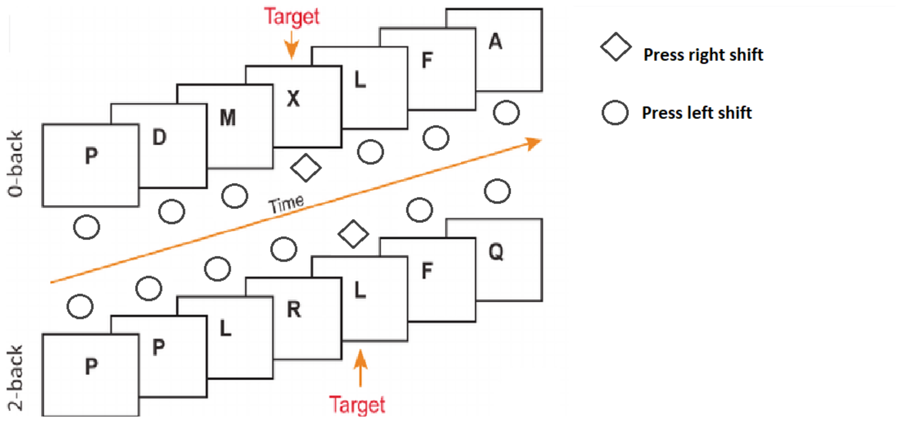

Figure 1. 3 n-back test carried out

We denote a (letter) stimulus, which is the same as the one *n* previously as a target. Subjects had to press the space key on a keyboard when they encountered a target. With increasing *n* the task difficulty increases, as the subjects have to remember more letters and continuously shift the remembered sequence. Performance in this task can be evaluated by measuring the amount of missed targets, when the subjects do not press the key for a target and through the amount of wrong reactions, when the subjects incorrectly identify a stimulus letter as a target (Herff *et al.*, 2014). We implemented the zero- and the two-back levels by exploiting the Psychology Experiment Building Language toolkit (PEBL) version 2.1 (freely available at http://pebl.sourceforge.net/download.html). In the 0-back task, testers responded to a predefined single target letter (i.e., "X"); while in the 2-back task, the targets were defined as any letter that was identical to the one presented two trials back. We carried out a within-subjects experiment by asking participants to execute two *n*-back test sessions corresponding to the two implemented levels. As subjective measures, we used participants ratings collected by administering the NASA-TLX questionnaire. As objective measures, we used both participants' performance (i.e. reaction-time, amount of missed targets), and physiological parameters extracted by monitoring heart-activity (i.e. HRV analysis).

In the period November 2019 - January 2020, experiments have been carried out in the Laboratory of Industrial System Engineering (LISE) at the Polytechnic University of Bari (LISE, https://research.poliba.it/laboratories/lise) in order to assess the mental workload of subjects involved in tasks of increasing complexity. Subjects participated in the experiments on a voluntary basis. We recruited 14 participants. They all had a Mechanical and Management Engineering background. Before starting the experiment, they all filled in a preliminary questionnaire in order to check whether their life habits and physical conditions allowed their participation in the trial (participants were required to maintain a regular sleep-wake cycle for at least one day before the study and to abstain from stimulating beverages or intense physical activity).

The experimental procedure consisted in the execution of the two implemented n-back task levels.

Before starting the experiment, each participant received written and verbal information explaining the experimental procedure and her/his task in the test. Then, in order to record the Electro- cardiographic signal (ECG), an experimenter posi- tioned three pre-gelled electrodes on the participant's chest. The ECG signal was acquired with a 1000 Hz sampling rate by using the BITalino®Plugged Kit BLE (https://bitalino.com/en/plugged-kit-ble), a low-cost multimodal platform for physiological signals acquisition (Batista *et al.*, 2019).

Before each level execution, each participant carried out a training phase to get used to the correct procedure. The execution order of the two "*n*-back" task levels was counterbalanced among participants. The zero-back level had 100 prompts and the two- back 102 prompts, both levels had an inter-prompt period of 3000 milliseconds (i.e. 500 ms of stimulus presentation and 2500 ms of fixed delay). Each level execution lasted about 5 minutes and had 33 targets that were prompted randomly.

Figure 1. 4 Experimental setting conducted

During the task execution, the ECG signal was recorded together with participants' performance (i.e. reaction time and error rate). At the end of each level each participant filled in the NASA-TLX questionnaire. The two "*n*-back" levels execution were interleaved with a resting phase of at least 5 minutes. During this phase, the ECG signal was recorded in order to obtain a baseline measure of the heart activity in rest conditions.

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3. New Formulations for Modelling Operator’s Mental Workload in Smart Manufacturing Systems

According to the chapters before it has become important to integrate the conditions of operators wellbeing, into traditional decision support models when designing and managing production systems (Grosse, Glock and Neumann, 2017). In this chapter, the operators' wellbeing and their productivity have been evaluated by the analysis of their mental workload.

Mental workload (MWL) is defined as the interaction between the operator and an assigned task (Bommer and Fendley, 2018). No clear and widely common definition is provided about MWL, due to its multi-faceted phenomenon. It can be defined as the amount of cognitive work required to perform a certain task during a given time period. However, other factors can influence MWL such as stress, mental effort, time pressure, and others (Longo, 2015). Measuring MWL is useful to predict the operator and system performance quantifying the mental cost required to perform a task (Cain, 2007).

This implies that it provides the awareness of when the performance might be unacceptable as task demand increases. In both mental underload and overload situation a performance weakening can occur (Young and Stanton, 2002); the optimal MWL has a positive impact on productivity and safety, user satisfaction, and system success (Longo, 2015).

According to Colombi et al. when the number or the difficulty of tasks to be performed increase, and/or the given time to perform a task decreases, the MWL rises (Colombi, J.M., Miller *et al.*, 2012).

MWL is associated with the individual amount of resources available; therefore, when the task demands exceed the individual amount available, high level of MWL occurs (Loft *et al.*, 2007) and/or the operator is not capable to perform the assigned task.

Analytical measures are able to estimate directly the operator's MWL, and both subjective and analytical data are collected with techniques such as expert opinion and mathematical models (Xie and Salvendy, 2000) (Patel *et al.*, 2002).

3.1. Information-based analytical framework developed to assess human cognitive capacity and information processing speed of operators in industry 4.0

In this chapter both subjective and analytical measures of MWL are adopted. These are used as baseline to develop the concepts of human cognitive capacity occupancy and human information processing speed (see next Section) and are the NASA-Task Load Index (TLX) and the Information-theory model, respectively.

The NASA-TLX was developed by US National Aeronautics and Space Administration (NASA) and is a multidimensional assessment tool of the perceived workload. It is applied across several areas such as computer users, car drivers, military cockpits, and medical profession. Moreover, it became a reference point for the development of new models and measures (Hart and Staveland, 1988b).

Six subjective sub-measures are adopted in the NASA-TLX: mental demand, physical demand, temporal demand, frustration, effort, and performance. The subject is provided of a brief description for each sub-measure and is asked, after the accomplishing of a task, to rate each of them on a 1 to 100 scale.

The overall MWL index is calculated as a weighted average of the six sub-measures score (d_i) obtained by the questionnaire filled by the subject (equation 3.1). The weights values (w_i) are obtained by means of a pairwise comparison of sub-measures carried out by the subject.

$$TLX_{MWL} = \left(\sum_{i=1}^{6} d_i \times w_i\right) \frac{1}{15} \tag{3.1}$$

Where the number 15 represents the paired comparisons between dimensions.

NASA-TLX is preferred if the aim is to predict the performance of a particular individual in a single task (Rubio *et al.*, 2004).

According to the information-theory, human brain can be modelled as a channel of limited capacity (McMillan and Slepian, 1962). When a subject performs a task, information is transmitted through this channel. One of the main limits of this model is the difficulty in quantifying the amount of information transmitted (Patel *et al.*, 2002).

According to the Shannon's Entropy (Shannon, 1948), the information is quantified in terms of bits, and the information volume (H) for “n” equiprobable choices a subject is facing with during the task execution is calculated as follow (eq. 3.2):

$$H = log_2 n \tag{3.2}$$

The amount of information that the individual can be process in the unit time (bit/second) is used as performance measures related to MWL (Rault, 1976).

The information-based model proposed here is based on both analytical and subjective MWL measures. The analytical model developed in 1994 by Bi and Salvendy (Bi and Salvendy, 1994) is used to describe the objective MWL prediction; while the NASA-TLX is used to characterize the operator’s perceived MWL. In 1994, an analytical model is proposed by Bi and Salvendy (Bi and Salvendy, 1994) in order to analyses in dynamic systems the cognitive tasks. MWL is modelled as a system's objective demand imposed on the operator and is independent by subjective factors. According to the authors, MWL can be obtained as follows:

$$H_{owl} = \frac{TL}{K_e \times K_{or}} \leq H_{owl,lim} \tag{3.3}$$

where H_{owl} is the MWL imposed on the subject and expressed in [bit/s], TL is the task load expressed in [bit/s], K_e is a dimensionless parameter evaluating the environmental factors, K_{or} is a dimensionless parameter evaluating the organizational factors, and $H_{owl,lim}$ is the MWL threshold expressed in [bit/s].

A scale ranging from 0 to 1 can be defined for K_e and K_{or}; in case of

$$K_e = K_{or} = 1 \tag{3.4}$$

the system is providing subject with satisfied stimuli and an ideal environment, if

$$K_e = K_{or} \rightarrow 0 \tag{3.5}$$

people cannot work properly. Bi and Salvendy (Bi and Salvendy, 1994) suggest mental workload threshold values can be obtained through empirical studies based on different population categories and task environments.

Our model is based on Bi and Salvendy model (Bi and Salvendy, 1994) for assessing MWL. In the model proposed, the TL is given dividing eq. 2 by the given time window (T) to complete the set of tasks, expressed in [s].

$H_{owl,lim}$ represents the maximum amount of MWL (bit/s) a subject is able to process. In case of H_{owl} exceeding $H_{owl,lim}$, the subject won’t be able to perform the assigned task in the available time window. The evaluation of $H_{owl,lim}$ requires ad-hoc experimental tests. Nevertheless, in this paper, $H_{owl,lim}$ values have been calculated by means of a linear regression analysis based on H_{owl} and NASA-TLX values obtained from experimental data. $H_{owl,lim}$ values have been calculated considering the maximum score (100) of the NASA-TLX.

Consequently, the concepts of Human Cognitive Capacity Occupancy and Human Information Processing Speed are modelled.

Human cognitive capacity occupancy (HCCO) is a rate of consumption of operator brain's capacity; it represents the cognitive occupation of the subject. HCCO (eq.3.6) is obtained by dividing eq.3.3 by $H_{owl,lim}$

$$HCCO = \frac{H_{owl}}{H_{owl,lim}} \leq 1 \tag{3.6}$$

Human cognitive capacity reserve (HCCR) is a rate of cognitive reserve of operator's brain capacity. HCCR is obtained by the eq. 3.7

$$HCCR = 1 - HCCO \tag{3.7}$$

For a given task load (*TL=cost*), when the boundary conditions decrease ($K_e=K_{or} \rightarrow 0$), HCCO increases and HCCR decreases. This means that the external stimuli can lead to increase the numbers of bits that the operator has to process in a given time window.

The efficiency can be an outcome of cognitive and physical efficiency (Kumar and Kumar, 2019). In the smart factory, due to the increasing adoption of innovative device the physical tasks are allocated to the machine and no more to the operators. Therefore, the demands of operator's manual tasks are negligible if compared with ones that required operator cognitive effort. So, according to Kumar and Kumar (Kumar and Kumar, 2019) the human efficiency can be evaluated considering only the cognitive efficiency.

Kumar and Kumar (Kumar and Kumar, 2019) evaluate the human efficiency through the cognitive load and task efficiency measurement (eq. 3.8).

In order to evaluate the time required by the operator to correctly process the information, it is possible to model the human information processing speed (HIPS) and task information processing speed (TIPS); the relationship between HIPS and TIPS is expressed by the eq. 3.8:

$$HIPS \times TIPS = TE \tag{3.8}$$

where HIPS is the speed in processing 1 bit of correct information by the operator expressed in [s/bit], TIPS is the task information processing rate at required speed expressed in [bit/s], and TE is the task efficiency expressed by the following equation according to the definition of Kumar & Kumar (Kumar and Kumar, 2019). TE represents the probability to perform the task correctly (eq. 3.9).

$$TE = \frac{Total_{tasks} - N_e}{Total_{tasks}} \tag{3.9}$$

TE is the ratio of the set of tasks performed successfully versus the total number of tasks performed ($Total_{tasks}$) and N_e identifies the number of errors made in tasks execution. TE expresses the process quality and represents the ratio between the amount of bits correctly processed by the operator and the total amount of bits that the operator must process. TE values range in a *[0;1]* interval.

This means that low HIPS values can be required to meet high TIPS values at a given process quality. However, low HIPS values and high TIPS values can cause low process quality. The ideal case occurs when *TE=1* (eq. 3.10), in this case the operator's performance is equal to 100% and this implies that the bits processed (per unit time) by the operator equals the bits required by the task; therefore, the information processing speed of the operator (HIPS) is equal to the inter arrival time of information to be processed (task execution time).

$$HIPS_{TE=1} = \frac{1}{TIPS} \tag{3.10}$$

TIPS is the arrival rate of bits to be processed; therefore, TIPS is the mental workload imposed on the operator (eq. 3.11)

$$TIPS = H_{owl} \tag{3.11}$$

and relation (3.8) becomes:

$$HIPS = \frac{TE}{H_{owl}} \tag{3.12}$$

When the operator reaches his or her maximum perceived mental workload at a given quality performance, the eq.3.12 becomes:

$$HIPS_{max} = \frac{TE}{H_{owl,lim}} \tag{3.13}$$

Whit the same TE values, being $H_{owl} \leq H_{owl,lim}$, it follows that $HIPS_{max}$ is less than or equal to HIPS. Since the bits to be processed by the operator per unit time are at most equal to the bits required by the task, when $H_{owl}=H_{owl,lim}$ the operator will have to process 1 bit of information in less time. $HIPS_{max}$ represents the operator's maximum speed in correctly processing information.

The optimal condition occurs when *TE=1*, in this case the time to correctly process information by the operator is equal to the time available to accomplish the task. (eq. 3.14)

$$HIPS_{TE=1,max} = \frac{1}{H_{owl,lim}} \tag{3.14}$$

3.1.1. Application of the model

In the period November 2019 - January 2020, experiments have been carried out in the Laboratory of Industrial System Engineers (LISE) at the Polytechnic University of Bari (LISE, https://research.poliba.it/laboratories/lise) in order to assess the mental workload of subjects involved in tasks of increasing complexity. Subjects participated in the experiments on a voluntary basis. We recruited 14 participants. They all had a Mechanical and Management

Engineering background. This section presents an application of the model explained previously. The model is applied to the experimental setting presented in the chapter 2.4.

Here, the weight of the six sub-measures of NASA-TLX have been determined for the 0- and 2-level of the n-back test by pair-wise comparison of sub-measures and are shown in table 3.1; the pair-wise comparison was carried out by each subject and then as weight of each sub-measure was considered the average value. For both levels the weight associated with the physical demand is equal to zero since the task does not require a physical effort.

Table 3. 1 Subscales' weight

Subscale	Weight 0-back task level	Weight 2-back task level
Mental demand	2	3
Physical demand	0	0
Temporal demand	3	5
Performance	5	1
Effort	4	3
Frustration level	1	3
SUM	15	15

The NASA-TLX scores for each subject calculated according to eq.3.1 are in table 3.2 for each level of the n-back test.

Table 3. 2 NASA – TLX scores

Subject	NASA-TLX Level 0	NASA-TLX Level 2
1	26.00	64.00
2	39.66	55.33
3	24.66	60.33
4	30.00	49.33
5	19.00	87.00
6	17.66	48.66
7	27.33	50.00
8	5.00	15.66
9	27.33	40.66
10	22.66	52.33
11	22.33	52.33
12	30.33	57.33
13	5.00	25.33
14	33.66	27.00

TL is the amount of information that must be process in the given time window. In the 0-back level the number of available decision alternatives is given by the comparison of the letter on the screen and the target letter "X" and it is equal to two, since the letter shown on the screen could be or not the target. In the 2-back level the number of available alternative decisions is equal to the sum of comparisons of the letter on the screen and the letter memorized two times before plus the two letters memorized. The number of available alternative decisions associated with the letter memorized is twenty-six. This amount corresponds to the letters of english alphabet according to Francikowski et al. (Francikowski *et al.*, 2016).

The letter is shown on the screen for 3 second, so the given time window in each n-back level is 3 second. In the 0-back level task one hundred subtasks (one subtask corresponds to one letter showed on the screen) must be performed, while in 2-back level task one hundred and two subtasks must be performed.

In case the subject did not react within this time limit, an error was associated to the subtask. Therefore, for each subject the TE evaluated in accordance with eq. 3.9, for 0- and 2-level of n-back test, is showed in figure 3.1.

The TL values obtained by dividing the result of eq. 3.2 by the given time window (T) to complete the set of tasks for 0- and 2-back level are summarized in table 3.3.

Table 3. 3 Task Load (TL - bits/seconds)

	Task Load
0-Back Task Level	0.33
2-Back Task Level	3.47

The MWL is modelled as an objective demand imposed on the subject (H_{owl}). The environmental (K_e) and organizational (K_{or}) factors are set equal to one for simplifying hypothesis.

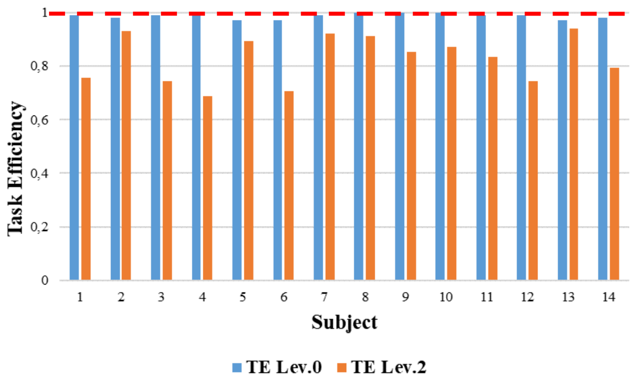

Figure 3. 1 Task Efficiency (TE) 0-level vs 2-level of n-back test

K_e and K_{or} values are independent by the subject and depend only by boundary conditions. Since the boundary conditions in the experimental sessions are the same for the two test levels performed, and K_e and K_{or} values affects in the same way H_{owl} for both levels, they have been considered unitary. The H_{owl} values evaluated in accordance with eq.3, for 0- and 2-back level, are summarized in table 3.4.

Table 3. 4 H_{owl} values ([bit/s]).

	H_{owl}
0-Back Task Level	0.33
2-Back Task Level	3.47

$H_{owl,lim}$ value for each subject is calculated by means of a linear regression analysis based on H_{owl} and NASA-TLX values obtained from n-back test. The experimental data obtained and the mean (μ), standard deviation (σ), and the coefficient of variation (cv) of $H_{owl,lim}$ are shown in table 3.5.

Table 3. 5 $H_{owl,lim}$ values ([bit/s])

Subject	$H_{owl,lim}$
1	6.44
2	12.40
3	6.95
4	11.68
5	4.07
6	8.66
7	10.38
8	28.24
9	17.77
10	8.50
11	8.45
12	8.41
13	14.97
14	-30.84
μ	10.49
σ	6.73
cv	0.64

The subject n.14 did not correctly fill the NASA-TLX, he/she rated at the maximum value the subscale "physical demand". Therefore, the $H_{owl,lim}$ of subject n.14 has not been considered. For each subject, the HCCO and HCCR values are obtained by means of eqs. 3.6 and 3.7, respectively.

For 0- and 2-back level, table shows the values of the mean (μ), standard deviation (σ), and the coefficient of variation (cv) for HCCO and HCCR.

Table 3. 6 Mean, standard deviation, and coefficient of variation for HCCO and HCCR

HCCO	0-Back Task Level	2-Back Task Level
μ	0.0370	0.3830
σ	0.0180	0.1840
cv	0.4810	0.4810

HCCR	0-Back Task Level	2-Back Task Level
μ	0.9630	0.6170
σ	0.0180	0.1840
cv	0.0183	0.2990

For each subject, the HCCO and HCCR experimental data obtained for 0- and 2-back level are shown in figure 3.2.

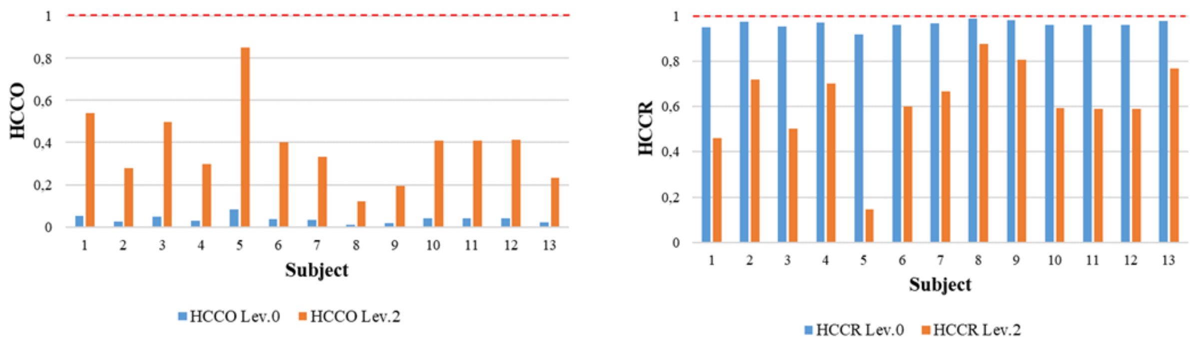

Figure 3. 2 Experimental data observed for 0- and 2-back level for HCCO and HCCR, respectively

The values of the mean (μ), standard deviation (σ), and the coefficient of variation (cv) for HIPS are showed on table 3.7, for 0- and 2-back level.

Table 3. 7 Mean, standard deviation, and coefficient of variation for HIPS (sec/bit)

HIPS	0-Back Task Level	2-Back Task Level
μ	2.9580	0.2420
σ	0.0323	0.0230
cv	0.0110	0.0930

By adopting a logarithmical scale to equation 13, the iso-performance curve can be obtained by the equation 3.15.

$$HIPS_{max} = e^{[\ln(TE) - \ln(H_{owl,lim})]} \tag{3.15}$$

The iso-performance curves for a TE equal to 100% and 60% are obtained and they are shown in figure 3.3.

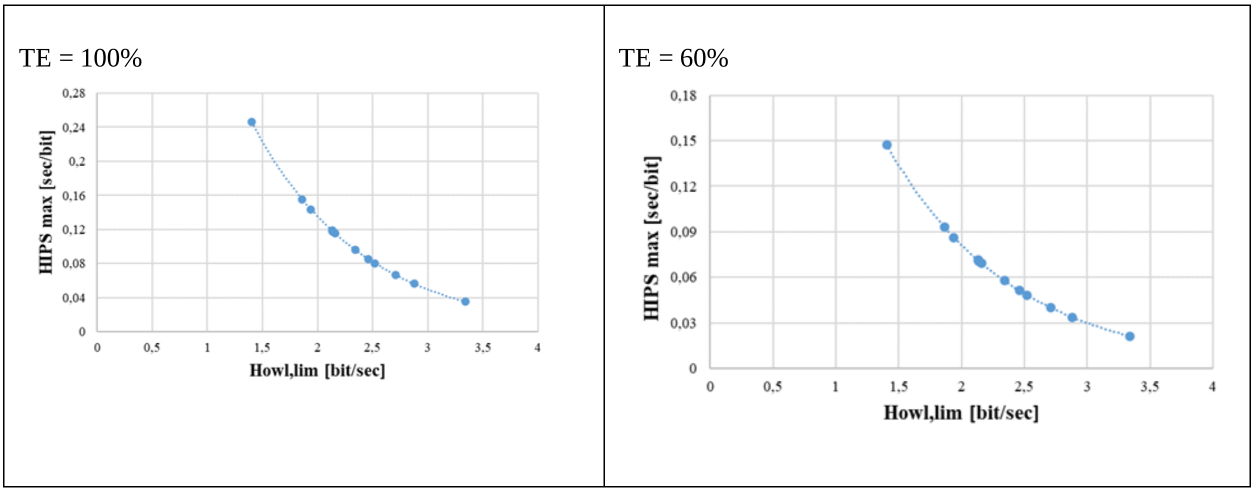

Figure 3. 3 Iso-performance curve

3.1.2. Conclusions on the results obtained

The aim of this study is to evaluate the brain's cognitive occupancy and the processing time of correct information when the quality performance is given. Indeed, the operator information processing rate will vary in accordance with the level of performance. The imposed MWL is an objective demand and depends on the environmental and organizational parameters and on the complexity of the task that the operator must perform.

In the study conducted, the MWL imposed on the operator has been simulated by means of the n-back test. Two levels of increasing complexity were considered (0- and 2-back level). Therefore, in each level was determined the number of available decisions, and the number of bits that the operator has to process in the given time window has been calculated (TL).

For each subject, the $H_{owl,lim}$ has been determined (table 3.5); $H_{owl,lim}$ represents the maximum amount of information that can be processed in the unit time and it is possible observe how it vary from subject to subject. The $cv(H_{owl,lim})$ value is equal to 0.64, this means that the $H_{owl,lim}$ values are spaced form the mean due to the subjectivity of $H_{owl,lim}$.

For each subject the HCCO and HCCR values are obtained by eq. 3.6 and eq.3.7, respectively. The figure 3.2 shows the subject's rate cognitive occupancy for both n-back level. Blue colour represents 0-back level data observed; while orange colour represents 2-back level data observed. Increasing the task's complexity, the HCCO increases and consequently the HCCR decreases. The cognitive reserve of all subjects in 0-level is close to one (figure 3.2). So, the mental effort required to perform the task is low.

The analysis of the values in table 3.6 as shown that the $\mu_{Lev.2}(HCCO)$ is about ten time the $\mu_{Lev.0}(HCCO)$; in 0-back the average HCCO value is about 4%, while in 2-back it is about 40%; this means that the mental effort in 0-back level is almost negligible. The growing up the variability around the average HCCO value, due to the task complexity increasing, is observed by the fact that the $\sigma_{Lev.2}(HCCO)$ is about one hundred time the $\sigma_{Lev.0}(HCCO)$. An equal value of $cv(HCCO)$ (0.481) in both levels is observed. The analysis of the values in table 3.6 as shown that the $\mu_{Lev.2}(HCCR)$ is about 1.5 time the $\mu_{Lev.0}(HCCR)$; in 0-back the average HCCR value is about 96%, while in 2-back it is about 60%. The subject's entire cognitive capacity is available in 0-back level. Comparing table 3.4 and 3.5, the HCCR standard deviation values are equal to the HCCO ones; the $\sigma_{Lev.2}(HCCR)$ is about one hundred time the $\sigma_{Lev.0}(HCCR)$ (table 9). The HCCR values are more variable in 2-back if compared with ones in 0-back, since the $cv_{Lev.2}(HCCR)$ is bigger than $cv_{Lev.0}(HCCR)$. The HCCO and HCCR values of standard deviation are smaller in 0-back if compared with ones in 2-back, respectively. With the same boundary condition, increasing the task complexity the $\mu(HCCO)$ value increases. This means that for more complex task, the HCCO is greater than for a simple task. The HCCO and HCCR values allow to understand if the operator is full or he/she can perform other tasks that involve more cognitive demand.

Figure 3.1 shows the subject's TE for both levels of the n-back test. Blue colour represents 0-back level data observed; orange colour represents 2-back level data observed. In 0-back level the TE of all subjects is almost equal to one.

Increasing the task complexity, the TE decreases (figure 3.1), thus showing the influence of the task complexity on human performance.

The analysis of the values in table 3.7 has shown that $\mu_{Lev.0}(HIPS)$ is about twelve time the $\mu_{Lev.2}(HIPS)$. A greater time to correctly process 1 bit of information is observed in 0-back if compared with than in 2-back. A decreasing in HIPS value from 0- to 2-back level is observed; this is due to two reasons: the TE decreases from 0- to 2-back level; moreover, considering the same boundary conditions in both n-back levels, the given time window to perform the subtasks in each level is the same (3 seconds), but the amount of information that the subject has to process is greater in the 2-back level.

The $\sigma_{Lev.0}(HIPS)$ and $\sigma_{Lev.2}(HIPS)$ values are comparable. Therefore, the variability around the average value is almost the same in both levels. The $cv_{Lev.2}$(HIPS) is about eight time the $cv_{Lev.0}$(HIPS); the HIPS value in 2-back is more variable than in 0-back level, since a greater cv value is observed.

The subject's maximum processing rate of 1 bit of correctly information when the TE is given is shown in figure 7. The iso-performance curves show how lower value of $H_{owl,lim}$ occurs when high value of $HIPS_{max}$ is required. In case of a TE equal to 100%, the amount of bits correctly processed by the operator is equal to the total amount of bits that the operator must process. The comparison between the two iso-performance curves shows that for the same value of $H_{owl,lim}$ when the quality performance required decreases the $HIPS_{max}$ value decreases.

The results obtained show that in case of an increasing quality performance level required, the maximum unitary processing time of correct information of an operator (characterized by an invariant value of $H_{owl,lim}$) grows. As a consequence, when a given quality performance level in performing a task is required (TE), the task completion time has to be set in order to not exceed the mental workload (MWL) threshold of the operator ($H_{owl,lim}$) assigned to that task.

From a managerial point of view, the developed concepts of HCCO, HCCR and $HIPS_{max}$ can be used to assign operators to tasks; avoiding that a specific operator is assigned a task that he/she is unable to perform, and avoiding a high operator's rate brain occupancy, which leads a decreasing operator's performance.

The model can be adopted in the job assignment (by investigating the capability of an operator to complete a task of a given mental workload) or to set the task execution time as a function of the quality performance level required.

Further investigation is required including large a sample of participants to test and more tasks at increasing cognitive demand; for instance, designing an experimental session where the subjects will have to carry out multiple levels of the n-back test.

A better estimation of the relation between H_{owl} and NASA-TLX is required by designing new experimental sessions; in these sessions, by increasing the test level or reducing the available time, $H_{owl,lim}$ values for subject of different age and sex should be evaluated. Moreover, the analytical approach could be applied and tested in experimental sessions simulating an assembly line.

3.2. Information-based analytical framework and the aging phenomenon

The In 2050 around half of workers in developed countries will be aged over 50, and the presence of older workers in production and operative roles will have an impact on economic growth and manufacturing efficiency (UNFPA, 2012) (European Agency for Safety and Health at Work; Dupont Claire; Benin Alice; Belgi and Milieu, 2016a). In the year 2050 the proportion of individuals over the age of 55 years will be 32% in Europe, 30% in North America, 21% in Asia, and 17% in Latin America according to the International Labor Organization (ILO). The decreasing of worker's ability happens in workers involved both in cognitive and physical tasks (Peruzzini and Pellicciari, 2017). The age of 45–50 years have often been used as the base criterion to refer to 'aging worker' (Ilmarinen, 2001). The worker's ability, in particular the physical one, starts decreasing at age of 30. The reduction of cognitive and physical abilities is a crucial point for the workers of age from 45 and 64. The decreasing of abilities in the aging worker is about 20-

25% with respect to the maximum performance manifested at about 30 years of age (Peruzzini and Pellicciari, 2017). Cardiovascular and musculoskeletal systems, body structure, and some important sensory systems reflect the change in physical work capacity. The maximal oxygen consumption in absolute and relative terms shows a linear decline with age among both male and female (Ilmarinen, 2001). The decline of oxygen consumption starts after full physical maturity has been reached, at the latest, after the age of 30 years (Shvartz and Reibold, 1990). It is recommended that physical work does not involve more than 50% of a worker's maximum oxygen consumption (Ilmarinen, 2000). The ability to perform different tasks that require intellectual and other kinds of mental effort is defined mental functional capacity. Changes in mental functions during the work life are related to the reduction of the speed of perception and precision. The changes concern the entire human system for processing information: the sensory perceptive system, the cognitive system, and the motor system.

The individual work ability is a process of human resources in relation to work (Ilmarinen, 2001). Human resources can be described by health and functional capacities (physical, mental, social), education and competence, values and attitudes, and motivation. When this comprehensive set of individual factors is related to work demands (physical, mental), work community and management, and work environment, the outcome can be called the individual work ability. The concept of work ability is a dynamic process that changes for several reasons throughout an individual's work life. One of the main factors inducing change is aging and its effects on human resources.

The phenomenon of population aging will become a serious issue in the next few years. Statistical projections state that in the next years the global average age expectation will increase to 76 years in 2050 and 81 years in 2100 (Bloom, 2011). The PSR indicator (potential support ratio), which is defined as the ratio of the number of people of the group 16-64 years by the number of over 65 years people, is expected to decline from 4.9 to 1.9 in 2100 in the United States and from 2.9 to1.4 in 2100 in Germany (Gerland *et al.*, 2014). In Europe the oldest age group (55-64 years) is expected to expand by 16.2% (9.9 million) between 2010 and 2030, with a decreasing trend of the other age groups (Ilmarinen, 2012). Furthermore, people tend to work until later ages due to multiple social and economic reasons such as delayed retirement and phased retirement (Alley and Crimmins, 2012; Beehr and Bennett, 2015; Cahill, Giandrea and Quinn, 2015; Martin and Xiang, 2015; Fisher, Chaffee and Sonnega, 2016) as long as their cognitive and physical health allows it (Fisher, Chaffee and Sonnega, 2016). This issue will bring to many implications in multiple fields and a better awareness of the workforce aging phenomenon is needed.

The aging phenomenon causes a change in the cognitive capability with a progressive deterioration of the brain functions: the decrease of the cognitive capability has an impact on both physical and cognitive abilities (Clouston *et al.*, 2013). The decrease of the physical abilities due to aging, causes declines in physical, physiological, perceptual, and motor processes: focusing on the workforce aging, the link between age and ergonomics issues (OCRA and RULA methods) is a wide confirmed aspect with direct consequence on the health of workers. The work-related musculoskeletal disorders (WMSDs) represent the most common occupational diseases (almost 40% of the whole occupational diseases), and about 30% of jobs in Europe involve incorrect work postures, handling of heavy materials or repetitive work (Ilmarinen, 2012). As a consequence, several studies have been focusing on physical abilities and on their impact on health and on well-being of older workers, but fewer studies focus on cognitive abilities (Fisher *et al.*, 2017), despite cognitive abilities being important predictors of task performance (Kanfer and Ackerman, 2004; Müller *et al.*, 2015), influencing mostly the worker's ability to learn and improve skills necessary to carry out mental activities (Schmidt and Hunter, 1998; Salthouse, 2012). Performance is expected to decrease with age mostly for those working activities where the required abilities decrease with age (cognitive abilities) against a small improvement of work performance due to experience (Silverstein, 2008). A decrease in performance is expected to appear in older worker for activities that require fast information processing without a useful base of the accumulated knowledge or experience (McDaniel, Pesta and Banks, 2012). In fact, if on one hand the ability to retrieve familiar information from the long-term memory is quite stable with the age due to the previous knowledge and the experience accumulated over the years (Ng and Feldman, 2008; Salthouse, 2012; Rudolph, 2016), on the other hand the aging may make it difficult to learn new concepts and processing them in the working memory, to retrieve complex and uncommon information from the long-term memory (e.g. operational procedures) and to perform a working activity with a high information processing rate. These concepts are expressed by the theory of the dual-component human intelligence (Cattell, 1943), in which cognitive abilities are divided into fluid cognitive capabilities (fluid intelligence) and crystalized cognitive capabilities (crystalized intelligence). The first refers to the ability to deal with new situations through the use of working memory and abstract reasoning, the second refers to the ability to solve problems using the knowledge acquired over the years (Cattell, 1963; Carroll, 1993). If on one hand the crystalized intelligence is quite stable during the years, the fluid intelligence declines with the age and its decay accelerates after the age 50 (Baddeley, 1992; Verhaeghen and Salthouse, 1997). From literature it turns out that any person has a limited memory capacity and limited information-processing resources (Miller, 1956; Rasmussen, 1974). In particular, the reduction of the working memory capacity is strictly related to the decrease of the processing speed (Salthouse and Babcock, 1991). Any worker must recur to the working memory and long-term memory to elaborate information. The working memory can process only a limited quantity of information, so to satisfy the cognitive requirements, the information stored in the long-term memory of the worker are recalled (Paas, Renkl and Sweller, 2003). Age-related changes in memory may lead to a lower capacity of the working memory, changes in the long-term memory storage, or retrieval problems (Ference and Vockell, 1994). Furthermore, elderly people prefer to rely more on their memory and on the knowledge acquired during the years, than learning new concepts for the execution of the task, hence leading to probable memory errors (Umanath and Marsh, 2014).

To summarise, the age-related changes have an impact on multiple cognitive abilities that refers to mental processes including thinking, reasoning, problem solving, learning, remembering and decision-making (Park, 2000). The age-related changes have multiple consequences on the performance of older workers in environments that require an increasing improvement of skills (Karpinska *et al.*, 2015; Raemdonck *et al.*, 2015), on the different processing speed of information (Salthouse, 1996; Hambrick, Salthouse and Meinz, 1999; Rozas, Juncos-Rabadán and González, 2008) for high demand cognitive tasks (Park, 2000; Salthouse, 2012; Salthouse and Madden, 2013) and on the decrease of the working memory capacity (Schulz and Stamov Roßnagel, 2010; Beier, Teachout and Cox, 2012; Wolfson, Cavanagh and Kraiger, 2014). If the effects of aging on the cognitive abilities of workers are not properly studied, there will be an adverse impact on the quality, productivity, and performance of the I4.0.

The changes introduced in I4.0 led to a workload shift, from physical to more cognitive activities, leading operators to perform tasks that require high cognitive demand (Pascual *et al.*, 2019) and to manage an increasing quantity of information and data during their decision-making processes. Workforce aging and the study of the influences of the aging on the cognitive abilities of operators in I4.0 or in activities of everyday life originate theoretical problems of scientific interest as well as a challenge for society which asks the scientific community to address problems providing effective and quick answers. Problems are quite complex. Dimensions of complexity are mainly attributed to

- High dynamic and stochastic variability of humans in performing cognitive tasks
- Large number of physiological and physical-physiological variables affecting human performance
- Mutual influence between motor and cognitive tasks
- Multidisciplinary competence required to analyse human cognitive performance in work environment as well as everyday life activities

Complexity dimensions of human cognitive capabilities justify limits of scientific investigations which have mainly been carried out for neurological/physical-physiological medical purposes and are less related to engineering applications in work environment or to the general daily human activities in the digital society. Several empirical test-based investigations have been carried out to observe human motor and cognitive abilities related to aging. Regression analyses on test-based investigations provide relations able to catch functional dependency among variables. However, a holistic approach able to integrate empirical results in a more general theoretical framework is less common.

3.2.1. Cognitive abilities related to aging: The experience of Deary & Der

In information theory, the amount of information processed to choose between two or multiple alternatives is measured in bit unit. In particular, in case of *n* equiprobable alternatives, each of them with an occurrence probability of p = 1/n, the amount of information processed defined by the Shannon Entropy (Shannon, 1948) is evaluated as follows:

$$H = -\sum_{i=1}^{n} p_i * log_2 \, p_i = log_2 \, n \qquad [bit] \tag{3.16}$$

In the study of Deary and Der (Deary and Der, 2005), an experimental research with a large number of participants tested the correlation of the Reaction Time (RT) of male and female populations differently aged. The size of the samples (900 subjects aged in 16-63 years) gives high reliability to the results obtained. The RT may be defined as the time between a stimulus and a response; it was measured using a portable device with a display and a five response keys; the keys were labelled 1,2,0,3,4 from left to right. For the evaluation of "single-choice" RT the subjects were asked to place a finger of their preferred hand on the central '0' key and they were instructed to press it as quickly as possible after the number zero appeared in the display. For the "four-choices" RT the subjects were asked to place the second and the third finger of each hand on the key labelled 1,2 (left hand) and 3,4 (right hand) and they were instructed to press the corresponding key when one of the four digits appeared on the display. In the former case, the subject processes one bit of information; in the latter case (four choices task) the subject processes 2 bits of information. Starting from the Hick's law (Damon et al., 2014; Hick, 1952) a linear dependency between the reaction time RT and the information volume to be processed is adopted:

$$RT = SRT + T_{p,c} * I_c \qquad [s] \tag{3.17}$$

where, SRT (Simple Response Time) is the sum of all-time delays not associated with decision-making, $T_{p,c}$ is the time to process one bit of information (measured as time per bit unit), and I_c is the information volume (in bit unit) processed in the cognitive task, as per Equation (3.16). From Equation 3.17, a model of information processed in the cognitive task (I_c) can be derived.

3.2.2. Motor abilities related to aging: Purdue Pegboard Test (PPT)

Using information theory, the amount of information processed during a task that requires movement of the subject can also be expressed in bit unit, similarly to the abovementioned cognitive tasks. Consider a subject executing a reaching task within a time interval called movement time, during which he processes a certain amount of information linked to the movement (Fitts, 1954). The amount of information processed during the reaching task is expressed by the Index Difficulty (ID) parameter, most commonly defined by MacKenzie (MacKenzie, 1992) as follows:

$$ID = log_2\left(\frac{D}{W} + 1\right) \qquad [bit] \tag{3.18}$$

where D is the distance from the hand's starting point to the centre of the target and W is the width of the target measured along the line connecting the two motion's endpoints.

In the Purdue Pegboard Test (PPT) participants are asked to pick up pegs from a bowl with their right hand, left hand, and then both hands (three runs) and place them in one of the 25 vertical holes of a plate. The test score is measured as the number of pegs the subject places within 30 seconds. This test indirectly evaluates manual dexterity. The more pegs they can place correctly in 30 seconds (one run), the higher their manual dexterity.

Based on the relationship given by Fitts (Fitts, 1954), a linear dependency between the movement time (MT - time needed by the operator to perform the task) and the information volume to be processed (I_m - bit unit) is adopted here:

$$MT = T_{p,m} * I_m \qquad [s] \tag{3.19}$$

where, $T_{p,m}$ is the time needed to process one bit of information (time unit/bit) and I_m is the information volume to be processed in the motor task. Based on models from information theory, the time required to perform a task with 0-bit information content must be 0, yielding a null Y-intercept for the Fitts' law (as in Eq. (3.19)), which is the working assumption used in the regressions evaluated in the next section.

Eq. 3.19 is applied to the PPT to obtain an information-based model of the motor task. The diameter of the holes is 0.25 cm, the distance between two contiguous centres equals five times the diameter of the holes, the distance between the bowl that contains the pegs and the centre of the first hole is 3.37 cm, and the MT (as the duration of the entire PPT test) is 30 seconds. The centre of the bowl and every hole of the board are aligned. For the PPT, the information volume involved in the motor task I_m is the sum of two components: the sum of each ID for the single reaching task, i.e. from bowl to hole, and $I_{m,MTM}$. The former refers to the aiming and reaching component of the motor task, while the latter refers to every other sub-tasks associated with the total n repetitive pick and place actions. As a result, the Fitts' law applied to the PPT is:

$$MT = T_{p,m} * \left(\sum_{i=1}^{n} log_2\left(\frac{D_i}{W}+1\right) + I_{m,MTM}\right) \quad [s] \tag{3.20}$$

where n is the total number of pegs placed by the subject in the board within MT, D_i is the distance from the starting point (bowl with all the pegs) to the i-th target (hole) at every reaching movement, and W is the width of the target (constant holes diameter).

During the test, after each pick and place movement, the operator is required to move his/her arm back to the bowl and grab another peg. For this sub-task it is quite difficult to clearly identify the amount of information to be processed. Nevertheless, it could be included in Eq. (3.20) via $I_{m,MTM}$, which is the information volume associated to the Methods-Time Measurement (MTM) standard time as clarified in the next Section. Method-Time Measurement (MTM) is defined as a system that “analyzes any manual operation or method into the basic motions required to perform it and assigns to each motion a predetermined time standard which is determined by the nature of the motion and the conditions under which the motion is made” (Maynard, Stegemerten and Schwab, 1948). MTM standard times are considered as a reference an individual's performance can be compare to. Equation 3.20, a model of information processed in the PPT motor task (I_m) can be derived.

In this Section, it has been shown how for some specific tests for evaluating human cognitive or motor abilities it is possible to quantify the corresponding volume of information processed and its rate, starting from fundamental experimental measures, such as reaction and movement time. In the next Section, cognitive and motor performance will be quantified starting from the results of previous experiments, which evaluate the age- and sex-dependent performance of individuals completing tasks with various cognitive content.

3.2.3. Human Cognitive and Motor Abilities in the Aging Workforce: An Information-Based Model

3.2.3.1. Cognitive Abilities

An extended research on subjects differently aged (900 subjects from 16 to 63 years old) (Deary and Der, 2005), based on the UK's Health and Lifestyle Survey (HALS) (Huppert and Whittington, 1993), is used as a reference in the present study to express the correlations between age, reaction time, and cognitive abilities in an information-theory perspective. Literature review shows that reaction time is a prominent variable in the field of cognitive gerontology, where there is an interest in the age-related changes in information processing. The role of speed of processing in aging research is emphasized, since “speed is often viewed not only as a behavioural measure but also as a fundamental property of the central nervous system” (Madden, 2001). The age-related decrease in reaction time is well established (Mathey, 2015), but there are debates about the correlation of this change with the age in subjects of different sex (Fozard *et al.*, 1994). In the test of (Mathey, 2015), male participants show better psychomotor performance than females. The reaction time is linked to cognitive abilities and when the subject's reaction time increases with the age, his/her cognitive abilities decrease (Deary and Der, 2005). This association allows to model the aging influence on cognitive ability based on reaction time and without the use of specific cognitive tests.

For the cognitive abilities, this study refers to previous experimental research where subjects with different age were tested in the study of (Deary and Der, 2005); the test consisted of identifying the right single or multiple choice answer out of several possible options. Here, the result of this study is used to express the correlations between age, reaction time, and cognitive abilities in an information-theory perspective and to propose an information-based model that evaluates the information volume that a subject (of a specific class of age and sex) has to process in order to accomplish a cognitive task. The RT is defined as the time for decision making and consists of different contributions, including elementary sensorial delays from input to action (Hick, 1952). Some delays do not depend on the information volume to be processed: they are due to neural transmission, latency of muscles, and sensory receptor delays. The sum of such delays is identified as Simple Response Time (SRT) (as in Eq. 5) and is responsible for a fraction k (30-40 %) of the overall RT. The complementary amount of 60-70 % of RT is due to the central processing delays. Single or multiple choices tasks, in the study of (Deary and Der, 2005), require the subject to process a different information volume I_c, resulting in different RT. Under these hypotheses and using Equation (3.17), the RT(I_c, s, A,) measured in the test has a biunivocal relation with the time to process a single information unit of subjects with the same sex and age, $T_{p,c}$(s, A), as follows:

$$RT(s, A, I_c) = \frac{T_{p,c}(s,A)}{(1-k)} * I_c \qquad [s] \tag{3.21}$$

being SRT = k * RT. Therefore, the $T_{p,c}$(s, A) value is obtained as follows:

$$T_{p,c}(s, A) = \frac{RT(s,A,Ic)*(1-k)}{I_c} \qquad \left[\frac{s}{bit}\right] \tag{3.22}$$

where k is a constant that can vary with the subject in the range: $0.3 \leq k \geq 0.4$. Consistently, the information processing rate of population of sex s and age class A in a cognitive task, can be obtained as:

$$IPR_c(s, A) = \frac{1}{T_{p,c}(s,A)} \qquad \left[\frac{bit}{s}\right] \tag{3.23}$$

In the experiments of Deary and Der (Deary and Der, 2005), the single-choice RT (SC-RT) and multiple-choice RT (MC-RT) were estimated for both male and female aged from 16 to 63 years. The mean RT values within an age class are shown for both sexes and for the single- and multiple-choices tests (Table 3.8).

Table 3. 8 Single-choice Reaction Time (SC-RT) and Multiple-choice Reaction Time (MC-RT) for different age class and sex (M for male, F for female) obtained from the experiments of Deary and Der (Deary and Der, 2005)

Age Class	**16**		**24**		**36**	
Age Range	**15-16**		**23-26**		**31-41**	
Sex	**M**	**F**	**M**	**F**	**M**	**F**
SC-RT (ms)	293.4	295	294.7	306	304.4	314.9
MC-RT (ms)	577.8	580.1	546	556.5	618.9	621.5
Age Class	**44**		**56**		**63**	
Age Range	**39-50**		**54-58**		**62-66**	
Sex	**M**	**F**	**M**	**F**	**M**	**F**
SC-RT (ms)	316.2	332.8	348.1	345.6	373.5	375.1
MC-RT (ms)	642.5	630.3	721.2	718.1	739.1	735

When male and female populations are considered altogether, RT values increase linearly with the age class (Figure 3.4), for single and four-choices tasks, with an increase of about 20-30% from age 24 to 60 +. Also, reaction times with higher information volumes are bigger.

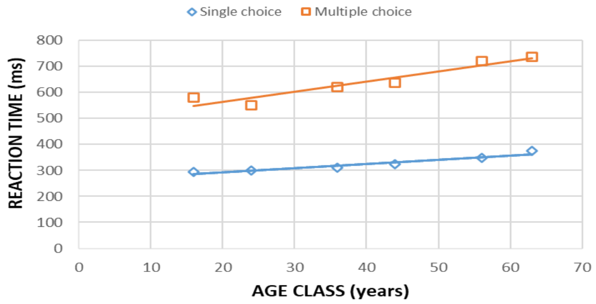

Figure 3. 4 Reaction time values of the overall population vs. age for single and multiple-choice cognitive tests obtained from (Deary and Der, 2005) **.**

By letting k = 0.35, $T_{p,c}$(s, A) values are computed (Eq. (3.22)) and shown for single- and multiple-choice tests, and their average (Table 3.9).

Table 3. 9 Processing Time $T_{p,c}$(s, A) in single-choice (SC) and multiple-choice (MC) tests (M for male, F for female) obtained from (Deary and Der, 2005)

Age Class	**16**		**24**		**36**	
Sex	**M**	**F**	**M**	**F**	**M**	**F**
$T_{p,c}$-SC (ms/bit)	190.7	191.8	191.6	198.9	197.9	204.7
$T_{p,c}$-MC (ms/bit)	187.8	188.5	177.5	180.9	201.1	202.0
Average $T_{p,c}$ (ms/bit)	189.3	190.1	184.5	189.9	199.5	203.3
Age Class	**44**		**56**		**63**	
Sex	**M**	**F**	**M**	**F**	**M**	**F**
$T_{p,c}$-SC (ms/bit)	205.5	216.3	226.3	224.6	242.8	243.8
$T_{p,c}$-MC (ms/bit)	208.8	204.8	234.4	233.4	240.2	238.9
Average $T_{p,c}$ (ms/bit)	207.2	210.6	230.3	229.0	241.5	241.3

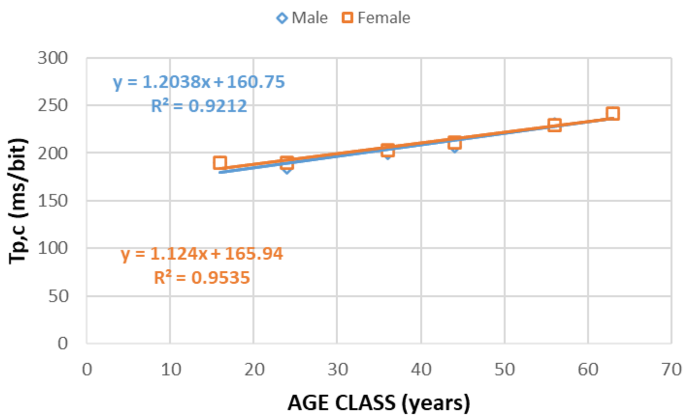

Figure 3. 5 $T_{p,c}$ values influenced by age and sex in case of cognitive tasks, obtained from RT values of (Deary and Der, 2005)

Since by definition, $T_{p,c}(s, A)$ is independent on the information volume (in this case, whether a task is single or multiple choice), its average values can provide a useful model of aging in processing time for different sex and age class (Figure 3.5). Trend lines for male and female subjects show no significant difference ($R^2 > 0.9$). This confirms that the time required to process a single information unit by older subjects is greater than the time to process the same amount of information by a young one, for both sexes. According to Figure 3, the linear trend observed between $T_{p,c}$ and age class for a given sex can be modelled as follows:

$$T_{p,c}(s, A) = \alpha_c(s) + \beta_c(s) * A \quad \left[\frac{s}{bit}\right] \tag{3.24}$$

Values of α_c and β_c constants are in Table 3.10:

Table 3. 10 Processing Time Values of α_c and β_c for each sex, to model processing time in cognitive tasks

Sex	α_c (ms/bit)	β_c (ms/bit)
Male	160.75	1.20
Female	165.94	1.12

The information processing rate in case of cognitive tasks $IPR_c(s, A)$ is evaluated as the inverse of $T_{p,c}(s,A)$ for differently aged classes of male and female subjects (eq. 3.23) resulting in decreasing values with age class for both sexes.

3.2.3.2. Motor Abilities

For the motor abilities, this study refers to two previous experimental research where subjects with different age were tested by means of the Purdue Pegboard Test (PPT): the first study refers to people aged from 15 to 40 years old (Yeudall *et al.*, 1986), the second study refers to people aged from 40 to 89 years old (Bolla-Wilson and Kawas, 1988), with a total of 437 subjects (219 females and 218 males). Here, the results of these studies are used to express the correlations between age, movement time, and motor abilities in an information-theory perspective and to propose an information-based model that evaluates the information volume that a subject (of a specific class of age and sex) has to process in order to accomplish a motor task with low cognitive content, such as the PPT. The time to perform the task in the PPT is the movement time (MT) of 30 seconds during each test. The MT is the time needed to perform a motor task with low cognitive content. Thanks to the studies above mentioned it is possible to link the performance of the test (number of pegs placed in the holes in 30 seconds) with the age and the sex of the subject (i.e., MT(s, A)). Data from the preferred hand of the subjects are considered (so to not influence the performance with the different manual dexterity of the hands). Under these hypotheses, Equation (3.19) represents the biunivocal relation between MT(s, A) and $T_{p,m}(s, A)$, for given sex (s) (male/female) and age class (A):

$$MT(s, A) = T_{p,m}(s, A) * I_m \qquad [s] \tag{3.25}$$

The processing time per information unit $T_{p,m}(s, A)$ is obtained as:

$$T_{p,m}(s, A) = \frac{MT(s,A)}{I_m} \qquad \left[\frac{s}{bit}\right] \tag{3.26}$$

Consistently, the information processing rate of population of sex s and age class A, can be obtained as:

$$IPR_m(s, A) = \frac{1}{T_{p,m}(s,A)} \qquad \left[\frac{bit}{s}\right] \tag{3.27}$$

As previously described, the amount of information to be processed in the motor task (I_m) is the sum of two terms:

$$I_m = I_{m,ID} + I_{m,MTM} = \sum_{i=1}^{n} \log_2\left(\frac{D_i}{W} + 1\right) + I_{m,MTM} \quad [bit] \tag{3.28}$$

The first term, $I_{m,ID}$, is the index of difficulty that quantifies the information volume associated with the n reaching movements. The second term, $I_{m,MTM}$, quantifies the amount of information associated with every other sub-tasks occurring in every pick and place movements, e.g. moving the arm back to the bowl, grabbing another peg, etc.

For the PPT, the MT is constant and equal to 30 seconds and the $I_{m,ID}$ can be easily evaluated via Eq. (3.18). However, the lumped term $I_{m,MTM}$ is not known and is in this study expressed by the Methods-Time Measurement (MTM) standard time. Here, an iterative calculation has been carried out, where $I_{m,MTM}$ is expressed as follows:

$$I_{m,MTM} = \frac{MTM}{T^*_{p,m}} \quad [bit] \tag{3.29}$$

where MTM is equal to the sum of Method-Time Measurement standard times of all n translating, picking, and placing movements of the hand. Method-Time Measurement (MTM) standard times are not provided for different age and sex. For this reason, in this paper it is assumed that they are related to the corresponding information content of movements (moving the arm back to the bowl, grabbing another peg, place the peg in the hole) through an average (on age and sex) value of the motor processing time ($T^*_{p,m}$). In order to evaluate this average value, an iterative procedure has been adopted. For a first approximation, $T^*_{p,m}$ is assumed as 250 ms/bit (named $T^*_{p,m,0}$). This value has been adopted to evaluate $I_{m,MTM}$ using equation (3.29) and then I_m from equation (16) for different values of n. For each subject observed during PPT (s, A), by using Equations (3.26), the corresponding $T_{p,m}$(s, A) value has been obtained. Finally, the mean of the $T_{p,m}$(s, A) values has been compared with initial assumed value $T^*_{p,m,0}$. At the first iteration a relative error of 9% on the initial approximate value of $T^*_{p,m}$ has been obtained. In the next iteration, the mean of the $T_{p,m}$(s, A) values has been adopted for $T^*_{p,m}$. After few iterations, the iterative calculation converged on $T^*_{p,m}$ = 180 ms/bit.

The $T_{p,m}$(s, A) average values for all considered (s, A) pairs can then be calculated and related to the performance (i.e., the number n of correctly placed pegs) of subjects performing the PPT, as observed in the two reference studies (Yeudall *et al.*, 1986; Bolla-Wilson and Kawas, 1988). The performance in relationship with age class and sex and the related $T_{p,m}$(s, A) average values are shown in Table 3.11. The performance values are the mean of the performances across multiple subjects.

Table 3. 11 Performances and processing times of the PPT (M for male, F for female) in case of motor tasks

Age Class	**18**		**23**		**28**		**36**	
Age Range	**15-20**		**21-25**		**26-30**		**31-40**	
Sex	**M**	**F**	**M**	**F**	**M**	**F**	**M**	**F**
Performance	15.56	16.69	15.54	16.64	16.22	17.25	15.35	15.94
$T_{p,m}$ (ms/bit)	274	253	275	254	261	244	278	265
Age Class	**45**		**55**		**65**		**75**	
Age Range	**41-49**		**50-59**		**60-69**		**70-79**	
Sex	**M**	**F**	**M**	**F**	**M**	**F**	**M**	**F**
Performance	14.6	15.9	14.4	15	13.6	14.6	13	13.8
$T_{p,m}$ (ms/bit)	295	267	299	285	319	295	336	314

As in the case of cognitive task, linear trends are observed (Figure 3.6), with large R^2 values for both male and female (~0.9) and negligible differences in the trend for the two sexes. Results from the model confirm that the time required to process a single information unit by older workers is greater than the time to process the same amount of information by a young one both in case of cognitive and motor task with low cognitive content.

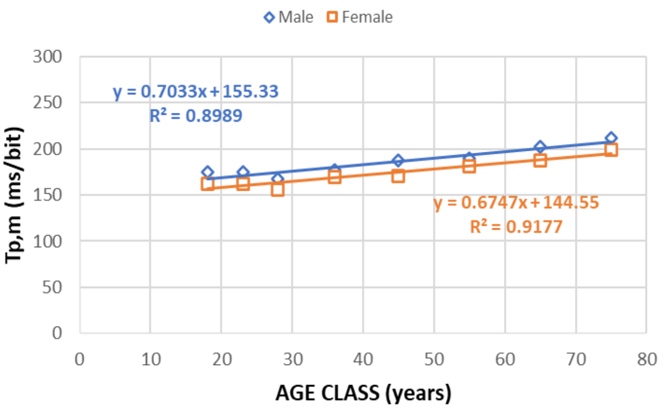

Figure 3. 6 $T_{p,m}$ values influenced by age and sex in case of motor tasks

The linear trend observed for $T_{p,m}(s, A)$ is as follows:

$$T_{p,m}(s, A) = \alpha_m(s) + \beta_m(s) * A \qquad \left[\frac{s}{bit}\right] \tag{3.30}$$

Values of α_m and β_m constants are in Table 3.12:

Table 3. 12 Processing Time Values of α_m and β_m for each sex, to model processing time in cognitive tasks

Sex	α_m (ms/bit)	β_m (ms/bit)
Male	155.33	0.70
Female	144.55	0.67

The information processing rate in case of motor tasks with low cognitive content (IPR_m) is evaluated as the inverse of $T_{p,m}(s,A)$ for differently aged classes of male and female subjects (eq. 3.27) resulting in decreasing values with age class for both sexes.

3.2.4. Formulation and Application of the model

The model considers the motor and cognitive abilities of a subject with different age and sex in order to evaluate his/her performance in term of completion time in accomplishing a given task with a known cognitive and motor information content:

$$Performance\ Time(I_c, I_m, s, A) = TC(I_c, s, A) + TM(I_m, s, A) \quad [s] \tag{3.31}$$

where:

- I_c [bit] = information content of the cognitive part of the task
- $TC(I_c, s, A)$ [s] = time to perform the high cognitive information content of the task (I_c) for given age and sex
- I_m [bit] = information content of the motor part of the task ($I_{m,ID} + I_{m,MTM}$)

- $TM(I_m, s, A)$ [s] = time to perform the high motor (low cognitive) information content of the task (I_m) for given age and sex

This model is based on a preliminary decomposition of the task in its components (high cognitive-low motor, and vice versa). The information content of the respective components (I_c, I_m) can be obtained by means of Eq. 3.16 and Eq. 3.28, respectively. The time required by the subject to complete the cognitive (TC) and the motor (TM) part of the task are calculated starting from the processing times $T_{p,c}(s, A)$ and $T_{p,m}(s, A)$, respectively. $T_{p,c}(s, A)$ can be obtained from Eq. (3.24) by adopting the parameters corresponding to the subject characteristics (Table 3.10); $T_{p,m}(s, A)$ can be obtained from Eq. (3.30) by adopting the parameters corresponding to the subject's characteristics (Table 3.12). The time required to complete the cognitive part of the task (TC) can be obtained as the reaction time (RT) to process the information content I_c (as per Eq. 3.21):

$$TC(s, A, I_c) = RT(s, A, I_c) = \frac{T_{p,c}(s,A)}{(1-k)} * I_c \quad [s] \tag{3.31a}$$

The time required to complete the motor part of the task (TM) with low cognitive content can be obtained as the movement time (MT) associated with the information content I_m (as per Eq. 3.25):

$$TM(s, A, I_m) = MT(s, A, I_m) = T_{p,m}(s, A) * I_m \quad [s] \tag{3.31b}$$

$$I_m = I_{m,ID} + I_{m,MTM} = \sum_{i=1}^{n} \log_2\left(\frac{D_i}{W} + 1\right) + \frac{MTM}{T^*_{p,m}} \quad [bit] \tag{3.31c}$$

where with $T^*_{p,m}$ = 180 ms/bit.

As said before, $I_{m,MTM}$ describes the amount of information associated to the delays due to simple movements (motor task with low cognitive content). The time required to perform single movements necessary for the completion of the task (with low information content), could be obtained in general cases by means of MTM standard time technique.

The proposed model allows to predict the human performance in the form of completion time for subjects of different sex and age involved in tasks characterized by both a cognitive and a motor component. When ID is used for the calculation of I_m, as in the present formulation, the model directly applies to reaching motor tasks; nevertheless, the model is quite general and by adapting the information content of the motor component, could be applied to different tasks and contexts, from everyday life activities, to rehabilitation medical treatments, to industrial environments.

The model defined in the previous section has been tested on a case study inspired by an assembly line of an automotive plant in which high pressure pumps for diesel injection systems are assembled. The line consists of highly automated workstations, and workstations with a small degree of automation. The line is operated on three eight hours shifts. The line has a cycle time of 45 [s]. One component of the pump, the flange, is pre-assembled on a sub-line consisting of three workstations (WSs), where the operators assemble the flange of the body pump following steps described in table 3.14. The sub-line is operated only in the first eight hours work shift and provide flanges for the subsequent three shifts, thus having a cycle time of 15 [s]. A semi-automated punching machine is operated in each WS. Workers are in charge of pre-assembling and verifying the right position of components on the body pump and of initiate the process on the machine. At the end of the process, operators of each module perform a (visual) quality control on the product in order to identify scraps. The case study considered allowed to test the model and to find the operator-machine allocation minimizing idle time or smoothing workload on the WSs (by minimizing idle time standard deviation). Furthermore, the developed model allows to verify if the operator is eligible to work on the WS or if his/her performance time is not compliant with cycle time. In this case study, three WSs and five operators are considered. The operator's characteristics (age and sex) are in table 3.13.

Table 3. 13 Operator's characteristics

Operator	Sex (M/F)	Age
A	M	25
B	F	35
C	M	50
D	M	60
E	F	60

In the first WS a thrust ring is set into the flange, in the second WS the oil seal is assembled onto the flange, and in the third WS a bushing is assembled into the triangular ring of the flange. Each WS is composed by multiple sub-tasks that can be classified in cognitive (I_c) and motor ($I_{m,ID}$ and the amount of information associated to simple movements [$I_{m,MTM}$]) For the $I_{m,MTM}$, as described before, the time required for the simple movement of upper limbs is obtained from MTM standard time. The measurement unit for each simple movement is expressed in TMU, with 1 TMU equal to 0.036 seconds. In table 3.14 are summarized the TMU values and the equivalent MTM time used for the simple tasks of reaching, grasping, moving and releasing.

Table 3. 14 TMU values for the simple actions: reach, grasp, move and release

	Reach	Grasp	Move	Release
Distance (cm)	40	---	30	---
TMU Value	11.3	2	12.9	2
MTM (s)	0.4068	0.072	0.4644	0.072

In table 3.15, for each single sub-tasks, a briefly described is provided as well as and its characteristic (information content [bit] of cognitive and motor tasks as well as of simple movements).

Table 3. 15 Sub-tasks performed in each WS

		TC	***TM***	
Sub-tasks	**Module 1: set the thrust ring into the flange**	**I_c [bit]**	**$I_{m,ID}$ [bit]**	**$I_{m,MTM}$ [bit]**
1	Grasp the flange			2.66
2	Place the flange under the magnifying glass		1.58	
3	Verify the presence of the defect	1.00		
4	Put the flange in the scrap basket in the presence of the defect*			2.98
5	Place the flange on the punching machine		1.32	
6	Grasp the thrust ring on the flange			2.66
7	Place the thrust ring on the flange		2.00	

8	Verify the correct position of the thrust ring	1.00		
9	Push the button start on the punching machine	2.00		
10	Push the button 'scrap'* on the punching machine (wrong punching)	1.00		
11	Grasp and put the flange in the basket (OK flange/NOK flange)			5.64
Sub-tasks	**Module 2: set the oil seal into the flange**	**I_c [bit]**	**$I_{m,ID}$ [bit]**	**$I_{m,MTM}$ [bit]**
1	Grasp the flange			2.66
2	Verify the punching (OK/NOK punching)	1.00		
3	Place the flange on the punching machine		1.32	
4	Verify that the oil seal side of the flange is facing upwards	1.00		
5	Grasp the oil seal			2.66
6	Place the oil seal on the flange		2.81	
7	Verify that the spring side of the oil seal is facing downwards	1.00		
8	Push the button start on the punching machine	2.00		
9	Push the button 'incorrect positioning'* (repeat action 7)	2.00		
10	Push the button 'scrap'* (wrong punching)	1.00		
11	Grasp and put the flange in the basket (OK flange/NOK flange)			5.64
Sub-tasks	**Module 3: set the bushing into the triangular ring of the flange**	**I_c [bit]**	**$I_{m,ID}$ [bit]**	**$I_{m,MTM}$ [bit]**
1	Grasp the triangular ring from the basket			2.66
2	Place the triangular ring on the punching machine		1.32	
3	Verify the correct position of the triangular ring	1.00		
4	Grasp the bushing from the basket			2.66
5	Place the bushing on the punching machine		2.81	
6	Verify the correct position of the bushing	1.00		
7	Push the button 'punching'	2.00		
8	Verify the correct punching	1.00		
9	Grasp and put the flange in the basket (OK flange/NOK flange)			5.64

*the corresponding time required to complete these sub-tasks is evaluated by considering 5% of scraps.

For all WSs show in table 8, the information content of the cognitive part of the task (I_c) and the information content of the motor part of the task (I_m) are calculated by Eq. 3.16 and eq. 3.25, respectively. For each operator on each module, the human performances are obtained by eq. 3.28 and are summarized in table 3.16. Machine time is 7.2 (s), 9.6 (s) and 8.6 (s), for WS one, two and three, respectively.

Table 3. 16 Human performances (times) evaluates for each module

Operator	$T_{module\ 1}$ (s)	$T_{module\ 2}$ (s)	$T_{module\ 3}$ (s)
A	11.157	13.719	12.675
B	11.169	13.760	12.713
C	11.624	14.221	13.170
D	11.811	14.422	13.368
E	11.612	14.235	13.181

The cycle time (T_c) of each module was assumed of 15 seconds. Consequently, the operator-WS allocation that minimizes the idle time (eq. 20) and the one allowing to level WSs workload (by minimizing the idle time standard deviation (eq. 3.34) was determined.

$$Min \sum_{k=1}^{3} (T_c - T_{i,k}) \ \ [s] \qquad (3.32)$$

Where i = 1,…,5 and represents the i-th operator, and k = 1,…3 and represents k-th module.

$$T_{c,k} - T_{i,k} = D_{t\ (i,k)} \ \ [s] \qquad (3.33)$$

Where $D_{t(i,k)}$ represents the i-th operator's idle time on k-th WS

$$Min \sum_{k=1}^{3} \sigma_{D_{t(i,k)}} \qquad (3.34)$$

Where $\sigma_{Dt(i,k)}$ is the standard deviation of idle time. The operator-WS allocations evaluated by means of eq. 3.32 and eq. 3.34, are shown in table 3.17; furthermore, table 3.17 summarises the values of standard deviation of idle time and the maximum operating time for each allocation.

Table 3. 17 Operator-WS allocation for T_c = 15 seconds

Operator-Module allocation	Standard deviation of idle time	Maximum operating time (s)
C-E-D (eq. 20)	1.329	14.234
D-A-E (eq. 22)	0.315	13.719

The model has been applied also to verify if an increase of the throughput of the line could be achieved. To increase the productivity, it has been set a cycle time of 14 [s]. As before the operator-WS assignments have been evaluated by eq. 3.32 and eq. 3.34 and results are shown in table 3.18.

Table 3. 18 Operator-WS allocation for T_c = 14 seconds

Operator-Module allocation	Standard deviation of downtime	Maximum module time (s)
C-B-D (eq. 20)	1.137	13.760
D-A-C (eq. 22)	0.315	13.719

3.2.5. Conclusions

The focus of this study is to assess the human performance as a function of operator's age and sex. In the case study considered, an assembly line with three WSs and five differently aged operators of both sexes have been considered. The developed model allowed to evaluate if an operator is able to perform a task in a completion time compliant with the assembly line cycle time. With age and amount of information per unit time increasing not all the workers are suitable to carry out all the tasks.

In the case study, for T_c equal to 15 [s] and 14 [s], the corresponding operator-WS assignments minimizing the overall idle time of the line and the standard deviation of the WSs idle times have been identified. Table 3.17 shows that when T_c is set to 15 seconds all the operators can be assigned to all the modules; on the contrary, when a T_c of 14 [s] is considered only the operators A and B (the youngest among profiles considered, see table 3.13) can be assigned to all the WSs, the other operators cannot be assigned to the second WS since their performance exceeds the cycle time T_c. When the cycle time decreases, the possibility to assign all the operators to all the WSs decreases too. In the case considered, when a cycle time of 14 [s] is considered, only the 40% of operator-WS assignment are eligible (that is compliant with T_C value), since those aged 50 or over cannot be assigned to all WSs.

The results obtained are based on only five differently aged and sexed operators, however the developed model fits well in predicting the operator's performance with certain characteristics. In this perspective more investigations are necessary in order to obtain a generalization of the statistical validity of the reached conclusions.

Results of the industrial case study considered showed potentials of the model in identifying operators' allocations allowing to minimize assembly line idle time or to balance workload among workstations (by minimizing idle times standard deviation value) when manpower of different age and sex is available. The model could also be applied in industrial context to evaluate the feasibility of a line productivity increase on the base of available manpower, or to identify workers' profiles most suitable for achieving this goal. This last application has important managerial implications, especially in that working environment in which aging could affect productivity. The example discussed could be considered a "direct" application of the model proposed in the previous section.

Using this human performance model based on the processing time evaluation, the operator performance could be readily assessed and used as part of a control mechanism in smart manufacturing systems. This could provide strategic guidelines to a firm that wants to increase the productivity, proving that the operators' fit in performing a task has some constraints. A model for aging-driven decrease on both cognitive and motor abilities has been provided, proving that the worker's time required to process a single unit of information increases with age.

3.3. Information-based processing time affected by human age evaluated by an objective parameters-based model

Physical and cognitive tasks are evaluated according to subjective and physiological methodologies. The most common subjective measures are NASA-Task Load Index (TLX) (Hart and Staveland, 1988a) and the subjective workload assessment techniques (SWAT) (Reid, Potter and Bressler, 1988). The main physiological measures are aerobic capacity, heart rate (HR), blood pressure, body temperature, electromyogram (EMG), and pupillary dilation. According to available studies, HR is considered a low-cost physiological measure identifying the biological response for different cognitive and (Ikehara and Crosby, 2005) physical workloads (Rodrigues *et al.*, 2012).

HR to assess the cognitive workload is well analyzed in the scientific literature. In many cases, the HR capability is investigated to identify the level of cognitive workload (CWL) (Henelius *et al.*, 2009). HR is adopted to evaluate the cognitive-motor performance of airline pilots. The analysis of the HR variability (HRV) measured for tasks with different complexity leads to the evaluation of the cognitive information workload and the human error probability (Gentili *et al.*, 2014). According to Hughes et al. (Hughes *et al.*, 2019), different cardiac activity indicators allow to evaluate the CWL. In occupational medicine, an indirect measurement of total and relative energy expenditure (EE) from HR is used to evaluate physical workload (Garet *et al.*, 2005). Hubert et al. adopt HR to compare the physical workload of standard and robotic-assisted laparoscopic procedures. The authors show that the standard laparoscopies require a higher physical workload of the assisted procedure, while the mental stress is the same for both techniques (Hubert *et al.*, 2013). Among individual factors impacting on workers' performance, high attention is being paid to the age from scientific community, policy-makers, and business leaders (Boenzi *et al.*, 2015). In 2050, around half of the workers will be aged over 50 in developed countries. The workload can be defined as an expressed function of time, quality, and quantity (Mittal *et al.*, 2019). Therefore, the presence of older workers in production and operative roles will impact economic growth and manufacturing efficiency (European Agency for Safety and Health at Work; Dupont Claire; Benin Alice; Belgi and Milieu, 2016b).

The present work represents an attempt to close a known research gap concerning data collection and model validation about the aging workforce, as also suggested by (Calzavara *et al.*, 2020). The present work is an extension of the model developed by Digiesi et al. (Digiesi *et al.*, 2020) illustrated in the previous chapter, since the model reliability is linked to experimental lab data.

3.3.1. The effects of the human aging on the cardiovascular system

The Evolutionary Theory defines the age-related decline as the reduction in reaction, poor quality homeostasis, and more prevalent pathologic events resulting from different stressors (Rubin, 2002). In 2003, Harman defines aging as the accumulation of various deleterious changes appearing in cells and tissues with advancing age responsible for the increased risk of disease and death (Harman, 2003). Analyzing the human cardiovascular system is shown that a similar response is identified for both physical and cognitive workload (Fredericks *et al.*, 2005). Indeed, physical stress implies a strength and energy demand on the human body, while cognitive stress implies a mental workload demand on the human body. In both cases, the cardiovascular system responds in similar ways to meet the muscles metabolic needs in cases of physical or mentally stressed (Govindaraju, 1997).

A good aerobic capacity (V_{O2}), i.e., the amount of oxygen that the body can utilize when stressed, implies a good cardiovascular function. The product of maximal cardiac output and the difference of oxygen concentration between venous and arterial blood, represent the maximal aerobic capacity (V_{O2max}) (Ihász *et al.*, 2016). V_{O2max} depends on maximal oxygen consumption, and it decreases with advancing age (Buskirk and Hodgson, 1987). According to Hagberg, the decreasing of V_{O2max} reduces the physiological functional capacity(Hagberg, 1994). The age-related decline in V_{O2max} is investigated by two complementary studies in individuals regularly exercising versus sedentary, for both sexes (Fitzgerald *et al.*, 1997; Wilson and Tanaka, 2000).

Many researchers investigated the age-influence of HR and V_{O2max} (Shaffer and Ginsberg, 2017). To evaluate the influence of sex on sympathetic and parasympathetic control of HR in middle-aged individuals and on the subsequent aging process, HRV is studied in normal women (n = 598) and men (n = 472) aged 40-79. Results show that the HRV decreases linearly with age in both sexes (Kuo *et al.*, 1999). Similarly, the studies on age-related changes in autonomic functions conducted by Parashar et al. show that sympathetic and parasympathetic responses are decreased with increasing age group (Parashar *et al.*, 2016). According to Umetani et al., the effects of age on the HRV show that with aging, the HRV decreases very gradually, reaching 60% of baseline (second-decade values) by the tenth decade. The general trend can be different for males and women (Umetani *et al.*, 1998).

3.3.2. Human Cognitive and Motor Abilities in the Aging Workforce: An objective Information-Based Model

The estimated time to process one bit of information (T_p), in case of cognitive ($T_{p,c}$) or motor tasks ($T_{p,m}$) expressed in time per bit unit, depends on the individual's age (A) and sex (s), in accordance to equations 3.35 and 3.36, respectively (Digiesi *et al.*, 2020).

$$T_{p,c}(s, A) = \alpha_c(s) + \beta_c(s) \cdot A \tag{3.35}$$

$$T_{p,m}(\mathrm{s}, \mathrm{A}) = \alpha_m(\mathrm{s}) + \beta_m(\mathrm{s}) \cdot A \tag{3.36}$$

V_{O2} is the individual oxygen consumption, and it is measured in O_2 volume rate (ml/min) per unit mass (kg) of an individual (ml kg/min). V_{O2} can be estimated for physical and cognitive task, according to equation 3.37 (Fredericks *et al.*, 2005).

$$V_{O_2} = v_1 \cdot RPP - v_2 \tag{3.37}$$

where v_1 is equal to $0.14 \cdot 10^{-2}$ (ml kg/beat mmHg), v_2 is equal to 6.3 (ml kg/min), and *RPP* is the rate–pressure product measured in beats per mmHg on minute.

A high correlation in oxygen consumption versus the product of the *HR* and systolic blood pressure (*SBP*) is determined by Kitamura et al. (Kitamura *et al.*, 1972).

$$RPP = HR \cdot SBP \tag{3.38}$$

where *HR* is the heart rate (bpm/min) and *SBP* is the systolic blood pressure (mmHg).

RPP is used to estimate the load on the heart during exercise. An increase in *RPP* indicates that the individual can increase the oxygen consumption to meet the metabolic demands imposed by a given level of task. The maximal *RPP* (RPP_{max}) can be considered to a measure of cardiovascular adequacy.

The maximum *RPP* (RPP_{max}) corresponds to maximum aerobic capacity. It is proved that RPP_{max} (eq. 3.39) decreases with the age (Bruce *et al.*, 1974).

$$RPP_{max} = k_1 - k_2 \cdot A \tag{3.39}$$

where $k_1$and k_2 are measured in (beats mmHg/min) and equal to 36400 and 58, respectively.

Therefore, V_{O2max} depends on the relation showed in eq. 3.40:

$$V_{O_2max} = v_1(k_1 - k_2 \cdot A) - v_2 \tag{3.40}$$

According to Karvonen et al., the maximum *HR* value (HR_{max}) is related to the individual's age (*A*) and sex (*s*) (Karvonen et al. 1957), as showed in equation 3.41:

$$HR_{\max}(s) = \gamma(s) - A \tag{3.41}$$

Standard values of $\gamma(s)$ are 220 and 226 for male and female, respectively.

V_{02} and V_{O2max} values can be estimated, by equations 3.42 and 3.43, respectively (Uth *et al.*, 2004):

$$V_{o_2} = 15\ \frac{HR}{RHR} \tag{3.42}$$

$$V_{o_2max} = 15\ \frac{HR_{max}}{RHR} \tag{3.43}$$

where *RHR* is the resting heart rate value (bpm) and *HR* is the heart rete value (bpm) detected from the measuring instruments. *RHR* values belong to different ranges varying the age class as shown in table 3.19 (Limmer et al. 2005).

Table 3. 19. Resting heart rate (RHR)-values per age class

Age class	*RHR (bpm)*	*Age class*	*RHR (bpm)*
Babies	90-180	Adolescents	70-120
Children	80-100	Adults	60-90

The *RHR* value can be obtained by instrumental measure with heart rate monitor. From a managerial point of view, dividing V_{O2} by V_{O2max} an index of V_{O2} consumption is obtained, and it allows to evaluate the operator eligibility in performing a task with prevalent cognitive or motor demand.

An age-oxygen consumption dependence of age (A) is provided by eq. 3.44.

$$A = \frac{1}{k_2}\left(k_1 - \frac{V_{O_2max}+v_2}{v_1}\right) \tag{3.44}$$

The maximum information-based processing time of motor and cognitive task as expressed function on V_{O2max} can be obtained by substituting equation (3.44) in (3.35) and (3.36), respectively.

$$T_{p,c}\left(V_{o_2max}\right) = \alpha_c + \beta_c \frac{1}{k_2}\left(k_1 - \frac{V_{O_2max}+v_2}{v_1}\right) \tag{3.45}$$

$$T_{p,m}\left(V_{o_2max}\right) = \alpha_m + \beta_m \frac{1}{k_2}\left(k_1 - \frac{V_{O_2max}+v_2}{v_1}\right) \tag{3.46}$$

$T_{p,x}$ (V_{O2max}) considers the information content of tasks as well as the physical and mental status of individuals differently aged and sexed. Both parameters are related to V_{O2max} consumption.

3.3.3. Application of the model

In terms of cognitive effort, the information-based processing time of a specific task was evaluated, analysing the main outcomes of the n-back test on a sample of 14 students. More details on the case study can be found in section 2.4.

The Electrocardiographic signal (ECG) is monitored while the test is run. The ECG allowed identifying the HR of each subject. In the time domain, the HR is assessed as mean of recorded values during the task execution. Details and results on the sample tested are in table 3.20.

Two data have been censured (i.e., ID02 and ID04,) since the HR evaluated in the second level of the n-back test is considered abnormal (too low). The HR value does not show significant differences between the two levels of n-back test in the population. While an increasing of the mean value less than 8% is observed from the 0- to the 2-back test, the coefficient of variation (CV) shows that the HR variability in relation to the mean of the population is quite constant.

Table 3. 20 Experimental data of the n-back tests

Subject	*Age*	*Sex*	*Cultural Level*	*HR 0-back (bpm)*	*HR 2-back (bpm)*	$T_{p,c}$ *(*V_{O2max}*) (ms/bit)*
ID01	24	M	MS	103.93	114.23	200.1
ID02	24	M	MS	77.66	29.64	-
ID03	32	M	PhD	69.51	75.08	225.4
ID04	28	F	MS	143.19	122.03	-
ID05	28	F	MS	92.03	94.05	196.7
ID06	30	M	MS	82.79	86.18	219.1
ID07	29	M	MS	60.01	63.21	215.9
ID08	30	M	PhD	78.76	90.22	219.1
ID09	25	M	MS	70.37	80.34	203.2
ID10	32	M	MS	94.60	101.42	225.4
ID11	23	M	MS	70.61	76.82	196.9
ID12	25	F	PhD	69.48	75.93	187.9
ID13	26	M	PhD	56.71	62.29	206.4
ID14	25	F	MS	77.08	79.24	187.9
Mean	-	-	-	77.2	83.3	207.0
Std.Dev.	-	-	-	14.13	15.05	13.65
CV	-	-	-	0.183	0.181	0.066

M: male; F: female; MS: Master of Science; PhD: Doctor of Philosophy student; HR 0-back: Heart rate for 0-back level; HR 2-back: Heart rate for 2-back level

V_{O2max} has been calculated for each tester. An RHR equal to 70 bpm has been assumed for each subject as they belong to the same age-class. The maximum time to process one bit of information in case of cognitive task considering the V_{O2max} ($T_{p,c}(V_{O2max})$) has been identified for each tester (eq. 3.45). The average $T_{p,c}(V_{O2max})$ value is equal to 207.00 ms/bit. For each subject, considering the V_{O2} value for 0- and 2-back level (eq.3.42), the cognitive information-based processing time ($T_{p,c}$) is estimated by eq. 3.45. Mean, standard deviation, and coefficient of variation of $T_{p,c}(V_{O2})$ for both n-back tests are in table 3.21.

Table 3. 21 Mean, Std. Dev., and coefficient of variation of cognitive information-based processing time ($T_{p,c}(V_{O2})$)

	$\boldsymbol{T_{p,c}\left(V_{O_2}\right)}$ (ms/bit)	
	0-back	2-back
Mean	570.9	551.8
Std. Dev.	46.80	48.32
CV	0.081	0.088

The average cognitive information-based processing time ($T_{p,c}$) does not show a significant difference between the two levels of n-back test; a decreasing of less than 3.5% is observed. Data show that as the task complexity increases (from 0- to 2-back test), a slightly higher dispersion around the mean value is observed. This means that, given the same time for the execution of both tasks, the time needed to process a single unit of information is less in the case of a more complex task compared to the time needed for a simpler task. Indeed, in the case of more complex tasks, the subject has to process more information in the given time. Therefore, the time to process a single unit of information decreases with increased task complexity (under the same work conditions). The rate (*R*) in the range 0-1 can be calculated for each subject dividing $T_{p,c}(V_{O2max})$ by $T_{p,c}(V_{O2})$ for both n-back levels (table 3.22).

Table 3. 22 Rate for 0-back ($R_{0\text{-back}}$) and Rate for 2-back ($R_{2\text{-back}}$) test

ID	01	03	05	06	07	08	09	10	11	12	13	14
$R_{0\text{-back}}$	0.41	0.33	0.39	0.36	0.32	0.35	0.33	0.38	0.34	0.35	0.31	0.36
$R_{2\text{-back}}$	0.44	0.34	0.40	0.37	0.32	0.37	0.35	0.40	0.35	0.36	0.32	0.37

Increasing the value of (*R*) rate, the operator eligibility to perform a task with prevalent cognitive demand decreases when the same stress and effort task condition are considered. On average the population is employed at *R*=0.35 in 0-back level, while at *R*=0.36 in 2-back level. The rate between V_{02} and V_{O2max}, evaluated for both n-back levels is calculated. Again, increasing this rate increase the stress of the worker. The rate average value for 0- and 2-back is equal to 0.40 and 0.43, respectively. No significative differences were found between the two level. This means that the cognitive effort required to perform the task in 2-back level is not excessively higher than 0-back level.

In terms of motor information-based processing time, the model has been applied to a case study to identify the information processing rate of four operators employed in the boiler sector. In the case study conducted physical workload literature data in boiler operations was considered (Rodrigues *et al.*, 2012). Most operators are overweight, and none of them practice physical activity; these conditions overload the heart during the workday. Concerning the Body Mass Index, operators ID1, ID2, and ID3 are classified as Pre-Obese, while operator ID4 has a normal weight. The details on the operators, and the HR and RHR values measured in the task performing are in table 3.23.

Dividing V_{O2} by V_{O2max} an oxygen consumption rate is obtained. The operator ID1 consumes 73% of his aerobic capacity, while ID2 consumes 75%. The operator ID3 consumes 86% of his aerobic capacity to perform the task. In contrast, operator 4 consumes 60% for the same task. This implies that the operator ID4 can perform a physical task that requires more physical demand when the same stress and effort task condition are considered. Experimental data of V_{O2max} are available in scientific literature, for individuals of different sex and age. The V_{O2max} range values are obtained by (Vivian H. Heyward, 2016) for different age cluster.

Table 3. 23 Operator data in the motor task case study

	ID1	*ID2*	*ID3*	*ID4*
Sex	M	M	M	M
Age	45	43	60	28
RHR (bpm)	74	76	82	70
HR (bpm)	127	132	138	115

RHR: Resting heart rate; HR: Heart rate; M: male

According to V_{O2max} values, operator ID 1, 2 and 3 are classified in 'Fair', while operator ID4 in 'Good'. The operator physical status classification based on V_{O2max} values is consistent with the operator classification in Rodrigues et al. (2012). Therefore, $T_{p,m}(V_{O2})$ values obtained by the developed model consider the actual status of individuals of different sex and age measured by V_{O2} consumption. The maximum time to process one bit of information in case of motor task considering the V_{O2max} ($T_{p,m}(V_{O2max})$) has been identified for each operator. Considering the V_{O2} value for each operator (eq.3.42), the motor processing time ($T_{p,m}$) is obtained by eq. 3.46. Dividing $T_{p,m}(V_{O2max})$ by $T_{p,m}(V_{O2})$ a rate (R) for each subject is obtained. Values are in table 3.24.

Table 3. 24 $T_{p,m}(V_{O2max})$, $T_{p,m}(V_{O2})$ and R value

	ID1	ID2	ID3	ID4
$T_{p,m}(V_{O2})$	318.4	315.7	322.7	327.9
$T_{p,m}(V_{O2max})$	234.5	239.2	288.0	185.6
R	73.6	75.8	89.2	56.6

$T_{p,m}(V_{O2max})$: maximum motor information-based processing time; $T_{p,m}(V_{O2})$:motor information-based processing time; R: rate

An age-related decreasing $T_{p,m}(V_{O2max})$ value is observed. The *R* value allows to evaluate if the operator can perform or not a task when more physical demand is required. The *R* value of operator ID3 is closely to the limit value; therefore, he will not be able to perform tasks in case of a greater amount of motor information must be processed in the unit time. On the contrary, operator ID4 can perform tasks with a greater amount of motor information being further from the maximum condition of the time needed to process the unit of information.

3.3.4. Conclusions

An objective parameters-based theoretical model is proposed to estimate the motor and cognitive task's information-based processing time. The experimental case studies proved a relation between the information-based processing time and the individual respiratory capacity. The results have shown the model's effectiveness in estimating the information-based processing time in accomplishing tasks with prevalent cognitive or motor demand. In the cognitive case study, no significant difference is showed between subjects included to the same age cluster for both male and female (Std. Dev. equal to 13.65) in terms of $T_{p,c}(VO_{2max})$. In the motor case study, the average value of $T_{p,m}(VO_{2max})$ decreases with increasing of the age of the workers considered. The parameters estimated led to a preliminary evaluation on the demand of a task and on the workers' capacity to perform it. The model's reliability must be validated in a real industrial setting, where more or less complex tasks (under cognitive and motor perspective) will be required to workers with different levels of experience.

Further research should investigate the model applicability in endurance-trained versus sedentary individuals; different values of information-based processing time should be obtained in individuals of having same sex and age by varying the health conditions (i.e. (un)healthy lifestyle, genetics.

3.4. References

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4. Complexity Models in Terms of Information Content

There is an increasing demand for product variability and operational efficiency in the current manufacturing context. Consequently, industries have faced many challenges in order to shift from traditional approaches (few models with long life cycles and a small variety of attributes) to new configurations able to meet the market requirements (St. John et al., 2001). In the actual manufacturing environment, a new production paradigm is recognized in high product variety, short lead time, and mass customization (Koren, 2010). This production paradigm provides different ways of managing and controlling the process, contributing to the increase of the flexibility level of the industry and of its competitiveness through products mass customization (Yin et al., 2018). Hence, a fundamental requirement for the assembly systems is that they must be reactive to the customers' needs and must provide high volumes of high-quality products with a wide variety. According to Rekiek *et al.* (Rekiek et al., 2000), mixed-model assembly lines are an enabler to manage increased variety. However, these systems are characterized by higher complexity than traditional assembly lines. The complexity and its challenges are widely acknowledged. A formal quantification of manufacturing complexity is a topic not yet fully studied in deep.

In a system, complexity means something that is "difficult to understand, describe, predict or control" (Sivadasan et al., 2006). Moreover, production complexity is defined as the interrelations between product variants, work content, layout, tools and support tools, and work instructions (Mattsson et al., 2018). Complexity is defined as 'the state of having many different parts connected or related to each other in a complicated way' (Merriam-Webster, 2016) without systematically quantifying it. In manufacturing contexts, the estimation of complexity is a challenge since it is defined in a vague way and under a subjective perspective due to the lack of common and standardized measures to assess it, especially in the presence of high product variety (Busogi et al., 2017).

Despite of the high automation level of modern manufacturing systems, operators still play a key role and they are asked to handle and manage many different tasks, gather information, interact with many different types of technologies and work in many modes of the production (Mattsson et al., 2020).

In modern assembly systems, traditionally characterized by high musculoskeletal disorder risk (Intranuovo et al., 2019), the tasks assigned to the operators tend to have a predominant cognitive content. In assembly systems, before starting a task, the operator receives a stimulus requesting him/her to select a specific part from a pool of alternative options. The choice process involves two subsequent steps. At first, the operator must recognize the received stimulus; secondly, he/she has to select the corresponding option (component). In the current work the skills level of the operator in accomplishing the assigned task is not considered, since the task difficulty is modelled as an objective demand imposed on the subject. In evaluating the complexity of choosing tasks accomplished by operators, the similarity between the chunks included in the mix variety has to be considered. Similarity impacts the choice complexity and could affect the operator and hence the overall system performance; however, it received less attention from researchers, probably due to a low perceived impact in a mass-production environment on operators' performance. Currently, where the number of options is increased due to the mass customisation, both the number of options and their similarities must be considered in evaluating the operator's choice complexity (Busogi et al., 2017). In this chapter choice complexity in 2D object recognition task is adopted to evaluate the mental workload required by a human operator in selecting a component from a number N of options (mix variety). In the model proposed, in order to measure operators' mental workload, the shape complexity of objects in the mix of alternatives as well as their similarities are considered.

Empirical and analytical studies are available on the evaluation of complexity in manufacturing context. By observing the complexity due to the variety of mix and the manufacturing performance, a negative correlation between complexity and performance is shown by Fast-Berglund *et al.* (Fast-Berglund et al., 2013).

According to ElMaraghy *et al.*, the complexity is related to the amount of information to be processed (ElMaraghy et al., 2005). More information is generated by the increase of the variety which provides opportunities for the product, process or system to behave in unexpected manners (Hu et al., 2008). Different research quantifies the complexity according to the entropy theory (Zhu, 2009),(Zhu et al., 2008).

Object recognition task is defined as the finding and labelling of parts of an image that match objects in a scene. Sometimes, in order to reduce the task difficulty, restrictions on the shapes and semantics of the scene are adopted. These restrictions are used by operators in object recognition tasks. An object is defined by its geometric and semantic characteristics as well as by its statistical properties (Tieng and Boles, 1997). The objects' comparison is based on their semantic (Ballatore et al., 2013), topological (Alharthi and Elsafty, 2016) and geometric (An et al., 2011) similarities. Semantic similarity is measured based on nonspatial information, such as the attributes of the objects; topological similarity is based on the relationship between spatial objects: even minimal differences may lead to different matching results; geometric similarity or matching is based on similarities in shape, often with the exclusion of the dimensional scale (Xu et al., 2020).

To perform a recognition task, one has to establish models or general descriptions of each object to be recognized. Different methods can be used in the classification of objects; the autoregressive model parameters that represent the shapes of object boundaries detected in images (Dubois and Glanz, 1986), the Fourier descriptors which have been found useful in recognition of industrial parts and characters (Persoon and Fu, 1977), and codons which are primarily image-based descriptors in closed 2D shapes are used as methods in object classification task (Richards and Hoffman, 1985). These methods are independent of object size and planar orientation.

Our goal is to measure the information content of the 2D object recognition task; in order to do this, a new information-based model to evaluate the 2D object recognition Task Difficulty (TD) is proposed. It integrates the objects' shape complexity and the similarities of objects included in the mix variety. Task Difficulty allows evaluating Mental WorkLoad (MWL). MWL is a multidimensional construct involving working memory processes ranging from attention and perception to memory and decision-making (Young et al., 2015). MWL represents the information processing rate required to accomplish a task in a given work environment. An increase in MWL proves to negatively affect the operator's performance (Colombi, J.M., Miller et al., 2012).

4.1. Object shape complexity

In defining the concept of complexity, Li (Li, 1991) stated that "The definition of complexity cannot be unique, simply because there are many different ways to quantify these difficulties. There are many different tasks concerning which the difficulties are to be quantified". This section discusses three different methods to quantify objects' shape complexity.

In a work conducted by Rigau *et al.* (Rigau et al., 2005), objects' shape complexity is evaluated through integral geometry and information theory tools, adopted by the Authors to perform an inner shape and an outer shape complexity measure. In their measures, the Authors refer to both the Shannon Entropy, quantifying the information content of a random variable (Shannon, 1948), and to mutual information, quantifying the shared information between two probability distributions.

Shape complexity can be analysed from two different perspectives: inside and outside the object. In the first case, its degree of structure (interdependence between its parts) is quantified. In this case, the information shared by the interior surfaces of the object is measured. A differential of the surface will be related to another differential of the surface by the uniformly distributed lines that join them, that is, make them visible to each other. In the second case, its degree of interaction between the object and its circumscribing sphere is calculated using the same uniformly distributed lines (Rigau et al., 2005). These complexity measures can be used as shape descriptors in fields such as object recognition and classification; however, the shape complexity is mainly evaluated by inner shape complexity measures (e.g.(Feldman and Singh, 2005; Page et al., 2003)). For more details on how to calculate the inner 2D shape complexity the reader should refer to (Rigau et al., 2005).

In (Chen and Sundaram, 2005), 2D shape complexity is estimated by means of correlates of Kolmogorov complexity – entropy measures of global distance and local angle. The model developed by the authors is tested on a dataset of 2D shapes. Results show that the 2D shape complexity is related to human perception; small complexity variations are easy to distinguish in simple 2D shapes; on the contrary, complex 2D shapes are hardly distinguished by small complexity variations. The model considers the measures of global distance entropy (C^e_{dis}), local angle entropy (C^e_{angle}), perceptual smoothness (P), and the randomness measure (R). A significant correlation to the structure of the shape is observed in C^e_{dis}, C^e_{angle}, and in P while the factor R express the structure stability. For more details reader should refer to (Chen and Sundaram, 2005).

The probability density function of a random variable (x) describes the statistics of x. In a continuous system, the entropy H is defined as follow:

$$H(x) = -\int_{-\infty}^{\infty} p(x) \log p(x)\, dx \tag{4.1}$$

If a 2-based logarithmic function is adopted, then the entropy is measured in units of bits. By discretizing p(x), eq. 4.1 becomes:

$$H(x) = -\sum_i p_i \log_2 p_i \tag{4.2}$$

The concepts of entropy described above are applied in (Page et al., 2003) to compute the shape information for 2D planar contours through an ad-hoc defined algorithm (see Fig. 1). The authors obtain the shape information content from discrete samples of continuous curves. Starting from a 2D curve α, the authors discretize it in the S samples $\alpha_j = \alpha(s_j)$ with $j = 1, \ldots, S$ and s_j the generic point of the curve α. Assuming a constant arc length $\Delta s = s_j - s_{j-1}$, since there is a uniform sampling along the curve, the curvature k_j is directly proportional to the turning angle θ_j between two consecutive segments ($\overline{\alpha_{j-1}\alpha_j}$ and $\overline{\alpha_j\alpha_{j+1}}$). The authors determine the probability density function of the curvature function from the θ_j estimates. At first, they assume a number M of clusters. For each cluster, a constant curvature range is considered ($\Delta\theta = (\theta_{max} - \theta_{min})/M$). Being B_i (i = 1, …, M) the number of curvature samples θ_j belonging to the i-th cluster ($\theta_j \in [\theta_{min} + (i-1)\cdot\Delta\theta; \theta_{min} + i\cdot\Delta\theta]$) the cluster probability p_i becomes:

$$p_i = \frac{B_i}{S} \tag{4.3}$$

and the shape information of the 2D contour is obtained as:

$$H(x) = -\sum_i \frac{B_i}{S}\, log_2 \frac{B_i}{S} \tag{4.4}$$

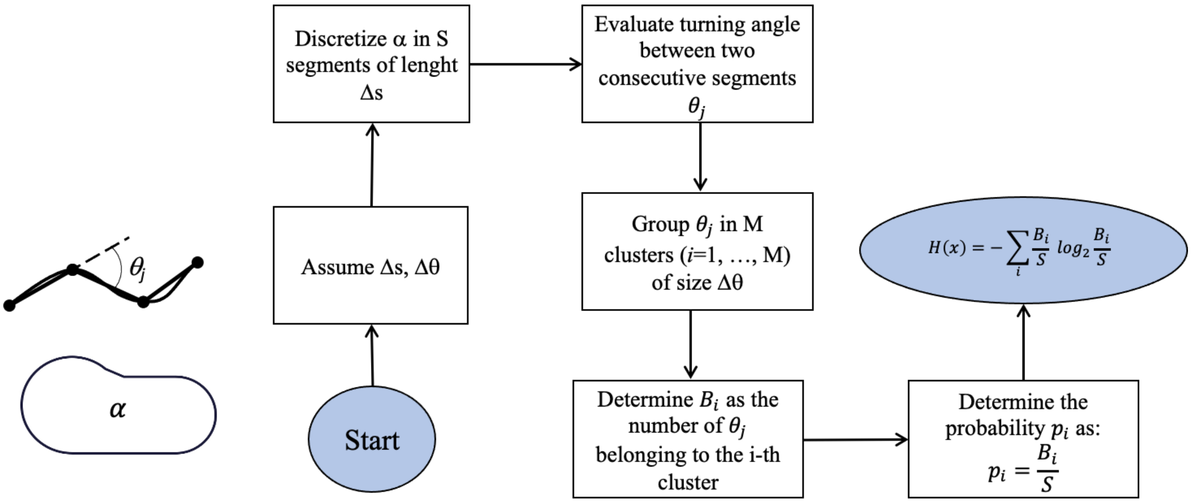


Figure 4. 1 Evaluation of a 2D contour shape information as per (Page et al., 2003)

4.2. Object shape similarities

The similarity effect on the 2D objects selection task performed by an agent depends on the brain activation (Kreiman et al., 2000). There is little existing research on objects similarities in the manufacturing context, although a formal similarity measure is formalized by psychologists (Nosofsky, 1992).

One of the most useful tools for the degree of similarity between objects is the similarity measure (Wei and Gao, 2018). In different fields of applications such as physical anthropology, automatic classification, ecology, psychology, citation analysis, information retrieval, patterns recognition and numerical taxonomy the functions expressing the degree of similarity of items are used (Ye, 2012). An important role is played by the measures of similarity/dissimilarity between the objects. The Jaccard, Dice, and cosine similarity measures in vector space for information retrieval, citation analysis, and automatic classification are the most used measures in vector space (Wei, 2019).

The formalisation of similarity measures is typically based on the semantic similarity; properties of objects are represented by means of their description (Zhang and Lu, 2004). The commonalities and differences between two semantic representations of objects can be taken as an indicator of similarity (Nosofsky, 1992). So, higher is the similarity if more commonalities and fewer differences occur.

One of the most adopted similarity measures based on the commonalities and differences between two objects is the feature-based similarity measure. In this case, the similarity between two objects A and B ($s(A, B)$) is expressed as a function (linear combination of an unstructured set of features) of their common ($A \cap B$) and distinct (*A*-*B* and *B*-*A*) features as shown in equation (4.5) (Tversky, 1977).

$$s(A, B) = F(A \cap B, A - B, B - A) \tag{4.5}$$

In psychology, geometric models were initially used to exploit the analogy to space for measuring similarity (ATTNEAVE, 1950). Geometric models are based on the notion of multi-dimensional vector spaces. Each dimension is used to describe the properties of objects (Schwering, 2008). Most geometric models focus on modelling only objects.

Multi-dimensional scaling (MDS) is a dimensionality reduction technique that converts multidimensional data into lower dimension space, while keeping the intrinsic information (Yang, 2008),(Saeed et al., 2018). MDS is a family of techniques for the analysis of proximity data on a set of stimuli to reveal the hidden structure underlying the data. The proximity data can be obtained from similarity judgments, identification confusion matrices, grouping data, same-different errors or any other measure of pairwise similarity (Steyvers, 2002).

Many parallels can be drawn between geometric models and multi-dimensional scaling (MDS) models (Nosofsky, 1992), but there exist also some differences: MDS uses as input subjects' judgments about pair-wise similarities and determines the number of dimensions. Geometric models adopt a given set of dimensions and determine their values to describe each object, so as similarity can be obtained by spatial distance calculation. Geometric models are based on the analogy of semantic to spatial distance.

The similarity is a function of the spatial distance, and the most adopted similarity measure is the Minkowski distance measure (eq. 4.6). In the Minkowski distance measure, stimuli are described by means of a set of dimensions collocating them as points in a multidimensional space; similarity between stimuli is inversely related to the distances of the corresponding points in the multidimensional space.

$$d_{ij} = \left[\sum_{k=1}^{n} \left|x_{ik} - x_{jk}\right|^{r}\right]^{\frac{1}{r}} \tag{4.6}$$

where n is the number of dimensions, x_{ik} is the value of dimension *k* for stimulus *i* and x_{jk} is the value of dimension *k* for stimulus *j*. In Minkowski measure, $r = 1$ results in the city-block distance and $r = 2$ in the Euclidian distance. The similarity is obtained as a linear (sometimes also exponentially) decaying function of the Minkowski distance d_{ij} (Melara et al., 1992), (Kianimajd et al., 2017).

Eq.6 considers the differences in the object properties. Some properties (e.g., volume, dimension, etc.) can be easily comparable, while others (e.g., complex shape, etc.) represent a big challenge. In the last case, the measure is often based on Boolean values (i.e., true or false) as in (eq. 7).

$$\left|x_{ik} - x_{ij}\right| = \begin{cases} 0 \ if \ both \ i \ and \ j \ possess \ feature \ x_k \\ 1 \ otherwise \end{cases} \tag{4.7}$$

The semantic distance d_{ij} is then converted into the similarity measure (eq. 4.8) (Gallistel and Pashler, 2002).

$$s(i, j) = e^{-c \times d_{ij}} \tag{4.8}$$

where $s(i, j)$ is the similarity measure between object *i* and *j*, and c is the sensitivity parameter.

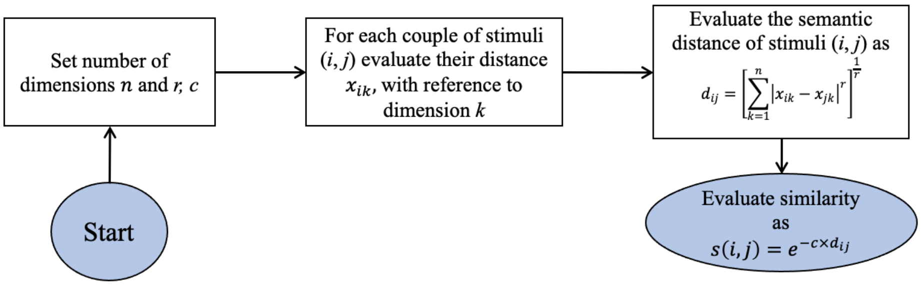


Figure 4. 2 Evaluation of similarity as per (Melara et al., 1992)**,**(Kianimajd et al., 2017)

A distance measure based on the Hausdorff distance between two points is defined in (Dubuisson and Jain, 2002). Twenty-four (24) different distance measures are compared in matching two sets of edge points extracted from two 2D shapes. The authors find that the modified Hausdorff distance (MHD) proposed performed better than the remaining 23 distance measure considered in object matching.

A framework allowing to measure the similarity of 2D objects images is developed in (Latecki and Lakamper, 2000) for simple (no self-intersection) polygonal curves. To reduce the noise of 2D image digitization, the authors propose a methodology to compare simplified shapes obtained through a digital curve evolution process.

In (Arkin et al., 1991), a recognition model is proposed for comparing couple (shape A and shape B) of 2D polygonal shapes. The authors define cost function $d(A, B)$ with the aim of measuring their dissimilarity. The cost function defined is a metric invariant to translation, rotation, and change-of-the-scale of shapes, and it is reasonably easy to compute

In (Magnier and Moradi, 2019), a normalized measure for assessing the contour-based object pose is developed. The developed measure is applied to binary images for the assessment of known-object recognition and localization.

4.3. Model formulation: 2D Object recognition task model

A novel model to quantify the information content in the 2D object recognition task is proposed here. The model is based on the Shannon's Entropy theory, and both shape complexity and object similarities are considered and quantified in the model. Originally used as a measure of uncertainty, the information entropy or so-called Shannon entropy, is widely adopted as a measure of complexity in many manufacturing processes.

The model proposed has been defined starting from the work of Busogi *et al.* (Busogi et al., 2017). The main features of the model of Busogi *et al.* are detailed in the following.

In a mixed-model assembly line, during the selection task, the operator receives a stimulus before he or she proceeds to select the right option. Several sequential choices such as tool choice, fixture choice and so on can be required at workstation level. Let $k = 1,2, \dots, K$ is the choice activities at the i-th station, where K is the maximum number of choices that can be made at the i-th station. Two random variables are defined: X_i^k is the outcome of the targeted variant and represents the stimulus at the k-th choice task, while Y_i^k is the corresponding operator's choice. Fig. 4.3 shows the mixed-model assembly line environment.

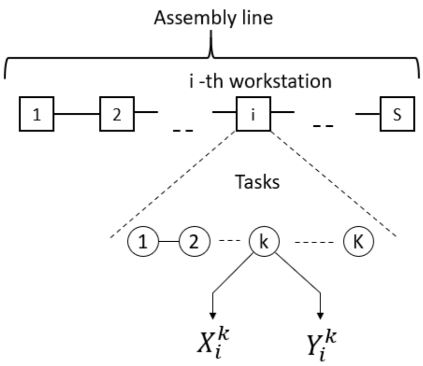


Figure 4. 3 mixed-model assembly line environment

The same sample space is used to define both X_i^k and Y_i^k(eq. 4.9)

$$X_i^k, Y_i^k \in \Omega_i^k = \{v_{ij}^k | j = 1, \ \dots, \ N\} \tag{4.9}$$

where v_{ij}^k is the j-th variant that can be selected in the k-th decision-making process of the i-th station, and N is the overall possible alternatives (variants) that can be selected in the k-th decision-making process of the i-th station.

In terms of information entropy, the successive juxtaposition of information is equivalent to the overall information entropy contained in variables $H(X_i^k Y_i^k)$ with joint distribution $p_{x_i^k y_i^k}$ (Busogi et al., 2017):

$$H(X_i^k Y_i^k) = H(Y_i^k | X_i^k) + H(X_i^k) \tag{4.10}$$

where $H(X_i^k)$ is the average information gained by acquiring the targeted variant (per stimulus), and $H(Y_i^k | X_i^k)$ is the average information required for the selection of the part after the acquisition of the stimulus. Eq. 4.10 is derived from the fundamental property of conditional entropy, and according to (Busogi et al., 2017) the eq. (4.10) becomes:

$$H(X_i^k Y_i^k) = -\sum_{j=1}^{N} \sum_{t=1}^{N} p_{X_i^k}(v_{ij}^k)\, p_{(Y_i^k | X_i^k)}(v_{ij}^k | v_{it}^k) \log_2 p_{(Y_i^k | X_i^k)}(v_{ij}^k | v_{it}^k) - \sum_{i=1}^{N} p_{X_i^k}(v_{ij}^k)\, log_2\, p_{X_i^k}(v_{ij}^k)$$
(4.11)

$p_{(Y_i^k | X_i^k)}(v_{ij}^k | v_{it}^k)$ is the probability that the operator selects v_{ij}^k after receiving the stimulus to select it. The probability of selecting part 'i' when 'j' is requested is denoted $p_{(i|j)}$ and based on a fuzzy logical model can be obtained as (Luce, 2014):

$$p_{(i|j)} = \frac{s(i,j)}{\sum_{l \in N} s(l,j)} \tag{4.12}$$

where $s(i,j)$ is the similarity between part 'i' and 'j', and N is the set of all alternatives. Thus, based on eq. 4.12, equation 4.11 can be extended as follows.

$$H(X_i^k Y_i^k) = -\sum_{j=1}^{N} \sum_{t=1}^{N} p_{X_i^k}(v_{ij}^k) \frac{s_{jt}}{\odot_{v_{it}^k}} \log_2 \frac{s_{jt}}{\odot_{v_{it}^k}} - \sum_{i=1}^{N} p_{X_i^k}(v_{ij}^k) \log_2 p_{X_i^k}(v_{ij}^k) \tag{4.13}$$

where $s_{jt} = s(v_{ij}^k, v_{it}^k)$ is the similarity between v_{it}^k (the target option) and v_{ij}^k (the j-th variant), $\odot_{v_{it}^k} = \sum_{l \in N} s(v_{il}^k, v_{it}^k)$ is the overall level of perceived similarity associated to target variant v_{it}^k and N is the set of all available alternatives. $p_{X_i^k}(v_{ij}^k)$ is the inverse of the total number of possible alternative variants, and $\sum_j p_{X_i^k}(v_{ij}^k) = 1$.

By substituting eq. (4.4) in (4.13), the overall information entropy is obtained as follow:

$$H(X_i^k Y_i^k) = -\sum_{j=1}^{N} \sum_{t=1}^{N} \frac{s_{jt}}{\odot_{v_{it}^k}} \log_2 \frac{s_{jt}}{\odot_{v_{it}^k}} - \sum_{i=1}^{S} \left(\frac{B_i}{S}\right)^k log_2 \left(\frac{B_i}{S}\right)^k \tag{4.14}$$

Eq. 4.14 represents the overall Task Difficulty (TD).

Mental WorkLoad (MWL) as shown in the previous Sections is generally defined as the interaction between operator and tasks (Paas et al., 2003). It represents the operator information processing load while performing an assigned task (Sheridan and Stassen, 1979). Before starting a task, an operator receives a stimulus requesting him/her to select a specific part from a pool of alternative options. The choice process involves two successive steps; the operator receives a stimulus and then he/she proceeds to select the corresponding option.

Starting from the Task Difficulty (TD), measured in bit units, the corresponding Task Load (TL) is obtained with reference to the given time window (T) to complete the subtask/task, according to eq. 4.15.

$$TL = \frac{TD}{T} \tag{4.15}$$

The Task Difficulty (TD) represents the task's amount of information in selecting the right alternative from a pool and is based on both (Busogi et al., 2017) and (Page et al., 2003) models. Therefore, both shape similarities and shape complexity in 2D object recognition task are considered. The TD of recognizing the object "A" from a pool of alternative options (N) is obtained according to eq. 4.16.

$$TD = Shape\ Similarity\ (SS) + Shape\ Complexity\ (SC) \tag{4.16}$$

$$SS = -\left(\frac{s(A,A)}{\sum_{l\in N} s(l,A)} log_2 \frac{s(A,A)}{\sum_{l\in N} s(l,A)}\right) [bit] \tag{4.16a}$$

$$SC = -\sum_{i=1}^{S} \left(\frac{B_i}{S}\right) log_2 \left(\frac{B_i}{S}\right) [bit] \tag{4.16b}$$

Eq. 4.16a considers the similarity between the objects considered and is based on the probability of selecting object 'A' when 'A' is requested, while eq. 4.16b considers the shape complexity of object A. In eq. 4.21a, the similarity is obtained as an exponentially decaying function of the Minkowski distance (eq. 4.8), and *s(A,A)* = 1.

According to Salvendy and Bii, the quantification of TL as well as of the environmental and organizational factors (Bi and Salvendy, 1994) allow evaluating the Mental WorkLoad (MWL) of the operator in performing the task (eq. 4.17, Fig.4.4).

$$MWL = \frac{TL}{K_e \times K_{or}} \tag{4.17}$$

where *MWL* is the Mental WorkLoad imposed on the subject and expressed in [bit/s], *TL* is the task load expressed in [bit/s], and K_e and K_{or} are dimensionless parameters evaluating the environmental and the organizational factors, respectively.

A scale ranging from 0 to 1 for K_e and K_{or} can be defined: in the case of $K_e = K_{or} = 1$ the system is providing a subject with satisfied stimuli and an ideal environment; if $K_e = K_{or} \rightarrow 0$ people cannot work properly.

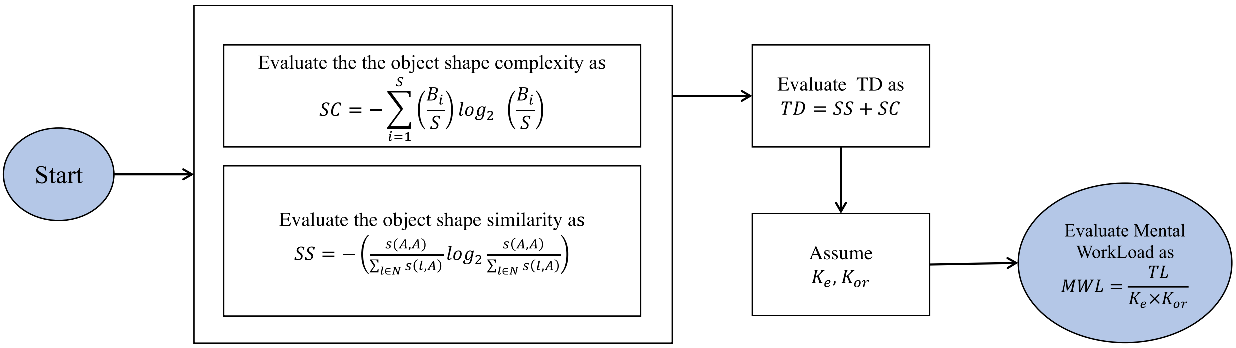


Figure 4. 4 Mental Workload evaluation

The organizational factors are represented by job stimuli and job satisfaction. According to Judge and Klinger (Judge and Klinger, 2008), many theories and measurements of job stimuli and job satisfaction are available. However, the two most extensively validated employee attitude survey measures are the Job Descriptive Index (JDI) (Smith et al., 1969; Yeager, 1981) and the Minnesota Satisfaction Questionnaire (MSQ) (Weiss et al., 1967). The JDI assesses satisfaction with five different job areas: pay, promotion, co-workers, supervision, and the work itself. This index is reliable and has an impressive array of validation evidence. The MSQ has the advantage of versatility (long and short forms are available), as well as faceted and overall measures.

The environmental factors are represented by danger, noise, temperature, and space. Acceptability of indoor environmental factors is assessed using scales ranging from 'clearly acceptable' (coded as 1) to 'clearly unacceptable' (coded as -1); the scales are presented in Standard EN 15251 (Brussels: European Committee for Standardization, 2007). The question about the acceptability of the indoor environment is formulated in the following way: "How do you assess thermal environment/air quality/sound quality/light quality/quality of the indoor environment at the moment?".

4.3.1. Application of the model analyzing the main outcome of the Token Test

In order to evaluate the MWL in the case of a 2D object recognition task, a numerical case study has been developed. The task difficulty (TD) of a specific task was evaluated, analysing the main outcome of the Token Test ad-hoc modified. The Token Test was introduced originally in 1962 as a brief test by De Renzi and Vignolo to examine auditory comprehension deficits in aphasic patients, by having patients respond gesturally to the tester's verbal command (Spreen and Risser, 1998). The Token Test is a portable test that contains 20 plastic token stimuli of two sizes (large and small), two shapes (square and circle), and five colours. Here, the selection of plastic token elements simulating the 2D object recognition task is considered. The sizes of the Token Test elements are in table 4.1.

Table 4. 1 square's side and circle diameter dimensions

SIZE	SQUARE (side[cm])	CIRCLE (diameter [cm])
SMALL	1.5	1.5
LARGE	3.0	3.0

Blue, black, red, green, and yellow are the five colours considered.

Four numerical cases (I to IV) were developed by varying the number of plastic token elements. The Task Difficulty (TD) of four selected plastic token elements according to eq. 4.16 was calculated for each numerical case. Consequently, the MWL was obtained by means of eq. 4.17.

By eq. 16b, the shape complexity of small/large squares and circles was calculated according to Page *et al.* (Page et al., 2003). Constant values of $\Delta S = 0.375$ (cm) and Dq=p/2 were assumed. For each element, calculation data and the amount of information related to the shape complexity are in table 4.2.

Table 4. 2 Shape Complexity [bit]

ELEMENT considered	Calculation data	Shape Complexity (SC [bit])
SMALL SQUARE	$S = 16; M = 2$ $p_1 = p(0 < \theta \leq \frac{\pi}{2}) = 4/16$ $p_2 = p(\frac{\pi}{2} < \theta \leq \pi) = 12/16$	0.8
LARGE SQUARE	$S = 32; M = 2$ $p_1 = p(0 < \theta \leq \frac{\pi}{2}) = 4/32$ $p_2 = p(\frac{\pi}{2} < \theta \leq \pi) = 28/32$	0.5
SMALL CIRCLE	$S = 8; M = 1$ $p_1 = p(\frac{\pi}{2} < \theta \leq \pi) = 8/8$	0.0
LARGE CIRCLE	$S = 24; M = 1$ $p_1 = p(\frac{\pi}{2} < \theta \leq \pi) = 24/24$	0.0

In the model of Page *et al*. (Page et al., 2003), the shape complexity of the circles is zero; it is considered as a reference shape.

To obtain the similarity between objects "i" and "j" (eq.4.8), the perimeter and colour were set as dimensions. The perimeter is measured in [cm], while colour is measured in [nm] since the hue defines the colour (green, red, etc.). Hue physically depends on the dominant wavelength. The wavelengths of the visible spectrum extend from 400 to 750 nm ($1nm = 10^{-9}\ m$) (fig. 4.5).

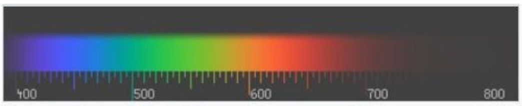


Figure 4. 5 Wavelengths of the visible spectrum

The perimeter values of small/large squares and circles are in table 4.3.

Table 4. 3 Perimeter values [cm]

SIZE	SQUARE (perimeter [cm])	CIRCLE (perimeter [cm])
SMALL	6.00	4.71
LARGE	12.00	9.42

The average dominant wavelength for the five colours considered is shown in table 4.4.

Table 4. 4 Average dominant wavelength [nm]

Colour	Average dominant wavelength [nm]
Blue	470
Black	750
Red	665
Green	525
Yellow	575

For both dimensions (perimeter and average dominant wavelength) by means of eq. 4.6 the Minkowski distance measure was calculated, by assuming $\varepsilon_i = r = 1$. The semantic distance obtained is then converted into the similarity measure using eq. 4.8. In eq. 4.8, a unitary value of the general sensitivity parameter is adopted ($c = 1$).

Note that for N number of options, a $N \times N$ distance matrix exists. Based on eq. 4.8, the distance matrix can be transformed into a similarity matrix (*Sim*), as shown in eq. 4.18.

$$Sim = \begin{bmatrix} S_{AA} & \cdots & S_{AV} \\ \vdots & \ddots & \vdots \\ S_{VA} & \cdots & S_{VV} \end{bmatrix} \tag{4.18}$$

The overall level of similarity is the sum of the pairwise similarities between the element to be selected and every other available option, which is the sum of the row corresponding to the i-th element to be selected of the similarity matrix. Next, the shape similarity amount of information (SS) between the objects included in the pool of alternatives options was calculated by eq. 4.16a.

The objects recognition tasks considered consist of selecting four elements form a pool of alternatives options (N=*variable*). Once the subject selects the element, it is relocated to the pool of alternatives options. So, the number of alternative options to be considered is always equal to the initial value. By using eqs. 4.16 for each of these four elements, the Task Difficulty (TD) is obtained.

Subsequently, by means of eq. 4.17, in the case of selection of the required element A (numerical case I, II and IV) and element L (numerical case III), the Mental WorkLoad (MWL) in the ideal case of $K_e = K_{or} = 1$ and the Mental WorkLoad (MWL^I) in the case of $K_e = K_{or} = 0.75$ are obtained.

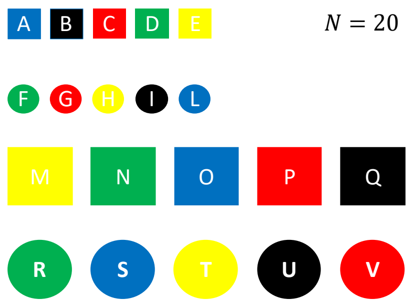
4.3.2. Results Obtained

The following section shows, for each numerical case, TD, MWL, and MWL^I values.

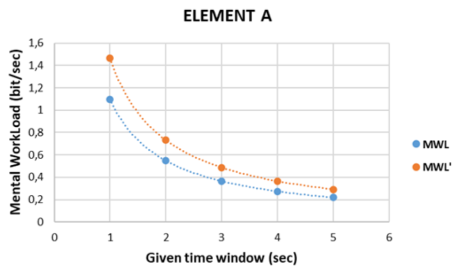
Numerical case I: $N = 20$; all elements considered; tasks: selecting the element-A -R -Q and -G (table 4.5)

Table 4. 5 Numerical case I

$N = 20$



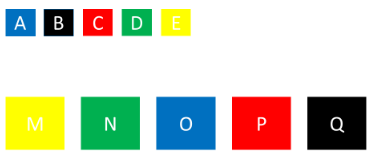
ELEMENT TO BE SORTED	TD [bit]
A	1.10
R	0.14
Q	0.60
G	0.28



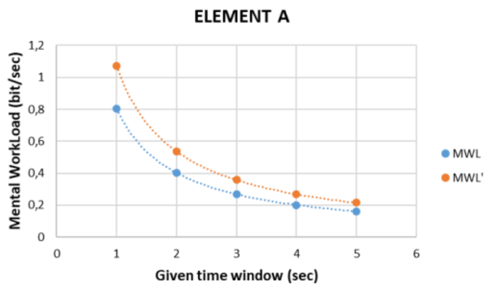
Numerical case II: $N = 10$; only squares elements considered; tasks: selecting the element-A -C -M and -Q (table 4.6).

Table 4. 6 Numerical case II

$N = 10\ square$



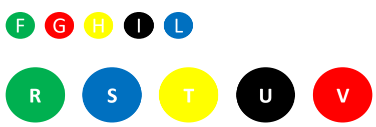
ELEMENT TO BE SORTED	TD [bit]
A	0.81
C	0.81
M	0.51
Q	0.51



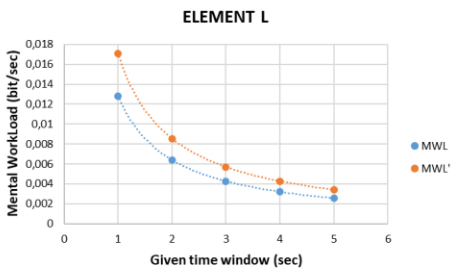
Numerical case III: $N = 10$; only circles elements considered; tasks: selecting the element-L -R -U and -G (table 4.7).

Table 4. 7 Numerical case III

$N = 10\ circle$



ELEMENT TO BE SORTED	TD [bit]
L	0.01
R	0.01
U	0.01
G	0.01

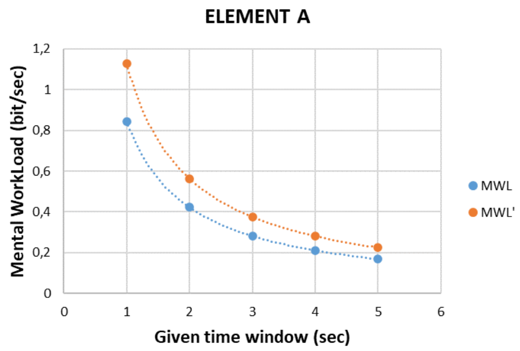


Numerical case IV: $N = 10$; both squares and circles elements considered; tasks: selecting the element-A -R -M and -G (table 4.8).

Table 4. 8 Numerical case IV

$N = 10\ mix$

ELEMENT TO BE SORTED	TD [bit]
A	0.84
R	0.11
M	0.51
G	0.58



In a mixed-model assembly line, at the workstation level, the operators make several sequential choices. The objects recognition tasks considered here consist in selecting in sequence the A- and R-element from a pool of alternatives options (N=*variable*). $N = 20$ (Numerical case I) and $N = 10$ (Numerical case IV) are considered as a pool of alternative options. In each numerical case study, the Overall Task Difficulty (OTD) is given by the sum of the Task Difficulty (TD) of the A- and R-element (Fig. 4.6).

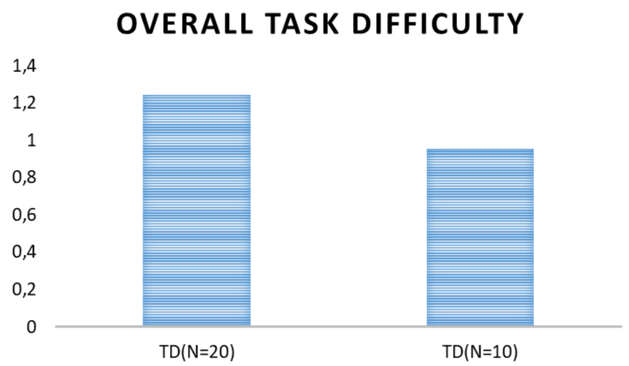


Figure 4.6 Overall Task Difficulty in case of $N = 20$ and $N = 10$ (Numerical case I and IV, respectively)

4.4. Conclusions

This study indicates that the information-based model developed can be adopted to assess the Task Difficulty (TD) and the Mental WorkLoad (MWL) of individuals in accomplishing tasks with prevalent cognitive demand. Here, the Task Difficulty (TD) represents the task's amount of information in selecting the right alternative from a pool; both shape similarities and shape complexity in 2D object recognition task are considered. The MWL is an objective demand and depends on the environmental and organizational parameters and on the TD of the task performed by the operator. In this Section different numerical cases are considered where the shape and the number of alternatives options vary. Four elements are selected from the pool of alternative options in each case considered. Consequently, the TD and the MWL (varying the given time windows T) have been calculated.

By comparing values in tables 4.5-4.8 it is noticed that the task difficulty is greater when the number of alternative options in the pool increases. Moreover, considering the numerical case III, the Task Difficulty obtained by eq. 4.16 is close to zero bit (table 4.7) for all the four elements considered: this is due to the fact that the amount of information associated with the circular shape complexity is equal to 0 bit (since the circle is the simplest shape). Indeed, such a curve is considered having zero information. Here, only the component linked to the amount of information due to the similarities between the elements included in the pool of alternative options is taken into account.

If the task to be performed is a sequence of elements to be sorted by the operator, the Overall Task Difficulty (OTD) is given by the sum of the Task Difficulty (TD) of task performed to select the single elements. Greater is the number of alternative options, the higher the OTD (Fig. 4.6).

In table 4.9 the TD values in selecting A-element (small blue square) for each numerical case considered are summarized.

Table 4. 9 A-element selection Task Difficulty (TD) in the numerical cases considered

Numerical case	TD [bit] (A-element selection)
I	1.10
II	0.81
IV	0.84

As shown in table 4.9, the TD of the A-element selection task varies both with the number of alternatives options and with the shape of the elements considered. Higher is the number of alternative options available, the greater the TD. Furthermore, if the number of alternative options to be considered is the same, the TD varies according to the shape of the elements in the pool of alternatives. Indeed, the TD value is lower if elements in the pool have the same shape.

For each numerical case considered in tables 4.5 - 4.8 the Mental WorkLoad (MWL) and MWL^I are represented in blue and orange colour, respectively. The MWL^I values are higher than MWL. This means that the external stimuli (independent of the task performed) can increase the number of bits that the operator has to process in a given time window (T) to perform the same task.

Suppose the operator's mental overload grows and he/she is unable to carry out the task in the given time window. In that case, the MWL must be reduced to avoid a decrease in his/her performance and the resulting (negative) effects on the production system. In these cases, it is possible to modify:

- Task Difficulty (TD): to decrease the TD by varying the number and/or type of alternative options to be considered;
- Time window (T): by increasing T, the MWL decreases;
- K_e and K_{or}: by improving the external stimuli, the MWL decreases.

The model proposed allows evaluating the operator's mental workload in cognitive-oriented tasks where 2D object recognition is required. In manufacturing contexts like mixed-model assembly lines, where objects' similarities and objects' shape complexity can affect operators' performance, mental workload evaluation could drive in optimizing human resources to guarantee acceptable levels of error rate and safety risk. It is observed that the gap between the complexity of a task and the capabilities of the human operator could lead to an increase in human error often leading to accidents (Gomes et al., 2015). Operators' performances are significantly affected by both too high or too low mental workload (Aricò et al., 2016).

Since task features (e.g., variety; similarity) affect mental workload, the re-design of critical tasks can reduce high mental workloads (Galy et al., 2012).

The model can also be applied in order to evaluate changes in operators' mental workload when the industrial setting varies due to the introduction of new products (increasing the tasks' complexity) and/or the adoption of new technologies (as in the case of I4.0 enabling technologies). In the former case, the model can be applied to verify the increase in the mental workload of critical tasks (e.g., final assembly, quality control) and the suitability of organizational strategies like job rotation in order to balance the mental workload among the operators; in the latter case, the model can be a valid theoretical support to evaluate the effectiveness (from a cognitive perspective) of technologies to be adopted.

4.5. References

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5. Analysing Operators' Performance in Accomplishing Assembly Tasks

In the industry 4.0 context, the concept of task complexity plays a crucial role to design and optimising manufacturing systems. The task complexity assessment is one of the most important challenges faced by manufacturing companies. Similarly, the strategies to reduce the complexity of the tasks represent one of the main impactful approaches to minimise costs and increase production performances (*Managing Complexity in Global Organizations*, 2012). Currently, the scientific literature does not provide a unique definition of "task complexity" (Blecker and Abdelkafi, 2006). In 1993, March and Simon identified the task complexity by evaluating three objective qualities: uncertainty in the possible alternatives, inexact or unknown data, and hardness to divide the task into independent sub-task (March and Simon, 1993). According to Latham and Yukl, complex tasks are characterised by performance identified with multiple quantitative and nonquantitative dimensions. In particular, the latter led to a significant increase in complexity (Latham and Yukl, 1975). At the aggregate level, complexity is defined as the difficulty degree in predicting the system proprieties (e.g., assembled product) when are given the properties of the system's parts (e.g., components) (WEAVER, 1948). Fast-Berglund et al. provide two definitions of complexity under an objective and subjective perspective (Fast-Berglund *et al.*, 2013):

Objective complexity depends on the nature of products, hierarchical structures, processes, variety, and strength of interactions.

Subjective complexity depends on different individuals' factors such as skills, competence, and experience.

An evaluation method to estimate the complexity degree of semifinished parts allowed for developing a guideline to design finished-product adopting ease assembled parts and considering the systems boundaries condition (i.e., work cycle, operative sequences equipment, and system layouts) (Samy and Elmaraghy, 2010). Boothroyd et al. introduced the Design for Assembly (DFA) method to assess the assembly's complexity, analysing different cycle times collected in a sample of empirical observations (Boothroyd, Dewhurst and Knight, 2010). Similarly, the assembly's complexity is related to the quality of the available data required to assemble the components (Morse, 2003).

ElMaraghy and Urbanic developed an information-based model to identify the product and process complexity in some manufacturing work environments. The model depends on the total quantity of information, diversity of information, and information content (ElMaraghy and Urbanic, 2003). Braha and Maimon proved that the total assembly time is a linear function of the information content (Braha and Maimon, 1998). A new entropy measure is introduced to quantify the assembly's complexity related to a possible number of alternatives needed to complete the task (Zhu *et al.*, 2008). Similarly, Busogi et al. evaluate the manufacturing choice complexity by considering the number of possible alternatives and the part similarity (Busogi *et al.*, 2017). In most cases, the current studies faced the performance of an assembly line, neglecting the losses due to aspects related to both human performance and task complexity. Generally, they are considered adopting different and independent assessments methods. The model proposed contributes to overcome this limit by jointly estimating the task complexity in terms of the amount of information to be processed (expressed in bits) and the operators' performance as a function of their dexterity skill.

5.1. Model description

Human performance in a manufacturing system is difficult to evaluate since it depends on multiple quantitative and nonquantitative (e.g., emotional) variables requiring complex analysis (Chen, 2020). In the case of repetitive tasks, cognitive experts stated that the human factor is strongly related to the worker's learning capacity, leading to reduced cycle time during the work shift. (Fan *et al.*, 2018). In 2009, an analytical model proved that, in the case of repetitive tasks, the cycle time decreases with the number of task repetitions (n), according to learning (λ) and tiredness (τ) phenomena depending on human behaviour (Digiesi *et al.*, 2009). Assuming a dexterity phenomenon (ε) given in equation 5.1, the time required to assemble one unit (MT), in the case of the repetitive manual task, can be evaluated according to equation 5.2.

$$\varepsilon = \lambda - \tau \tag{5.1}$$

$$MT(n) = MT(1) - \varepsilon \ln(n) \, [sec] \tag{5.2}$$

Where $MT(n)$ is the time required to perform the task at n repetition, $MT(1)$ is the time required to perform the task at the first repetition, and n identifies the number of repetitions. Similarly, the Fitts law (eq. 5.3) proved a linear dependency between MT and the corresponding amount of information to be processed (I_c), depending on β-constant estimated on empirical observations (Fitts, 1954):

$$MT = \beta \cdot I_c \tag{5.1}$$

Samy and Elmaraghy estimate the amount of information required to accomplish an assembly manual task (I_c) as shown below (eq. 5.4) (Samy and Elmaraghy, 2010).

$$I_c = \left[\frac{n_p}{N_p} + CI_{product}\right] \cdot \left[log_2(N_p + 1)\right] + \frac{n_s}{N_s} \cdot log_2(N_s + 1)\ [bit] \tag{5.2}$$

Where, N_p and N_s are the total numbers of parts and fasteners, respectively, n_p and n_s are the number of unique parts and fasteners, respectively, and $CI_{product}$ is the product assembly complexity index depending on the physical characteristic of the part (i.e., handling and insertion attributes).

In the present work, the operator's performance index (IP), defined as the performance of the operator to accomplish a manual assembly task, is evaluated by the rate between the information required to accomplish an assembly manual task (I_c) and the time required to perform the task at n repetition ($MT(n)$), as shown in equation 5.5.

$$IP(n) = \frac{I_c}{MT(n)}\ [\frac{bit}{sec}] \tag{5.5}$$

IP is a positive value increasing with the operator's dexterity skill to perform a specific manual assembly task.

5.1.1. Model application in real industrial case study

The proposed model is tested on an assembly line of a large automotive company located in the south part of Italy. A campaign to collect the time required to perform each task's repetition (MT) has been planned in a manual workstation (WS) of an assembly line of pumps of a high-pressure diesel injection system. The assembly line consists of 15 WSs grouped in 6 highly automated (WA), 4 completely manual (WM), and 5 with small degrees of automation (WSA). The configuration of the flowline is shown in Figure 5.1.

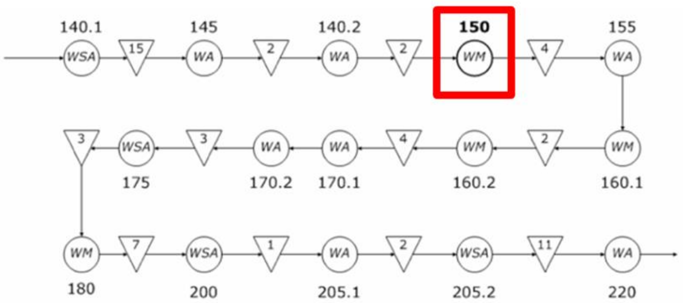

Figure 5. 1 Flowline of the assembly line of pumps

In the WM assessed, identified with code 150, the body of the pump is manually assembled with a polygonal ring, an eccentric shaft and a flange. The first task consists of checking the presence of the o-ring and of a bushing in the flange; this inspection is out of the evaluation since it is not considered an assembly task. The second task consists of assembly flange (4) with eccentric shaft (3); the polygonal ring (2) is assembled with (3) and (4), and the body of pump (1) is assembled with (4), (3), and (2). Finally, the operator inserts six screws (5) on the flange. The screws will be screwed up in the next WA. In Fig. 5.2, the body and the components assembled in the WS are shown.

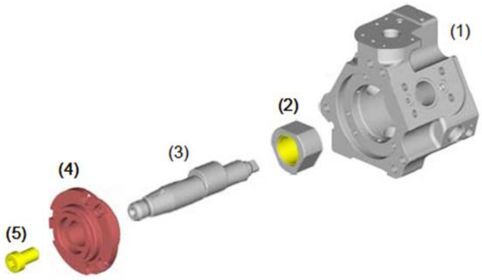

Figure 5. 2 Body and components to be assembled. Pump body (1); polygonal ring (2); eccentric shaft (3); flange (4); screw (5)

The $CI_{product}$ is evaluated according to (Samy and Elmaraghy, 2010), and it is given by the individual assembly complexity indices of all parts (CI_{part}). For this purpose, the weighted average values of the part assembly complexity factors (C_{part}) are estimated assuming the average difficulty factors for handling (C_h) and insertion (C_i). The "complexity matrix" (tables 5.2 and 5.3) allows identifying C_h and C_i, is built-up assuming the type of components parts (as a row) and the corresponding assembly attributes obtained by table 5.1 (as a column). For this purpose, the different handling and insertion are examined separately.

Table 5. 1 Manual assembly attributes from Design for Assembly methodology

Group	Attribute	Symbol	Description	Average difficulty factor
Handling attributes	Symmetry ($\alpha+\beta$)	Sym	$\alpha+\beta<360$	0.70
			$360\leq\alpha+\beta<540$	0.84
			$540\leq\alpha+\beta<720$	0.94
			$\alpha+\beta=720$	1.00
	Size	Siz	$>15\ mm$	0.74
			$6\ mm<size\leq 15\ mm$	0.81
			$<6\ mm$	1.00
	Thickness	Th	$>2\ mm$	0.27
			$0.25\ mm<size\leq 2mm$	0.50
			$\leq 0.25\ mm$	1.00
	Weight	W	$<4.53\ kg$	0.50
			$\geq 4.53\ kg$	1.00
	Grasping and manipulation	GM	Easy to grasp and manipulate	0.91
			Not easy to grasp and manipulate	1.00

	Assistance	Ass	Using one hand	0.34
			Using one hand with grasping aids	1.00
			Using two hands	0.75
			Using two hands with assistance	0.57
	Nesting and tangling	NT	Parts do not severely nest or tangle and are not flexible	0.58
			Parts severely nest or tangle or are flexible	1.00
	Optical magnification	Op	Not necessary	0.80
			Necessary	1.00
Insertion attributes	Holding down	Hd	Not required	0.54
			Required	1.00
	Alignment	Al	Easy to align or position	0.86
			Not easy to align or position	1.00
	Insertion resistance	In	No resistance	0.87
			Resistance to insertion	1.00
	Accessibility and vision	AV	No restrictions	0.57
			Obstructed access or restricted vision	0.81
			Obstructed access and restricted vision	1.00
	Mechanical fastening processes	Mfp	Bending	0.34
			Riveting	0.58
			Screw tightening	0.42
	Non-mechanical	Nmfp	Bulk plastic deformation	1.00
			No additional material required	0.58

	fastening processes		Soldering processes	0.67
			Chemical processes	1.00
	Non-fastening processes	Nfp	Manipulation of parts or sub-assemblies (fitting or adjusting of parts)	0.75
			Other processes (liquid insertion)	1.00

Table 5. 2 Handling complexity matrix

Part name (i)	N	Attributes								J	S	C_h
		Sym	Siz	Th	W	GM	Ass	NT	Op			
Pump body	1	1.00	0.81	0.27	1.00	0.91	0.75	1.00	0.80	8	6.54	0.82
Polygonal ring	1	0.70	0.81	0.27	0.50	1.00	0.34	0.58	0.80	8	5.00	0.63
Eccentric shaft	1	0.84	0.81	0.27	0.50	1.00	0.34	0.58	0.80	8	5.14	0.64
Flange	1	0.70	0.81	0.27	1.00	1.00	0.75	0.58	0.80	8	5.91	0.74

Table 5. 3 Insertion complexity matrix

Part name (i)	N	Attributes							K	S	C_i
		Hd	Al	In	Av	Mfp	Nmfp	Nfp			
Pump body	1	1.00	0.86	0.87	0.57				4	3.30	0.83
Polygonal ring	1	0.54	1.00	1.00	0.57				4	3.11	0.78
Eccentric shaft	1	0.54	1.00	0.87	0.57				4	2.98	0.75
Flange	1	0.54	0.86	0.87	0.57	0.42			5	3.26	0.65

With J and K the numbers of handling and insertion attributes of each part, respectively, the sum of the average difficulty factor (S) allows for evaluate C_h and C_i shown in equation 5.6 and 5.7, respectively.

$$C_h = {}^{S}/_{J} \tag{5.3}$$

$$C_i = {}^{S}/_{K} \tag{5.4}$$

Then, C_{part} for each of the four components can be estimated according to equation 5.8.

$$C_{part} = \frac{[C_h \cdot (S \cdot C_h) + C_i \cdot (S \cdot C_i)]}{S \cdot C_h + S \cdot C_i} \tag{5.8}$$

CI_{part} and $CI_{product}$ are identified from equations 5.9 and 5.10, considering the amount of the part to be assembled (N), respectively.

$$CI_{part} = x_p \cdot C_{part} \tag{5.9}$$

$$CI_{product} = \sum CI_{part} \tag{5.10}$$

Where x_p is the percentage of the x-th dissimilar parts (i.e., N_i/N_{tot} according to the number of parts (N) shown in tables 5.2 and 5.3).

The amount of information to be processed (I_c) referred to the case study considered, identified by equation 5.4, provides 4.25 $[bit]$. According to equation 5.5, the operator's performance index over time, $IP(n)$, depends on I_c and on time required to perform the task at *n* repetition, $MT(n)$. Starting from data collected on WM150 (three days, one work shift (8 hours) per day, same operator), the $MT(n)$ have been computed (figs. 5.3-5.5), and the corresponding $IP(n)$ have been estimated (fig. 5.3-5.5).

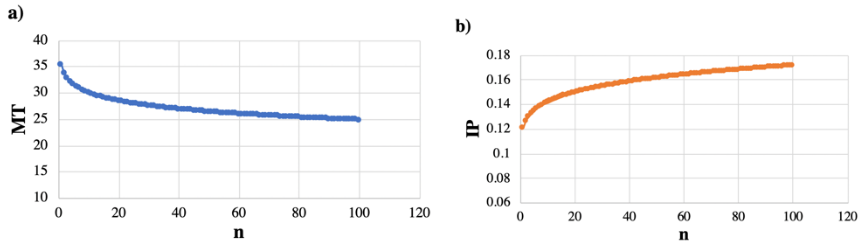

Figure 5. 3 Movement Time (a) and operator's performance index (b) estimated at day 1

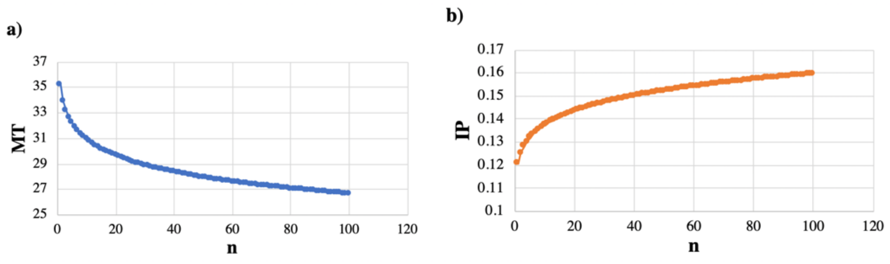

Figure 5. 4 Movement Time (a) and operator's performance index (b) estimated at day 2

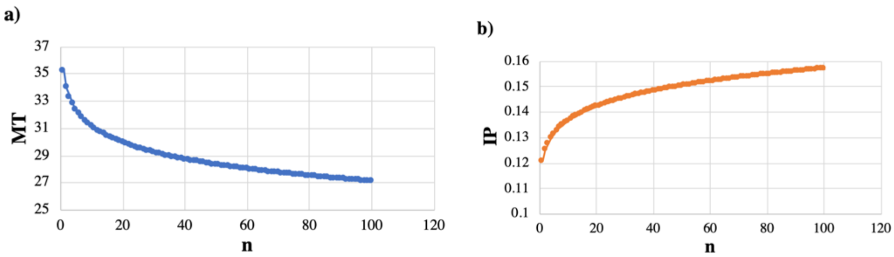

Figure 5. 5 Movement Time (a) and operator's performance index (b) estimated at day 3

In the case study considered, the assembly job at WM 150, was conducted by a woman of 45 years, highly experienced. The dexterity (ε) of this worker was evaluated per each work shift (eq. 5.2). The daily average IP and ε are shown in figure 5.6.

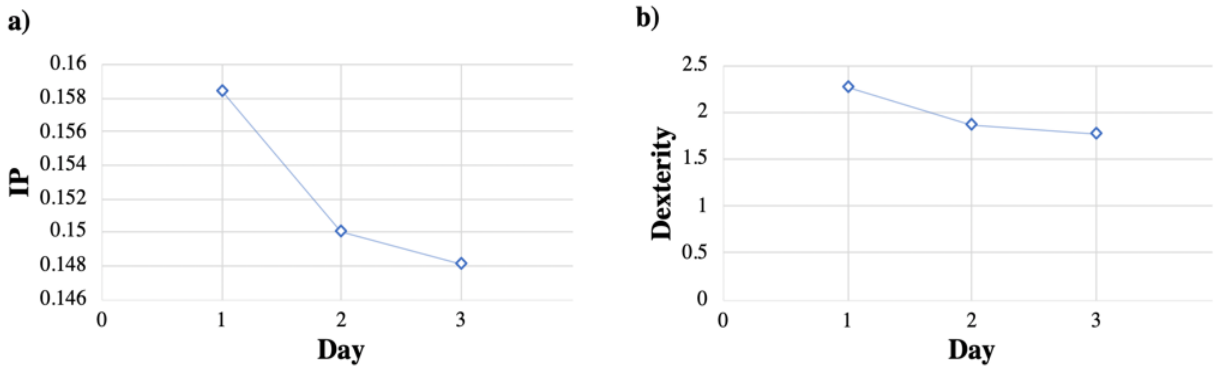

Figure 5. 6 Average IP (a) and dexterity (b) values per day

5.2. Discussions and conclusions

The information-based model developed allows estimating the operator's performance index, IP; it is evaluated from the time needed by operators at the first repetition, $MT(1)$, the dexterity of the worker, ε, depending on $MT(n)$, and the manual assembly task complexity, I_c. In the case study developed, the model allowed identifying IP in accomplishing an assembly task of a pump of a high-pressure diesel injection system.

The results achieved proved that IP is strongly related to both the task features and to human behaviour, evaluated in terms of information content, I_c, and worker's dexterity, ε, respectively.

The outcomes shown in the previous section proved that the operator's performance index, IP, increases with decreasing in $MT(n)$, observed in the same work shift (figs. 5.3-5.5). This means that the operator's performance in the same work shift improves over time. In other words, the amount of information processed in the unit time of the same operator for the same task in the same work shift increases with the increase of the number of repetitions.

On the contrary, the average IP, evaluated on different work shifts slightly decreased over time (fig. 5.6a). This means that if, on the one hand, the operator's performance improves in the same workday, on the other hand, the operator's performance slightly worsens on different workdays. This effect, consistent with the existing scientific research (Coburn, 2019)(Ward, 2021), could be a consequence of the worker's alienation in the repetition of the same jobs. The model's capability to identify this phenomenon depends on the reduction of the effect due to the operator's dexterity (ε) over time (fig. 5.6b), resulting from the impossibility to optimise the manual performance beyond a certain limit.

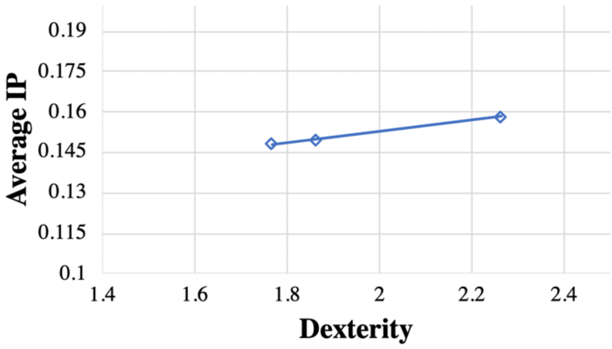

Figure 5. 7 Average IP-dexterity dependence

Interestingly, the IP, evaluated on different workdays, assumed very similar values (i.e., included between 0.145 and 0.16) for the same operator. This highlights the model's capability to identify a single performance index per operator. It emerged, indeed, that the changes in dexterity (ε) lead to minimal changes in the operator performance (fig. 5.7). Consistent with this consideration, the case study proved that IP provides a joint indication, including human behaviour (related to dexterity) and task complexity (related to I_c). In other words, IP will assume a single value per operator to identify him/her performance in accomplishing an assigned task.

According to information theories background, IP can be defined as that parameter that allows estimating the processing speed of 1 bit for each operator when the amount of information and the time needed to perform the set of tasks are known.

A model allowing to evaluate the operator's performance index in accomplishing a manual assembly task with prevalent physical efforts is developed. Consistent with the purpose of the work, the model allowed to estimate the amount of information processed in the unit time to accomplish an assembly job evaluating both the amount and the content of information of the task and the corresponding time needed by operators, with different dexterity skill, to accomplish it. From a managerial perspective, the operator's performance index can be used as an indicator to assign the operator to a specific task to improve the human-system performance. The developed model allows understanding the performance changes during the work shift and on the different workdays. The model paves the way for industrial applications having important managerial implications, especially in digital work environments where subjective aspects could affect productivity. Since the model application is based on only one operator and three observed days, further analysis on a more extensive and heterogeneous sample (e.g., man/woman, different level of experience, different age) and multiple days of observation, are required. Therefore, further research should investigate the model's applicability to a larger sample of participants and to different tasks to evaluate the variability of the operator's performance index.

5.3. References

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6. Conclusions

According to the main topics presented in the Abstract of the thesis and the outlines in evidence at the end of each chapter, the main concepts addressed are depicted in Figure 6.1.

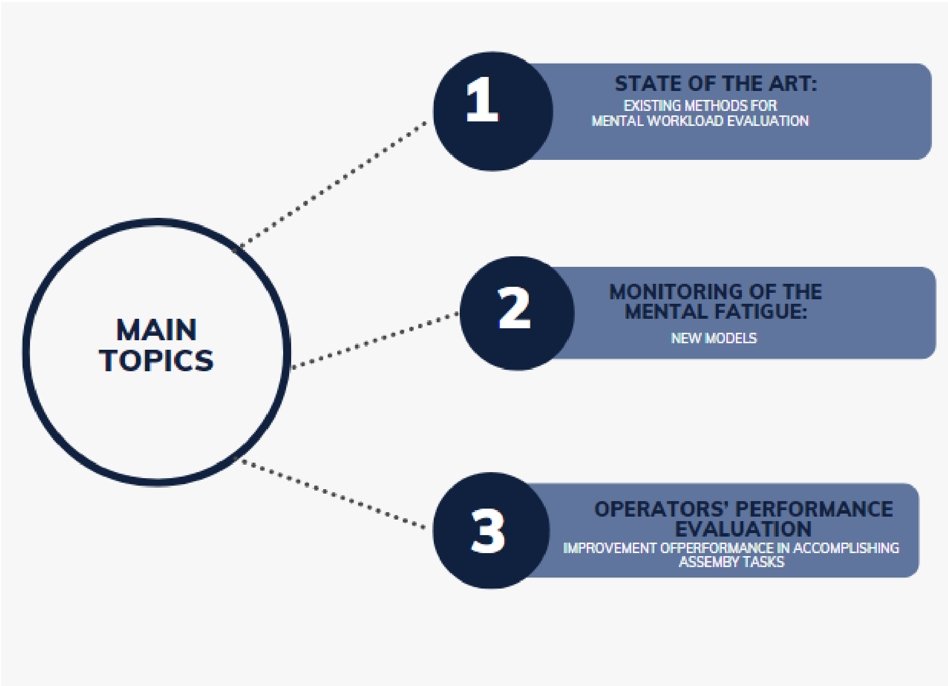

Figure 6.1 - PhD Thesis outline

The analysis of the state of the art regarding existing methodologies used for assessing the Mental Workload has helped to understand what needs to be improved in the analysis of human factors related to mental fatigue in the production process.

This thesis aims to evaluate the impact of human factors on the tasks performed in the digital factory; it is strictly focused on modelling the mental workload experienced by the operators to implement the existing research focused on evaluating human performance. In fact, until now, the literature has yet to focus on evaluating mental fatigue and how it should be manipulated to minimise its impact on human performance. To reach this contribution of the literature focused on the operators' wellbeing, different models evaluating the mental fatigue level of an operator can be developed.

According to this, Chapter 2 presents the n-back test as a standardised tool to simulate tasks with different cognitive complexities; it consists of standardised working memory and attention tasks with four incremental levels of difficulty. Here, both objective and subjective methodologies are used to evaluate the mental workload during the experimental sessions. The case study presented in Chapter 2 was used to simulate a real industrial context that explains how operators have to make more and more decisions due to the increase in cognitive tasks.

In addition, the n-back test and literature data have been used to create a new formulation for setting the value of the mental workload and the human performance time in Chapter 3. The formulations presented can take into account the subjective and objective parameters and the ageing phenomenon to take into account more the human factors in the production process in the digitalisation era.

In Chapter 4, the complexity of 2D object recognition tasks was investigated. The formulation presented allows modeling the task difficulty and the related mental workload.

Finally, in Chapter 5, human performance in repetitive tasks was investigated. Here, the operator's performance to accomplish a manual assembly task is evaluated by the rate between the information required to accomplish a manual assembly task (I_c) and the time required to perform the task at n repetition.

The modelling of mental workload, task difficulty evaluation and operators' performance carried on in this thesis can give suggestions to a practitioner on the improvement which can be obtained if the assignment is optimised considering different kinds of activities and operators. The operator's well-being will play a crucial role in the task assignment. The mental workload evaluation can be applied in job-rotation schedules regarding mental workload minimisation. As explained in the Introduction, the proposed formulations can fill the gap in existing literature related to the considerations of the human factors in the digitalised factory.

Therefore, in this thesis, the operator's mental fatigue is evaluated as a function of the mental workload. In the present work, both subjective parameters and objective parameters were evaluated (e.g. propensity to learn, age, gender, heart rate).

The entire dissertation addresses mental fatigue and cognitive performance by introducing new information theory-based models. The proposed models consider the entire human behaviour for the execution of tasks with prevalent cognitive effort. The mental fatigue and the related operators' performances are investigated and discussed from a new point of view, where features of the work-environment and individual's abilities influence the operator's mental workload (demanded or executed) and the related his/her performance. All the models are tested on a specific case study. Both literature data and ad hoc experimental setting are used. Results show the effectiveness of the models proposed, underlying the importance of the mental effort and execution of the task in predicting the mental workload for the correct balancing.

Moreover, the proposed models have general validity in accordance with the fact that different scenarios were used to test them, not limited to specific applications/work environments, paving the way to a novel perspective in human behaviour evaluation that is domain independent.

6.1. Final considerations on the future developments

The main goal is the necessity to properly train the operators skills with easiness, while guaranteeing safety conditions.
In all the developed methods presented in this dissertation, the mental workload is considered as a synthetic measure/index that evaluates if the operator can perform or not a specific task. Indeed, quantifying the mental workload, the optimal operator's workstation allocation can be identified and improving his/her performances.
A future goal is to use the developed models to create ad hoc practical instructions and examples on how to correctly execute the tasks and thus reduce the mental workload of the operators involved in the execution of the tasks. A series of laboratory tests will be performed on different clusters of participants (e.g., sex, age, physical condition, psychological condition and so on). Here, after cognitive ergonomic experts confirm that performed tasks have been correctly executed, the related recorded data should be employed as a reference for the operator behaviours. Indeed, as presented in this PhD dissertation, the mental workload model can also be applied in repetitive tasks where the phenomenon of learning and forgetting are considered.
The main goal is the necessity to train the operators' skills with easiness properly while guaranteeing safe conditions.
As far as future developments of the research presented in this PhD thesis are concerned, monitoring the general mental fatigue level by using a predictive model can also be helpful in the design phase of the workplace. The mental workload evaluation in real-time is the future challenge. In fact, by integrating it with immersive reality and a system for monitoring the physiological parameters of the operators, it can be carried on a complete analysis of the ergonomic and fatigue aspects of the operator.
In general, collecting data by these devices during the execution of the tasks can be useful to evaluate the goodness and effectiveness of a specific configuration of a workplace during the design phase. This can be done by determining a set of specific mental workload indicators (KPIs), referring e.g. to time, ergonomics and performance.
This would allow real-time feedback inherent to possible changes that have to be done to improve the operator's performance in the workstation (e.g. increasing or reducing the amount of data to be processed). As already pointed out in previous research, during the workplace design phase, it is necessary to include the technological variables related to the market demand, the product and the assembly process as well as the human variables. These variables are linked to the physiological and psychological wellbeing of the workforce and can be revealed by monitoring e.g. heart rate, change in the pupils, electroencephalogram, and so on. Integrating these variables in the developed models can point out the influence of each task on the operator's mental fatigue, measured through a mental workload increase.
The possibility of having an overall view of the impact of a specific workplace setting on the operators using these KPIs can help define the priorities of intervention and understand when (and how) the workstation is ready to be realized in practice. Therefore, the virtual workplace can be modified according to these criticalities and immediately verified with

the system. Comparing a set of data (it can be obtained in a laboratory test) permits estimating the best workplace configuration before it is built.
Future research will better develop the use of such an integrated system by future research with the actual application of an industrial context.

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