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Cognitive Manufacturing in Industry 4.0 toward Cognitive Load Reduction: A Conceptual Framework

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Abstract: Cognitive manufacturing utilizes cognitive computing, the industrial Internet of things (IoT), and advanced analytics to upgrade manufacturing processes in manners that were not previously conceivable. It enables associations to improve major business measurements, for example, productivity, product reliability, quality, and safety, while decreasing downtime and lowering costs. Considering all the facts that can prejudice the manufacturing performance in Industry 4.0, the cognitive load has received more attention, since it was previously neglected with respect to manufacturing industries. This paper aims to investigate what causes cognitive load reduction in manufacturing environments, i.e., human–computer interaction technologies that reduce the identified causes and the applications of cognitive manufacturing that use the referred technologies. Thus, a conceptual framework that links cognitive manufacturing to a reduction of the cognitive load was developed.

1. Introduction

Industry 4.0 (I4.0) is the mainstream name given to the Fourth Industrial Revolution introduced by the digital age. Some experts trust that Industry 4.0 is more evolutionary than revolutionary since computers were the establishment of the last revolution and remain the establishment of Industry 4.0 [1]. Different technological developments resulted in Industry 4.0. This new paradigm faces the challenge of being exceptionally computerized and financially savvy, as well as producing custom products in a large-scale manufacturing condition, and it can change the role of traditional assembly lines by altering how goods are produced and services are offered [2]. The rapid advancement of technologies such as cloud computing, big data, mobile internet [3], augmented reality (AR), virtual reality (VR), and artificial intelligence (AI) has resulted in substantial work in these areas [4]. Furthermore, the combination of these information technologies and the assembly industry has instigated the current fiercely debated issue of intelligent manufacturing (IM) [5].

Cognitive manufacturing (CM) utilizes cognitive computing, the industrial Internet of things (IIoT), and advanced analytics to upgrade manufacturing processes in manners that were not previously conceivable. It enables associations to improve major business measurements, for example, productivity, product reliability, quality, and safety, while decreasing downtime and lowering costs [6].

In 1990, Ref. [7] emphasized how the cognitive imprecision of data and vulnerability in user awareness of the computing environment were significant components of human–computer interaction, which should be imprecision-tolerant take into account the inexact mode of communication. Considering this, before the time of big data, cognitive technologies were unrealistic, as their systems need data to analyze. For most manufacturers, having enough information is no longer an issue. Indeed, most manufacturers deal with more information than they can break down, leading to a use of more seasoned techniques [1]. Cognitive systems are fit for automating routine decisions, and they support Industry 4.0 by creating significant experiences that help human decisionmakers to manage anomalies or other abnormal and complex business decisions. Cognitive systems can comprehend vast quantities of factors that uncover underlying causes of issues or point to more effective courses of action [1].

The enthusiasm for cognitive aspects of human performance has drastically expanded as of late in manufacturing, supplementing the zone of physical ergonomics, and the spotlight on cognitive aspects may offer critical insights to industries. Significantly increased interest has been aimed at cognitive aspects and their impact on human performance and production outcome [8].

Although the term "cognitive manufacturing" has never been directly related to reducing human cognitive load in manufacturing, it is interesting to assess points where the subjects are interlinked. This paper aims to investigate what causes cognitive load reduction in manufacturing environments, i.e., technologies that reduce the identified causes and the applications of cognitive manufacturing that adopt the referred technologies. In this study, an investigation of the subject was performed through the following research question:

RQ1: Is cognitive manufacturing a term that can be extended to a technology that reduces the human cognitive load in manufacturing?

To help deconstruct the main research question, three sub-questions were developed:

- SRQ1: What causes cognitive overload in manufacturing environments?
- SRQ2: Which are the technologies that are able to reduce the cognitive load in manufacturing environments?
- SRQ3: Which are the cognitive manufacturing applications that use technologies that reduce the cognitive load?

The structure of this paper starts, from this point on, with a literature review of cognitive manufacturing, followed by a literature review of the cognitive load in manufacturing, before moving to a description of the materials and methods used to perform this investigation and the subsequent results, concluding with the discussion and conclusions of the work developed.

1.1. Cognitive Manufacturing

Cognitive manufacturing gathers significant data in real time and applies analytics to help attain previously impossible insights into the manufacturing process. It mechanizes reactions dependent on its discoveries and conveys actionable information as continuously updated knowledge to workers [6]. It is powerful since it joins sensor-based data with machine learning and other AI capabilities to discover patterns in data, structured or not, aligning relevant information together in real time [9].

Cognitive technologies can discover importance in these data in manners that, until recently, only the human brain could fathom. This degree of understanding can be viewed as essential in the modern manufacturing era, where competitiveness and cost sensitivities request new degrees of agility, responsiveness, and innovation from manufacturers [6].

These technologies, such as AI, in general, can be characterized as the capacity of machines to comprehend, learn, and resonate so as to emulate the cognitive functions of the human brain [10].

Manufacturers can utilize cognitive technologies to tackle fundamental business challenges, discover new value in their assembled information, improve quality, and upgrade knowledge in their

organizations. Cognitive manufacturing empowers organizations to set a focus on quality throughout the life cycle of a product's development [6].

1.2. Cognitive Load in Manufacturing

Traditionally, the focal point of HCI has been on the most effective method to guarantee that the technology serves the users' needs. Throughout the years, HCI has progressed, and the human share of technology is additionally changing, whereby humans have become increasingly attentive and demanding. Therefore, human methodologies face increased difficulties to underlie an increasingly trustworthy and valuable connection between humankind and technology [11].

Considering all the facts that can prejudice the manufacturing performance, the cognitive load has received more attention, since it was previously neglected with respect to manufacturing industries.

When exposed to stimuli, the cognitive system experiences what is commonly referred to as cognitive load [12]. Cognitive load refers to the mental load that performing a specific task imposes on the human's cognitive system [13].

The theory of cognitive load states that effective instructional material encourages learning by coordinating cognitive assets toward exercises that are significant to learning as opposed to preliminary to learning [14]. This theory is concerned with the way in which cognitive assets are engaged and utilized during learning and problem solving [15].

In cognitive load theory, three types of cognitive load are considered [16]:

- Intrinsic—cognitive load related to a topic or task. We can consider this type as the objective difficulty of a task;
- Extraneous—the manner in which the data or tasks are exhibited. How we find data decides the assets we have available to interpret it;
- Germane—the germane load is created by the development of schemas; it helps in learning new skills and other data.

For manufacturing purposes, the intrinsic and extraneous loads are the most relevant [17].

High intrinsic difficulty occurs in manufacturing work because most routine tasks are performed by automated systems, while assigning complex and variable tasks to the human worker. Furthermore, significant extraneous load is experienced by manufacturing workers once the structure and type of work are not helpful for precise execution, in addition to a lack of technological support, often resulting in written instructions and manual data collection. Traditional workflows and tools augment the cognitive load on workers [17].

Human performance is affected by a cognitive load that is excessively high, whereby information concerning the job and the importance of a cognitive human in an assembly domain could possibly have a noteworthy impact on the production result (quality and productivity). Significant causes of quality defects in manufacturing are currently appointed to both product and process errors [8].

There may be similarities among humans and machines; however, human cognition is the result of a human's interactions with the environment, demonstrating that there are cognitive activities that rely upon the cooperation of the human body (musculoskeletal system and peripheral nervous system) with sensory inputs from the environment, as well as the working of the brain, commonly referred to as distributed cognition [18].
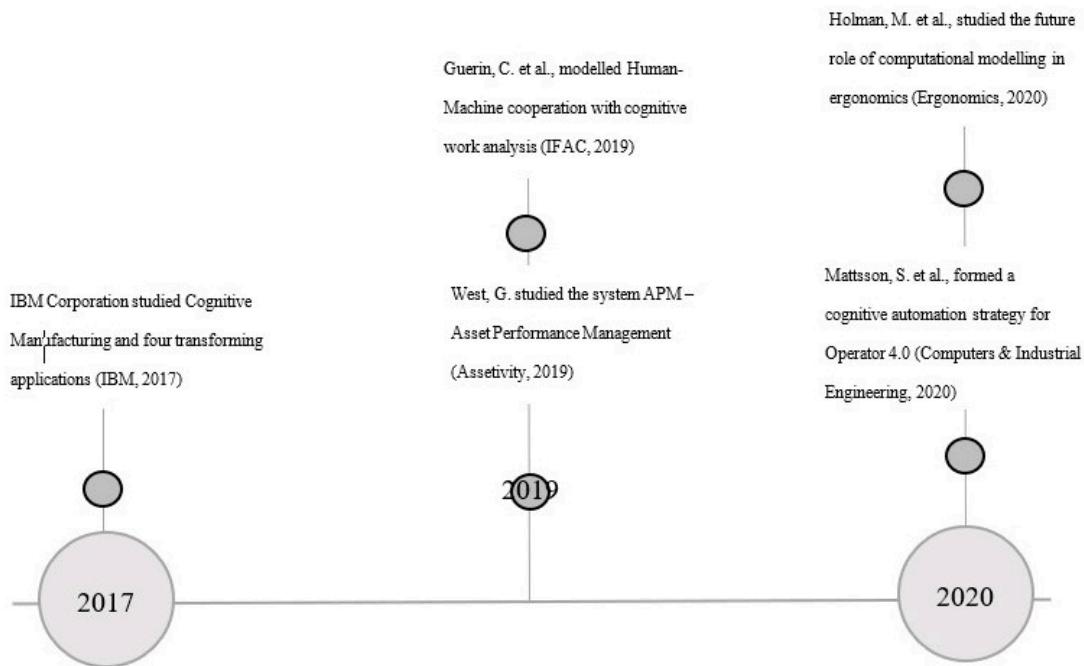
2. Materials and Methods

Cognitive manufacturing remains a yet moderately new subject in academic literature, and gaps were identified in relating the topic to a reduction of the cognitive load experienced by workers in the manufacturing field. Along these lines, there is a need to get a handle on what has been investigated and where results are scarce. As this investigation was being developed, the current literature was reviewed, finding that no author previously investigated cognitive manufacturing and cognitive load, highlighting the importance of this study.

A comprehensive investigation and preliminary study were the first steps of this research to comprehend and identify the problem, thereby obtaining deeper knowledge of the research area. This led to the development of the research question. After the preliminary examinations, a literature review was carried out to obtain a more extensive comprehension of the exploration territory, leading to a restraint of the scope and the generation of a theoretical framework. This also allowed a better understanding of the concept of cognitive load. The perceptions of cognitive manufacturing, its applications, and the technologies that reduce the cognitive load were also deepened.

To address SRQ2 and SRQ3, the following keywords were defined as criteria for the inclusion and exclusion of articles: (cognitive manufacturing) AND (cognitive load), as well as ("human–computer interaction") AND ("cognitive load"), which were combined using Boolean operators. The search was conducted on the basis of the title, abstract, and keywords. The search was also limited to studies in English and Portuguese. For this, two recognized databases were selected: Scopus and Web of Science. As explained previously, due to the lack of relevant results, other sources were also consulted (books, white papers, and gray literature). A graph was developed to enhance comprehension of the publications used to support the answers to SRQ2 (Figure 1) and SRQ3 (Figure 2).
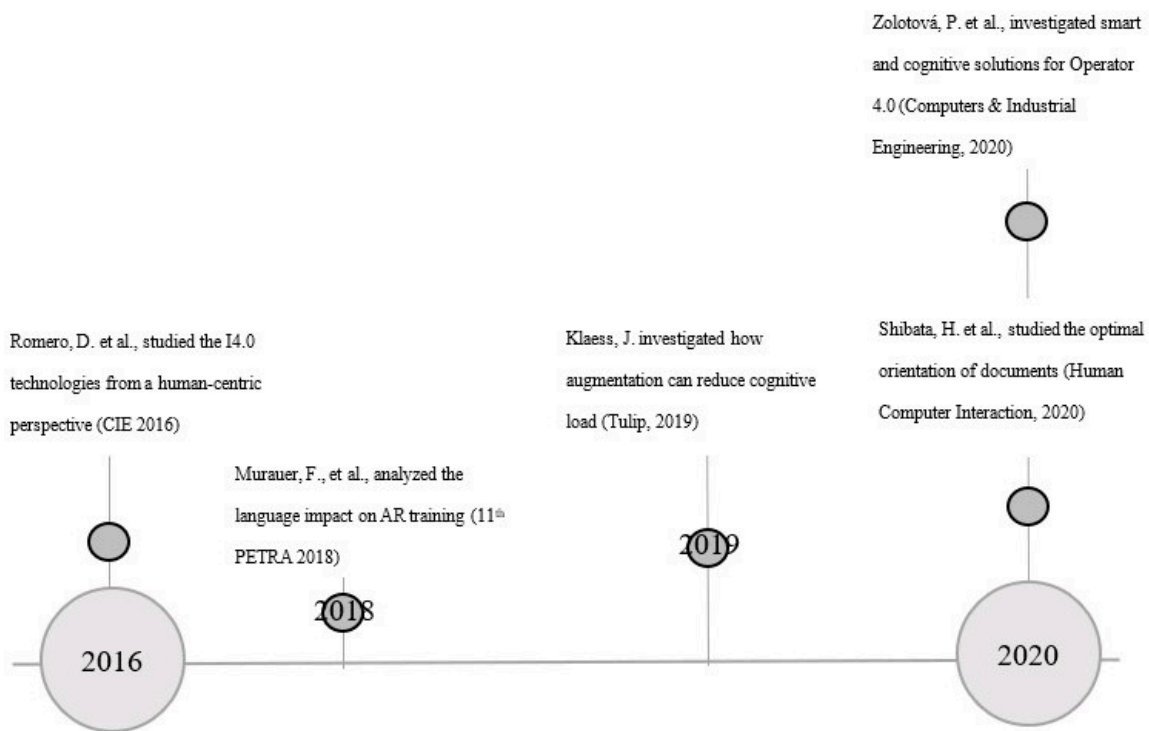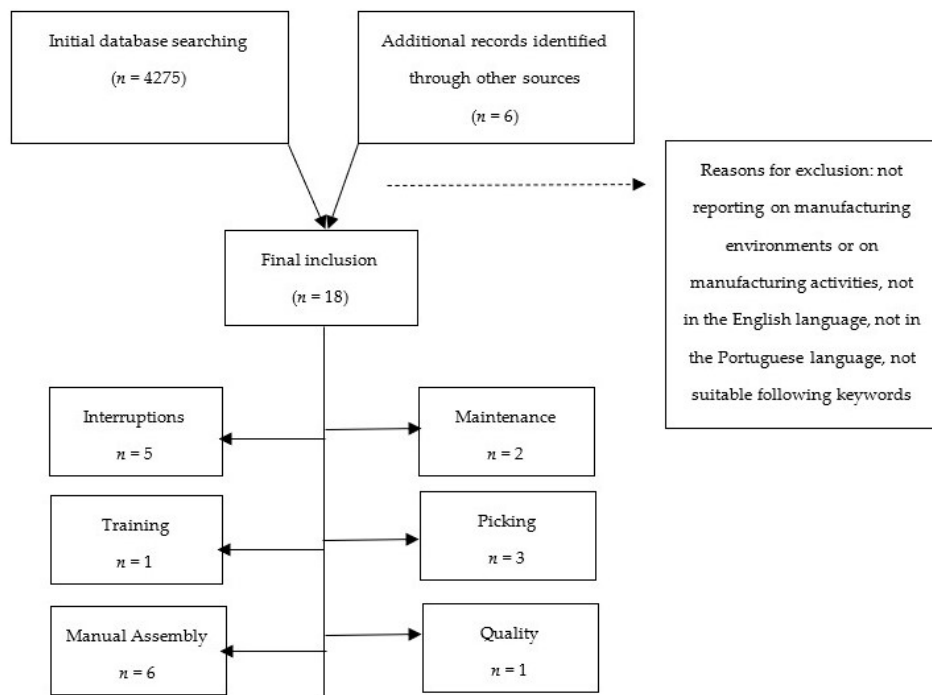
Figure 1. A visual history of the most relevant literature related to human–computer interaction technologies that reduce the cognitive load.

Holman, M. et al., studied the future role of computational modelling in ergonomics (Ergonomics, 2020)

Guerin, C. et al., modelled Human-Machine cooperation with cognitive work analysis (IFAC, 2019)

IBM Corporation studied Cognitive Manufacturing and four transforming applications (IBM, 2017)

West, G. studied the system APM – Asset Performance Management (Assetivity, 2019)

Mattsson, S. et al., formed a cognitive automation strategy for Operator 4.0 (Computers & Industrial Engineering, 2020)

2019

2017

2020

Figure 2. A visual history of the most relevant literature related to cognitive manufacturing applications using technologies that reduce the cognitive load.

To address SRQ1, the available literature was reviewed through the use of the Scopus database, using the following string: TITLE-ABS-KEY ("cognitive overload" OR "cognitive load") AND (LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "ENGI")). Additional records were identified through other sources. The flow chart of the literature search for this first research question can be found in Figure 3.

Initial database searching
($n = 4275$)

Additional records identified through other sources
($n = 6$)

Final inclusion
($n = 18$)

Reasons for exclusion: not reporting on manufacturing environments or on manufacturing activities, not in the English language, not in the Portuguese language, not suitable following keywords

Interruptions
$n = 5$

Maintenance
$n = 2$

Training
$n = 1$

Picking
$n = 3$

Manual Assembly
$n = 6$

Quality
$n = 1$

Figure 3. Flow chart of the literature search for RQ1.

A graph was developed to enhance comprehension of the publications used to support the answer to this sub-question (Figure 4).
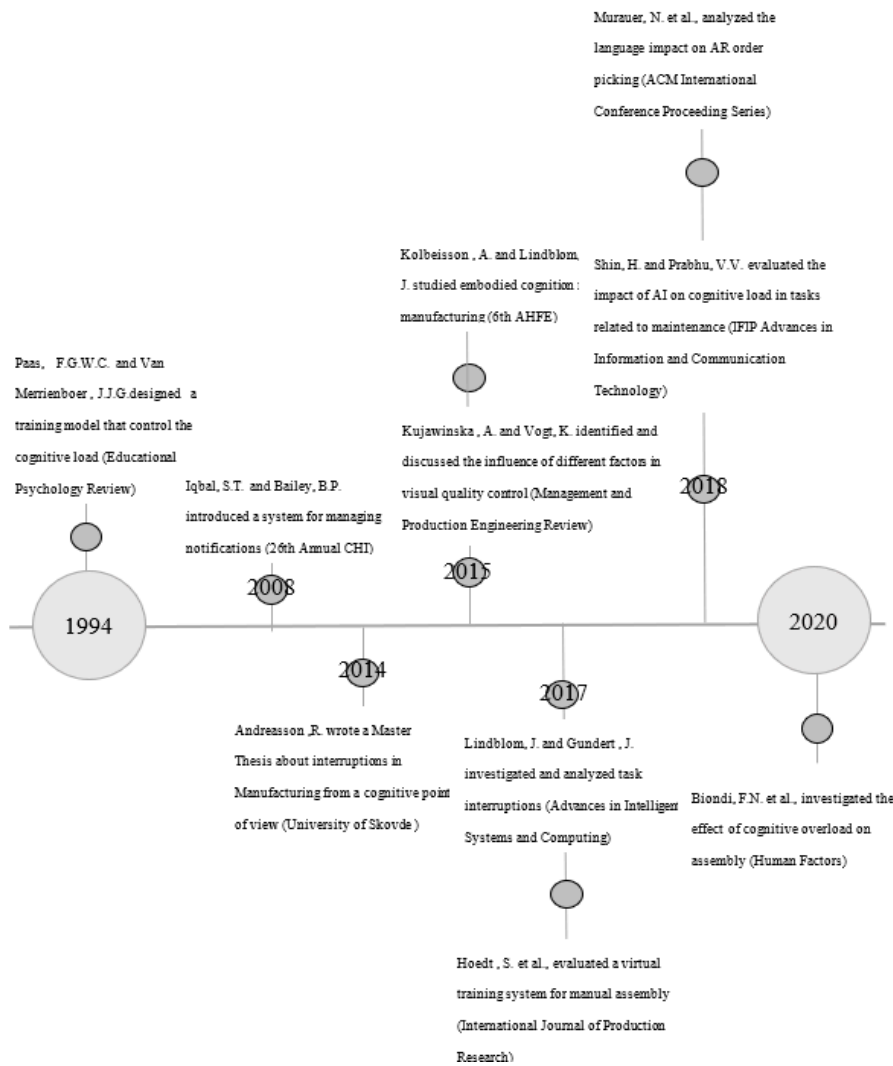
Figure 4. A visual history of the most relevant literature related to cognitive overload in manufacturing environments

Through the analyses of the available literature and according to the conceptual framework developed, a system to discuss and analyze the results was established to answer the research question, as presented in Section 4.

3. Results

In this section, a discussion and analyses of the findings from the sub-questions are presented.

3.1. SRQ1: What Causes Cognitive Overload in Manufacturing Environments?

According to [19], the performance of a job is influenced by its nature, i.e., if the assignment requires the operators to use more or less cognitive power. Table 1 shows the causes of cognitive overload in manufacturing environments, according to the available literature. It is important to consider that manufacturing environments include different tasks that might or might not require excessive use of the human cognitive function. Thus, by identifying the causes of cause cognitive overload, it is possible to access what technological tools can be used to reduce that overload and in what sectors of the manufacturing environment these tools should be implemented.

Table 1. Causes of cognitive overload in manufacturing environments.

Causes of Cognitive Overload	Literature
Interruptions	According to [20–23], interruptions are identified as being an essential driver to cognitive overload, which influences the human's capacity to perform effectively. The authors of [24] stated that interruptions are identified as being an essential driver to cognitive overload, which influences the human's capacity to perform effectively.
Training/instructional situations	The authors of [25] stated that training in some areas commonly speaks to circumstances that are near the breaking point of trainees' capacities, forcing cognitive overload.
Manual assembly	The authors of [9] mentioned that, because of the strategies of manufacturing companies, manual assemblers face a bigger cognitive load than in past times. The authors of [26] demonstrated that the work performed under cognitive overload affects assembly task completion times. The authors of [27] studied a reduction in cognitive load in complex assembly systems. The authors of [28] mentioned the information management strategies in manual assembly. The authors of [29] evaluated the guidelines for assembly instructions. The authors of [8] developed a method for cognitive load assessment.
Maintenance activities	The authors of [30] developed an AI tool to test if, among other aspects, the cognitive load of the maintenance workers using an AI-based system would be lower. The authors of [31] studied a cognitive perspective and methodology for reverse engineering tools.
Order picking	The authors of [32] stated that order picking is a demanding task at the cognitive level. The authors of [33] demonstrated the significant effect of for pinking tasks on human capacities and error rate by recording the human cognitive load, while the authors of [34] studied the order picking process using a projector helmet.
Visual inspection/quality inspection	The authors of [35] based their work on the knowledge that visual control does not ensure a completely correct assessment, due to constrained human reliability that is influenced by several elements which impact the capacity of a human to properly evaluate the quality of the procedure and/or product.

3.2. SRQ2: What Are the Human–Computer Interaction Technologies That Reduce the Cognitive Load in Manufacturing Environments?

Creating a working framework by empowering workers to boost their mental and physical assets might be the secret to decreasing the cognitive load. For this, manufacturers ought to consider equipping their lines with tools that allow workers to concentrate on the job that needs to be done. Innovative technologies can limit the impacts of stress and time pressure while bringing the numerous factors that the worker cannot control under management [17]. The cognitive work of smart factories can be supported by the technologies of Industry 4.0 [36].

As the transfer of cognitive burden continues rising, society will undergo a cognitive revolution, characterized by technology's capability to augment the cognitive potential of humans [30]. Industry 4.0 is rich in new technologies; however, for the purpose of this research, it was important to separate the technologies related to human–computer interactions and a reduction in cognitive load, in order to keep track of the actual technologies that concerned this investigation.

Different types of stimulus material are perceived differently in terms of cognitive processes. For example, remembrance of information from complex messages is often superior when the material is read rather than heard; however, simple material is better retained when it is heard [37]. Furthermore, traditional HCI focuses on preventing usability problems and, according to [38], it should also

generate remarkable quality experiences and add to a better quality of life. The ideal approach to decrease cognitive load is through augmentative technologies, which does not necessarily refer only to augmented reality when it comes to manufacturing [32]. The following technologies help workers on the job, and they can be integrated into the environment to improve worker capacity [17]:

- Digital work instructions guide workers through complex procedures, progressing with them, introducing them to the data they need when they need it, decreasing stress, and removing common sources of error [17]. As summed up in [39], reading on high-quality computer displays can be done as fast as reading on paper. A smarter operator [40] interacts with an AI personal assistant, thereby reducing the probability of mistakes happening [41]. This interaction can happen through virtual or augmented reality (virtual operator or augmented operator [40]). Some relevant Industry 4.0 technologies are in-view instructions using head-mounted displays, tablet instructions, projection-based in situ instructions, and step-by-step instructions that guide the worker through the whole process [42].

- Digital training applications help streamline the learning procedure by exhibiting data to the learner through focused, interactive modules. These applications can be designed explicitly for the assignment being referred to, so that workers can be instructed on the exact task that they will perform [17]. Industry 4.0 technologies related to training might include virtual, augmented, and smarter operators [40], whereby workers can be trained using, for example, e-learning [43], virtual reality [44], and augmented reality [45].

- Real-time analytics dashboards can help lessen the attention and energy given to pre-analysis of data by indicating expert data on the performance of humans and machines, thereby simplifying how data are gathered and introduced [17]. This can only be performed due to the use of Industry 4.0 technology such as machine learning, turning "big data" into "smart data" [46], and using AI incorporated into human–machine interfaces to support decision-making [47].

- Augmented reality (AR) reduces human errors and lightens the memory use of the operator, safely replicating the environment [47]. With AR, there is no compelling reason to change focus between the digital and physical worlds and no compelling reason to withdraw from a task to chase applicable data about what to do straight away or how to do it [30]. Augmented operators [40] have their working environment enriched by digital information, which reduces human error and improves decision-making by displaying feedback in real time [41].

- Inline quality checks allow addressing some quality issues that are extremely small and barely detectable by eye, as well as others that are the consequence of worker fatigue. Regardless of the reason, numerous quality issues are accepted due to failures in identifying them. All manufacturers have some convention for checking quality inline; however, if the workers have the correct tools, they will be able to catch more nonconformances, prompting fewer rework hours [32]. Some examples of Industry 4.0 technologies for quality checks are automated solutions [48] and machine vision systems [49,50].

It is important to state that not only operators benefit from technologies that reduce the cognitive load; these tools are also important to anybody doing physical or intellectual work on the shop floor [32].

3.3. SRQ3: Which Are the Cognitive Manufacturing Applications That Use Technologies That Reduce the Cognitive Load?

Cognitive manufacturing completely uses the data from hardware, systems, and procedures to infer significant knowledge over the whole value chain through various procedures (design, manufacture, and support activities). Cognitive manufacturing is based on the establishments of IoT and employing analytics joined with cognitive technologies [51].

From the SRQ2 above, we were able to identify the human–computer technologies that reduce the cognitive load. Below, we analyze these cognitive manufacturing applications to fulfill the purpose of this investigation and link cognitive manufacturing to a reduction in cognitive load.

According to the available literature, the following cognitive manufacturing applications were identified:

- Asset performance management (APM) frequently catches information and data that are connected with asset condition, to provide a comprehensive perspective of the performance of the asset. The data are then used for reliability analytics and asset health visualization, to help the improvement and tweaking of different asset models [52]. Companies can use cognitive APM to sense, diagnose, and communicate performance issues to lessen unwanted downtime. The application can envision a potential failure and then investigate data from important user manuals or technician logs to comprehend how a previous similar issue was resolved, using this information to prescribe explicit activities or answers to fix the issue [6].

- Process and quality improvement are represented throughout the manufacturing process. The numerous attributes that impact product quality can be monitored and understood by utilizing cognitive manufacturing tools. Potential quality issues can be recognized earlier by using analytics, algorithms, automated visual inspections, and machine learning instead of customary methods [6]. The symbiosis between the operator and the cyber-physical system (CPS) allows new margins for controlling and improving picking activities [36]. New strategies were suggested where operator cognition is enhanced by moving between assembly modes [53].

- Resource optimization in cognitive manufacturing can help in guaranteeing laborer safety and health. Equipment with sensors that identify immediately hazardous circumstances ensure laborer safety and improve operations in energy resource optimization. Moreover, the use of IoT, data analytics, and machine learning allows evaluating the factors that contribute to energy consumption and in improving floor planning and scheduling. This can be done to optimize the configuration of a production line to balance the workload between stations, as well as use labor more efficiently, increase the rate of production, and optimize available plant capacity [6]. To perform this, ergonomic aspects must be considered, since they are changing as the world advances to Industry 4.0; thus, the discipline must adapt to this new paradigm and its new methods [54].

- Supply chain optimization in cognitive manufacturing gathers different data from structured and unstructured data sources so as to limit supply chain costs, disruptions, and risks. Alerts that describe the threat and present the information in a proper manner to help in decision making, as well as search for alternative suppliers and recommend solutions, represent some of the solutions that a cognitive manufacturing tool can offer [6]. Most companies poorly integrate technology into their supply chain, whereas an optimized supply chain will develop new value propositions and allow meeting new business needs [55].

4. Discussion

In order to flourish in the Industry 4.0 era, manufacturers should look toward the potential of legacy, real-time, and unstructured data to settle on everyday choices that equalize quality and throughput. Having in mind that the average manufacturing site runs hundreds of software applications, it is an extremely significant challenge to make that information accessible and actionable.

The human cognitive load is currently being pushed to the limits. The fact that humanity needs cognitive manufacturing shows that the human brain has boundaries that can be suppressed by the use of machine learning, AI, and other technologies. Reducing the cognitive load by merging the digital and physical worlds allows the gap between the two worlds to diminish.

From the literature review in this paper, we can conclude that both terms can be related with respect to cognitive manufacturing technologies developed to reduce the human workload, whereby they are equally developed to perform activities on which the human worker would spend a vast amount

of time, resources, and money, consequently reducing the cognitive load associated with the task. Some activities might not even be possible to execute if not through the use of technology, although there is a lack of literature stating that cognitive manufacturing might lessen the cognitive load of workers.

This investigation was dedicated to cognitive load reduction in Industry 4.0 and cognitive manufacturing issues and it can be qualified as a work in progress. We intend to keep searching for new efficient methods to demonstrate the link between cognitive manufacturing and reduced cognitive load, working with industrial manufacturers through case studies. The next steps of this work will concern the construction and evaluation of data analyses in order to characterize the usefulness of the suggested conceptual framework.

5. Conclusions

To explore the problem found during the literature review, the conceptual framework in Figure 5 was developed. The framework demonstrates the relationships among the factors affecting cognitive overload causing manufacturing errors and how that overload can be lessened using cognitive technologies applied in cognitive manufacturing applications.
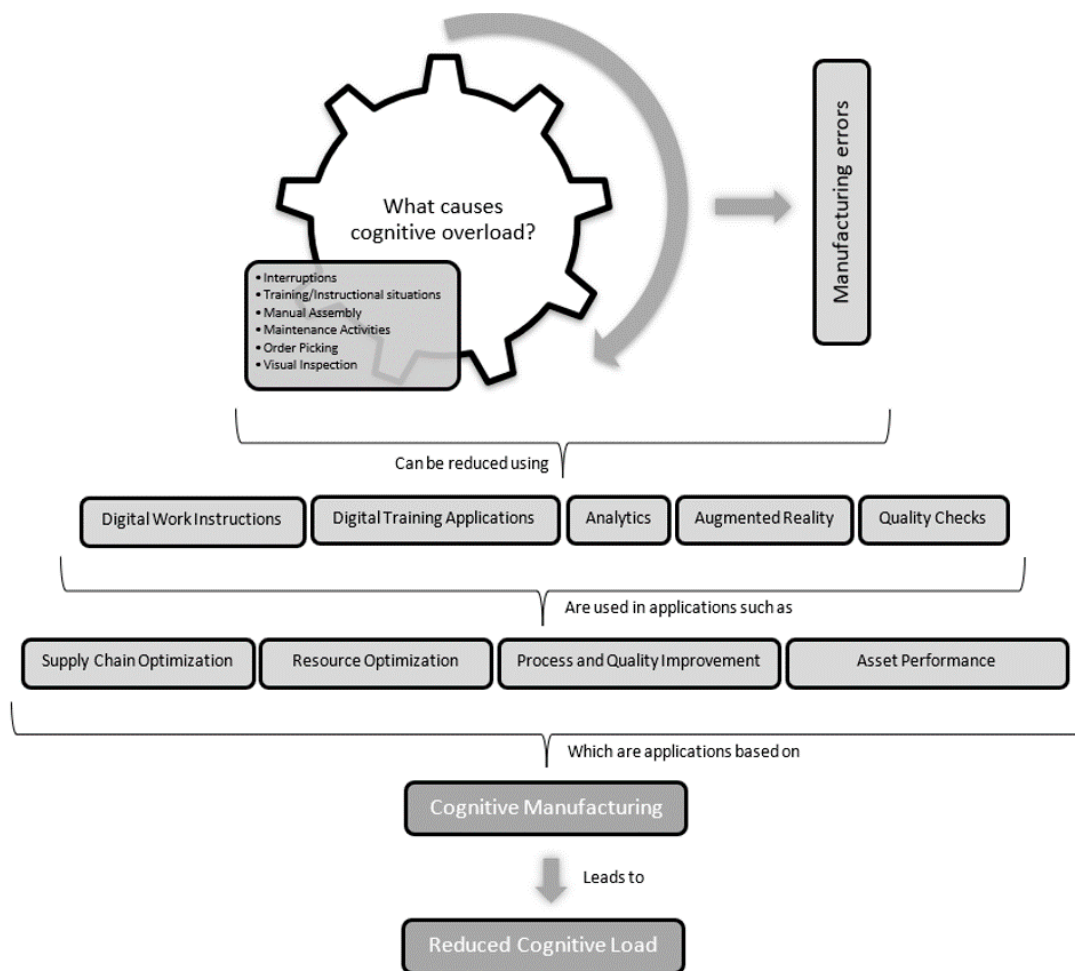
Figure 5. The conceptual framework for cognitive load minimization using cognitive manufacturing applications.

Further research will explore how Industry 4.0 can benefit from a lower burden on human cognitive load, using different tools such as Augmented Reality (AR), allowing investment in cognitive manufacturing to be extended. It will also be interesting to analyze if an investment in cognitive

manufacturing tools, aimed solely at reducing the cognitive load of the working force, translates into a good investment for a company.

However, it is safe to conclude that Industry 4.0 technologies play a very important part in the way that cognitive aspects of the operator are processed.

Although this investigation evaluated the relationship between cognitive manufacturing and reduced cognitive load, another aspect which must be taken into consideration is the financial investment in these technologies.

To develop this conceptual framework, the relationship between human–computer interaction technologies and cognitive manufacturing applications that reduce the cognitive load was established on the basis of Industry 4.0 technologies. This investigation represents the starting point for further research on the subject of the relationship between the use of cognitive manufacturing applications and a reduced cognitive load, which was not previously identified in the literature.

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