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## Why human factors science is demonstrably necessary: historical and evolutionary foundations

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### ABSTRACT

We review the theoretical foundation for the need for human factors science. Over the past 2.8 million years, humans and tools have co-evolved. However, in the last century, technology is introduced at a rate that exceeds human evolution. The proliferation of computers and, more recently, robots, introduces new cognitive demands, as the human is required to be a monitor rather than a direct controller. The usage of robots and artificial intelligence is only expected to increase, and the present COVID-19 pandemic may prove to be catalytic in this regard. One way to improve overall system performance is to 'adapt the human to the machine' via task procedures, operator training, operator selection, a Procrustean mandate. Using classic research examples, we demonstrate that Procrustean methods can improve performance only to a limited extent. For a viable future, therefore, technology must adapt to the human, which underwrites the necessity of human factors science.

**Practitioner Summary:** Various research articles have reported that the science of Human Factors is of vital importance in improving human-machine systems. However, what is lacking is a fundamental historical outline of why Human Factors is important. This article provides such a foundation, using arguments ranging from pre-history to post-COVID.

### ARTICLE HISTORY

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### KEYWORDS

General ergonomics; individual differences; learning and skill acquisition; allocation of functions; robotics and cybernetics

## 1. Introduction

Human factors science has been defined as '*the scientific discipline concerned with the understanding of interactions among humans and other elements of a system*' (International Ergonomics Association 2000). It is evident under many other names and labels (e.g. ergonomics, human-computer interaction, or more recently: human-robot interaction). Regardless of terminology, the discipline focuses on the human-machine system, defined as a system '*in which the functions of the man and the machine are interrelated and necessary*' (NASA 1965). Some of the fundamental roots of human factors date back to the mid-1800s (Jastrzębowski 1997), but human factors as a recognised scientific discipline originated in the time of the Second World War (e.g. Chapanis et al. 1947; Fitts 1951; Fitts, Jones, and Milton 1950) in response to the rapid introduction of war-time technologies, such as radar and sonar. One of the original goals of human

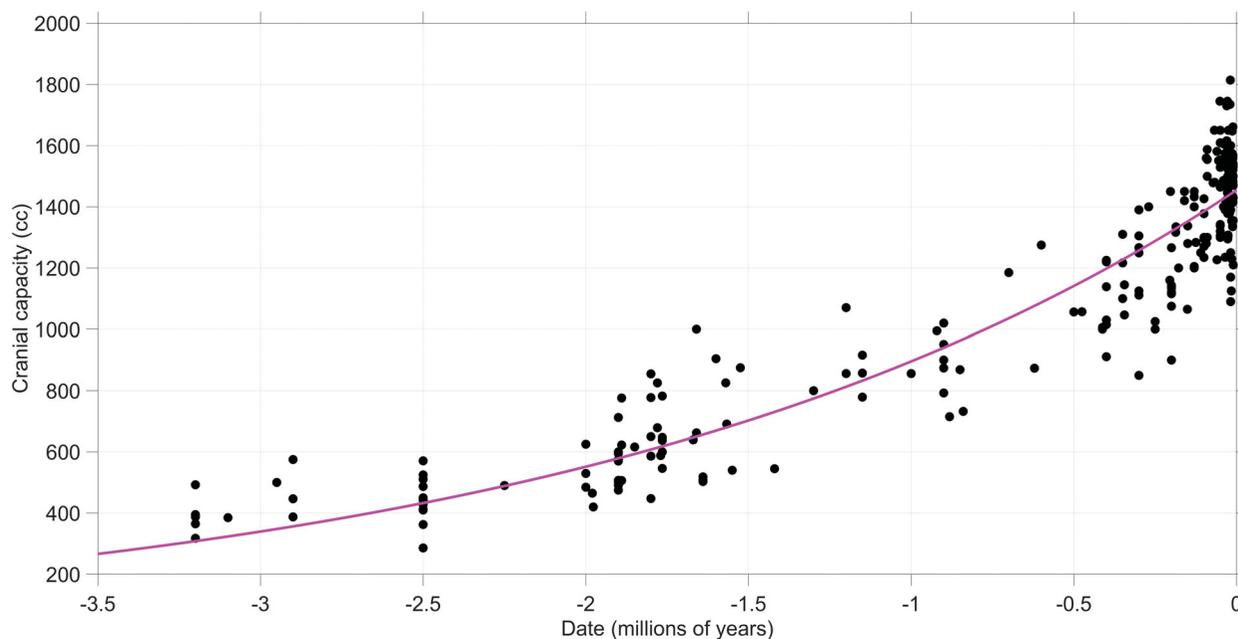
factors science was to examine how the properties of technologies (tools, machines, etc.) can be adjusted to enhance system performance.

Various writers have reflected on the importance of human factors science by emphasising that the design of technology must cater to the information-processing (cognitive) capacities and limitations of their human users (e.g. Chapanis 1979; Fitts and Jones 1947; Hancock 1997; Wickens 1992). Although the importance of human factors has been well-established and documented in science, the discipline still has a low exposure amongst engineers who design and fabricate modern-day technologies. As a result, systems are sometimes produced that exhibit little or no understanding of, or empathy with, human needs or capabilities, nor are they specifically acknowledging human foibles, failures, and propensity to error. In consequence, we witness catastrophic systems failures that can be explained by improper

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**Figure 1.** Cranial capacity of hominins across time (data were taken from Du et al. 2018; Henneberg and De Miguel 2004; Shultz, Nelson, and Dunbar 2012). The Pearson product-moment correlation between the date and the logarithm of cranial capacity equals 0.95 ( $n = 247$ ).

human-machine interaction (such as industrial accidents involving robotic manipulators: Sanderson, Collins, and McGlothlin 1986; self-driving cars being involved in fatal accidents: Calvert et al. 2020; crashes of aircraft using automation features: Woods 2019; or incidents with oil platforms: Skalle, Aamodt, and Laumann 2014). We believe that an evaluation of this scientific discipline's nature is required, from developmental and theoretical perspectives, to disseminate its rightful utility more fully.

In this article, we aim to evaluate the fundamentals of the relationship between humans and machines. To do this, we adopt an evolutionary perspective. We illustrate our points by comparing inferred human capacities with the manifest rates of modern technological advance. Our point of departure is thus a consideration of human evolution over the recent millions of years.

## 2. Human evolution

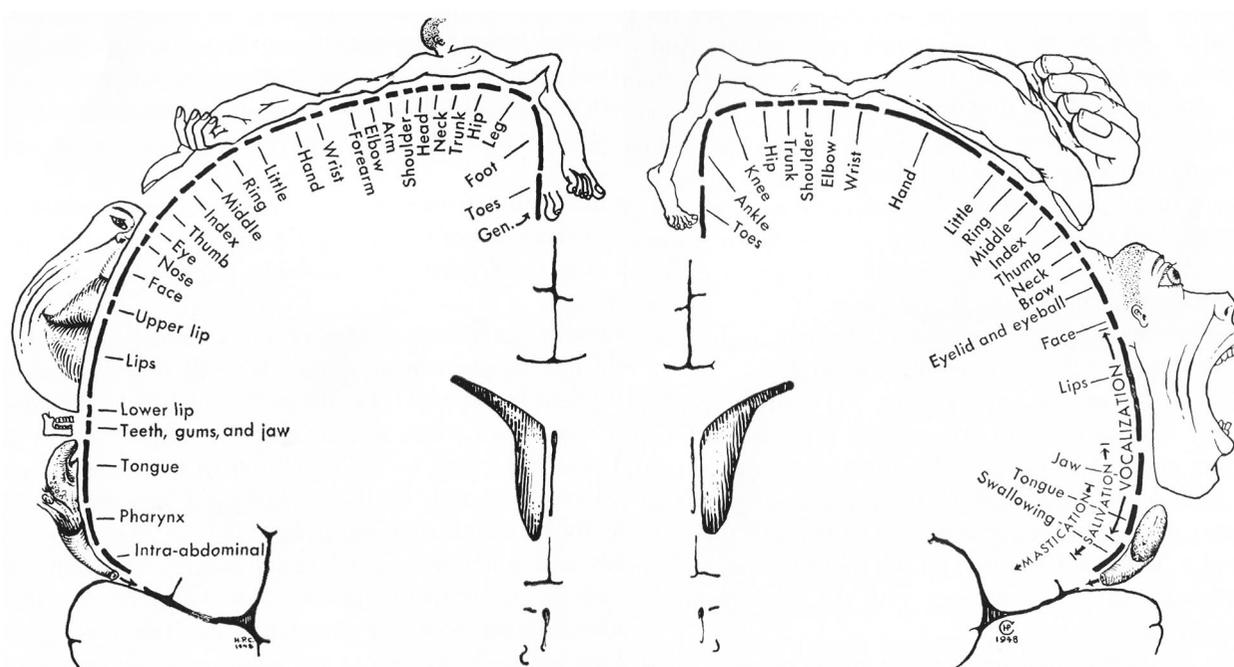
Henneberg and De Miguel (2004) have described the progression of human encephalization, i.e. the evolutionary increase in the brain's complexity and size. In primates, gross brain size is often used as a proxy for cognitive capabilities (Deaner et al. 2007). Henneberg and De Miguel (2004) provided an overview of all 215 available estimates of cranial capacity of hominins that have lived from 5 million years ago up until

approximately 10,000 years ago. Their results reveal an accelerating trend in cranial capacity across time, without any visible disruption or discontinuity. We complemented these data with 18 more recent findings documented by Du et al. (2018) and a further 14 findings listed in Shultz, Nelson, and Dunbar (2012). Using these raw data, we have fitted the following exponential function to cranial capacity (CC) measurements, with time expressed here in millions of years (Equation (1) and Figure 1).<sup>1</sup>

$$CC = 1454.4 \times e^{0.485 \times \text{time}} \quad (1)$$

This accelerating pace can appear impressive when plotted on a linear scale (as in Figure 1). However, the absolute size of these changes is negligible across the course of a single millennium, with cranial capacity being  $1453.6 \text{ cm}^3$  1000 years ago and  $1454.4 \text{ cm}^3$  today. Since the data are extracted from the fossilised remains that have been excavated, we have to remain cognisant of differences in the populations from which these limited samples come. The illustrated increments follow directly from our exponential fit of the data as depicted in Figure 1, and such data are not necessarily accurate. However, the overall rate of human evolutionary change is rather limited, especially if we confine ourselves to recent centuries.<sup>2</sup>

Apart from absolute brain volume, brain structure also has evolved. Most especially, in humans, this is reflected in the growth of the prefrontal cortical areas,



**Figure 2.** Illustration of Penfield's 'homunculus' illustrating the areas of innervation for both the sensory (Left) and motor (Right) cortices, respectively. Figure reused from Penfield and Rasmussen (1950).

compared to the rest of the brain (Verendeev and Sherwood 2017). It can be argued that this selective growth of these specific brain regions acts to differentiate humans from all other species. Structure, to a degree, mirrors function. We can examine Penfield's sensor and motor homunculi, which specify the relative areas to which the brain is connected to specific body appendages. Figure 2 indicates that the brain 'sees' the hand and the tongue as its most important instruments. These plots confirm our conscious experience that most of our human interaction with the world occurs through language (Hancock and Volante 2020) via the tongue, or muscularly manipulated tools via the hands (Rothenberg 1995).

### 3. From biological evolution to technological evolution

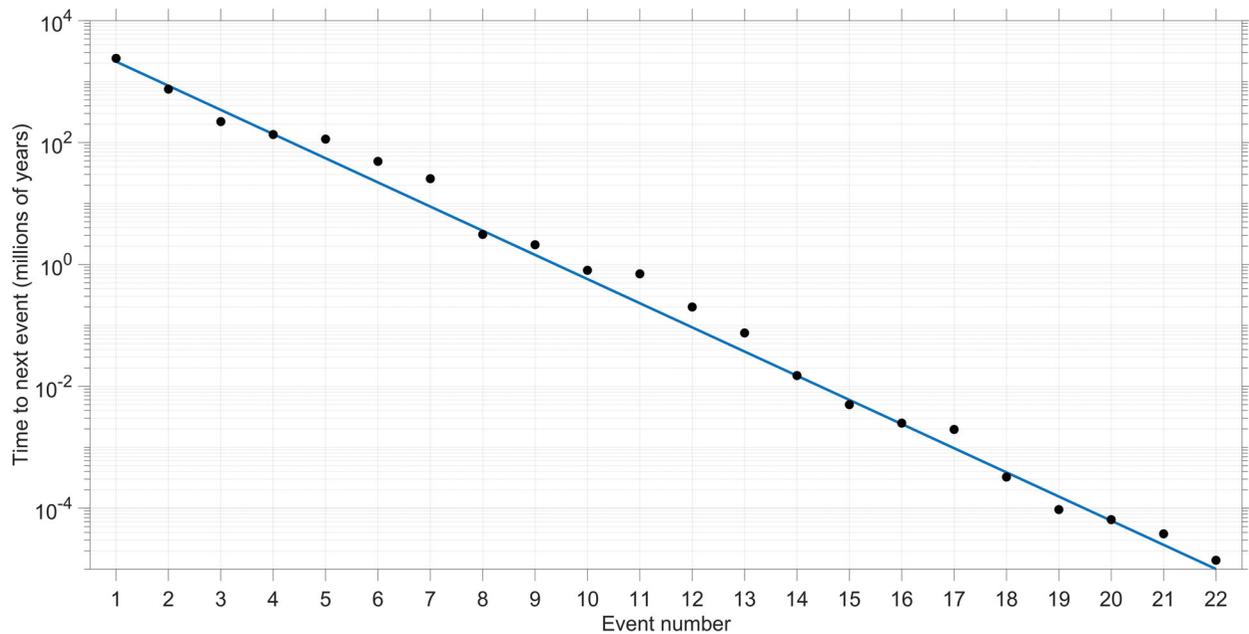
In his book from 2005, Kurzweil has provided data that allows us to approach a comparable quantification of the rate of technological evolution. Specifically, he offered a figure in which he placed the 'key milestones of both biological evolution and human technological development on a single graph' (24). The x-axis represents historical time, and the y-axis represents the time difference between two subsequent events, also referred to as the 'paradigm-shift time'. Using a logarithmic y-axis, we find essentially a straight line indicating continual acceleration (Figure 3). We have

calculated that the paradigm shift time reduces by approximately 60% for each new event. Thus, according to Equation (2), there is an exponential relationship specified by:

$$\text{Time to next event} = 5290 \times e^{-0.9128 \times \text{Event-nr}} \quad (2)$$

Kurzweil (2005) explained this acceleration as follows: 'In technology, if we go back fifty thousand years, not much happened over a one-thousand-year period. But in the recent past, we see new paradigms, such as the World Wide Web, progress from inception to mass adoption (meaning that they are used by a quarter of the population in advanced countries) within only a decade' (28). The technological progress depicted in Figure 3 is paralleled by other trends, such as the continual growth of the academic literature (Bornmann, Mutz, and Haunschild 2020) and the number of patents filed each year (U.S. Patent and Trademark Office 2020), including patents in the area of artificial intelligence (Ernst, Merola, and Samaan 2019).<sup>3</sup>

In the industrial revolution, powered machines were introduced, which allowed humans to delegate physical work. Also noteworthy in the evolution of technology is the development and incorporation of the computer: since the 1960s, computers have gradually taken over cognitive work from humans. Machines are becoming intelligent and could acquire their own information, make their own decisions, and act on the environment, for certain portions of certain



**Figure 3.** Event rate (paradigm shift time) versus event number. Examples: Event 1 = Life, Event 5 = Class Mammalia, Event 10 = Genus Homo, stone tools, Event 15 = Agriculture, Event 20 = Telephone, radio, electricity, Event 19 = Industrial revolution, Event 22 = Personal computer. Data from Kurzweil (2005). Event numbers 1–9 concern biological evolution; event numbers 10–22 concern technological evolution.

tasks. These developments were first seen in aerospace engineering, aviation (flight management systems), and process control rooms.

Now, in 2020, robots (i.e. intelligent self-controlling machines) are widespread in many facets of life, including driving (automated driving), households (e.g. robotic vacuum cleaners), warehouses, and agriculture. Moore's law (Moore 1965), the notion that the number of transistors on a computer chip doubles about every two years, suggests that computers will enable increasingly intelligent applications. With new developments in reinforcement learning, an increase in machine intelligence and a more widespread use of computers/robots, is anticipated.<sup>4</sup> Some have argued that technological developments are slowing down and that Moore's law is coming to an end. This statement appears to be incorrect, as recent data show that the number of transistors on a chip continues to increase exponentially until the present day (Schwierz and Liou 2020; Sun et al. 2019).

#### 4. Humans and technology on a single illustration: new demands on the human

If we now juxtapose human and technological evolution on a single graph (Figure 4), it becomes evident that, in our current times, technological evolution drastically outpaces human evolution. Since the vertical axes' units are not coincident for human and

technology, a direct equivalence cannot be justified. However, it is clear that technological progress has been immense in recent decades. While the human brain has co-evolved with tool use (see Figure 2), human evolution has manifestly failed to keep pace with current technological developments.

During and directly after the Second World War, human-machine interaction consisted of manual control tasks (illustrated in Figure 5, left) and information-processing tasks. It turned out that anti-aircraft gunners were unable to track fast-moving aircraft (Wiener 1942, 1954), and pilots made serious control errors during the manual landing of aircraft because of the cluttered design of the cockpit (Chapanis, Garner, and Morgan 1949; Fitts and Jones 1947) or the confusing layout of the altimeter (Grether 1949). In this respect, Hollnagel and Woods (2005) stated: '*Since the new conditions for work were predicated on what technology could do rather than on what humans needed, the inevitable result was that the human became the bottleneck of the system*' (35). Elsewhere, Hollnagel and Cacciabue (1999) noted that '*our capacity to digest and interpret data has not developed to keep pace with the machines*' (4).

Due to the integration of computers into human-machine systems in the 1960s and 1970s, a new type of work arose, called supervisory control. In supervisory control, the human has to monitor displays and provide inputs to the computer, where the computer

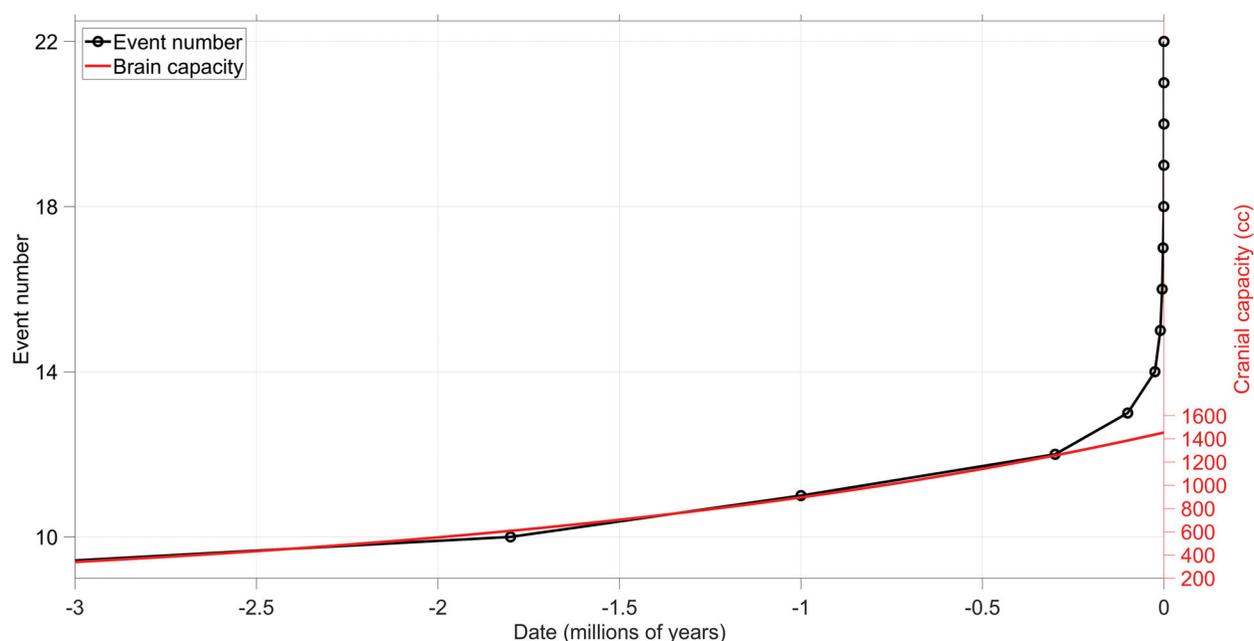


Figure 4. Event number and cranial capacity across time (and see Hancock 2019a, for a similar illustration).

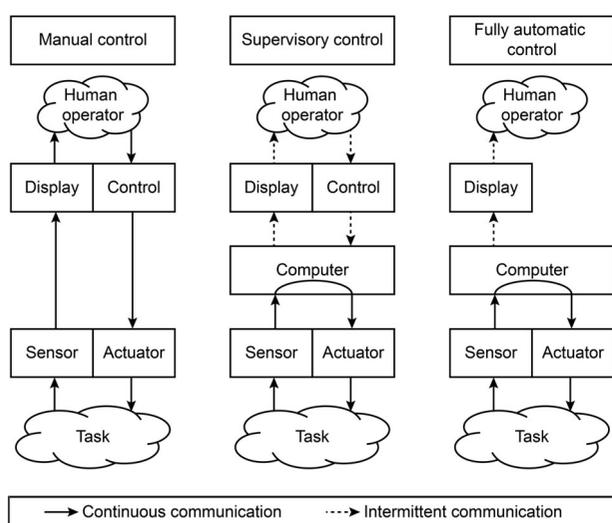


Figure 5. Manual (left), supervisory (middle), and fully automatic control (right). In manual control, the human directly controls the machine via actuators and continuously receives information via a display. In supervisory control, the computer closes the control loop via sensors and actuators while the human operator intermittently controls the machine via the computer and receives information via a display. In fully automatic control, the human is out of the control loop (adapted from Sheridan 1992; see also Heikoop et al. 2019).

is in control of the task environment (Figure 5, middle). The formalisation of supervisory control first arose in the late 1960s in remote space operations such as those on the moon and beyond (Ferrell and Sheridan 1967). Space is a domain where supervisory control is

imperative, often because of the hazards involved (i.e. the manipulator is located in a vacuum) and transmission delays (e.g. the round trip communication delay between Mars and Earth is about 20 min; NASA. 2020). These circumstances can make manual control impossible. A Mars Rover, for example, is equipped with AI and accepts intermittent targets as received from Earth; waiting for visual feedback for providing a manual steering correction is highly impractical and could also lead to unstable control. Today, supervisory control is found everywhere; an evident example is the use of the Tesla Autopilot (so-called SAE Level 2 automation), a system available to an increasing share of households.

Supervisory control introduces a new set of cognitive demands, as the human becomes responsible for additional tasks such as maintaining situation awareness, planning, and diagnosing system failures and reclaiming manual control if needed. Unfortunately, however, humans are not naturally adept at this supervisory role (Parasuraman, Sheridan, and Wickens 2000). Research shows that there is a risk that human operators fail to remain attentive and monitor what the machine is doing (Warm, Matthews, and Finomore 2008), lose situational awareness (Stanton, Chambers, and Piggott 2001), and become cognitively overloaded if the automation fails (Sheridan, Vámos, and Aida 1983; Zhang et al. 2019). Aviation provides a primary illustration of such ironies of automation (Bainbridge 1983). In principle, many commercial and

military aircraft can fly automatically, but automation did not entirely supplant the pilot. Two or three highly-trained crew members are needed to fly such modern aircraft. Aviation has become much safer compared to the past (Barnett 2020), but in relative terms, 70% of the accidents within aviation are primarily caused by human error (Hobbs 2004). The pilot is now a supervisor of automation in an 'airborne office' with only a few hours of manual 'stick time' per year (Doyle 2009). In driving also, there are ample indications that humans who are engaged in non-driving tasks cannot efficiently reclaim control when the automated vehicle fails to resolve a traffic situation (Victor et al. 2018). Misuse and disuse of automation are common as well (Parasuraman and Riley 1997). In summary, the rapid pace of technological evolution places new burdens on humans, burdens that need to be understood and remediated.

In some systems, there is no role for the human at all, except setting an initial target goal (see Figure 5, right). So far, except for highly bounded systems (e.g. elevators, dishwashers, telecommunication services), full automation remains rare. Although some forces seem set on fostering the redundancy, or total replacement, of all human involvement, it seems that supervisory control will be the norm for the coming decades. Human-supervised robots will be present in a diverse area of applications, including agriculture, education, and healthcare, amongst others (Sheridan 2016). The COVID-19 pandemic may prove to be catalytic to the development of digital technology, artificial intelligence, and robots (Ting et al. 2020). For example, it has been argued that humanoid robots can help reduce virus spread in transportation systems, hotels, and restaurants (Zeng, Chen, and Lew 2020), that autonomous delivery robots may see have growth potential (Pani et al. 2020), that remotely supervised social robots may be used to counter loneliness (Yang et al. 2020), and that agricultural robots can be used to cope with the reduced mobility of seasonal workers (Mitaritonna and Ragot 2020).

## 5. Procrustean approaches: adapting the human to the machine

As explained above, the rapid pace of technological progress sets new demands on human operators. Technologies introduced around the Second World War, such as radar, and the introduction of the computer in the 1960s, which is now becoming widespread in the form of robots, may contribute to

operator confusion, excessive workload, and errors, and in some cases, accidents.

One way of dealing with these demands is to adapt the human to the machine, using what has been referred to as 'Procrustean' methods. Research into such methods arose before the Second World War, before the birth of systematic human factors science. In part, this approach continues to the present day.

The term Procrustes, also used in statistics, refers to a situation where an exact fit to a model is required. Procrustes derives from a Greek mythological figure who made sure that his guests *exactly* fitted in his beds; if they were too short, he stretched them to make them fit. If they were too long, he cut parts off of them.<sup>5</sup> In human factors science, Procrustean methods refer to adapting the human to the demands set by technology. Various 'Procrustean' methods have been used to increase cognitive and physical output. Here we highlight three such Procrustean strategies: (1) procedures and incentives, (2) training, and (3) selection. These are considered below.

### 5.1. Procedures and incentives

Frederick Taylor's scientific management was an innovation that sought to analyse workflows to improve efficiency and productivity. Fordism (viz. Henry Ford) was a similar economic production system founded upon work division and task standardisation. Followers of scientific management and Fordism argued that productivity was enhanced through proceduralization and standardisation, allied to economic incentives. After trying various sizes and weights of coal shovels until an optimal shovelling rate was identified, Taylor proved that he could improve worker productivity by a factor of three. Another example of this is the bricklaying research by Frank and Lillian Gilbreth. In their 'time and motion studies,' the Gilbreths improved efficiency by removing demonstrably unnecessary actions (Gilbreth and Gilbreth 1917). Accordingly, the number of motions per brick was reduced from 18 to 5, while the bricklaying pace increased from 120 to 350 bricks per hour (Taylor 1911).

The research of innovators such as Taylor, Ford, and the Gilbreths represent specific exemplars and therefore not representative of all that is currently known about the effects of procedures and incentives on human performance. Nonetheless, from the examples provided, it seems reasonable to propose that by adopting strict procedures, standardisation, and incentives, the output rate can increase by a factor of at

least three relative to traditional craftsmanship. Of course, this strictly econometric form of measurement neglects other dimensions of work (e.g. the satisfaction it produces for the worker). The risk is that efficiency becomes everything and then is rarely questioned by those remote from the work process itself.

## 5.2. Training

A second way to fit the Procrustean bed is to raise human output via training the required skills and knowledge. The outcome of training is reflected in the degree of 'learning,' which has been defined as the relatively permanent change in knowledge or behaviour (Kihlstrom 2011). Performance, as a function of trial number, typically follows a power law (see e.g. Equation (3)). The picture is especially clear after averaging multiple trials from different performers. This means that performance versus trial number can be depicted linearly in log-log space.

$$Time = b \times N^a \quad (3)$$

The observations of these forms of learning curve emanate from the nineteenth century, e.g. Ebbinghaus (1885) and Thorndike (1898). Such results have been confirmed in critical studies since that time (e.g. Blackburn 1936; Crossman 1959).

We have used data provided by Seibel (1963) as an example of what can be achieved through extensive practice (see also Newell and Rosenbloom 1981). Seibel (1963) applied a task of information processing (10 bits, or  $2^{10} - 1 = 1023$  response alternatives) across an impressive 75,000 recorded trials. The data depicted in Figure 6(a) show that the power law provides a convincing fit with  $b = 12.33$  and  $a = -0.32$ . However, this fit only holds up to a point. After approximately 40,000 trials, the response plateaus, presumably due to absolute biological limits, such as limits in nerve conduction velocity and constraints on the exertion of muscular force. By comparing the first trial's reaction time (1.2 s) with the last batch of trials (0.4 s), a three-fold improvement can be confirmed.

Figure 6(b) offers learning data involving cigar making from a classical study by Crossman (1956). More specifically, ten factory operators (female, aged 15–50 years) were observed in a human-machine interaction task called bunch-making. According to Crossman, the bunch-maker lays 'binder' leaf on the apron, and the machine ejects 'filler' leaf and rolls the binder around it, making it a tubular bunch. The operator then transfers the bunch to a drum in the other half of the machine, which puts on the 'wrapper'. The

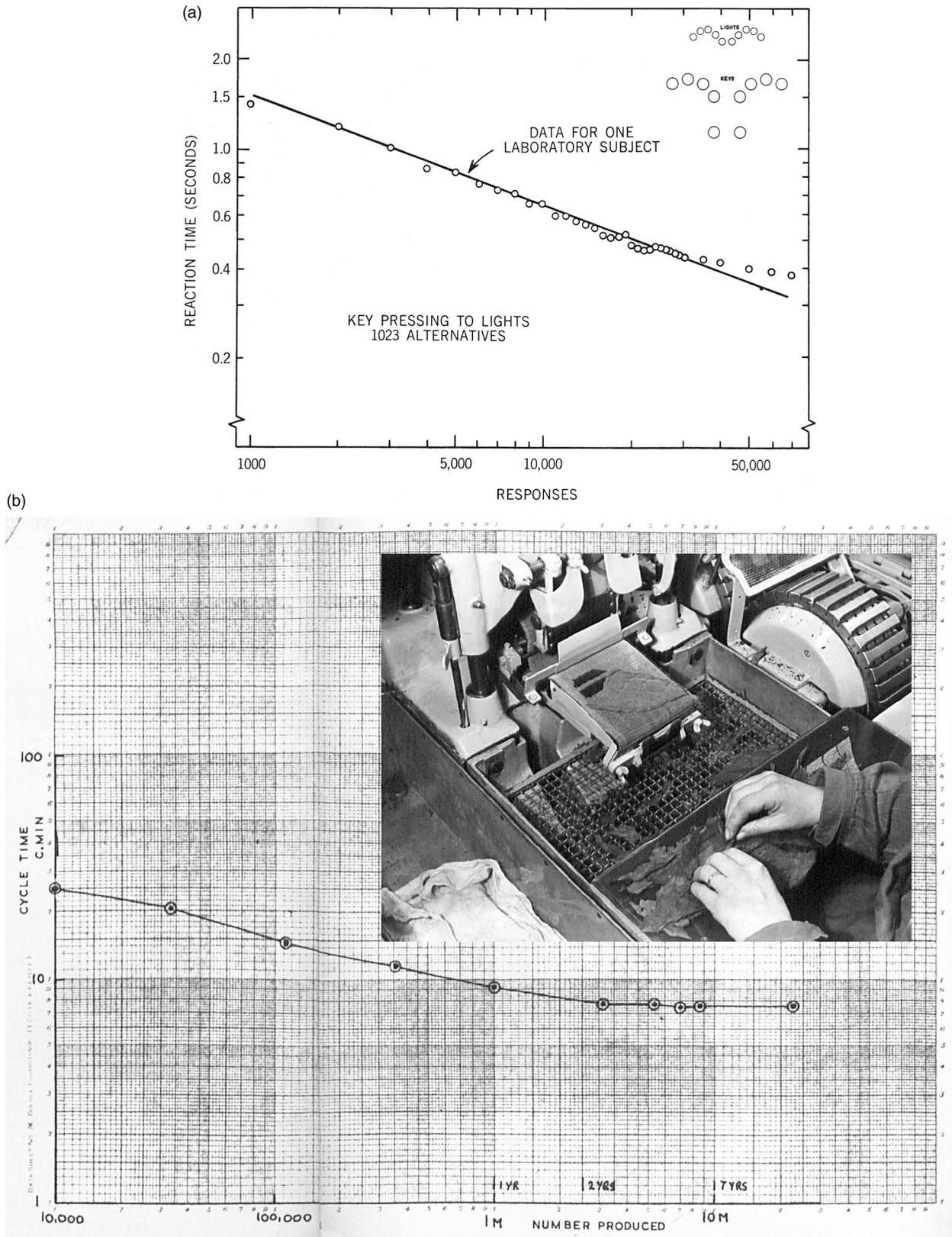
operator is paced by her partner involved in the task of 'wrapper-laying'. The lower limit for completing the bunch-making task was set by the machine, and was approximately 4 seconds. The task was said to involve high workload, both physically and perceptually, as there was large cycle-to-cycle variation in the quality of the leaf. It can be seen from Figure 6(b) that more experienced operators, having produced 3 million bunches so far, performed the bunch-making task about three times as fast than the beginner operator, having 'only' 10,000 trials of experience.

Learning curves apply not only to perceptual-motor tasks, but are found for essentially all tasks, including memorisation tasks as well as performing complex routines such as driving a car (Groeger 2000) or flying an aircraft (Kellogg 1946), and even intelligence tests (Denney and Heidrich 1990; but note that learning how to perform a specific intelligence test does not imply that one has become more intelligent). It may be argued that now that the human operator has become a supervisory controller, perceptual-motor tasks have become irrelevant, as the machine is in control. The irony here is that automation does not supplant human activity; it merely changes human activity (Parasuraman, Sheridan, and Wickens 2000). Unless a task is wholly automated, which is rare as we explained above, safety will be determined by how effectively human operators intervene and reclaim control. For example, in automated driving, the human driver must reclaim control when the automated vehicle exceeds its operational design domain. Research shows that take-over performance can be (and should be) learned, as illustrated in Figure 7. In other words, automating a particular task does not imply we escape the Procrustean mandate.

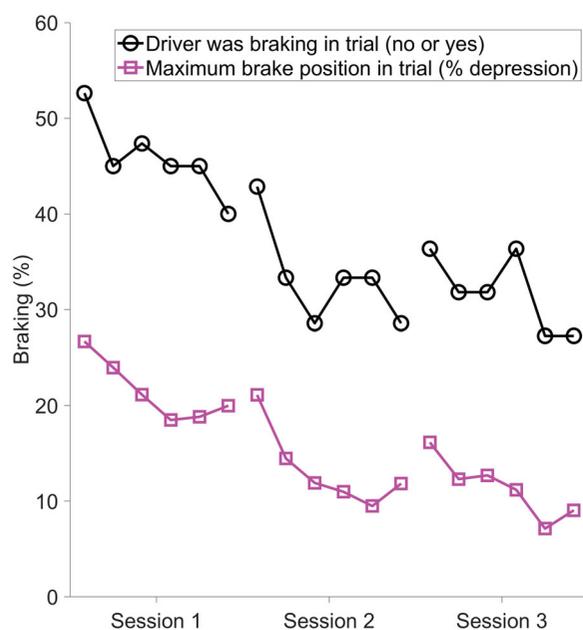
Although training can be powerful, it comes with inherent limitations. In particular, what has been learned for a specific task can easily fail to transfer to another type of task. Worse, in some cases, it can induce negative transfer where performance on a new task is inhibited (Wickens et al. 2015). Transfer is an issue in many areas of human factors, including driver training (De Winter and Kováčsová 2016; Groeger and Banks 2007) and aviation (Lintern and Boot In Press).

## 5.3. Selection

At the beginning of the 20th century, industrial psychologists developed both instruments and tests for measuring performance. These included tests of reaction time and intelligence (e.g. Farmer 1925; Greenwood and Woods 1919; Henig 1927; Moss and



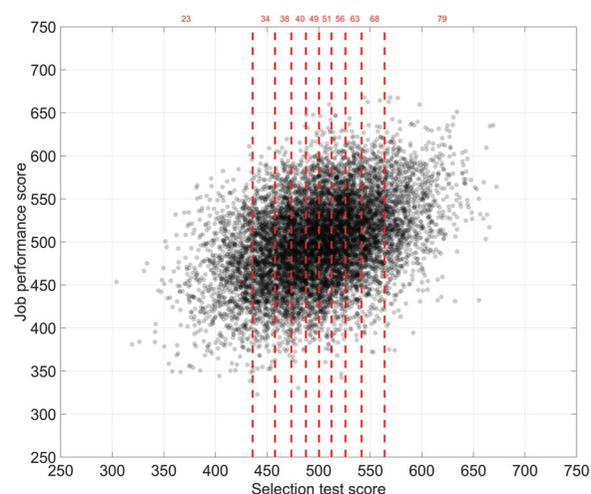
**Figure 6.** (a) Exemplar learning curve which is plotted from the data of Seibel (1963). The participant rested the 10 fingers on 10 response keys shaped to fit a resting hand's natural position. Ten stimulus lights were configured isomorphically to the response keys. A subset of the 10 lights turned on, equalling a total of 1023 possibilities (10 bits of information). The points in the graph show the mean reaction time per 1023 trials. Figure reused from Fitts and Posner (1967) with lights/keys inset from Seibel (1963). (b) Learning curve in bunch-making. Each marker represents one operator's performance averaged over three weeks. Figures reused from Crossman (1956).



**Figure 7.** Learning curve in take-over performance when reclaiming control from an automated driving system. In this experiment with 24 participants, multiple take-overs were performed. The participants gradually learned that they did not have to slam the brakes in response to a static object on their lane and that making an immediate lane change was sufficient. Figure reused from Petermeijer et al. (2017).

Allen 1925; and see Militello and Hoffman 2008). Such knowledge was used for defining pilots' and drivers' productivity and accident proneness, and for personnel selection (Burnham 2009). The basic principle of these selection approaches is illustrated via the scatter plot shown in Figure 8. This figure depicts a typical relationship between test performance on the abscissa and job performance on the ordinate. The test score can be any predictive-valid measure such as cognitive ability, physical ability, psychomotor skill, personality, job experience/knowledge, or a combination of any of these. The job performance criterion may be a measure of performance reported by a supervisor or an objective measure of the worker's quality and productivity. The predictor and criterion variables are normally distributed, both illustrated using an arbitrary mean of 500 and a standard deviation of 50. In this case, the correlation coefficient equals 0.4, which we regard as a realistic number based on previous research in industrial psychology (e.g. McDaniel, Schmidt, and Hunter 1988).

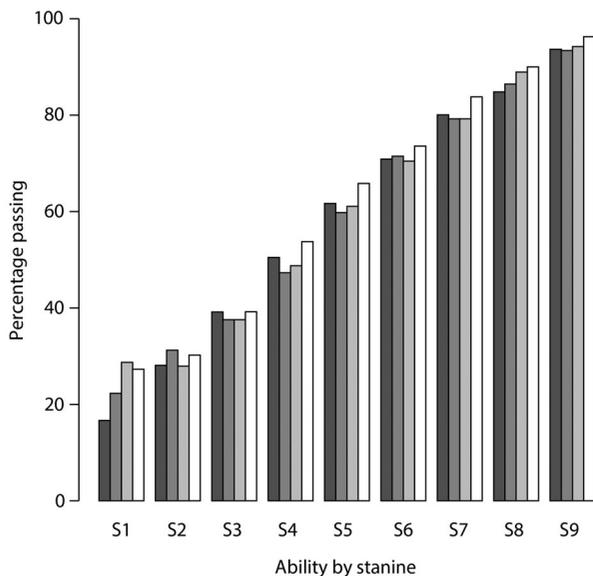
A measure with a high correlation coefficient (also called 'validity coefficient') is useful for selection because employers can then assume that applicants receiving a high score on the test will perform well on the job itself. Setting a high cut-off score will only be feasible when there are a high number of applicants.



**Figure 8.** Simulated correlated ( $r=0.4$ ) bivariate normal data. Both variables have been normalised so that the mean equals 500 and the standard deviation equals 50. The vertical dashed lines delineate the deciles. The red numbers on the top of the figure show the percentage of subjects exceeding the threshold score of 500. The total number of subjects equals 10,000. A similar figure was presented by De Winter et al. (2019).

Figure 8 shows that with these realistic parameters, people in the lowest decile have a 24% probability of performing above average. In the upper decile, 77% of people perform above this threshold. Thus, with a valid selection procedure, the pass rate of candidates may again be improved by the emergingly common factor of three. These synthetic observations match empirical data, as shown in Figure 9. For example, Revelle, Wilt, and Condon (2011), based on the work of Dubois (1947), illustrated the power of worker selection in a military context. They stated: '... point biserial validities for cognitive and psychomotor tests for predicting training success, for example for pilots, navigators, and bombardiers, were roughly .45 across various samples and could be presented graphically in a manner that showed the powers of selection' (11). The criterion variable in their case was whether the trainees completed or were eliminated from training due to flying deficiencies, fear of flying, or at their own request. The predictor variable was a weighted sum of intellectual tests, perceptual tests, motor performance tests, and personality information.

The selection of operators comes with its limitations. In particular, there may simply not be enough people for the job, and selection risks excluding certain people altogether. Selection raises ethical questions of various sorts, for example, regarding inclusivity and fairness of judging people based on a statistical metric.



**Figure 9.** Percentage of four cohorts of pilots passing their flight training as a function of selection test scores (grouped in nine stanines: S1–S9, total sample sizes per stanine for all four cohorts combined: 452, 1046, 3852, 6460, 8201, 7500, 5847, 3583, 3989; sample sizes per cohort ranged between 9617 and 11010). The differently shaded bars represent different cohorts. Figure reused from Revelle, Wilt, and Condon (2011), based Dubois (1947).

Present-day technology, such as household robots, should be accessible to a wide array of people, not just a narrowly selected subset of the population, such as astronauts or control room operators.

## 6. Conclusion: the need to adapt the machine to the human

This paper evaluated the relationship between human and machine, from the viewpoint of human biological and technological evolution. As pointed out above, the genus homo and the first stone tools appeared about 2.8 million years ago. In the past few million years, humans and technology have co-evolved in a fashion whereby the increasingly sophisticated tools offered access to richer food resources, safer habitats, etc., which fuelled the development of the brain (Ambrose 2001; Hancock 2000). However, the development of technology has increased exponentially, which means that human limitations have become increasingly evident, especially now that machines have become intelligent and the human has become a supervisory controller, who has to monitor, plan, and diagnose. With the proliferation of robots into everyday lives, supervisory control is becoming more and more prevalent.

Our analyses have shown that Procrustean approaches provide limited potential for coping with the increasing demands posed by technology: By adapting the human to the machine in some fashion, and by selecting the right person for each job, a threefold improvement can anticipatably be achieved, as was illustrated using various examples.<sup>6</sup>

In summary, adapting the human to the machine is effective to a certain extent but cannot represent a satisfactory lasting solution for coping with the increasing complexities of technology. We, therefore, conclude that the interaction between human and machine needs to be studied and that the machine (robot) needs to be adapted to the human.<sup>7</sup> Our observation is in line with an earlier article on the birth of human factors science by Taylor (1960), which was written before the advent of computers, and which stated that '*machinery had finally outrun the man's ability to adapt*' and that, as a consequence, the limitations of the Procrustean approach had been reached (see also Taylor and Garvey 1959). The current paper offers a renewed outline of the importance of human factors, bearing in mind that now robots are being introduced to increasing extents.

We end this paper with an overview of research methods since the 1900s, and a brief outlook for future research. As illustrated in Table 1, research into Procrustean methods thrived before the Second World War. This is not to say that these research findings are currently unimportant. In fact, it is important to train and select operators: as we have shown, these methods are highly useful, but only to a limited extent. Contemporary research into training and selection, in many cases, yields little new scientific knowledge but merely confirms the findings from classical studies from a century ago. In the past, operators may learn to use a manually controlled system, and today, operators may learn how to use an automated system or robot. Still, the fundamental limitations of humans remain the same. In fact, when using automation, loss of skills is a concern, because the automation (flight management system) rather than the human is in control for most of the time (Parasuraman 2000).

Since the Second World War, technology developed so quickly that the need for human factors, that is, to fit the machine to human cognitive abilities, has become imperative. We recognise multiple post-WWII areas illustrative of human factors science, listed by their introduction era. Table 1 demonstrates that research topics in human factors shadow the state of technology. In the 1950s, human factors research was mostly focussed on eliminating gross errors caused by

**Table 1.** Historical overview of developments in human factors.

Period of dominance	Topic and example questions
Pre-WWI: research into Procrustean methods: adapting the human to the machine	
1900s	<b>Training:</b> How do people learn a task, and how can we steepen the learning curve? In 1898, Thorndike published the first-known learning curves (Thorndike 1898), and in later years studied how students and workers learn a diverse set of tasks (Thorndike 1912; Thorndike and Gates 1929).
1910s	<b>Procedures:</b> How should work procedures be created, and how should labour be divided into simple repetitive tasks, so that productivity is maximized? In 1911, Taylor published his landmark book called <i>Scientific Management</i> (Taylor 1911).
1920s	<b>Selection:</b> How can we predict which human operators are more productive than others, and more likely than others to be involved in an accident? (Greenwood and Woods 1919). Much research on this topic followed in subsequent decades.
Post-WW2: human factors research: adapting the machine (robot) to the human	
1940s	<b>Birth of human factors science.</b> The first human factors studies were conducted, including a study on how well naval personnel could remain attentive to a radar screen (Mackworth 1950), a study on how cockpit instruments should be designed so that pilots distribute their visual attention efficiently (Fitts, Jones, and Milton 1950), and a study on the errors pilots made in cockpits (Fitts and Jones 1947). These studies were conducted before the Second World War, and published after it.
1950s	<b>Knobs and dials research.</b> Researchers set up labs at universities. It was investigated by means of which display and control design principles performance could be improved (Chapanis and Lindenbaum 1959; Fitts and Seeger 1953). There was not much of a theory or mathematical model of human factors science.
1960s	<b>Borrowed engineering models.</b> The knobs and dials phase gradually became exhausted, and human factors researchers started to examine whether human performance could be mathematically modelled by using theories from the engineering domain (control theory, detection theory, information theory). Do these models allow us to better understand how humans cooperate with machines, especially in manual control (tracking) tasks (McRuer and Jex 1967; Senders 1964)?
1970	<b>Human-automation interaction research.</b> How do humans behave in the role of a supervisory controller, for example, in aviation? What type of feedback and support would human operators need (Bainbridge 1983; Sheridan 1976)?
1990s	<b>Adaptive automation.</b> Can a new form of human-machine cooperation arise by letting the automation automatically adapt, or trade control to the human, as a function of the state of the environment, task performance, or human state (e.g. attentiveness, stress) (Byrne and Parasuraman 1996; Scerbo 1996)?
2000s	<b>Shared control.</b> Supervisory control implies a human <i>versus</i> machine perspective. Proponents of shared control would argue that it is a human <i>and</i> machine perspective that we ought to adopt. Would it be meaningful and fruitful to let a human and machine perform a complex task, such as car driving, at the same time? (Abbink, Mulder, and Boer 2012; Griffiths and Gillespie 2004). Whether the future role of humans will be a symbiotic relationship form of shared control is yet unknown.
2010s	<b>Towards a broader use in real-world applications,</b> for example: How do drivers reclaim control from an automated vehicle (Gold et al. 2013; Zhang et al. 2019)? What type of human-machine interface is needed for automated driving?
2020s	<b>Human-robot interaction and connectivity.</b> How do multiple humans interact with multiple robots in a complex setting? How should information and knowledge be distributed? How can the robot learn from the human, and how can the human be supported by the robot (Tabone et al. 2020)? How should teleoperated robots be supervised in healthcare and agriculture, amongst others?

poor control and display design, such as found in cockpits of aircraft. We again note that scientific knowledge is cumulative; thus, the fact that research was conducted many decades ago, does not mean that it is in any way irrelevant as of today. Sheridan (2002) has stated: *'This early empirical phase has often been called (disparagingly) 'knobs and dials engineering.' The design of displays, controls, and workplace layouts, however, has remained as important as it ever was.'* Similarly, Chapanis (1979) explained: *'The words 'knobs and dials' are usually spoken in a disparaging, or at least condescending, tone of voice. I don't think that working with knobs and dials is anything that any of us should be apologetic about. I am constantly impressed by how often very simple principles of good display and control design are still violated in the many tools and devices we see around us.'* In later decades, the knobs and dials phase became exhausted, and human factors researchers started to use engineering methods to

model human performance, a research phase called 'borrowed engineering models' (Sheridan 2002).

The decades that followed, the research focus became more on how humans and computer-based/automation system should either trade or share work. Since about 2010, research in human factors has become mainstream, as automated products and robots have appeared on our roads and households, amongst many other domains. Present-day research questions concern how robots and humans should cooperate) and distribute knowledge, developments that match technological innovations such as the Internet of things.

## 7. Outlook

Much of our discourse has been directed to understanding why human factors is an essential aspect of developing a technologically founded civilisation. But

what of the future? Much has been written about such prospects, even within the human factors literature (Bartlett 1962; Hancock 2008).

As pointed out in this paper, our age is characterised by automation. Ever greater swathes of human work are being subsumed under automation's inexorable tide. The current epidemic appears to have been catalytic to automation, as demonstrated by the growth of companies that rely on connectivity and robotics, including videoconferencing, cloud computing, and e-commerce businesses.

Discrete human professions are, generation upon generation, 'forgotten' and foregone, as the technological substitute proves more cost-effective. Residual human tasks remain solely due to the inability to provide robotic replacements. But this and other barriers are frangible to the innovations of technologists, and once breached, we do not go back (cf., Hancock 2009).

Although it has been opined that no fully autonomous system is yet proved, it can be debated that certain large-scale social media enterprises are optimising goals beyond human agency control. Autonomous systems are essentially artificial organisms let loose in the world to exploit opportunities, contingent upon their initial optimisation programming. Largely software-based agents, they are beginning to have a physical presence in our world through innovations such as advanced road vehicles. Where one form of autonomy has invaded the physical world, others will be quick to follow. Of course, their efficiency imperative will drive humans from these work domains; our grandchildren will have to look up words like truck driver and taxi driver since it will no longer be in common parlance.

Upon these bases, we can begin to point where human factors science is heading as a discipline. Whether humans' future role will be a collaborative relationship with (tele-)robots in the form of shared control, or a purgatory monitoring of automation systems that set the pace, is yet to be determined. The optimists cling to a belief that new collaborative work is engendered for emerging human-robot teams. However, they may be wrong: it is not so much that we *cannot* generate such new collaborative working patterns but rather under the driving imperative of profit-centered, as opposed to human-centered, motives, we do not. And until some catastrophic circumstances demand such change, we presumably will not. Of course, autonomy's influence need not necessarily take this direction, but at this present time, it is unlikely to change direction radically. However, we cannot, for the optimists, rule out the notion that autonomies, *sui generis*, may themselves take a more beneficial direction.

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## Notes

1. Which types of equations are most appropriate (e.g. exponential vs. power law) is uncertain. For example, it has been argued that an exponential decay function offers a good fit to empirical learning data just as well or even better than a power law (Heathcote, Brown, and Mewhort 2000). Note that we aimed to illustrate the rate of change of human versus technological capabilities, and it will not matter much what the mathematical function provides the most parsimonious fit. We believe that the exponential function has popular appeal in the media and among futurists and that the widespread popularization of exponentiality may be exaggerated (and see Sandbach 1978).
2. **Are humans still evolving?** Although we argue that biological evolution is negligible compared to technological evolution (see Figure 5), some have posited that humans have been evolving rapidly in the last 10,000 years (Cochran and Harpending 2009). It has even been proposed that human evolution operates on time scales as short as a single century. For example, 'heterosis' has been proposed as an explanation of the Flynn effect of rising intelligence test across the immediate past decades (Mingroni 2007). Nonetheless, even a substantially more rapid human evolution than is depicted in Figures 1 and 4 does not undermine the essence of our present arguments.
3. It can be argued that the rapid introduction of technology does not imply that this technology is actually adopted rapidly. Indeed, only a portion of technological inventions are commercialized, and it seems to take at least two decades for innovations to become adopted on a wide scale (Gross et al. 2018; Woo and Magee 2017). However, this does not negate our argument that the pace of technological change is accelerating, both for researchers (i.e. the pre-commercialization phase) and the public.
4. **The Robots Are Coming.** These technological and societal developments are paralleled in research and education. University programs worldwide explain artificial intelligence and robotics. At TU Delft, for example, a new MSc study 'Robotics' has recently been inaugurated. This degree, which originated in the faculty of mechanical engineering, explicitly addresses the fact that machines are becoming intelligent and are able to move around in complex human-inhabited environments.
5. Procrustes ('the man who beats out'), also called Damastes ('he who lays people low'), was a Greek mythological bandit, who represented an antitype to civilized behaviour (Mills 1997). Procrustes was known for 'offering hospitality to the passers-by, he laid the short men on the big bed and hammered them, to make them fit the bed; but the tall men he laid on the little bed and sawed off the portions of the body that projected beyond it' (Apollodorus 1921, 133). Procrustes was killed by Theseus, who represents the embodiment of the

idealized image of Athens (Mills 1997; Walker 1995). The story of Procrustes and fellow bandits was invented around 510 B.C.E. (Brommer 1982), possibly for political reasons (Walker 1995).

6. **Is the Factor Three Veridical?** We provided examples that showed that training, procedures, and selection can yield a threefold improvement in task performance. The factor three is only an estimate that is contingent upon various assumptions. The three Procrustean methods can be applied in isolation or in combination (e.g. training combined with procedures), in which case promised improvements of  $3^3 = 27$  may even potentially be attainable, assuming that the three effects are multiplicative. Also, the factor three might be an underestimate because sometimes an extremely high mastery of skills can be acquired through several thousands of hours of deliberate practice (Ericsson 2014). So, the fit parameters  $a$  and  $b$  of Equation 2 certainly depend on the type of task that has to be learned, with higher degrees of learning (and corresponding individual differences) being likely for tasks that involve large amounts of domain knowledge (Ackerman 2007). The factor three may also be an overestimate. For example, Fordism is known to have led to job dissatisfaction and hampered worker's productivity in the long term. The ineffectiveness of training for raising intelligence (e.g. Chooi and Thompson 2012; Redick et al. 2013) illustrates that training may have only limited effects that transfer poorly to new contexts (see also Groeger and Banks 2007). Furthermore, prior knowledge on the task and possible ceiling effects in the performance measure will necessarily influence the degree of learning. Yet, regardless of how optimistic we are concerning such factors as selection and training, it is still the case that these methods alone will be of limited use in human-machine interaction.
7. **The Importance of Human Factors: An Illustration.** The significance of human factors science can be illustrated using a classical example: the Space Shuttle. In early test flights of this spacecraft, there appeared to be an unstable and potentially highly dangerous mis-coupling between astronaut and spacecraft. Even though the test pilots were extensively trained and biologically fit, they were unable to prevent this oscillation, which occurred during landing. The underlying cause turned out to be that the pilot's inputs to the flight control computer were taking approximately 250 ms to exert an effect upon pitch responses. The result of this time-delay proved to produce a control instability, known as a pilot-induced oscillation. To correct this problem, researchers at the Dryden Flight Research Center developed a suppression filter that automatically reduced the Shuttle's stick gain for high-frequency inputs (Smith and Edwards, 1980). This example of the Space-Shuttle clarifies that not only the properties of technology but also the cognitive (and biomechanical) abilities of the human (i.e. 'human factors') determine the behaviour of the dyadic human-machine system. In recent decades, the science of human factors has been extended from the focus on momentary manual control in human-machine

operations towards a primacy of supervisory control of automation systems (e.g. Dul et al. 2012; Sheridan 2002).

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