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# EFFICIENCY 4.0 FOR INDUSTRY 4.0

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Abstract: *Operators of cyber-physical production system (CPPS) will use handheld interactive control panels for supervising production processes. These interactive and handheld control panels will present numerous sensors data. Processing of such complex data for task fulfilment in critical scenario will cause cognitive workload on operators. The prevalent industry efficiency measures so far have focused on human physical workload measures; the human cognitive load has not been considered in industrial practices. Smart factories in the near future will begin to integrate intelligent machines with complex communication network systems between human and machines. In this paper, we argue that the changing industrial scenario requires developing new measures of production efficiency. As a result, we propose a theoretical framework for a smart factory efficiency measure as a function of the combined efficiencies of the human cognitive system, smart machines, and their shared communication systems.*

Keywords: *Industry 4.0, HCI, human cognitive efficiency, production efficiency.*


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## INTRODUCTION

With successive industrial revolutions, the workload of factory operators increasingly has shifted from physical exertion to cognitive workload due to the increase in complexity of information and the increasing use of information communication technology in factory automation (Wittenberg, 2015). In Industry 1.0, often a single operator was appointed to supervise the complete production process from the electromechanical dials attached locally to machines (Deane, 1965; Streans, 2013). The operator had to walk around the factory, going from machine to machine to gather information about the status of the machines and the production process. In Industry 2.0, it became possible to monitor the mass production process parameters from isolated control rooms. Large control panels with dedicated sections for machine parameters were monitored by multiple specialized operators (Astrom, 1985). In Industry 3.0, the current iteration in industrial evolution, computer-based manufacturing systems are integrated into the production operations and often involve multiple computers (i.e., the programmable logic controller & the supervisory control and data acquisition systems). In some operations, robots are used to supervise the production process remotely (Bailey & Wright, 2003; Briones, Bustamante, & Serna, 1994).

Industry 4.0, predicted as the fourth industrial revolution, will bring together information technology and factory automation (MacDougall, 2014). Industry 4.0 will use the Internet of things (IoT) in production systems to create a cyber-physical production system (CPPS; Lee, Bagheri, & Kao, 2015). The CPPS is envisioned as the core technology of Industry 4.0, which will comprise technologies such as wireless embedded network systems, IoT, and network cloud computing in a manufacturing setting (Sniderman, Mahto, & Cotteleer, 2016). CPPS is characterized by sharing production operation information over the Internet with multiple systems in the smart factory. Additionally, machines will be able to communicate production data with each other using embedded network systems. In Industry 4.0, the use of small, handheld mobile devices to control and monitor the production system will become prevalent. Finally, most factory data will be supervised through IoT-based human–computer interaction (HCI) systems. With the merging of information communication technologies (ICTs) with automation in a CPPS, production units will become smarter but also more complex at the visual, auditory, and other sensory levels (Wittenberg, 2015). The consecutive industrial revolutions are shown in Figure 1, as the ways humans and machines interact have evolved from Industry 1.0 to Industry 4.0 technology.

The increasing information complexity and its influence on production efficiency is a multidisciplinary challenge, where knowledge from cognitive psychology, ergonomics, operations management, communication technology, computer science, industrial design, HCI, manufacturing technology, instrumentation engineering, and others, must be addressed for the optimal design of control and display units in CPPSs. In this paper, we have drawn on concepts from multiple disciplines to develop a measure of industrial efficiency within this increasingly information-complex context.

Contemporary research literature has shown that the CPPS concept enables an ecosystem of cyber manufacturing in the factory environment (Lee et al., 2015). In the CPPS environment, smart machines process the production data through a wireless embedded network system to manufacture smart products (Li et al., 2017). This was demonstrated in a case study of a wireless network design prototype in small factory conducted by Wang, Wan,

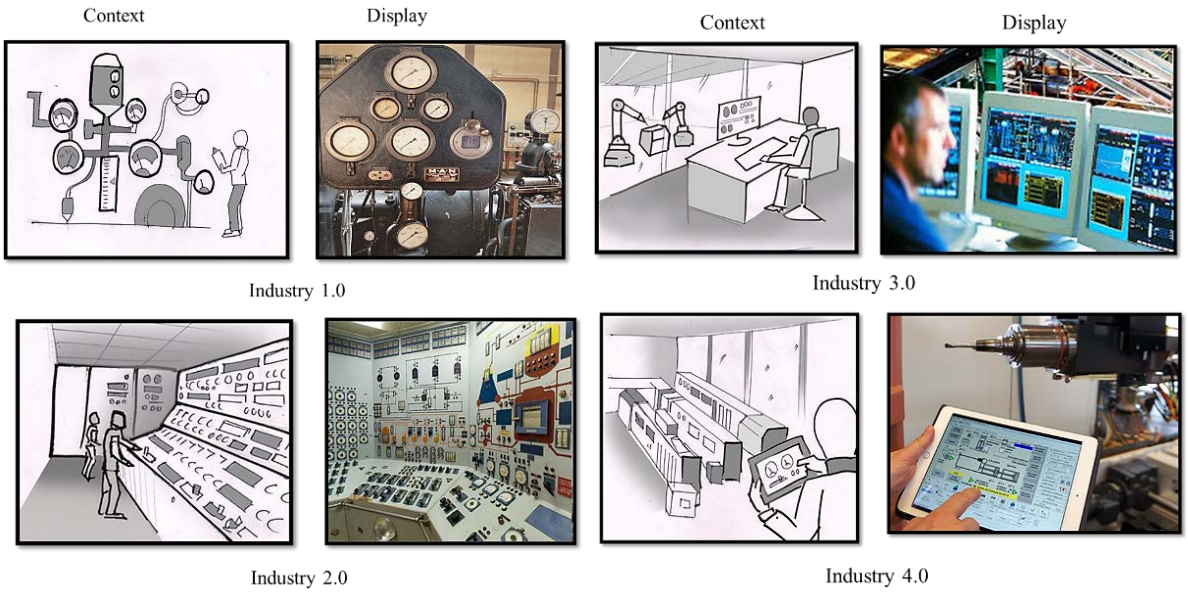


**Figure 1.** The significant changes in the process scenarios of human–machine interaction from Industry 1.0 to Industry 4.0.

Li, and Zhang (2016). As the manufacturing industry has slowly developed, the concept of Industry 4.0 (Posada et al., 2015), smart factories (MacDougall, 2014), networked manufacturing (Davis, J., Edgar, T., Porter, J., Bernaden, & Sarli, M., 2012), and other new frameworks (e.g., Wu, F. J., Kao, Y. F., & Tseng, Y. C., 2011; Zhang, D., Wan, J., Liu, Q., Guan, X., & Liang, X., 2012) have been proposed. Meanwhile, new ICTs, such as the industrial cloud (Wan, J., Zhang, D., Zhao, S., Yang, L., & Lloret, J., 2014), big data (Chen, M., Mao, S., & Liu, Y., 2014), wireless cloud networks (Wan et al., 2013), the industrial Internet of things (Lee et al., 2015), and high performance embedded systems have been introduced into the manufacturing processes to meet the demands for higher productivity.

Moreover, due to technological interventions in CPPSs, production information can be stored to and retrieved from networked clouds anywhere and anytime by human operators and as well as smart machines. Human operators can access production information through Internet-operated HCI devices. Smart machines can record sequences of human actions on machine interfaces to develop intelligent algorithms and, subsequently, reduce human workload in the production processes. Adaptive automation is the term used for this phenomenon (Kay, 2006; Villani et al., 2017).

Although CPPS machines are becoming more intelligent and may control and monitor the processes on their own by employing machine-learning algorithms (Lee et al., 2015), human interventions in production processes will still be required. Research in this area suggests that this monitoring of CPPSs will involve handheld mobile devices with rich interactive user interfaces (Meixner, Petersen, & Koessling, 2010) to monitor and operate the factory machines, often presenting complex information for real-time decisions (Villani et al., 2017; Zhong, Dai, Qu, Hu & Huang, 2013). This increased complexity in the data for humans in control operations will create increasing loads on the human information processing system; this information load in the brain is known as cognitive load (Sweller, 1988). Due to higher attentional requirements in the tasks, human working memory is likely to be severely strained with relevant and irrelevant data

(Brunken, Plass, & Leutner, 2003). Such data overload will increase the possibilities for human errors in tasks and a decrease in overall human performance. Thus, we posit here that the cognitive load caused by the design of these complex interfaces will become an important factor in the efficiency measure of the Industry 4.0 factories.

In current manufacturing processes, the efficiency of production units is measured by machines and manpower utilization functions (Subramaniam, Husin, Yusop, & Hamidon, 2009). While physical manpower played a central role in industrial efficiency of the first industrial revolution (Subramaniam et al., 2009), successive industrial revolutions have decreased the burden on human's physical workload while increasing the cognitive load due to an upward trend in information complexity and task complexity (Wittenberg, 2015). However, the efficiency measures prevalent in industry are still using manpower utilization as the central concept. Hence, modern industry needs to accommodate the cognitive workload in the efficiency measures (Subramaniam et al., 2009). In this paper, we propose a framework to measure the *human cognitive efficiency* (HCE) as a factor in overall industry efficiency.

Further, because ICTs in Industry 4.0 will use multiple communication protocols and network devices for making production processes functional across multiple shop floors, the centralized supervision of machines will become possible (MacDougall, 2014; Zhong et al., 2013). Therefore, we posit that the communication efficiency of network systems will increasingly affect the efficiency in future smart factories in Industry 4.0. To accommodate the network efficiency within the industry efficiency measure, we propose a *communication system efficiency* (CSE) component as part of the overall industry efficiency measure.

Moreover, as machines become endowed with increased information-processing capacity, the efficiency of the machines will require alternative considerations beyond the mere manual output-to-input ratio that is used presently in industry efficiency measures. Although machine efficiency measures as part of industrial production efficiency have been reported in literature (Daniel, 2006; Muchiri & Pintelon, 2008; Subramaniam et al., 2009), large data storage and fast processing capabilities of smart machines have not been factored into present measures. Smart machines in CPPSs are envisioned to have artificial intelligence algorithms that will optimize the production process operations automatically (Lee et al., 2015). Thus, we also propose in this paper the concept of *smart machine efficiency* (SME) as a factor in the overall production efficiency measure.

Thus, we employ the term *smart factory efficiency* (SFE) in this paper to represent the overall industrial efficiency measure. We propose that SFE be measured as a function of the above three measures, namely HCE, CSE, and SME. Table 1 provides a reference guide for the multiple terms and abbreviations used in is paper.

The aim of this paper is to highlight the need to reconsider the industrial efficiency measure within the changing context of the CPPS and then to propose a new framework for the efficiency measure. Thus, the contributions of this paper to the field are (a) the introduction of new industrial efficiency parameters, namely, HCE, CSE, and SFE, (b) the proposal of a mathematical relationship to measure cognitive load in industrial context, (c) a proposal of mathematical relationship to measure communication speed in industrial context, and (d) a proposal of a mathematical relationship to measure smart machine efficiency in industrial context.

In the following sections of this paper, we discuss prevalent production efficiency measures. We then propose a novel of smart factory efficiency measure, develop and discuss new

**Table 1.** Definitions of Significant Abbreviations in the Smart Factory Efficiency Framework.

| Abbreviation | Term/Definition |
|---|---|
| CL | Cognitive load (on human mental processing) |
| CPPS | Cyber-physical production system |
| CSE | Communication system efficiency |
| HCE | Human cognitive efficiency |
| HE | Human efficiency |
| HPE | Human physical efficiency |
| K | Demographic and psychographic constant |
| OEE | Overall equipment effectiveness |
| SFE | Smart factory efficiency |
| SME | Smart machine efficiency |
| TE | Task efficiency |

mathematical models to measure cognitive load, communication accuracy, and machine efficiency. We conclude the paper with a discussion of the implications of the proposed framework.

## PREVALENT PRODUCTION EFFICIENCY MEASURES

At the beginning of industrialization, measurement of production efficiency was estimated by a simplistic output-to-input ratio. Later, more sophisticated measures were developed. For example, Cobb and Douglas (1928) proposed a mathematical relationship between inputs—namely, physical capital, labor, and the amount of output produced. The "Cobb-Douglas production function" is expressed as $Q (L, P) = A * L^{\beta} * P^{\alpha}$, where, Q (the quantity produced from the inputs) is a function of L (the amount of labor spent in the production), and P (the physical capital like machines, factories, computers, etc.). Further, in Cobb-Douglas production function, A is the measure of change in output that is not the result of the input (e.g., factors like the technology in a manufacturing setup), while $\alpha$ and $\beta$ are the output elasticity, that is, the change in output that results from a change in either L or P values. For example, if $\alpha = 0.60$ and P is increased by 20% then output increases by 11%, given that other factors are constant.

Another measure, the overall equipment effectiveness (OEE), is quoted often in the literature (Muchiri & Pintelon, 2008; Nakajima, 1988). OEE has been used widely in industry as a production efficiency measurement. A direct relationship between the machine efficiency and manpower utilization in the OEE calculation also has been reported (Subramaniam et al., 2009). The term OEE was derived originally from the philosophy of the total productive maintenance concept, which states that the greater the level of factory automation in industry, the greater will be the cost reduction (Nakajima, 1988). OEE has been defined as a measure of total equipment performance (Muchiri & Pintelon, 2008) and it has been calculated as in Equations 1–5.

$$\text{OEE} = \text{AR} * \text{PR} * \text{QR} \tag{1}$$

$$\text{Availability Rate (AR)} = \frac{\text{Operating time} * 100}{\text{Loading time}} \tag{2}$$

$$\text{Operating time} = \text{Loading time} - \text{Down time} \quad (3)$$

$$\text{Performance Rate (PR)} = \frac{[\text{Machine cycle time} * \text{Actual output}]}{\text{Operating time}} \quad (4)$$

$$\text{Quality Rate (QR)} = \frac{\text{Total production} - \text{Defect amount}}{\text{Total Production}} * 100 \quad (5)$$

Although the OEE tool has been one of the most prevalent measures of production efficiency of manufacturing units, it has been criticized as well. Reports in the literature state that the calculation of OEE alone is not sufficient because no machine is isolated in the production unit (Oechsner et al., 2002). Scott and Pisa (1998) argued that the production process is a complex network of interactions among materials, machines, humans, and other processes; these interdependent factors have not been merged together to measure the production efficiency. Lee (2015) suggested a five-function framework for CPPS, involving smart communication, data-to-information conversion, cyber-level, cognition level, and configuration level. He has compared prevalent production efficiency measures with proposed Industry 4.0 production system efficiency factors and argued for improvement in OEE equations when applied to Industry 4.0. Similarly, Chen et al. (2018) reported a case study of the application of OEE in the Industry 4.0 context and argued for need to include more factors in the efficiency measure. Because the differentiating factor in Industry 4.0, as compared to Industry 3.0, is the use of information technology in machines that will increase the complexity of interactions (Gorecky, Schmitt, Loskyll, & Zühlke, 2014), we argue here for expanding the OEE to accommodate the changed environment of production. Additionally, there is a need to identify the factors that will affect the new measures in SFE.

## PROPOSAL OF A FRAMEWORK FOR SMART FACTORY EFFICIENCY (SFE) MEASURE

The context of Industry 4.0 will shift the focus from production as an equipment-led activity to a smart factory activity that uses intelligent communication technology for industrial production processes. Up to now, the industrial production efficiency has been measured as OEE, which is calculated as a product of availability, performance, and quality as in Equations 1–5 (Muchiri & Pintelon, 2008; Nakajima, 1988). We are proposing a new framework, the SFE, to cover the newer dimensions that have emerged in production efficiency. The SFE is measured as a function of HCE, CSE, and SME, as expressed in Equation 6.

$$\text{SFE} = f(\text{HCE}, \text{CSE}, \text{SME}) \quad (6)$$

The next subsections present each of these three efficiency measures in detail. Then, following that, we provide a comparative discussion of OEE versus SFE.

### Human Cognitive Efficiency (HCE)

Human efficiency in the industrial context can be an outcome of the combined cognitive and physical efficiencies, as in,

$$\text{HE} = f(\text{HCE}, \text{HPE})$$

where HE is human efficiency, HCE is human cognitive efficiency, and HPE is human physical efficiency.

However, due to the adaptive automation movement in the design of industrial information systems (Kay, 2006), the human physical tasks are increasingly being allocated to the machines. Still, the HPE will require "human-in-the-loop" control models that will necessitate increased cognitive abilities with aid of intelligent human–machine interfaces (Romero, Bernus, Noran, Stahre, & Fast-Berglund, 2016). Smart factory supervision will demand higher cognitive workloads (Villani et al., 2017). Thus, the cognitive load will become a far more important consideration within the HE measurement in the Industry 4.0 context, as compared to the physical workload. Hence, in our research, HE has been proposed to be measured as a function of cognitive efficiency alone, as represented in Equation 7.

$$HE = f(HCE) \tag{7}$$

Paas and Van Merriënboer (1993) reported an attempt to measure "mental efficiency." They proposed an empirical formula for "performance and mental effort" as a measure of mental efficiency, as in Equation 8.

$$\text{Mental Efficiency} = \text{Mental Effort} - \text{Performance}/\sqrt{2} \tag{8}$$

As per Paas and Van Merriënboer (1993) in Equation 8, mental effort is the effort toward holding task information within one's cognitive capacity, whereas performance is one's success in the task. They had proposed this relationship based on the subjective self-assessed mental effort reported by problem solvers. However, in Paas & Van Merriënboer model, subjective self-reported ratings on performance and mental effort were gathered after task fulfillment. Therefore, although individual users can be asked for subjective rating, it will be difficult to model HE across the industry using "felt" mental effort. One of the reasons is that the mental effort in an industrial task can result from various factors, including the industrial scenario, task performance, the environment, time pressure, criticality, and so forth. Some researchers have argued that mental effort indicates some portion of the cognitive load that is imposed exclusively by the type of the task, the time on task, response time, errors, and the environmental demand (Cain, 2007; Kablan & Erden, 2008). Cognitive load thus becomes a better measure of HE then mental effort. Therefore, we propose a framework to measure HE through a cognitive load measure. We propose to define HCE as

$$HCE = TE/CL \tag{9}$$

where CL is cognitive load and TE is task efficiency, to be measured as

$$TE = \frac{\text{Total number of correct tasks within given time}}{\text{Total number of tasks}} \tag{10}$$

TE is proposed to be a ratio of the successful tasks versus the total number of tasks. This ratio is also indicative of HE, but we argue that unless it is factored by the total cognitive load that the user underwent in task fulfillment, the TE itself is not a clear measure of the HCE. Therefore, the CL factor has been included in Equation 9 for measurement of HCE.

As per Equation 9, when a task is completed with a lower CL investment, the HCE will be higher. Thus, Equation 9 paves a way to measure the HCE within the context of a given design. As a result, the design of a control panel should enable the user to achieve the same task

outcomes with a lower CL, thus making it a cognitively more efficient design. This also can indicate that the person has utilized fewer mental resources and therefore the operator has been more efficient. This approach to the HE measures has many implications. For example, the design quality judgment and personal evaluation of operators will become possible with the present framework. However, Equation 9 needs further detail in order to make such assessments possible. Thus, we propose that CL be measured as

$$CL = K * I_P/t \tag{11}$$

where, K represents a constant that reflects user's demographic and psychographic factors such as age, stress level, competency, and so on. $I_P$ is the information to be processed during task (unit: meaningful chunks) and t signifies the time for the task duration (unit: minutes).

Equation 11 is proposed to measure CL in terms of information processed ($I_P$) by users' during task fulfillment in the CPPS context where, for instance, they need to make sense of complex shop floor data, decide on a course of actions, and then complete those actions through the HCI modules that may be stationary or mobile, remote or localized. The information processed per task is proposed to be measured in the unit of "number of meaningful chunks of information" because CL theory emphasizes the constraints on the human cognitive process due to limits on working memory capacity. This is in line with previous research, where units of meaningful chunks of information has been noted as the measurement for working memory capacity (Atkinson & Shiffrin, 1968). Miller reported that a human brain can store in the working memory a maximum of nine meaningful chunks of information at a time, on average (Miller, 1956). Saaty and Ozdemir (2003) added that, when a person is making preference judgments on pairs of elements in a group, the number of elements in the group should be no more than seven. However, recent studies have suggested that the working memory capacity is reduced to three to five meaningful items (Cowan, 2016). Thus, based on the literature (Cowan, 2016; Miller, 1956), meaningful chunks of information ($I_P$) has been proposed as a measure for CL.

The unitless constant K is proposed to serve as a personal demographic and psychographic factor that can influence the user's cognitive performance and can be attributed to the elements such as the age, stress level, and task competency level of the user. Studies have reported the influence of age on cognitive performance. For example, Caplan and Waters (2005) reported slower speed in judgment and paragraph comprehension tasks by elderly study participants. Salthouse, Babcock, and Shaw (1991) reported that older adults were less accurate than young adults in mathematical tasks and hypothesized it to be caused by decreased working memory capacity. Similarly, stress has been reported to influence memory performance (Lupiena & Lepage, 2001). Thus, the constant K in Equation 11 captures these personal constructs affecting the CL. Although prevalent literature reveals the influence of age, stress, and competency on the experienced CL, little evidence is available on the exact proportion of effect of these factors on CL. Therefore, we do not address in this paper the possible values or methods to calculate a constant K.

We argue here that the quality of CPPS-based HCI designs can be measured in terms of the CL. Higher the complexity in task and information, more improvement in the interface design would be require. As per Equation 11, the effort to redesign user interfaces can be directed toward increasing the semantic quality of interfaces. We coined the term *semantic quality* here to address the lack of an appropriate term to describe the ease with which the user of an interface can perceive meaningful information within the context of a task. Because working memory capacity

is measured in terms of meaningful chunks of information, any improvement in the semantic quality of the user interface design will reduce the number of chunks of information required to be held in working memory for task fulfillment, thus reducing the redundant information and/or increased the time needed to comprehend a given set of information. The guidelines in Equation 11 will aid designers of HCI systems in increasing HE in the context of a CPPS.

We note that the proposed HCE is a measure of total mental effort spent in course of completing successful tasks. It is a system measure and not an individual capacity measure. This construct measures the cognitive efficiency of the (generic) human in a cyber-physical production system due to the design quality of the system.

Further, the literature identifies CL as comprising three types (see Paas, Renkl, & Sweller, 2003), namely, extraneous CL (the load caused due to adding irrelevant information in the task), intrinsic CL (the inherent level of task complexity), and germane CL (the load required to develop a new schema). We therefore propose that, in order to investigate the specific causes of CL in specific tasks in a CPPS, the measurement of HCE should zoom into the type of CL required of the user for each task. Thus, we posit here that the CL on a user can be calculated as a function of the three types of CL, as in Equation 12:

$$\text{CL} = f(\text{Intrinsic CL, Extraneous CL, \& Germane CL}) \tag{12}$$

Intrinsic CL has been defined as a function of task complexity and can be calculated by the total information to be processed to complete the task (Paas et al., 2003). For example, the multiplication of two single-digit numbers requires a lower intrinsic CL as compared to multiplying two three-digit numbers (Kumar & Kumar, 2016). Therefore, intrinsic CL can be calculated by estimating the complexity of the task, indicated by the number of steps involved in the task. Intrinsic CL can be written as Equation 13:

$$\text{Intrinsic CL} = \text{CL (Task Complexity)} = f(\text{no. of steps in task, amount of information to be processed in each step of task, frequency of task, etc.}) \tag{13}$$

Further, in cognitive load theory, extraneous CL is defined as CL caused due to presentation of irrelevant information in the task to the user (Paas et al., 2003). Thus, we propose here that, in the context of a CPPS, extraneous CL be measured as CL caused by the difficulty in the semantic interface that results from poor design quality in the user interface, specifically presenting irrelevant information, low-information graphics, incomprehensible textual content and metaphors, inconsistent layout, gratuitous use of colors, incomprehensible feedback, undifferentiable tactile responses, and so on. Hence, extraneous CL can be represented as in Equation 14:

$$\text{Extraneous CL} = \text{CL (Semantic interface)} = f(\text{consistency of layout, legibility of text and information graphics, ease and efficiency of navigation, contrast between foreground \& background color schemes choice of displays, buttons, menus, etc.}) \tag{14}$$

Germane CL is caused by the person's need to create a new schema in the brain because of interacting with the new task or design of the system (Paas et al., 2003). In context of CPPS-

based HCI systems, we propose that the germane CL be measured by *task novelty*, which is the effort exerted by the user to learn the new way of task fulfillment. Germane CL be measured as in Equation 15:

$$\text{Germane CL} = \text{CL(Task Novelty)} = f(\text{difference between the old and new layout of designs/task steps/input methods, display methods, etc.}) \quad (15)$$

Task novelty can be understood as the effort expended by the user to create a new mental model (Johnson-Liard, 2005), or a new schema of the task within the user, that is, creating new internal guidance to complete the task. The new schema is stored in the long-term memory and can be fetched by the user into the short-term memory during task completion. A robust and easily comprehensible schema of the task resulting from the design of the interface will thus help in the HE factors. However, a change in technology and the user interface designs means such schemas will be created by repeated task fulfillment activities rather than mastered in one go. Thus, as depicted in Equation 15, germane CL can be measured as a function of difference between the old and new mental models (Johnson-Laird, 2005) presented through layout designs, steps in tasks, input methods, display methods, and so forth.

The purpose of zooming into the causes of CL challenges at the level of specific HCI design elements by using these equations is to aid the systems designer in identifying possible new options to optimize the cognitive costs of tasks design. Moreover, the HCI designer can refer to prior research on human cognitive capacity (e.g., Cowan, 2016; Miller, 1956) to estimate the optimum level of CL requirements by distributing the information of tasks and time durations to assist the operators. Thus, the HCE measure using these equations can evaluate not only the status of the system, but it also can guide the designers of a CPPS to improve the system during the design process.

This section has proposed equations to measure a technology system's HCE as a factor of three types of CL, namely, intrinsic, extraneous, and germane. We also discussed the factors influencing these types of CL in the CPPS context. Next, the CSE is discussed.

## Communication System Efficiency (CSE)

In CPPSs, smart machines communicate wirelessly with other machines and humans. These smart machines also have the capacity to process large amounts of information in a very short time. A CPPS will reduce the need for human intervention, but human activity typically will be required to monitor and make critical decisions. Efficiency in a CPPS's communication system also will depend upon the speed and accuracy of information as it travels machine to machine, machine to human, and human to human. Developing a CSE measure requires a discussion of the context of a communication system within Industry 4.0

Complicated usage of wireless communication is a given in Industry 4.0. Wireless communication technologies—such as Bluetooth, machine-to-machine communication, radio frequency communications, Wi-Fi, Zigbee—will be used over a secured Internet protocol (Da, We, & Li, 2014). As a continuation of electronic communications started in Industry 3.0, Industry 4.0 will increase the types of communication protocols to manage the types and amount of information. We posit, therefore, that the CSE is a measure of how quickly the correct information will reach to the desired nodes in the system. Equation 16 presents CSE as

a function of speed and accuracy of the information.

$$CSE = f(\text{Speed of information, accuracy of the information}) \quad (16)$$

In order to argue for the development of Equation 16, we provide a likely picture of the CPPS environment in Figure 2. A typical CPPS system will consist of multiple smart machines within each production unit that could be spread across several shop floors and/or at multiple locations. Figure 3 presents a schematic diagram of a small section of the CPPS communication system. From this, one can observe that information is flowing from machines (M1 to M4) to the human operator (H1) through network nodes (N1 to N4).

Figure 3 shows a section of the CPPS communication nodes where information from various machines (M1, M2, M3, & M4) flows into the network nodes (N1, N2, N3, N4) and is finally received by the human (H1) for factory production process supervision and making decisions. A factory operator can supervise multiple process parameters of the shop floor through HCI devices from remote locations. For example, a hypothetical user interface of an HCI device has been developed to present the CPPS scenario (shown in Figure 4). A factory

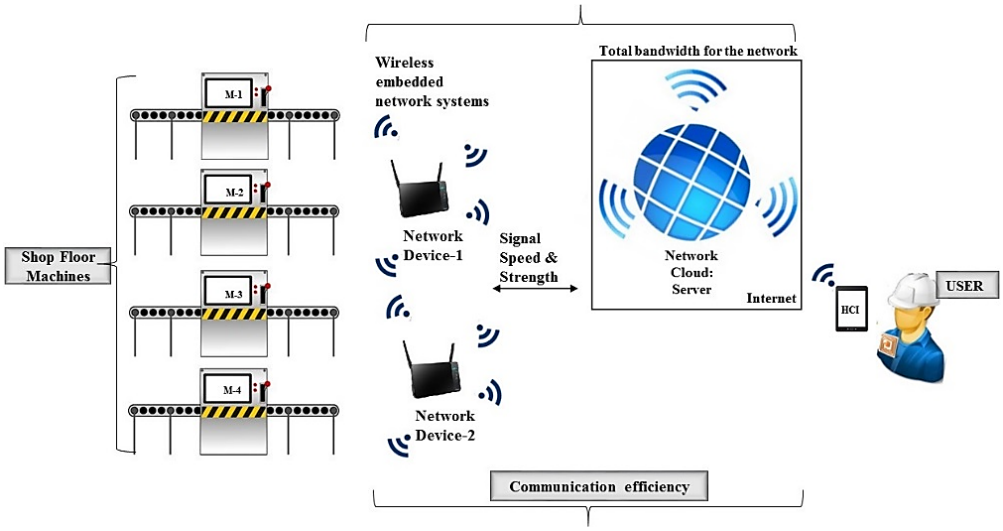


**Figure 2.** A human and machine communication scenario in a cyber-physical production system (CPPS) shop floor.

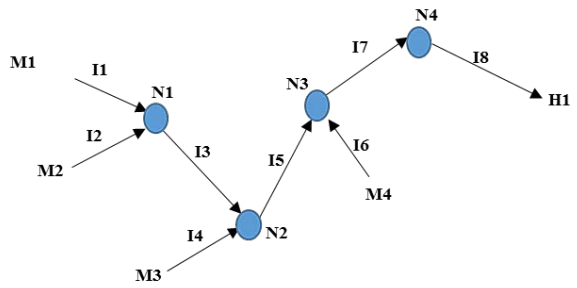


**Figure 3.** An example of machines-to-human communication via network nodes (N1–N4). In this schematic, I = information, N = network nodes, M = any variation of machine, and H = the human operator.

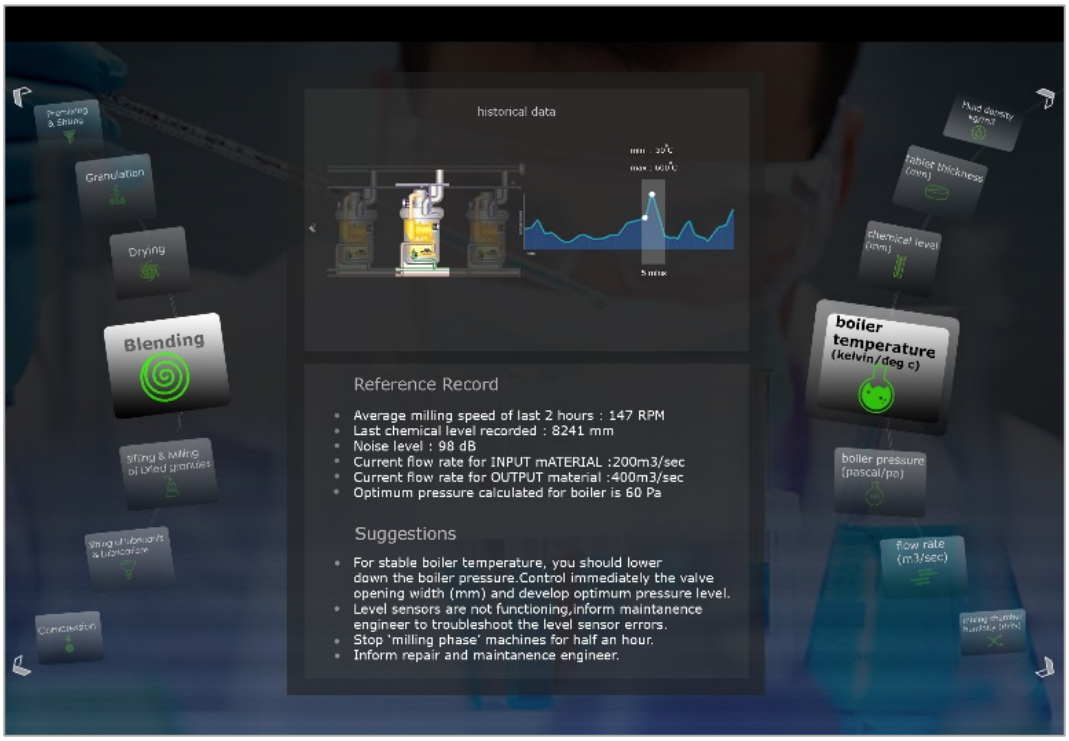


**Figure 4.** A hypothetical user interface of an HCI device.

operator (H1 in Figure 3) of a pharmaceutical manufacturing company can supervise the entire production process in real-time through this HCI device.

In Figure 4, a hypothetical user interface shows a monitoring screen with various production sections (blending, grinding, milling, etc.) of a CPPS. Process parameters also are represented visually in the user interface. Suppose the operator (H1 in Figure 3) needs the boiler temperature information available as I1 from machine M1; this information travels to the node N1. The total information received by the node N1 is I1+I2 (I1 & I2 are two process parameters, as there is another machine M2 connected with node N1). Similarly, other machines in the CPPS can send information (I3, I4, I5, etc.) to H1 through various other nodes. In this network of communications, the nodes are intermediaries between the human and the machine(s). We posit here that the summation of the individual communication efficiencies between the nodes will affect the SFE of the CPPS.

The efficiency of communication between the nodes can be measured as function of the speed of communication between nodes and the accuracy of the information communicated as depicted in Equation 16. Further, we propose that the speed of communication between nodes will be a function of bandwidth between the nodes, amount of information to travel, type of communication protocol, processing time, relay time, signal strength, number of nodes in a path, and so on, as presented in the Equation 17.

$$\text{Speed of information between nodes} = f(\text{bandwidth between the nodes, amount of information, type of communication protocol, processing time, relay time, signal strength, no. of nodes in a path, etc.}) \quad (17)$$

Similarly, the accuracy of information measurement is a function of loss of data packets between nodes, technical failure of nodes, and duration of waiting time of the information because of bandwidth congestion, as presented in Equation 18.

$$\text{Accuracy of the information between nodes} = f(\text{loss of data packets, technical failure of nodes, delay in information delivery}) \quad (18)$$

In the scenario depicted in Figures 3 and 4, a loss of data due to situations such as low signal strength, signal drop, and so on, will provide inaccurate or incomplete information at the user's end. Similarly, a delay in information delivery at the interface (Figure 4) will exhibit inaccurate, incomplete, or outdated monitoring data to the operator.

The combination of speed and accuracy will provide a measure of communication efficiency in CPPS. The result will indicate the optimum transfer of information from machines ($M_1$ to $M_n$) through nodes ($N_j$ to $N_k$) to reach human operators ($H_1$ to $H_n$) such that the interaction of operators with HCI interfaces, like in Figure 4, will receive timely and accurate data and act appropriately. Summing up the CSE of the overall different nodes in CPPS, we propose Equation 19 to measure the overall efficiency as a summation of the speed across the nodes.

$$S(N) = \sum_i \sum_j^k Ii(Nj - k)/t \quad (19)$$

The speed of the information in CPPS communication network is represented as S(N). Integers i, j, & k represent the number of information packets, node numbers, and total numbers of nodes, respectively. The i is the information amount to travel between the nodes, t is the total information travel time, and N is a node in the network.

## Smart Machine Efficiency (SME)

Measures of efficiency in machines within the industry have been reported in the literature (e.g., Muchiri & Pintelon, 2008; Nakajima, 1988). However, as machines become smarter with capability of information processing and programmed logic within them, there is need to reassess at the machine efficiency measure. As a continuation of the arguments presented in the Introduction, we propose here that the measure of efficiency of the smart machines in a CPPS includes factors such as total time to produce all the product, total lost time in defective product manufacturing, total manufacturing time, machine information processing time, machine run time, machine delay time, machine errors, and so forth. We propose that measurement of SME as Equation 20:

$$SME = [(T_P - T_D)] / M_T \quad (20)$$

where $T_P$ represents the total time to produce products, $T_D$ means time lost in defective product production, and $M_T$ is total manufacturing time. Further, total manufacturing time ($M_T$) is proposed to be calculated as

$$M_T = M_R + D_T + M_W + M_P \quad (21)$$

where, $M_R$ designates machine run time, $D_T$ represents delay time due to technical failures (errors), $M_W$ manual work time before and after the start of machine, and $M_P$ the machine's information processing time.

The SME measured in Equation 20 is proposed to ascertain the percentage of time spent per non-defective product. As in Equation 21, the total time calculation is envisioned to consider all the various stages in the machine operation. For example, $M_P$ indicates the time spent in information processing by a smart machine. These types of processing inefficiencies could be due to hardware or software design of the smart machines. Although currently this time is negligible and hence often is discarded in calculations, as machines become better integrated with computing capabilities in Industry 4.0, we argue for this computing time also to be considered in the SME measure. Similarly, $D_T$ measures the delay due to technical failure in mechanical parts of the machine, electronic hardware, malwares in the software, power failures, and so on. The $M_W$ measures the delay in machine operation due to the machine operators' pre- and postproduction planning efforts.

Additionally, we argue that, despite the automation, the CPPS efficiency also will depend upon smartness of the smart machine operators. Any delay caused by programming the information into the smart machines before production starts also will need to be included when designing the CPPS. Hence, the training of operators, the design of machine programming that leads to the need for more manual time, the intuitive design of user interfaces of the smart machines, and so forth, will contribute to the $M_W$.

To sum up, we discussed in this section that the prevalent machine efficiency measures are dependent upon manpower and machine run-time calculations, such as the ratio of operating time upon loading time as in Equations 2 and 3 (Nakajima, 1988; Subramaniam et al., 2009). Therefore, we have argued for the need to include these factors due to the smartness of new machines that will impact information processing time, delay time, manual operator time, and more within the SME measure.

## Comparison Between Smart Factory Efficiency (SFE) and Overall Equipment Effectiveness (OEE)

Along the lines of prevalent practice of measuring the OEE (Muchiri & Pintelon, 2008; Nakajima, 1988), an overall SFE has been proposed here as a product of HCE, CSE, and SME, as in Equation 22:

$$SFE = HCE * CSE * SME \tag{22}$$

SFE was developed from the OEE measure as depicted in Equations 1–5. Equation 1 is presented again here for a comparative discussion of SFE and OEE measures:

$$OEE = AR * PR * QR$$

where, AR designates the availability rate, PR the performance rate, and QR the quality rate. In OEE, the overall production efficiency measure depends upon manpower and machine run-time calculations, meaning the ratio of the operating time upon loading time, as discussed in Equations 2 and 3 (Nakajima, 1988). Manpower utilization has been an important factor in prevalent efficiency measures (Subramaniam et al., 2009). Equation 22, however, shows the shift in the focus of the man–physical power calculation from physical load to cognitive load, in line with the tenets of Industry 4.0. Further, due to the improving smartness of current and future machines, the efficiency measure has been accommodated in the SME calculations, and the increase in information load due to smart factories has been accommodated in the HCE

measure. While the HCE reflects human cognitive performance, the SME integrates the total manufacturing time with the time to produce quality products. Thus, the SME is a modified representation of the quality rate of the OEE measure depicted in Equation 5. Similarly, the OEE measure uses performance and quality factors that have been accommodated in HCE and SME measures in the SFE framework.

## A CASE STUDY FOR HUMAN COGNITIVE EFFICIENCY (HCE) MEASUREMENT

In order to identify the HCE (Equation 9), we provided measures for the TE (Equation 10) and the CL (Equation 11). To validate the empirical equations of HCE, we undertook a brief experiment. For the experiment, an interactive touch-based control panel application was developed and installed onto a tablet device and then tested on single participant with 10 trials over consecutive days.

The participant was given a controlling task and the scenario was explained. The task was to control the process variable when it reaches above the critical values using the knobs provided on the test control panel. The total time for a complete session was five minutes, and the participant performed a total 16 controlling actions using the knobs on the control panel. When process variable value rose above the critical limit, the participant was to respond via the controlling knob. Response times of and the number of errors by the participant were recorded automatically by the control panel application.

The test participant, aged 24 years, possessed a fare knowledge of the dials and knobs needed to perform the experiment well. To ensure the collection of reliable response time and task error from the participant, we inquired into his medical history of eyesight and head injury; the participant had no medical issues that would negatively impact the experiment.

The control panel was designed based on a hypothetical pharmaceutical manufacturing company in the context of Industry 4.0. The control panel design had four display dials, namely boiler temperature, boiler pressure, station voltage, and motor speed, as well as four controlling knobs, namely steam-flow rate, valve-opening width, station load, and time. The testing facilitator provided the control panel tablet to the participant and then left the room. From that point onward in the experiment, the scenario was narrated by the control panel application software. The audio message provided by the machine began when the operator received a call from the machine:

> *Hello Sir, I am machine number #627. There is an urgent action required in plant operation.*
>
> *In the blending phase, level sensors have stopped working. System variables such as boiler temperature, pressure, motor speed, and station voltage have become unstable. I have tried to set all the parameters in calculated optimum range but could not succeed. Next, I am sending you the overall machine control of the blending phase. Try to keep all the display parameters in a stable range and give your response to critical conditions only. Click END BUTTON to receive the machine control.*

Figures 5 to 9 show the screens to the participant interacted with during the tasks. Figure 5 shows what the participant saw when receiving the call from the machine reporting the situation in the production process at the smart factory. With the presentation of Figure 6, the decision-making tasks (such as overall control) were given to the participant with the help of an audio message. Figure 7 shows that two parameters of the blending phase have reached a

critical condition and the participant must control both the parameters one by one. Before that response, however, the participant must consider the machine-generated suggestions that are shown in Figures 8 and 9. Figure 8 presents the boiler temperature status and the suggestion generated by the machine. Similarly, Figure 9 provides boiler pressure information. The information provided the participant by Figures 8 and 9 established the parameters that demanded immediate controlling task from the participant.

In order to check the TE and CL of the operator, we created just one critical scenario as an example. However, a real-world scenario could involve many operational tasks and for different scenarios. For example, what if an error occurred in multiple phases (e.g., blending, drying) and with multiple process variables (e.g., flow, humidity, blower speed)? In such a situation, the way information of the multiple process variable is presented could become one of the factors for an operator to respond slower or faster on the knobs, which increases the operator's CL and affects the TE of the operator. Hence, considering the HCE as a measurement in SFE is important in task success in an Industry 4.0 environment.

During the trials, the participant sat on an isolated closed room and performed the task on an 8-inch tablet hosting the interactive control panel (see Figure 10). Both task response time and task errors were recorded automatically by the control panel application software during the task execution. Task response time is the amount of time expended by the participant while controlling the critical values of the display parameters. Regarding task errors, two types were recorded during the test. The first type of error was the wrong attempt, when the participant


**Figure 5.** The screen demonstrates what the test participant saw when the machine called the operator to report factory critical condition.

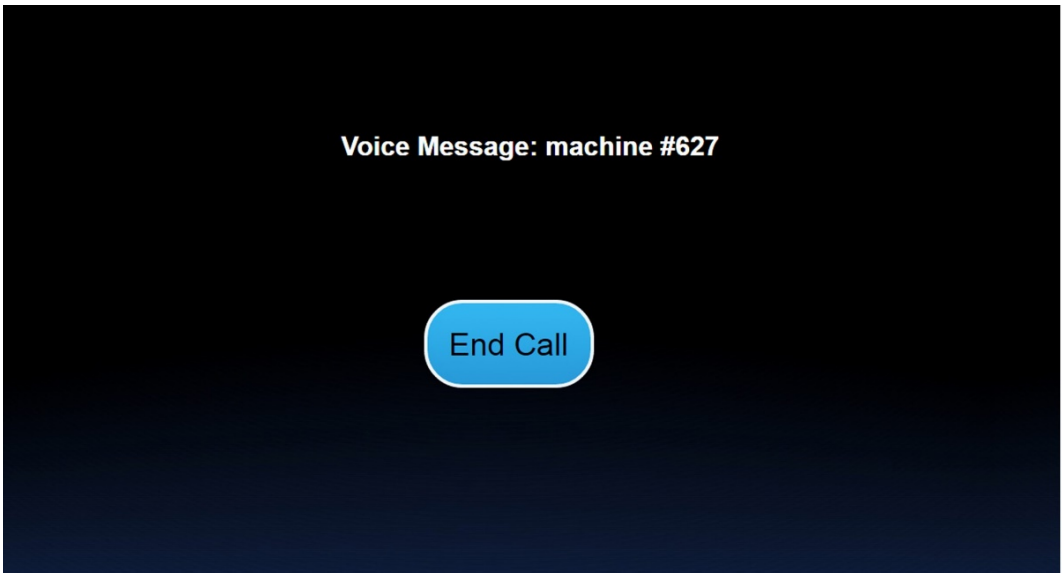


**Figure 6.** This screen appeared after the machine reported the problem to the operation and established a means for handing over factory machine control to the operator.

touched the wrong control slider. The second type was the missed chance that occurred when the participant did not respond within 10 seconds of the display of the critical value. A total error count was calculated by summing both types of errors.


**Figure 7.** The test operator saw this main screen that displayed the critical conditions for the two parameters.

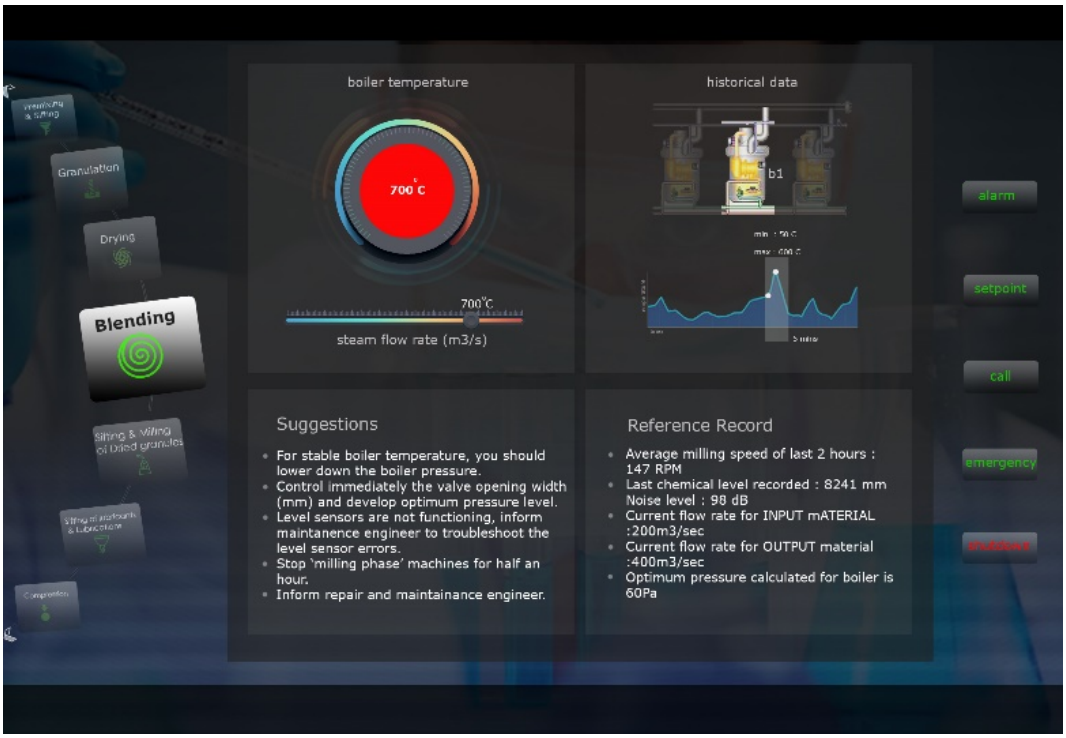


**Figure 8.** This control panel screen showed the operator the machine-generated status and suggestions for the boiler temperature parameter.

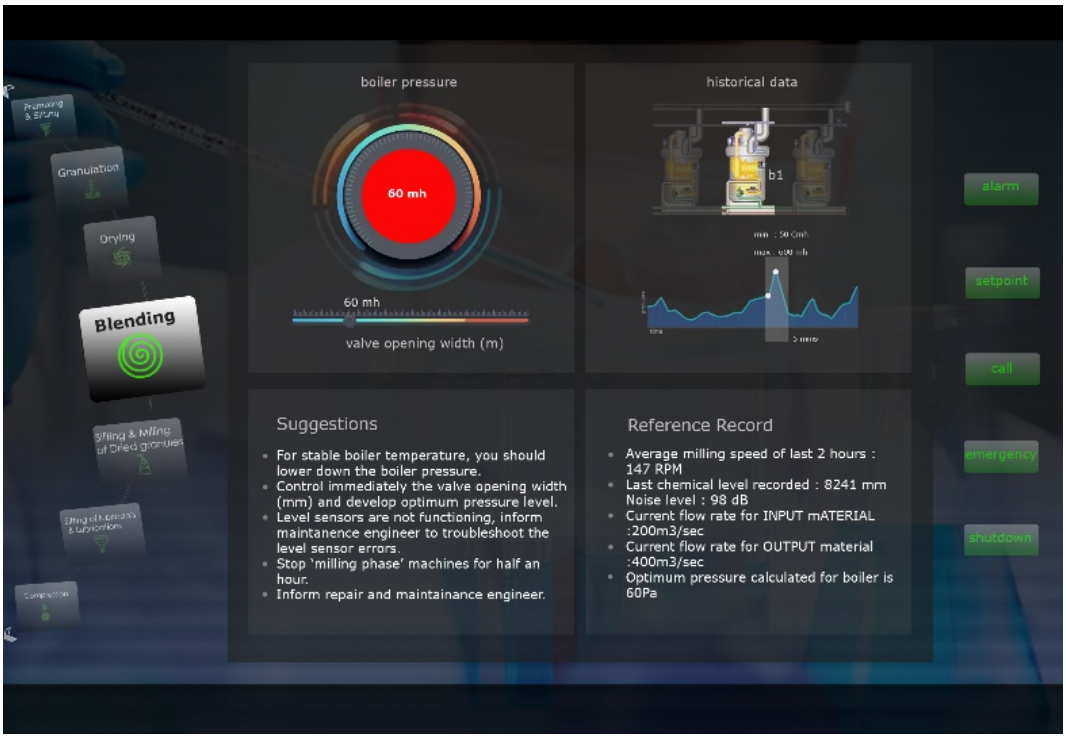


**Figure 9.** This control panel screen provided the machine-generated status and suggestions for the second critical condition: the boiler pressure parameter.

**Figure 10**. In line with the experimental setup, the participant used a touch-based control panel to perform each task in all 10 trials.

Based on the task errors, we were able to calculate the total number of correct tasks within a given time as compared to the total number of given tasks. With this information, we calculated the TE, which is presented in Table 2.

According to Equation 9, HCE = TE/CL. As per Equation 10, TE was being measured in the test case scenario. In our test, the average TE for a single user (the operator of the smart factory) with 10 trials was 0.8187 (i.e., TE = 81.87 %). Moreover, TE is directly proportional with HCE. If TE increases, HCE will also increase. TE has a direct relation with HCE.

From this result, we concluded that the TE of a factory operator can be measured in a critical Industry 4.0 scenario. The TE measurement can assist control panel designers to design efficient control panels for specific Industry 4.0 tasks and scenarios. However, based on Equation 11, the CL (CL=K*Ip/t) cannot be formally measured because researchers still must discover the way to calculate the value of the constant K in the equation.

While research has shown that human cognitive performance is influenced by age (Caplan & Waters, 2005), stress (Lupiena & Lepage, 2001), and competency level (Salthouse et al., 1991), the literature offers little regarding the proportionate effect of these factors on CL. Thus, this

**Table 2.** Task Efficiency Calculation as the Comparison of the Total Number of Correct Tasks Divided by the Total Number of Tasks over the 10 Trials.

| No. of control panel trials | Total no. of correct tasks (T1) | Total no. of tasks (T2) | Task Efficiency TE=(T1/T2) |
|---|---|---|---|
| 1 | 14 | 16 | 0.875 |
| 2 | 16 | 16 | 1 |
| 3 | 7 | 16 | 0.4375 |
| 4 | 9 | 16 | 0.5625 |
| 5 | 14 | 16 | 0.875 |
| 6 | 14 | 16 | 0.875 |
| 7 | 14 | 16 | 0.875 |
| 8 | 15 | 16 | 0.9375 |
| 9 | 12 | 16 | 0.75 |
| 10 | 16 | 16 | 1 |

paper has not proposed an exact method of calculation of K. However, this inability does not affect the relevance of the proposed efficiency measure in that efficiency is a relative concept where increases or decreases need to be measured. Even without an exact value for K,' the equation is still useful. Further research to calculate K is necessary to strengthen the means to measure CL and overall HCE.

## CONCLUSIONS

The current efficiency measurement practices in Industry 3.0 lacks the consideration of human cognitive load even though workers' cognitive load is on a rise due to the increase in information complexity. Prior industry frameworks to measure production efficiency are not practically useful at this point in industrial evolution and certainly will not be able to do justice to the changed scenario of production and productivity of Industry 4.0. Hence, new theoretical models will be needed.

Moreover, although cognitive load theories, production efficiency theories, and communication theories have outlined the need to reconsider the production processes as a sustainable and profitable human activity, the theoretical frameworks to implement these theories adequately have yet not evolved. However, we have proposed a theoretical measure for SFE comprising three functions, namely, HCE, CSE, and SME (see Table 1 for abbreviation definitions). We have positioned the need for a new theoretical framework in context of the Industry 4.0. This rethinking of the industrial context is necessary because the Industry 4.0 environment will place an increased CL on the humans, reflect increasing smartness in new machines, and require increasing levels of communication between machines. These conditions form the argument underlying our proposal for the new framework.

We observed one common trait in these three functions (HCE, CSE, and SME): "information." The role of information in current and emerging industrial realities affects not only the technical side of the equation but, most importantly, the human operator. If information effects the human cognitive system due to increased information complexity, task complexity, and critical scenarios, then human cognitive efficiency will suffer. If an overload of information across multiple nodes (i.e., exchange of data from servers to different nodes) creates malfunctions or errors in the communication protocol—or is not presented clearly to the human operator, then communication system efficiency will suffer. Similarly, if irrelevant information or noise in the machine's interrupts or delays data processing in any, then smart machine efficiency will suffer. Therefore, we advocate for the need to look anew at production efficiency and consider information as a central component for the measurement of smart factory efficiency. The framework presented in this paper is our attempt to open discussion and re-vision efficiency measurement in current and future work environments.

Every research process is constrained by limitations. The most significant limitation of this work has been that the proposed theoretical framework does not quantify the individual contributions on the three efficiency measures toward an overall SFE measure. We are unable to do so at this time because the research field has not yet been able to define a value for a constant K, and so the proposed Equation 11 measurement for CL is not yet fully developed. This will change in the future as researchers conduct experimental studies to measure K.

What could be considered another weakness of the proposed framework is that the role of physical workload has been removed completely from the mathematical models based on the assumption of full automation of the industrial environments in Industry 4.0. However, we do acknowledge that some industrial contexts will continue where human physical labor will be used to some extent in the production process. Therefore, we see that this framework will require improvements.

For the proposed framework to gain popularity in mainstream industrial efficiency measures, further research work is required. The evaluation of the design quality of HCI-based control systems using the CL measures and HCE framework can be one area of future research studies. Similarly, aspects of CSE and SME can be evaluated by simulations of a futuristic CPPS to assess effectiveness of the proposed system designs.

## IMPLICATIONS FOR RESEARCH OR APPLICATION

As technology advances on multiple levels, the impact on industrial practices will change as well. Current manufacturing and other factory environments and processes have already reflected increased reliance on computers and smart machinery. In years to come, with the emergence of Industry 4.0, machines will be the primary drivers of factory work, with humans serving in the troubleshooting and oversight roles. Our research looks toward that future in presenting a framework specifically envisioned to assist industry managers and workers in establishing and measuring the efficiency of their operations—specifically regarding their workers overseeing the operations.

From a practical perspective, our framework allows industrial technology designers and engineers to look differently at what measurements are useful in creating systems that are efficient not only from the technological perspective but also from the human perspective. In particular, understanding how technology advances may challenge the human workers' cognitive load (which in turn affects their efficiency) can lead to optimal HCI design (with sufficient technology communication efficiency and smartness) and, especially, better technology interfaces for human interaction with the machines. Our framework also provides a practical means—through read-to-use formulae—to evaluate efficiency at the various levels of the future factory environment.

Apart from the practical contributions, our research contributes to the future development of industrial efficiency measurement by way of our bringing together interdisciplinary knowledge to create a framework. The case study of human cognitive efficiency measurement provides groundwork upon which future researchers can continue to test and develop the framework. The proposed mathematical equations open a scope for researchers to investigate more fully the human factors, telecommunication technology, and embedded systems in order to make information technology more efficient.

## REFERENCES

Astrom, K. (1985). Process control: Past, present and future. *IEEE Control System Magazine*, *5*(3), 3–10.

Atkinson, R. C., & Shiffrin, R. M. (1968). Human memory: A proposed system and its control processes. *Psychology of Learning and Motivation*, *2*, 89–195.

Bailey, D., & Wright, E. (2003). *Practical SCADA for industry*. Burlington, MA, USA: Elsevier.

Briones, L., Bustamante, P., & Serna, M. A. (1994). Wall-climbing robot for inspection in nuclear power plants. In *Proceedings of the IEEE International Conference on Robotics and Automation* (pp. 1409–1414). San Diego, CA, USA: IEEE.

Brunken, R., Plass, J., & Leutner, D. (2003). Direct measurement of cognitive load in multimedia learning. *Educational Psychologist*, *38*(1), 53–61.

Cain, B. (2007). *A review of the mental workload literature* (NATO RTO report). Toronto, Ontario, Canada: Defense Research and Development.

Caplan, D., & Waters, G. (2005). The relationship between age, processing speed, working memory capacity, and language comprehension. *Memory*, *13*(3-4), 403–413.

Chen, B., Wan, J., Shu, L., Li, P., Mukherjee, M., & Yin, B. (2018). Smart factory of Industry 4.0: Key technologies, application case, and challenges. *IEEE Access*, *6*, 6505–6519.

Chen, M., Mao, S., & Liu, Y. (2014). Big data: A survey. *Mobile Networks and Applications*, *19*(2), 171–209.

Cobb, C. W., & Douglas, P. H. (1928). A theory of production. *The American Economic Review*, *18*(1), 139–165.

Cowan, N. (2016). *Working memory capacity*. New York, NY, USA: Psychology Press.

Da, X. L., We, H., & Li, S. (2014). Internet of things in industries: A survey. *IEEE Transaction on Industrial Informatics*, *10*(4), 2233–2243.

Daniel, D. (2006). Overall input efficiency and total equipment efficiency. *IEEE Transaction on Semiconductor Manufacturing*, *19*(4), 496–501.

Davis, J., Edgar, T., Porter, J., Bernaden, J., & Sarli, M. (2012). Smart manufacturing, manufacturing intelligence and demand-dynamic performance. *Computers & Chemical Engineering*, *47*, 145–156.

Deane, P. (1965). *The first industrial revolution.* Cambridge, UK: Cambridge University Press.

Gorecky, D., Schmitt, M., Loskyll, M., & Zühlke, D. (2014). Human-machine-interaction in the Industry 4.0 era. In *12th International Conference on Industrial Informatics* (pp. 289–294). Porto Alegre, Brazil: IEEE Xplore.

Johnson-Laird, P. N. (2005). Mental models and thought. In K. J. Holyoak, & R. G. Morrison (Eds.), *Cambridge handbook of thinking and reasoning* (pp. 185–208). Cambridge, UK: Cambridge University Press.

Kablan, Z., & Erden, M. (2008). Instructional efficiency of integrated and separated text with animated presentations in computer-based science instruction. *Computers & Education*, *51*(2), 660–668.

Kay, M. (2006). Adaptive automation accelerates process development. *Bioprocess International Magazine*, *4*(4), 70–78.

Kumar, N., & Kumar, J. (2016). Measurement of efficiency of auditory vs visual communication in HMI: A cognitive load approach. In *Proceedings of the International Conference on Advances in Human–Machine Interaction* (pp. 1–8). Bangalore, India: IEEE. https://doi.org/10.1109/HMI.2016.7449168

Li, X., Li, D., Wan, J., Vasilakos, A. V., Lai, C. F., & Wang, S. (2017). A review of industrial wireless networks in the context of Industry 4.0. *Wireless Networks*, *23*(1), 23–41.

Lee, J. (2015). Smart factory systems. *Informatik-Spektrum*, *38*(3), 230–235.

Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for Industry 4.0 based manufacturing systems. *Manufacturing Letters*, *3*, 18–23.

Lupiena, S., & Lepage, M. (2001). Stress, memory, and the hippocampus: Can't live with it, can't live without it. *Behaviour and Brain Research*, *127*(1-2), 137–158.

MacDougall, W. (2014). *Industry 4.0: Smart manufacturing for the future*. Berlin, Germany: GTAI.

Meixner, G., Petersen, N., & & Koessling, H. (2010). User interaction evolution in the SmartFactory$^{KL}$. In *Proceedings of the 24th BCS Interaction Specialist Group Conference* (pp. 211–220). Dundee, UK: British Computer Society.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, *63*(2), 81–97.

Muchiri, P., & Pintelon, L. (2008). Performance measurement using overall equipment effectiveness (OEE): Literature review and practical application discussion. *International Journal of Production Research*, *46*(13), 3517–3535.

Nakajima, S. (1988). *Introduction to TPM: Total productive maintenance*. Cambridge, MA, USA: Productivity Press.

Oechsner, R., Pfeffer, M., Pfitzner, L., Binder, H., Müller, E., & Vonderstrass, T. (2002). From overall equipment efficiency (OEE) to overall fab effectiveness (OFE). *Materials Science in Semiconductor Processing*, *5*(4-5), 333–339.

Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist*, *38*(1), 1–4. https://doi.org/10.1207/S15326985EP3801_1

Paas, F., & Van Merriënboer, J. J. (1993). The efficiency of instructional conditions: An approach to combine mental effort and performance measures. *Human Factors*, *35*(4), 737–743.

Posada, J., Toro, C., Barandiaran, I., Oyarzun, D., Stricker, D., De Amicis, R., & Vallarino, I. (2015). Visual computing as a key enabling technology for industrie 4.0 and industrial internet. *IEEE Computer Graphics and Applications*, *35*(2), 26–40.

Romero, D., Bernus, P., Noran, O., Stahre, J., & Fast-Berglund, A. (2016). The operator 4.0: Human cyber-physical systems & adaptive automation towards human-automation symbiosis work systems. In I. Nääs, O. Vendrametto, J. Mendes Reis, R. F. Gonçalves, M. T. Silva, G. von Cieminksi, & D. Kiritsis (Eds.), *Advances in Production Management Systems: Initiatives for a Sustainable World* (Vol. 488, pp 677–686). Cham, Switzerland: Springer.

Saaty, T. L., & Ozdemir, M. S. (2003). Why the magic number seven plus or minus two? *Mathematical and Computer Modelling*, *38*(3-4), 233–244.

Salthouse, T. A., Babcock, R. L., & Shaw, R. J. (1991). Effects of adult age on structural and operational capacities in working memory. *Psychology and Aging*, *6*(1), 118–127.

Scott, D., & Pisa, R. (1998). Can overall factory effectiveness prolong Mooer's law? *Solid State Technology*, *41*(3), 75–81.

Sniderman, B., Mahto, M., & Cotteleer, M. J. (2016). *Industry 4.0 and manufacturing ecosystem.* London, UK: Deloitte University Press.

Streans, P. (2013). *The industrial revolution in world history.* New York, NY, USA: Westview Press.

Subramaniam, S., Husin, H. S., Yusop, Y., & Hamidon, A. H. (2009). Machine efficiency and man power utilization on production line. In the *8th WSEAS International Conference on Electronics, Hardware, Wireless and Optical Communication* (pp. 70–75). Cambridge, UK: ACM Digital Library.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2), 257–285.

Villani, V., Saattini, L., Czerniak, J. N, Mertens, A., Vogel-Heuser, B., & Fantuzzi, C. (2017). Towards modern inclusive factories: A methodology for the development of smart adaptive human-machine interfaces. In *International Conference on Emerging Technologies and Factory Automation* (pp. 1–7). Limassol, Cyprus: IEEE Xplore. https://doi.org/10.1109/ETFA.2017.8247634

Wan, J., Zhang, D., Zhao, S., Yang, L., & Lloret, J. (2014). Context-aware vehicular cyber-physical systems with cloud support: Architecture, challenges, and solutions. *IEEE Communications Magazine*, *52*(8), 106–113.

Wan, J., Zou, C., Ullah, S., Lai, C. F., Zhou, M., & Wang, X. (2013). Cloud-enabled wireless body area networks for pervasive healthcare. *IEEE Network*, *27*(5), 56–61.

Wang, S., Wan, J., Li, D., & Zhang, C. (2016). Implementing smart factory of industrie 4.0: An outlook. *International Journal of Distributed Sensor Networks*, *12*(1), 1–10. https://doi.org/10.1155/2016/3159805

Wittenberg C. (2015). Cause the trend Industry 4.0 in the automated industry to new requirements on user interfaces? In M. Kurosu (Ed.), Human-computer interaction: Users and contexts. *Lecture Notes in Computer Science* (Vol. 9171, pp. 238–245). Cham, Switzerland: Springer.

Wu, F. J., Kao, Y. F., & Tseng, Y. C. (2011). From wireless sensor networks towards cyber physical systems. *Pervasive and Mobile Computing*, *7*(4), 397–413.

Zhang, D., Wan, J., Liu, Q., Guan, X., & Liang, X. (2012). A taxonomy of agent technologies for ubiquitous computing environments. *KSII Transactions on Internet & Information Systems*, *6*(2), 547–565.

Zhong, R. Y., Dai, Q. Y., Qu, T., Hu, G. J., & Huang, G. Q. (2013). RFID-enabled real-time manufacturing execution system for mass-customization production. *Robotics and Computer-Integrated Manufacturing*, *29*(2), 283–292.

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