Journal of Computer Engineering
ISSN 10003428

Original Research Article
Vol 13, Issue 4, 2024 | ISSN: 1000-3428

Enhancing Workforce Performance: An Information-Based Model of Cognitive and Motor Abilities in Aging Workers

Dr. Andrew Zisserman
University of Oxford, UK.

Abstract: In the digital society, individuals are in charge of performing tasks based on the information gathered by huge amount of data and effectively use them to manifest their cognitive and motor abilities. In this paper, on the basis of experimental studies available in literature concerning lab tests on motor or cognitive abilities of differently aged subjects, an information-based theoretical model is proposed. The model allows to quantify the information content of a motor or a cognitive task and provides estimates of information processing time of individuals of different age and sex in accomplishing tasks with prevalent motor or cognitive nature, in spite of the fact that a "pure" cognitive or a "pure" motor task are rarely observed in practical cases. The model is then applied to a case study from automotive industry in which workforce aging phenomenon is experienced. Potential applications of the model go beyond the case study developed. Quantifying the information content of a general motor-cognitive task paves the way to new understanding and modelling of movements and performance time of both natural and artificial systems with applications in industrial robotics (e.g., human-robot cooperation), biomechanics, and neurorehabilitation.

1. Introduction

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 [1]. The potential support ratio indicator, which is defined as the ratio of the number of people of the group 16–64 years over the number of 65 or more years people, is expected to decline from 4.9 to 1.9 in 2100 in the United States and from 2.9 to 1.4 in 2100 in Germany [2]. 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 [3]. Furthermore, people tend to work until later ages due to multiple social and economic reasons such as delayed retirement [4–8] as long as their cognitive and physical health

How to cite: University of Oxford, UK. (2024). Enhancing Workforce Performance: An Information-Based Model of Cognitive and Motor Abilities in Aging Workers. Journal of Computer Engineering, 13(4), 25–48. DOI: https://doi.org/10.5281/zenodo.19351998

allows it [4]. This issue will bring to many implications in multiple fields and a better awareness of the workforce aging phenomenon is needed.

In 2050, the presence of older workers in production and operative roles will have an impact on economic growth and manufacturing efficiency [9,10]. The decreasing of worker's ability happens in workers involved both in cognitive and physical tasks [11]. The age range of 45–50 years has often been used as the base criterion to refer to an "aging worker". The reduction of cognitive and physical abilities is a crucial point for workers aged from 45 to 64 [3]. Changes in mental functions affect the

human sensory perception and information processing speed and accuracy. The key enabling technologies introduced by the new production paradigm of "Industry 4.0" can support aged operators [12,13]; nevertheless, in the Industry 4.0 environment, the operators are asked to perform complex cognitive tasks that require high cognitive efforts [14]. Fast information processing [15] in continuous learning processes is required in spite of a performance decrease of aged workers [16– 18]. An increasing gap between cognitive tasks in production systems and cognitive capacities of aged operators is expected to become a serious issue as humans have limited information-processing capacity [16–19].

A recent wide literature review on workforce aging in manufacturing systems as well as a research agenda is proposed in [20]. Here, a comprehensive analysis of modelling of aging workers' functional capacities in industrial systems is provided.

Due to limits of human information processing, a general theoretical framework to assess information content of tasks is required. To this concerns, conceptual models available in the information and communication theory represent a challenging reference to be followed [21,22].

In this paper, the authors propose an information-based model to estimate performance time of differently aged and sexed subjects in processing information during the execution of motor or cognitive tasks. Despite of the fact that a "pure" cognitive or motor task are rarely observed in reality, in the paper we refer to "motor" task as a task with prevalent motor content and low cognitive content; similarly, we refer to "cognitive" task as a task with low motor content and prevalent cognitive content.

The paper is organized as follows: In Section 2, the phenomenon of aging and its influence on the cognitive abilities of individuals are discussed. In Section 3, field tests available in the scientific literature that allow to evaluate the influence of aging on human motor and cognitive abilities are considered and information theory models based on Shannon entropy measures are adopted to evaluate information content of test runs; related cognitive processing rate of individuals subjected to test runs are evaluated. Regression analyses of tests data allowed the authors to model the effects of the aging phenomenon on human physical and cognitive abilities. The operator's cognitive and motor performance time have been combined in a holistic information-based model detailed in Section 4. The model is applied to a numerical case from automotive industry (Section 5). Discussion on research findings can be found in Section 6. Finally, summary and conclusions are in Section 7.

2. Aging and Human Cognitive Abilities in the Workforce

The aging phenomenon causes a change in both physical and cognitive abilities [23].

Focusing on the physical abilities, the link between age and ergonomics of workplaces (OCRAOCcupational Repetitive Actions and RULA-Rapid Upper Limb Assessment methods) is a wide recognized issue which impacts 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 [3,24]. As a consequence, several studies have been focused on physical abilities and on their impact on health and well-being of older workers.

In spite of the influence of cognitive abilities on task performance [25,26], as well as in the worker's ability to learn and carry out mental processes [27,28], "*less research has focused on cognitive functioning*" in work environments [29].

Any cognitive mental activity can be enabled by human memory. However, any person has a limited memory capacity and limited information-processing resources [19,30]. Human memory is divided into sensory memory, working memory, and long term memory (Figure 1) [31]. Sensory memory has infinite capacity and can hold any data for a very short period of 0.25 to 2 s, but most of the information does not reach the working memory. The working memory has a limited capacity and can actively process simultaneously a limited amount of information. Long-term memory theoretically has an infinite capacity to store information and contains cognitive schemes called chunks. The structure of the human memory is depicted in Figure 1.

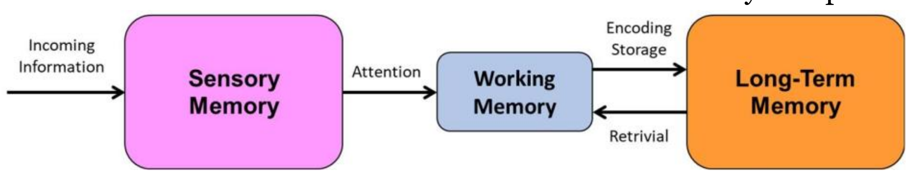

Figure 1. Sensory memory, working memory, and long-term memory.

Working memory and information processing speed decline with age [32,33]. Phenomena are strictly related [34]. The effects of aging on working and long-term memory justify why elderly people prefer to rely more on their memory and on the knowledge acquired over many years instead of learning new concepts for the execution of a task; such behavior often leads to probable memory errors [35].

Modelling of cognition in differently aged subjects can be carried out by two approaches: The psychometric and the neuropsychologic approaches.

The former is a classical approach known as dual-component human intelligence framework [36] where a distinction between "fluid" and "crystalized" intelligence is made. Fluid intelligence refers to the human ability to deal with new situations through the use of working memory and abstract reasoning; crystallized intelligence refers to the ability to solve problems by using knowledge acquired over the years [37,38]. Crystalized intelligence is quite stable over the years; on the contrary, fluid intelligence declines with the age and its decay accelerates after age 50 [39,40]. Cognitive abilities are expected to gain small improvements in work performance due to experience [41]. 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 [28,42,43].

The latter, the neuropsychology approach represents a more recent theoretical framework for modelling cognition in the presence of the aging phenomenon. The approach considers cognition as a function of brain-behavioral relationships [44] expressed by brain functions. The executive functions, which are part of the brain functions, execute cognitive processes involving the working memory and information processing speed; this is the case of planning, monitoring, organization, coordination, and implementation of working activities [45]. Albinet et al. [46] state that relations between processing speed and executive functions are understudied and poorly understood.

To summarize, human aging impacts multiple cognitive abilities that refers to mental processes including thinking, reasoning, problem solving, learning, remembering, and decision-making [47]. The age-related changes have multiple consequences on the performance of older workers in environments that require high information processing speed [12,15] to meet an increasing demand of cognitive tasks [28,47,48].

Effects of aging on the cognitive abilities of workers cause adverse impacts on the quality, productivity, and performance of people in the digital society and workers operating in I4.0 production environments. Adverse impacts is a new field of scientific investigations. Research on the effects of aging on the cognitive abilities of I4.0 operators or of people in a digital society originate theoretical problems of scientific interest as well as a challenge for the society. The problems are quite complex. The main dimensions of complexity are:

- High dynamic and stochastic variability of humans in performing cognitive tasks;
- large number of physical-physiological-psychological variables affecting human performance;
- Mutual influence between motor and cognitive tasks;
- Multidisciplinary competence required to analyze cognition.

Complexity dimensions of human cognitive capabilities justify the limits of scientific investigations which are mainly related to medical purposes instead of engineering applications.

Several empirical test-based investigations have been designed and carried out to observe human motor and cognitive abilities related to aging.

3. A Review of Experimental Tests of Motor-Cognitive Abilities from Information Theory Perspective

Experimental tests on the effects of aging on human motor or cognitive abilities are available in literature. In this paper some tests have been selected and related results considered to estimate, by regression analysis, the performance time in test execution by differently aged subjects.

Standard tests require subjects to perform cognitive or motor tasks, depending on the test purpose. Tasks have to be performed in a given time under standardized conditions.

During a task run, a subject is asked to process an information volume. In the following section, the information volume will be evaluated for each test by the Shannon entropy measures [21,22].

In the next sub-sections, tests to investigate cognitive or motor abilities are introduced, and related information volume evaluated.

3.1. Tests on Cognitive Abilities

Information volume of tests on cognitive abilities is evaluated by the Shannon's entropy measure for "n" equiprobable choices a subject is facing with during a test run:

$$H \quad \log n \tag{1}$$

3.1.1. Digit Symbol Substitution Test (DSST)

DSST consists of digit-symbol pairs followed by a list of digits. Different versions of DSST test can be found in [49]. The DSST version adopted in this paper is described in [50,51]. Under each digit, the subject should write down the corresponding symbol as fast as possible in the allowed time of 90 s. The number of correct associations of digit-symbol pairs within the allowed time is the score. The DSST indirectly measures the working memory because it requires the subject to remember the corresponding symbols and numbers memorized and to write down the symbol corresponding to each given number. The Information Processing Rate (IPR) of the subject is the amount of information processed in the time unit [bit/s]; it can be calculated as follows:

$$\mathrm{IPR} \quad \frac{2 \quad D \quad \log 2 \quad D \quad n \quad \log 2}{90} \; \frac{\mathrm{bit}}{\mathrm{s}} \tag{2}$$

where D is the total number of digit-symbol pairs (for each digit there is a corresponding symbol) and n are the identified pairs in 90 s. The quantity log2(2 D) is the amount of information to be processed to recognize one symbol or one digit, 2 D log2(2 D) the amount of information needed to recognize all symbols and digits (2 D), log2(2) the amount of information to be elaborated to identify a single pair, and n log2(2) the overall amount of information elaborated to identify n digitsymbol pairs in 90 s.

3.1.2. Reaction Time (from CANTAB)

The CANTAB (Cambridge Neuropsychological Test Automated Battery) is a set of tests defined for multiple purposes [52]; the test version adopted in this paper is the reaction time test and can be found in [53]. The test measures the reaction time (RT) of subjects; RT is defined as the time between a stimulus and a response. During the test, the subject holds down a button at the bottom of a screen. The screen shows some circles (one for the simple mode, and five for the five-choice mode) and in one of them a yellow dot will appear. Once the yellow dot appears, the subject has to release the button as quickly as possible. Every time the subject releases the button (when she/he sees the yellow dot), the amount of information processed is 1 bit (log2(2)). The IPR of the subject can be evaluated as follows:

$$\mathrm{IPR} \quad \frac{\;}{\;} \left[\frac{\;}{\;}\right] \tag{3}$$

RT is the observed time elapsed between the stimulus (the appearance of the yellow dot on the screen) and the response (the release of the button). This test is not associated with memory, as it does not require the subject to memorize any figure, symbol, digit, or letter.

3.1.3. Paired Associate Learning (from CANTAB)

Paired Associate Learning (PAL) is a test that allows to evaluate the visual episodic memory. During the test, the screen displays firstly 6 boxes and shows the interior of each box in randomized order to briefly reveal patterns in boxes [53]. The total number of patterns (n) goes from 2 to 6 (some boxes can be empty). After this phase, patterns are showed in the middle of the screen and the subject is asked to identify the right box to which it belongs. The time available to perform the test is 30 s. This test is an indirect measure of decision making, response control, and visual memory. The IPR of the subject can be evaluated as follows:

$$\mathrm{IPR} \quad \frac{n \quad \log n \quad m \quad \log 6}{30} \ \frac{\mathrm{bit}}{\mathrm{s}} \tag{4}$$

where m is the number of patterns (m ≤ n) correctly associated to boxes. The amount of information needed to recognize one pattern is log2(n), n log2(n) is the total amount of information to be elaborated in order to recognize all the n patterns. The amount of information to be elaborated to identify the box associated with a pattern is log2(6) (the subject always chooses between 6 equiprobable alternatives (boxes)), and m*log2(6) is the information volume elaborated by the subject in identifying the m patterns in 30 s.

3.1.4. The Experience of Deary and Der

In the study of Deary and Der [54], 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 was measured using a portable device with a display and a five response keys; the keys were labelled 1, 2, 0, 3, and 4 from left to right. For the evaluation of "single-choice" RT the subjects were asked to place a finger of their preferred hand over the central "0" key and they were instructed to press it as quickly as possible after the number "0" appears on the display. For the "four-choices" RT, the subjects were asked to place the second and the third finger of each hand over the keys 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 appears on the display. In the former case (single choice RT), the subject processes one bit of information in each test run; in the latter case (four choices RT) the subject processes 2 bits of information. Starting from the Hick's law [55] a linear dependency between the reaction time RT and the information volume to be processed is adopted:

$$\mathrm{RT} \quad \mathrm{SRT} \quad T_{,} \quad I \ \mathrm{s} \tag{5}$$

where, SRT (Simple Response Time) is the sum of all-time delays not associated with decisionmaking, Tp,c (s/bit) is the time to process one bit of information, and Ic is the information volume (in bit) processed in the cognitive task, as per Equation (1).

3.2. Tests of Motor Abilities

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. Let us consider a subject executing a reaching task within a time interval called movement time. During the movement, the subject processes an amount of information [56] expressed by the "Shannon formulation" of the Fitts's Index Difficulty (ID) parameter [22]; based on the theorem 17 of Shannon [21], ID can be expressed as follows:

$$ID \quad \log \quad \frac{D}{W} \quad 1 \text{ bit} \tag{6}$$

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

Purdue Pegboard Test (PPT)

In the Purdue Pegboard Test (PPT) participants are asked to pick up pegs from a bowl by their right hand, left hand, and then by both hands (three runs) and place them in one of the 25 vertical holes of a plate. 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. The test score is measured as the number of pegs the subject places within 30 s [57,58]. The test evaluates manual dexterity. The more pegs the subject can place correctly in 30 s (one run), the higher his manual dexterity is.

Based on the relationship given by Fitts [56], a linear dependency between the movement time (MT-time needed by the operator to perform the task) and the information volume to be processed (Im-bit) is adopted:

$$MT \quad T_{,} \quad I \quad s \tag{7}$$

where, Tp,m (s/bit) is the time needed to process one bit of information and Im is the information volume to be processed during 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 Equation (7)), which is the working assumption used in the regressions performed in the next section.

Equation (7) is applied to the PPT to quantify the amount of information of a test run. The diameter of the holes is 0.25 cm, the distance between two contiguous centers equals five times the diameter of the holes, the distance between the bowl that contains the pegs and the center of the first hole is 3.37 cm, and the MT (as the duration of the entire PPT test) is 30 s. The center of the bowl and every hole of the board are aligned. Under these test conditions, the movement time (MT) of the test run is obtained by adopting Equation (7) where Im is calculated as:

$$I \quad I_{,} \quad I_{,} \quad \sum \log \quad \_ \quad 1 \quad I_{,} \quad \text{bit}. \tag{8a}$$

The first term, Im,ID, is the index of difficulty that quantifies the information volume associated with the n reaching movements, i.e., the number of pegs placed by the subject in the board within MT; Di is the distance from the starting point (bowl with all the pegs) to the i-th target (hole), and W is the width of the target (constant holes diameter). The second term, Im,MTM, is the amount of information associated with translating, picking and placing movements not considered in Im,ID. Im,MTM is obtained by the Method-Time Measurement (MTM) standard time as follows:

$$\text{MTM}$$
$$I_{,} \quad \underline{\quad} T_{*,} \text{ bit} \tag{8b}$$

where MTM is equal to the sum of Method-Time Measurement standard times of all n translating, picking, and placing movements of the hand, and T*p,m is an average (on age and sex) value of the motor processing time. Method-Time Measurement (MTM) is defined as a system that "analyses 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" [59].

In the next Section, on the basis of Deary and Der [54] and Purdue Pegboard Test data available in literature [57,58] and Equations. (1, 5, 6, 7, 8a, and 8b), performance time of differently aged and sexed individuals involved in tasks with different cognitive content will be evaluated.

4. An Information-Based Model for Age- and Sex-Dependent Performance Time of Workers

4.1. Cognitive Tasks

Assessing processing speed of an individual has been carried out by different types of observable variables mainly related to the research field of investigation. In [60] six different variables are identified. In the field of psychometric research, decision speed and perceptual speed are adopted; decision speed refers to moderately complex cognitive tests; on the contrary, perceptual refers to very simple tasks like elementary comparison search and substitution operation to be performed in a specified time. When manual tasks are considered, psychomotor speed is the variable observed in psychometric and experimental field of research. Psychophysical speed variables are investigated to asses decision accuracy of individuals subjected to visual or auditorily stimuli; this is the case of inspection time-based activities. Time course of internal responses is a further variable investigated in psychophysical researches. A widely adopted variable to measure processing speed is the reaction time [54], evaluated as the time required by an individual to explicit a choice (by means of an action) when subjected to visual stimuli. 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 behavioral measure but also as a fundamental property of the central nervous system" [61]. The age-related decrease in reaction time is well known [62]; however, there are debates about the correlation of change of reaction time with age and sex [63].

In this paper, processing speed is measured by the reaction time as it is a variable mainly concerned with cognitive abilities in simple choice decision making and related manual responses. Such tasks are more and more required by differently aged individuals in modern work environments and daily activities.

Consistently, we refer to experimental data available in [54]. Here, an extended research on subjects differently aged (900 subjects from 16 to 63 years old), based on the UK's Health and Lifestyle Survey (HALS) [64]. The experiments consisted of identifying single or multiple right choice out of several possible options. In this paper, data have been used to find correlations between age and reaction time in an information-theory perspective.

An information-based model evaluating the information volume to be processed to accomplish a cognitive task is proposed. The related cognitive processing time (Tp,c) required by an individual of a specific class of age and sex to accomplish the task is evaluated. The reaction time (RT) is defined as the time for decision making and consists of different contributions, including processing time and further elementary sensorial delays from input to action [65]. 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 Equation (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 time. Single or multiple choices tasks, in the study of [54], require the subject to process a different information volume Ic, resulting in different RT.

Under these hypotheses and by using Equation (5), the processing time of subjects with the same sex (s) and age (A), Tp,c(s, A), can be evaluated by RT (Ic, s, A), measured in [54] as follows:

$$T_{,}\ s, A \qquad \frac{RT\ I\ , s, A \quad 1 \quad k \quad s}{I \qquad\qquad bit} \tag{9}$$

where Ic is the volume of information of the cognitive task and k is a constant ($0.3 \le k \le 0.4$) representing the fraction of the RT due to delays not depending on central processing time (SRT k RT). Consistently, the information processing rate of population of given sex and age class in accomplishing a cognitive task, can be obtained as:

IPR s, A —— [–, .
(10)

,

In the experiments of Deary and Der [54], the single-choice RT (SC-RT) and multiple-choice RT (MC-RT) were estimated for both male and female individuals, aged from 16 to 63 years. The mean RT values for different age classes are shown for both sexes and for the single-choice and multiplechoices tests in Table 1.

Table 1. Mean single-choice reaction time (SC-RT) and mean multiple-choice reaction time (MC-RT) for different age classes and sex (M for male, F for female). Source: Authors' elaboration of data from [54].

Age Class						
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						

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 2), for single and four-choices test runs, with an increase of about 20–30% from age 24 to 60 +. Also, Higher reaction time values are observed in case of higher information volumes processed (four choices test runs).

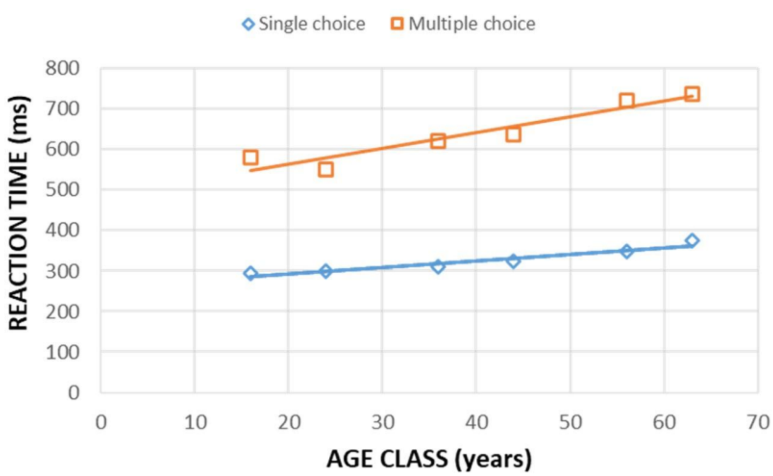

Figure 2. Mean reaction time values of the overall population vs. age for single and multiple-choice cognitive tests. Source: Authors' elaboration of data from [54].

On the basis of data in [54] and Equation (9) of the model proposed (by assuming k = 0.35), Tp,c
(s, A) values are computed for both single-choice and multiple-choice tests. Results are in Table 2.

Table 2. Cognitive processing time Tp,c (s, A) in single-choice (SC) and multiple-choice (MC) tests (M for male, F for female) derived from Equation (9) on the basis of data from [54].

Age Class						
Sex	M	F	M	F	M	F
Tp,c-SC (ms/bit)	190.7	191.8	191.6	198.9	197.9	204.7
Tp,c-MC (ms/bit)	187.8	188.5	177.5	180.9	201.1	202.0
Average Tp,c (ms/bit)	189.3	190.1	184.5	189.9	199.5	203.3
Age Class						
Sex	**M**	**F**	**M**	**F**	**M**	**F**
Tp,c-SC (ms/bit)	205.5	216.3	226.3	224.6	242.8	243.8

Tp,c-MC (ms/bit)	208.8	204.8	234.4	233.4	240.2	238.9
Average Tp,c (ms/bit)	207.2	210.6	230.3	229.0	241.5	241.3

As shown in Figure 3, a linear trend ($R^2 > 0.9$) of Tp,c vs. age is observed for male and female; for each age class, sex slightly affects processing time.

Figure 3. Tp,c values vs. age and sex from Equation (9) on the basis of data from [54].

The linear regression analysis leads to:

$$\overset{s}{} \quad Tp,c\ s, A \quad \alpha c\ s \quad \beta c\ s \quad A \text{ bit} \tag{11}$$

where regression parameters αc and βc are in Table 3.

Table 3. Parameters αc and βc values for male and female individuals.

Sex	**αc (ms)**	**βc (ms/bit)**
Male	160.75	1.20
Female	165.94	1.12

By (Equation (10)), the information processing rate IPRc (s, A) can be easily evaluated for differently aged male and female subjects.

4.2. Motor Tasks

In order to evaluate the information based processing time in case of motor task with low cognitive content (Tp,m), experimental test data from to two previous researches have been considered [57,58]. Data are obtained by the Purdue Pegboard Test (PPT); they refer to individuals with different age with a total of 437 subjects (219 females and 218 males). The first study [57] provides data referring to people aged from 15 to 40 years old; the second study [58] focuses on people aged from 40 to 89 years old. Data available from the literature are used to evaluate the correlations between age and movement time by an information-based approach. An information-based model evaluating

the information volume to be processed to accomplish a motor task is proposed. The related motor processing time (Tp,m) required by an individual of a specific class of age and sex to accomplish a motor task with low cognitive content is evaluated.

The time to perform the task in the PPT is the movement time (MT) of 30 s during each test run. Only data related to 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 (7) is considered to evaluate the motor processing time for a given sex and age (Tp,m (s, A)) as:

, ,

T ,s, A [–]

. (12)

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

IPR s, A [–], .

(13)

,

In order to evaluate the motor processing time (Tp,m (s, A)) from data provided by the PPT, the
Im,MTM (Equation (8b)) has to be calculated.

MTM standard provides average standard time not distinguishing age and sex. As a consequence, an average information volume corresponding to MTM standard times can be calculated by means of Equation (8b) where an average (on age and sex) value of the motor processing time (T*p,m) is considered. In order to evaluate this value (T*p,m), an iterative procedure has been adopted. At the first iteration, T*p,m is assumed equal to 250 ms/bit (named T*p,m,0). This value has been adopted to evaluate Im,MTM using Equation (8b) and then Im from Equation (8a) for different values of n. For each subject observed during PPT (s, A), by using Equation (12) (MT equal to 30 (s)), the corresponding Tp,m (s, A) value has been obtained. Finally, the mean of the Tp,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. The initial value of the second iteration has been set equal to the mean value obtained by the first iteration. After four iterations, the calculation converged on T*p,m = 180 ms/bit. Evaluating Im by Equation (8a), the Tp,m (s, A) average values for all pairs (s, A) can be calculated by Equation (12). Tp,m (s, A) values are shown in Table 4.

Table 4. Performances (average number of placed pegs (#)) and motor processing times (Tp,m) of the Purdue Pegboard Test (PPT) (M for male, F for female). Source: Authors' elaboration of data from [57,58].

Age Class								
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
Tp,m (ms/bit)	274	253	275	254	261	244	278	265
Age Class								
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
Tp,m (ms/bit)	295	267	299	285	319	295	336	314

As in the case of cognitive task, linear trends are observed (Figure 4), with large R^2 values for both male and female (~ 0.9) and small differences (~ 6.5%) in the Tp,m values between male and female for each age class.

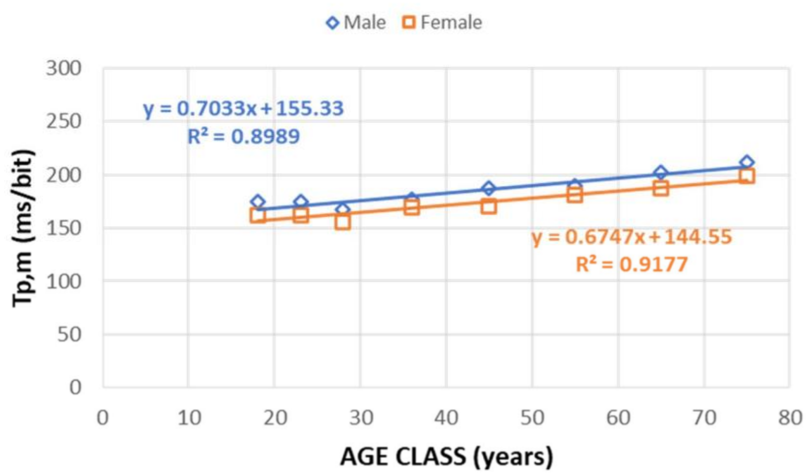

Figure 4. Tp,m values influenced by age and sex in case of motor tasks.

The linear trend observed for Tp,m (s, A) is as follows:

$$T_{p,m}\, s, A \quad \alpha_m\, s \quad \beta_m\, s \quad A_{\,\text{bit}} \qquad (14)$$

Values of αm and βm parameters are in Table 5:

Table 5. Parameters αm and βm values for male and female individuals.

Sex	αm (ms)	βm (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 (IPRm) can be evaluated as the inverse of Tp,m (s,A) for differently age classes of male and female subjects (Equation (13)); decreasing values of IPRm are observed with age for male and female.

4.3. Information-Based Model of Human Motor-Cognitive Performance

The model considers the motor and cognitive abilities of a subject with given 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:

$$\text{Performance Time}\ I\,,\ I, s, A\ \ RT\ I\,, s, A\quad MT\ I, s, A \qquad (15)$$

where:

- Ic [bit] = information content of the cognitive part of the task;

- RT(Ic, s, A) = reaction time (refer to Equation (9));
- Im [bit] = information content of the motor part of the task (Im,ID + Im,MTM); and
- MT(Im, s, A) = movement Time (refer to Equation (12))

This model is based on a preliminary decomposition of the task in its components (high cognitive-low motor, and high motor-low cognitive). The information content of the two components (Ic, Im) can be obtained by means of Equations (1) and (8a), respectively. The time required by the subject to complete the cognitive (RT) and the motor (MT) part of the task are calculated starting from the processing times Tp,c (s, A) and Tp,m (s, A), respectively. Tp,c (s, A) can be obtained from Equation

(9) by adopting the parameters corresponding to the subject characteristics (Table 3); Tp,m (s, A) can

be obtained from Equation (12) by adopting the parameters corresponding to the subject's characteristics (Table 5). The proposed model allows to predict the human performance in the form of completion time for subjects of different age and sex involved in tasks characterized by both a cognitive and a motor component. When ID (Equation (6)) is adopted for the calculation of Im,ID 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 operations in production systems.

5. A Case Study from the Automotive Industry

The model defined in the previous section has been tested on a case study inspired by an assembly line of an automotive factory 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 8. 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. Operators are in charge of pre-assembling and verifying the right position of components on the flange and of initiating the process on the machine. At the end of the process, operators of each WS perform a (visual) quality control on the product in order to identify scraps. The case study allowed to test the model and to find the operator–machine allocation minimizing idle time of the line or equalizing workloads of the WSs. Furthermore, the developed model allows to verify whether an operator is eligible to work on a WS or whether his/her operating time (performance time + machine time) is not compliant with the cycle time. In the case study, three WSs and five operators are considered. The operator's characteristics (age and sex) are in Table 6.

Table 6. Operator's characteristics.

Operator	Sex (M/F)	Age
A	M	
B	F	

C	M
D	M
E	F

In the first WS a thrust ring is set into the flange; in the second WS the oil seal is assembled onto the flange; 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 as having more cognitive or motor information content. For each WS, the information content of the cognitive part of the task (Ic) and the information content of the motor part of the task (Im) are calculated by Equations (1) and (8a), respectively. As far as Im,MTM term is concerned (Equation (8b)), the time required for the simple movement of the upper limbs is obtained from MTM standard times. The time measurement unit for each simple movement is expressed in TMU (Time Measurement Unit), being 1 TMU is equal to 0.036 (s). TMU values and the equivalent MTM times used for the simple actions of reaching, grasping, moving and releasing are in Table 7.

Table 7. TMU values for the simple actions: Reach, grasp, move and release. MTM: Method-Time Measurement.

	Reach	Grasp	Move	Release
Distance (cm)		-		-
TMU Value	11.3		12.9	
MTM (s)	0.41	0.07	0.46	0.07

For each single sub-task of the WSs, the information content is provided in Table 8.

Table 8. Information content of sub-tasks performed in each workstation (WS).

		Ic		Im
Sub-Tasks	WS1: Set the Thrust Ring into the Flange	Ic [bit] (Equation (1))	Im,ID [bit] (Equation (8a))	Im,MTM [bit] (Equation (8b))
	Grasp the flange	-	-	2.66
	Place the flange under the magnifying glass	-	1.58	-
	Verify the presence of the defect	1.00	-	-
	Put the flange in the scrap basket in the presence of the defect *	-	-	2.98
	Place the flange on the punching machine	-	1.32	-
	Grasp the thrust ring on the flange	-	-	2.66
	Place the thrust ring on the flange	-	2.00	-
	Verify the correct position of the thrust ring	1.00	-	-
	Push the button start on the punching machine	2.00	-	-

	Push the button "scrap" * on the punching machine (wrong punching)	1.00	-	-
	Grasp and put the flange in the basket (OK flange/NOK flange)	-	-	5.64
Sub-Tasks	**WS2: Set the Oil Seal into the Flange**	**Ic [bit] (Equation (1))**	**Im,ID [bit] (Equation (8a))**	**Im,MTM [bit] (Equation (8b))**
	Grasp the flange	-	-	2.66
	Verify the punching (OK/NOK punching)	1.00	-	-
	Place the flange on the punching machine	-	1.32	-
	Verify that the oil seal side of the flange is facing upwards	1.00	-	-
	Grasp the oil seal	-	-	2.66
	Place the oil seal on the flange	-	2.81	-
	Verify that the spring side of the oil seal is facing downwards	1.00	-	-
	Push the button start on the punching machine	2.00	-	-
	Push the button "incorrect positioning" * (repeat action 7)	2.00	-	-
	Push the button "scrap" * (wrong punching)	1.00	-	-
	Grasp and put the flange in the basket (OK flange/NOK flange)	-	-	5.64
Sub-Tasks	**WS3: Set the Bushing into the Triangular Ring of the Flange**	**Ic [bit] (Equation (1))**	**Im,ID [bit] (Equation (8a))**	**Im,MTM [bit] (Equation (8b))**
	Grasp the triangular ring from the basket	-	-	2.66
	Place the triangular ring on the punching machine	-	1.32	-
	Verify the correct position of the triangular ring	1.00	-	-
	Grasp the bushing from the basket	-	-	2.66
	Place the bushing on the punching machine	-	2.81	-
	Verify the correct position of the bushing	1.00	-	-
	Push the button "punching"	2.00	-	-
	Verify the correct punching	1.00	-	-
	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 each operator assigned to each WS, the performance times are obtained by Equation (15). In Table 9 are summarized the operating times as the sum of the operator performance times calculated and machine times. Machine time is 7.2 (s), 9.6 (s), and 8.6 (s), for WS one, two and three, respectively. **Table 9.** Operating times of WSs including operator and machine times.

Operator	TWS1 (s)	TWS2 (s)	TWS3 (s)
A	11.16	13.72	12.67
B	11.17	13.76	12.71
C	11.62	14.22	13.17
D	11.81	14.42	13.37
E	11.61	14.23	13.18

Being the cycle time equal to 15 (s), the operator-WS assignment that minimizes the idle time of the line can be obtained by solving the following optimization problem:

$$\underset{,}{\text{Min}} \quad T \quad T_{,} \quad x_{,} \tag{16a}$$

subjected to:

$$T \quad T_{,} \; 0 \; \forall \; i, k \tag{16b}$$

where i = 1,…,5 is the i-th operator, k = 1,…3 is the k-th WS, and xi,k is a boolean variables of the assignment problem (xi,k = 1 if the i-th operator is assigned to the k-th WS; xi,k = 0 otherwise).

In order to balance the workload among the WSs, the following optimization problem can be formulated aiming at minimizing the standard deviationof the WSs idle times:

$$\underset{,}{\text{Min}} \; \sigma_{,} \tag{17a}$$

subjected to:

$$T \quad T_{,} \; 0 \; \forall \; i, k \tag{17b}$$

where $\sigma_{Dt(i,k)}$ is the standard deviation of the Dt(i,k) values obtained as:

$$D_{,} \quad T \quad T_{,} \; x_{,} \; \forall \; i, k \tag{17c}$$

where Dt(i,k) represents the idle time of the k-th WS operated by the i-the operator; xi,k is a boolean variables of the assignment problem (xi,k = 1 if the i-th operator is assigned to the k-th WS; xi,k = 0 otherwise). The operator-WS assignments and related objective functions values evaluated by solving problems (16-Case 1) and (17-Case 2) are in Table 10 in case of cycle time Tc = 15 (s).

Table 10. Operator-WS assignments for Tc = 15 s.

			Operator-WS Assignment (WS1-WS2-WS3)
Case 1 (problem 16a)	Minimum idle time (s)	4.88	D-B-C
Case 2 (problem 17a)	Minimum idle time Std. Dev. (s)	0.31	D-A-E

To increase the line productivity, a reduction of the cycle time to 14 (s) has been considered in solving problems (16a-Case 1) and (17a-Case 2). New operator-WS assignments have been obtained. Results are in Table 11.

Table 11. Operator–WS assignments for Tc = 14 s.

			Operator-WS Assignment (WS1-WS2-WS3)
Case 1 (problem 16a)	Minimum idle time (s)	1.89	D-B-C
Case 2 (problem 17a)	Minimum idle time Std. Dev. (s)	0.31	D-A-C

Synthesis of the Results

Starting from data available in the scientific literature on cognitive and motor tasks, processing time of humans with different age and sex have been obtained in the framework of the information theory (Section 4). Human cognitive and motor performance have been combined in a holistic model. The model has been applied to a case study from automotive industry in order to identify the optimal assignment of operators with different age and sex to workstations of an assembly line.

In the case study, five operators of different age and sex have been considered (Table 6). At first, sub-tasks of each workstation have been classified according to their prevalent nature, i.e., prevalent cognitive or motor nature. For each sub-task, the information content has been evaluated for both cognitive sub-tasks (Ic, Equation (1)) and motor sub-tasks (Im, Equation (8a)). The RT (Equation (5)) and MT (Equation (7)) of each operator in processing the information volumes (Ic, Im) evaluated for sub-tasks have been calculated. Finally, the operation time of each WS has been calculated by summing the operator performance time (calculated by Equation (15)) and the machine time (Table
9).

Two optimization problems have been defined to identify operator-WS assignments. In the first case the objective function consists of minimizing the overall idle time of the assembly line (case 1); in the second case, the minimization of the standard deviation of the idle times of the WSs has been searched for (case 2). Table 10 shows results of the optimization problems in case of Tc = 15 (s). It can be observed that operating times of each operator (Table 9) is lower than Tc = 15 (s): Hence, all operators are eligible to be assigned to each WS. By reducing the cycle time to Tc = 14 (s), so as to meet higher productivity of the line, only the youngest operators (operators A and B, Table 6) can be assigned to each WS (Table 9).

It should be observed that the simple case study developed referring to only 5 operators and 3
WSs does not limit the general applicability of the model on a larger scale.

6. Discussion of Research Findings

The results of this study indicate that the information processing model developed can be adopted to assess the performance time of differently aged and sexed individuals accomplishing cognitive (i.e., with low motor content) or motor (i.e., with low cognitive content) tasks. Section 4 shows that for both types of task the processing time increases with age. No significant difference in cognitive processing times of males and females have been observed, while sex shows a slight influence on motor processing times. Results of the case study in Section 5 show the capability of the developed model in industrial contexts to plan the job assignment on the basis of operators' characteristics (sex and age) mainly in I4.0 work environment.

Further Research

Further research should be focused on validating this model in different production systems observing operators' performance time in accomplishing task of different nature (cognitive/motor) ranging from quality control to production planning activities to mention a few. Observations will validate performance time provided by the model.

A further stream of research will be focused on assessing the role of physical properties of workers or robotics systems in task execution under a common information-based approach. As it has been shown in chapter 3, tasks with prevalent cognitive or motor content are characterized by a given amount of information that an operator has to process. Shannon entropy measures have been adopted to evaluate the information content of a task. We referred to the Shannon entropy formulation for "n" equiprobable choices, in case of cognitive tasks, and to the "Shannon formulation" of the Fitts' Index Difficulty, in case of motor tasks.

The operator can be an artificial or a natural system. A robot or a worker or a cobot (human/robot system) are asked to accomplish a task. The accomplishing of a task in a given time requires the system (natural or artificial) to follow a "trajectory", i.e., to follow a sequence of states the system can reach. States of a system are possible configurations the system can assume. Configurations depend on physics and dynamics of the body, number and power of "actuators" (servors or muscles), number of degrees of freedom of each actuator. The set of possible configurations expresses the "information" the operator (system) displays through its body as it is stated in [66]. Here, a general framework based on the Shannon Entropy measures for equiprobable states is adopted to measure information expressed by moving bodies.

Following this approach, information processed by the system in following a "trajectory" can be estimated. At a given time, the system is in a state, i.e., assumes one the possible configurations. In a discrete time range, the system can reach the successive state in the "trajectory", i.e., can assume a configuration among the possible ones, consistent with the task to be accomplished. The "choice" of the state to be reached requires the system to process an information volume depending on the number of possible reachable configurations starting from the starting state. A continuous feedback control mechanism of the brain-body-environment allows the system to follow the designed "trajectory" in order to minimize errors between the actual and the designed state to be reached [67]. It should be observed that a state can be characterized by a set of variables like position, velocity/acceleration vectors and distribution of masses, power/forces available. In other words, the wide meaning of state allows defining the system "trajectory" as a temporal sequence of physical configurations the system assumes over time in accomplishing a task.

Following this theoretical framework, a new information-based approach can be adopted to interpret the behavior of moving bodies. The approach is referred to as "morphological intelligence" of bodies. Let us introduce the concept by simple line of reasoning.

Most human motor activities are governed by a continuous feedback control mechanism of the brain–body–environment system; the phenomenon would be almost impossible to carry out at a usual human information processing speed, due to both the time delays of the neural transmissions between brain and upper/lower limbs and limits of the brain processing speed.

For example, muscles' elasticity can enable a man (biological system) to run on a disconnected ground (the environment) without requiring the brain to process information coming from the environment at a high information rate. Further evidence can be found in motor and cognitive activities of aged people. Decreases in motor functions of adults are experienced in walking stability, reduced gait speed, and increased falls while decline in working memory and processing speed are main effects of deterioration of cognitive processes [16].

Similarly, the walking and balance behaviors of a robot is the result of physical interactions of its physical structure and properties (stiffness of materials, weight distribution, length of arms and legs, …) with the environment (ground morphology, friction, and stiffness, gravity…) [68,69]. A proper design of structures and choice of materials could help reducing information processing (computational demand) and energy of actuators.

Fast interactions between brain, body, and environment can be managed by the limited brain capacity if an "embodied intelligence" is admitted in the morphological features of the body. "Embodied intelligence" is a form of artificial intelligence. In this regard, referring to embodied cognition theory can help interpreting the role of body in cognitive processes. According to the traditional cognitivist theory, the sensory-motor system of a body gathers information to be transferred to and processed by the brain. Cognitive processing is considered conceptually separated from the sensory modalities. The traditional paradigm is similar to the classical SOR (stimulus– organism–response) paradigm adopted in work environments. Here, perceptual, mediation, and communication/motor processes interacting with human memory are considered to model operators' behavior in a man–machine system [65]. In the classical sandwich model, systems responsible for thinking are considered "sandwiched" between systems responsible for sensing and acting.

Classical cognitive paradigms are discussed and criticized in [70] where the embodiment effects on mental phenomena are discussed.

According to the embodied cognition theory, the sensory-motor systems of a body and cognitive processes interact and cooperate. Theory states that the body is not merely an input of information for computational processes of the brain; instead, body actions are co-producers of cognitive processes. A review of traditional and embodied cognition theoretical frameworks is in [71]; here effects of age on motor and cognitive processes are interpreted by the embodied cognition theory.

The role of the body in information processing pertains both natural and artificial systems as the body partially reduces the computation performed by the brain (natural or artificial). Information processed by the body depend on its morphological features.

Under this perspective, the concept of "morphological computation" is introduced to consider the capability of the body interacting with the environment in limiting information transmitted to the brain, information that otherwise would have to be processed by the brain [72].

A "morphological computation" can be interpreted as a process performed by a "morphological intelligence" of a body; the concept is relevant in the study of biological and robotic systems. The theoretical framework of the "morphological intelligence" can be found in [73]: The framework is based on coupling systems dynamics with the entropy-based morphological intelligence measures. The framework offers a unifying approach for modelling human cognitive/motor performances from an information-based perspective.

Biological systems show higher performance than artificial ones in processing information within the brain-body-environment sensory-motor loop. This becomes evident for robotic systems that, while outperforming humans in terms of central processing speed and local latencies, cannot replicate nor exceed human-like walking and balance performances [74,75] due to a poor "embodied intelligence". A targeted robot morphology (e.g., mechanical design, actuation) can significantly contribute to reduce the information volume to be processed by the CPU and reduce the overall computational needs and energy consumption of robots.

The approach here outlined paves the way to future research finalized to interpret and model motor or cognitive tasks to be performed by natural or artificial operators under a holistic information-based approach. Configurations of an operator, i.e., states the human or robotic system can assume, will lead to focus on the abilities' offered by the operators in performing a task or to design proper devices (e.g., exoskeleton, cobot) supporting the operator in assuming the required configuration. The approach is promising as it is consistent with the same information-based approach followed in this paper to characterize a task. A number of possible applications are expected in designing robots, coupling robot-operator, assigning workers of different age and physical abilities to a given task. Biomechanics and neurorehabilitation research would also benefit from such an information-based model, where the effects of age, pathology, and training exercise can be studied from the lenses of information processing speed and time.

7. Summary and Conclusions

The focus of this paper is to assess the performance time of operators of different age and sex involved in cognitive or motor task. Starting from data coming from experimental test available in the scientific literature, a model to predict information processing time has been proposed and applied to a case study.

The case study deals with an assembly line with three WSs and five differently aged and sexed operators. The model allowed to evaluate the optimal assignment of an operator to each workstation in order to meet the cycle time of the line. The model paves the way to industrial applications having important managerial implications, especially in digital work environments where workforce aging could affect productivity.

The model proposed is based on a holistic information-based approach that revealed effective in capturing performance time of operators. Since model evaluations are based on statistical samples of individuals subjected to predefined test runs, further analysis aiming at estimating the statistical variance of results should be carried out, possibly based also in further test data available in the literature. Investigation on statistical variance could confirm the robustness of the model and his effectiveness in assessing cognitive abilities by performance time of operators, in spite of the controversial findings on this concern provided by the available research. Improvements in the understanding of such complex phenomena (cognitive abilities) will require a multidisciplinary approach and competence that will characterize future research.

References

1. Bloom, D.E. 7 Billion and counting. *Science* **2011**, *333*, 562–569.
2. Gerland, P.; Raftery, A.E.; Ševčíková, H.; Li, N.; Gu, D.; Spoorenberg, T.; Alkema, L.; Fosdick, B.K.; Chunn, J.; Lalic, N.; et al. World population stabilization unlikely this century. *Science* **2014**, *346*, 234–237.
3. Ilmarinen, J. Promoting Active Ageing in the Workplace. European Agency for Safety and Health at Work. 2012. Available online: https://ec.europa.eu/eip/ageing/library/promoting-active-ageing-workplace_en (accessed on 1 June 2020).
4. Fisher, G.; Chaffee, D.; Sonnega, A. Retirement timing: A review and recommendations for future research. *Work. Aging Retire.* **2016**, *2*, 230–261.
5. Cahill, K.E.; Giandrea, M.D.; Quinn, J.F. Retirement patterns and the macroeconomy, 1992-2010: The prevalence and determinants of bridge jobs, phased retirement, and reentry among three recent cohorts of older Americans. *Gerontologist* **2015**, *55*, 384–403.
6. Alley, D.; Crimmins, E. The demography of aging and work. In *Aging Work 21st Century*; Lawrence Erlbaum Associates Publishers: Mahwah, NJ, USA, 2012.
7. Beehr, T.A.; Bennett, M.M. Working after retirement: Features of bridge employment and research directions. *Work. Aging Retire.* **2015**, *1*, 112–128.
8. Martin, B.; Xiang, N. The Australian Retirement Income System: Structure, Effects and Future. *Work. Aging Retire.* **2015**, *1*, 133–143.
9. UNFPA. Envelhecimento no Século XXI: Celebração e Desafio. In *Fundo Popul. das Nações Unidas*; UNFPA and HelpAge International: New York, NY, USA; London, UK, 2012.
10. Dupont, C.; Benin, A.; Belgi; Milieu, U. Safer and healthier work at any age: Review of resources for workplaces. *Anim. Genet.* **2016**, *39*, 1–55.
11. Peruzzini, M.; Pellicciari, M. A framework to design a human-centred adaptive manufacturing system for aging workers. *Adv. Eng. Inform.* **2017**, *33*, 330–349.
12. Calzavara, M.; Battini, D.; Bogataj, D.; Sgarbossa, F.; Zennaro, I. Ageing workforce management in manufacturing systems: State of the art and future research agenda. *Int. J. Prod. Res.* **2020**, *58*, 729–747.
13. Facchini, F.; Oléskόw-Szłapka, J.; Ranieri, L.; Urbinati, A. A maturity model for logistics 4.0: An empirical analysis and a roadmap for future research. *Sustainability* **2020**, *12*, 1–18.
14. Pascual, D.G.; Daponte, P.; Kumar, U.; Pascual, D.G.; Daponte, P.; Kumar, U. *Handbook of Industry 4.0 and SMART Systems*; CRC Press: Boca Raton, FL, USA, 2019; pp. 239–285.

15. McDaniel, M.A.; Pesta, B.J.; Banks, G.C. Job Performance and the Aging Worker. In *The Oxford Handbook of Work and Aging;* Oxford University Press, Inc.: New York, USA, 2012.
16. Salthouse, T.A. The Processing-Speed Theory of Adult Age Differences in Cognition. *Psychol. Rev.* **1996**, *103*, 403–428.
17. Rozas, A.X.P.; Juncos-Rabadán, O.; González, M.S.R. Processing speed, inhibitory control, and working memory: Three important factors to account for age-related cognitive decline. *Int. J. Aging Hum. Dev.* **2008**, *66*, 115–130.
18. Hambrick, D.Z.; Salthouse, T.A.; Meinz, E.J. Predictors of crossword puzzle proficiency and moderators of age-cognition relations. *J. Exp. Psychol. Gen.* **1999**, *128*, 131–164.
19. Miller, G.A. The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychol. Rev.* **1956**, *63*, 81–97.
20. Botti, L.; Calzavara, M.; Mora, C. Modelling job rotation in manufacturing systems with aged workers. *Int. J. Prod. Res.* **2020**, *58*, 69–85.
21. Shannon, C.E. A Mathematical Theory of Communication. *Bell Syst. Tech. J.* **1948**, *27*, 379–423.
22. MacKenzie, I.S. Fitts' Law as a Research and Design Tool in Human-Computer Interaction. *Hum. Comput. Interact.* **1992**, *7*, 91–139.
23. Clouston, S.A.P.; Brewster, P.; Kuh, D.; Richards, M.; Cooper, R.; Hardy, R.; Rubin, M.S.; Hofer, S.M. The dynamic relationship between physical function and cognition in longitudinal aging cohorts. *Epidemiol. Rev.* **2013**, *35*, 33–50.
24. Intranuovo, G.; De Maria, L.; Facchini, F.; Giustiniano, A.; Caputi, A.; Birtolo, F.; Vimercati, L. Risk assessment of upper limbs repetitive movements in a fish industry. *BMC Res. Notes* **2019**, *12*, 1–7.
25. Kanfer, R.; Ackerman, P.L. Aging, adult development, and work motivation. *Acad. Manag. Rev.* **2004**, *29*, 440–458.
26. Müller, A.; De Lange, A.; Weigl, M.; Van der Heijden, B.; Ackermans, J.; Wilkenloh, J. Task performance among employees above age 65: The role of cognitive functioning and job demand-control. *Work. Aging Retire.* **2015**, *1*, 296–308.
27. Schmidt, F.L.; Hunter, J.E. The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychol. Bull.* **1998**, *124*, 262–274.
28. Salthouse, T. Consequences of Age-Related Cognitive Declines. *Annu. Rev. Psychol.* **2012**, *63*, 201–226.
29. Fisher, G.G.; Chaffee, D.S.; Tetrick, L.E.; Davalos, D.B.; Potter, G.G. Cognitive functioning, aging, and work: A review and recommendations for research and practice. *J. Occup. Health Psychol.* **2017**, *22*, 314–336.
30. Rasmussen, J. The human data processor as a system component. Bits and pieces of a model. *Risø Natl. Lab.* **1974**, *1722,* 600–608.
31. Young, J.Q.; Van Merrienboer, J.; Durning, S.; Ten Cate, O. Cognitive Load Theory: Implications for medical education: AMEE Guide No. 86. *Med. Teach.* **2014**, *36*, 371–384.
32. Schulz, M.; Stamov Roßnagel, C. Informal workplace learning: An exploration of age differences in learning competence. *Learn. Instr.* **2010**, *20*, 383–399.

33. Kuo, H.K.; Leveille, S.G.; Yu, Y.H.; Milberg, W.P. Cognitive function, habitual gait speed, and late-life disability in the National Health and Nutrition Examination Survey (NHANES) 1999–2002. *Gerontology* **2007**, *53*, 102–110.
34. Francikowski, J.; Łozowski, B.; Rozpędek, M.; Kaczmarzyk, M. The influence of context on the usage of working memory capacity expressed in bits. *Sens. J. Mind Brain Cult.* **2016**, doi:10.7790/sa.v0i0.419.
35. Umanath, S.; Marsh, E.J. Understanding How Prior Knowledge Influences Memory in Older Adults. *Perspect. Psychol. Sci.* **2014**, *9*, 408–426.
36. Cattell, R.B. The measurement of adult intelligence. *Psychol. Bull.* **1943**, *40*, 153–193.
37. Carroll, J.B. Human cognitive abilities: A survey of factor-analytic studies: Review. *Can. J. Exp. Psychol.* **1993**, 38, 1074.
38. Cattell, R.B. Theory of fluid and crystallized intelligence: A critical experiment. *J. Educ. Psychol.* **1963**, *54*, 1–22.
39. Verhaeghen, P.; Salthouse, T.A. Meta-analyses of age-cognition relations in adulthood: Estimates of linear and nonlinear age effects and structural models. *Psychol. Bull.* **1997**, *122*, 231–249.
40. Baddeley, A. Working memory: The Interface between Memory and Cognition. *J. Cognitive Neuroscience* **1992**, 4, 281-288.
41. Silverstein, M. Meeting the challenges of an aging workforce. *Am. J. Ind. Med.* **2008**, *51*, 269–280.
42. Rudolph, C.W. Lifespan developmental perspectives on working: A literature review of motivational theories. *Work. Aging Retire.* **2016**, *2*, 130–158.
43. Ng, T.W.H.; Feldman, D.C. The Relationship of Age to Ten Dimensions of Job Performance. *J. Appl. Psychol.* **2008**, *93*, 392–423.
44. Lezak, M.D.; Howieson, D. *Neuropsychological Assessment*, 5th ed.; Oxford University Press: New York, NY, USA, 2012.
45. Rabbitt, P. Introduction: Methodologies and models in the study of executive function. In *Methodology of frontal and Executive Function*; Psychology Press: East Sussex, UK, 1997; pp. 1–38.
46. Albinet, C.T.; Boucard, G.; Bouquet, C.A.; Audiffren, M. Processing speed and executive functions in cognitive aging: How to disentangle their mutual relationship? *Brain Cogn.* **2012**, *79*, 1–11.
47. Park, D.C. (Ed.) The basic mechanism, accounting for age-related decline in cognitive function. In *Cognitive Aging: A Primer*; Taylor & Francis: New York, NY, USA, 2000; pp. 3–19.
48. Salthouse, T.A.; Madden, D.J. *Information Processing Speed and Aging*; Taylor & Francis: Boca Raton, FL, USA, 2013.
49. Jaeger, J. Digit symbol substitution test: The case for sensitivity over specificity in neuropsychological testing. *J. Clin. Psychopharmacol.* **2018**, *38*, 513–519.
50. Rosano, C.; Simonsick, E.M.; Harris, T.B.; Kritchevsky, S.B.; Brach, J.; Visser, M.; Yaffe, K.; Newman, A.B. Association between physical and cognitive function in healthy elderly: The health, aging and body composition study. *Neuroepidemiology* **2005**, *24*, 8–14.

51. Rosano, C.; Perera, S.; Inzitari, M.; Newman, A.B.; Longstreth, W.T.; Studenski, S. Digit symbol substitution test and future clinical and subclinical disorders of cognition, mobility and mood in older adults. *Age Ageing* **2016**, *45*, 687–694.
52. Dassanayake, T.L.; Ariyasinghe, D.I. Sex-, age-, and education-adjusted norms for Cambridge
Neuropsychological Test Automated Battery in literate Sri Lankan adults. *Clin. Neuropsychol.* **2019**, *33*, 106– 124.
53. Pangelinan, M.M.; Zhang, G.; VanMeter, J.W.; Clark, J.E.; Hatfield, B.D.; Haufler, A.J. Beyond age and gender: Relationships between cortical and subcortical brain volume and cognitive-motor abilities in school-age children. *Neuroimage* **2011**, *54*, 3093–3100.
54. Deary, I.J.; Der, G. Reaction time, age, and cognitive ability: Longitudinal findings from age 16 to 63 years in representative population samples. *Aging Neuropsychol. Cogn.* **2005**, *12*, 187–215.
55. Hick, W.E. On the Rate of Gain of Information. *Q. J. Exp. Psychol.* **1952**, 4, 11–26.
56. Fitts, P.M. The information capacity of the human motor system in controlling the amplitude of movement. *J. Exp. Psychol.* **1954**, *47*, 381–391.
57. Yeudall, L.T.; Fromm, D.; Reddon, J.R.; Stefanyk, W.O. Normative data stratified by age and sex for 12 neuropsychological tests. *J. Clin. Psychol.* **1986**, 42, 918-946.
58. Bolla-Wilson, K.; Kawas, C.H. Purdue Pegboard Age and Sex Norms for People 40 Years Old and Older. *Dev. Neuropsychol.* **1988**, *4*, 29–35.
59. Maynard, H.B.; Stegemerten, G.J.; Schwab, J.L. *Methods-Time Measurement*; McGraw-Hill: New York, NY, USA, 1948.
60. Salthouse, T.A. Aging and measures of processing speed. *Biol. Psychol.* **2000**, *54*, 35–54.
61. Madden, D.J. Speed and Timing of Behavioral Processes. In *Handbook of the Psychology of Aging*; Academic Press: San Diego, CA, USA, 2001; pp. 288–312.
62. Mathey, F.J. IV. Psychomotor Performance and Reaction Speed in Old Age. In *Patterns of Aging*; S. Karger: Berlin, Germany, 2015; pp. 36–50.
63. Fozard, J.L.; Vercruyssen, M.; Reynolds, S.L.; Hancock, P.A.; Quilter, R.E. Age differences and changes in reaction time: The Baltimore longitudinal study of aging. *J. Gerontol.* **1994**, *49*, 179–189.
64. Huppert, F.A.; Whittington, J.E. *Changes in Cognitive Function in a Population Sample*; Springer: Berlin/Heidelberg, Germany, 1993.
65. Park, K.S. *Human Reliability, Prediction, and Prevention of Human Errors*; North Holland: Amsterdam, The Netherlands, 1987; Volume 7.
66. LaViers, A. Counts of mechanical, external configurations compared to computational, internal configurations in natural and artificial systems. *PLoS ONE* **2019**, *14*, e0215671.
67. Beamish, D.; Bhatti, S.; Chubbs, C.S.; MacKenzie, I.S.; Wu, J.; Jing, Z. Estimation of psychomotor delay from the Fitts' law coefficients. *Biol. Cybern.* **2009**, *101*, 279–296.
68. Mummolo, C.; Mangialardi, L.; Kim, J.H. Concurrent contact planning and trajectory optimization in one step walking motion. In Proceedings of the International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Boston, MA, USA, 2–5 August 2015; pp. 1–7; Paper No: DETC2015-47745, V008T13A018.

69. Mummolo, C.; Peng, W.Z.; Gonzalez, C.; Kim, J.H. Contact-dependent balance stability of biped robots. *J. Mech. Robot.* **2018**, *10*, 1–13.
70. Foglia, L.; Wilson, R.A. Embodied cognition. *Wiley Interdiscip. Rev. Cogn. Sci.* **2013**, *4*, 319–325.
71. Costello, M.C.; Bloesch, E.K. Are older adults less embodied? A review of age effects through the lens of embodied cognition. *Front. Psychol.* **2017**, *8*, 267.
72. Ghazi-Zahedi, K.; Haeufle, D.F.B.; Montúfar, G.; Schmitt, S.; Ay, N. Evaluating morphological computation in muscle and DC-motor driven models of hopping movements. *Front. Robot. AI* **2016**, *3*, 1–10.
73. Ghazi-Zahedi, K. *Morphological Intelligence: Measuring the Body's Contribution to Intelligence*; Springer: Berlin/Heidelberg, Germany, 2019.
74. Mummolo, C.; Cursi, F.; Kim, J.H. Balanced and falling states for biped systems: Applications to robotic versus human walking stability. In Proceedings of the 2016 IEEE-RAS 16th International Conference on Humanoid Robots (Humanoids), Cancun, Mexico, 15–17 November 2016; pp. 1150–1160.
75. Mummolo, C.; Kim, J.H. Passive and dynamic gait measures for biped mechanism: Formulation and simulation analysis. *Robotica* **2013**, *31*, 555.