

Diplomarbeit

Development of a framework for the selection of cognitive assistance system for maintenance tasks

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Unterschrift

Erklärung zur Verfassung der Arbeit

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Ich erkläre an Eides statt, dass die vorliegende Arbeit nach den anerkannten Grundsätzen für wissenschaftliche Abhandlungen von mir selbstständig erstellt wurde. Alle verwendeten Hilfsmittel, insbesondere die zugrunde gelegte Literatur, sind in dieser Arbeit genannt und aufgelistet. Die aus den Quellen wörtlich entnommenen Stellen, sind als solche kenntlich gemacht.

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Ich nehme zur Kenntnis, dass die vorgelegte Arbeit mit geeigneten und dem derzeitigen Stand der Technik entsprechenden Mitteln (Plagiat-Erkennungssoftware) elektronisch-technisch überprüft wird. Dies stellt einerseits sicher, dass bei der Erstellung der vorgelegten Arbeit die hohen Qualitätsvorgaben im Rahmen der geltenden Regeln zur Sicherung guter wissenschaftlicher Praxis „Code of Conduct“ an der TU Wien eingehalten wurden. Zum anderen werden durch einen Abgleich mit anderen studentischen Abschlussarbeiten Verletzungen meines persönlichen Urheberrechts vermieden.

Wien, 27. Juni 2024

Christoph Rauch

Abstract

Even though the development of Industry 4.0 brings multiple benefits, it also increases the complexity and mental workload of machine operators in maintenance to a further extent. Cognitive assistance systems support operators while performing maintenance tasks to cope with this burden. Properly designed, these support the worker to reduce mental workload and avoid errors. Even though these systems have high potential, there is still a lack of research on selecting the proper cognitive assistance systems for specific tasks to improve certain Key Performance Indicators (KPIs).

Consequently, this thesis aims to answer the research question of how a proper cognitive assistance system can be selected to improve the efficiency and quality of maintenance tasks. For that purpose, this thesis develops an algorithm that matches the requirements of maintenance tasks with the capabilities of cognitive assistance systems. This matching framework is the main artifact of this work.

To do so, the thesis starts with an analysis of the state-of-the-art, which contains a systematic literature review to evaluate and classify the existing cognitive assistance systems. After this, the matching framework is set up, which is based on a numerical rating of the cognitive assistance system's capabilities and the requirements of the selected task. Using mathematical operations, these independent ratings are combined and result in scoring for each system.

This matching algorithm is used to solve an exemplary case and evaluate the framework. It guides through the overall process and delivers a qualitative evaluation of the developed framework. In conclusion, this matching algorithm is simple to use and serves as a sound starting point in the selection process.

In summary, this thesis's key findings are a classification of cognitive assistance systems, a classification of maintenance processes, and a matching framework to select cognitive assistance systems for given maintenance tasks. Strengthening the connection of cognitive assistance systems with maintenance tasks is the main contribution to the body of knowledge.

Kurzfassung

Obwohl die Entwicklung hin zur Industrie 4.0 viele Vorteile bringt, wird jedoch durch sie die Arbeitsbelastung und Komplexität der Ausführenden abermals erhöht. Um diesem Umstand zu entgegenen, unterstützen kognitive Assistenzsysteme die Fachkräfte während der Wartungsarbeiten. Richtig gewählt und umgesetzt, reduzieren diese die mentale Belastung und helfen dabei Fehler zu vermeiden. Obwohl diese Systeme ein hohes Potential haben, fehlt es noch an Forschung zur korrekten Auswahl eines passenden kognitiven Assistenzsystems um gewisse Leistungskennzahlen eines Instandhaltungsprozesses effektiv verbessern zu können.

Aus diesem Grund beantwortet diese Arbeit die Forschungsfrage, wie ein passendes kognitives Assistenzsystem gewählt werden kann, um die Effizienz und Qualität von Instandhaltungsprozessen zu verbessern. Zu diesem Zweck wird im Rahmen dieser Arbeit ein Algorithmus entwickelt, welcher die Anforderungen des Instandhaltungsprozesses mit den jeweiligen Fähigkeiten der verschiedenen kognitiven Assistenzsystemen verknüpft. Dieses Matching-Framework stellt das Artefakt dieser Arbeit dar.

Um dies umzusetzen beginnt die Arbeit mit einer Analyse des aktuellen Standes der Forschung, welche eine systematische Literaturrecherche zur Evaluation und Klassifikation aller bereits entwickelten kognitiven Assistenzsysteme umfasst. Darauf aufbauend wird das Matching Framework aufgestellt, welches auf einer numerischen Bewertung der Fähigkeiten der Assistenzsysteme, sowie der Anforderungen der Instandhaltungsaufgabe beruht. Diese werden anschließend mittels mathematischer Operationen verknüpft und resultieren schließlich in einem Scoring der Systeme.

Zur qualitativen Evaluierung wird ein Beispielsfall gelöst, bei welchem das Framework angewendet wird. In diesem wird Schrittweise durch den Selektionsprozess geführt. Hierbei zeigt sich, dass der Algorithmus einfach anzuwenden ist, dabei aber gute Ergebnisse liefert, welche als Startpunkt für den weiteren Auswahlprozess dienen.

Zusammenfassend sind die zentralen Ergebnisse dieser Arbeit zum einen eine Klassifizierung von kognitiven Assistenzsystemen sowie von Instandhaltungsprozessen, als auch ein Matching Framework zur Auswahl eines passenden kognitiven Assistenzsystems für einen beliebigen Instandhaltungsprozess. Diese Verknüpfung von kognitiven Assistenzsystemen mit Instandhaltungsprozessen stellt den Beitrag dieser Arbeit zum Body of Knowledge dar.

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CHAPTER 1

Introduction

1.1 Motivation and problem statement

"Any customer can have a car painted any color that he wants, so long as it is black " [Ford, 1922, p. 72].

This quote shows how the change toward mass production and cheap consumer goods in the past century was highly driven by a price of the reduction of variants and the standardization of processes [Wang et al., 2017].

In the past decades, on the contrary, there was a trend towards highly customizable and personalizable products, with production costs as in regular mass production [Pokorni et al., 2022]. Consequently, information technologies such as computers led to the third industrial revolution, also called the "Mass customization production (MCP)" in the late 1980s [Wang et al., 2017]. In the last years, there was a further shift towards increasing customer satisfaction and towards maximization of stakeholder value [Martin, 2010]. Therefore, products must be personalizable, more flexible, and of better quality [Haslgrübler et al., 2018]. This shapes the ground for introducing the 4th industrial revolution (aka Industry 4.0), which is also called "Mass personalization production (MPP)" [Wang et al., 2017].

These MPP Industry 4.0 processes, characterized by small lot sizes and increased flexibility, can often not be carried out fully automatized due to the demand for prior knowledge and experiences for handling problems, long set-up times, and complex manufacturing structures [Wiesbeck, 2014]. Therefore, humans will play an essential role in these future manufacturing environments due to their high flexibility, creativity, and intuition [McKinsey & Company, 2022]. However, this manual and flexible manufacturing process is driven by a high amount of data, frequent changes of tasks, and highly needed flexibility,

which leads to a high work intensity of the laborer, reduced efficiency, and lower quality [Zhou et al., 2018].

One way to handle this is by using cognitive assistance systems, which support human workers in the manufacturing process. These systems are defined in the following way:

"Cognitive assistance systems are technical systems that process information and support humans in performing their tasks, enhancing the worker's capabilities. These systems provide the worker with the right knowledge and information in the right way and at the right time and can also comprise alarms of hazards, notifications, automatic intervention, documentation, and control of the correct execution of work tasks in the assembly system."
[Pokorni et al., 2022]

Thus, cognitive assistance systems provide detailed information on how and when to do a specific task and can also detect mistakes to improve the quality of the process. Klapper et al.'s potential analysis of cognitive assistance systems in production areas found that 36% of the surveyed companies use cognitive assistance systems, while 32% consider using them [Klapper et al., 2020]. Most of the participants expect higher productivity (79%), better process control (69%), and higher quality and cost-effectiveness (66%) [Klapper et al., 2020]. For example, a study found a time savings potential of 75% in searching for relevant information in a maintenance process using cognitive assistance systems [Mueller et al., 2020].

On the other hand, selecting the right system for a specific task is very important to ensure acceptance and an increase in productivity [Sochor et al., 2019] and [Mark et al., 2022b]. The survey by Klapper et al. revealed that there is still a "[...] challenge of finding the right assistance system for the individual company [...]" [Klapper et al., 2020]. Another problem is that although research into cognitive assistance systems is developing rapidly and new technologies are coming onto the market every year, there is still a lack of classification of the countless systems in the field of maintenance [Mark et al., 2022b].

This leads to the following problem definition: Firstly, there is a lack of knowledge about the classification of cognitive assistance systems in maintenance. It should be possible to name (almost) mutually exclusive groups of cognitive assistance systems. Secondly, there is a lack of understanding about how maintenance tasks can be broken down into cognitive basic actions to determine where cognitive assistance is needed most. Thirdly, there is a lack of knowledge about selecting the right cognitive assistance system for given maintenance tasks to improve efficiency and quality.

1.2 Research questions and expected outcomes

This thesis will answer the following main research question to solve the problems stated in the prior section: How can a cognitive assistance system be selected to improve KPIs such as efficiency or quality of given maintenance tasks? To answer this question, an

artifact is created, which is a framework to select the matching cognitive assistance system for a given maintenance task. It should be capable of creating relevant benefits, considering the properties of the specific task.

To answer this main research question, some sub-questions must be examined. Firstly, the thesis explains cognitive assistance systems and why they are needed in maintenance. Secondly, the various cognitive assistance systems are classified. Thirdly, this work gives an overview of maintenance tasks and their classification. Finally, the question of selecting the right cognitive assistance system for a given maintenance task is answered using the knowledge of these sub-questions. The capabilities of the framework are then evaluated using a qualitative example.

The expected outcome is a matching algorithm, which simplifies selecting a proper cognitive assistance system. It should be easy to use while delivering sound recommendations for any maintenance task.

1.3 Methodology of Research

This master thesis is based on the Design Science Research (DSR) methodology by Alan Hevner, who describes it as a paradigm "to extend the boundaries of human and organizational capabilities by creating new and innovative artifacts" [Hevner et al., 2004]. Therefore, it aims not to develop and justify theories but to create an artifact. To do so, Hevner provides seven guidelines for proper design science research [Hevner et al., 2004].

As a foundation of the research, the surrounding environment defines the space of the DSR [Brocke et al., 2020]. The artifact is developed regarding the organization, its people, and existing or planned technologies [Brocke et al., 2020]. The need is defined by the culture, structure, work processes, or organizational structure [Brocke et al., 2020]. According to the DSR methodology, the research is driven by the stakeholder's needs [Brocke et al., 2020]. The knowledge base is used and applied to meet these needs, which consists of prior research, theories, frameworks, experimentation, etc. [Brocke et al., 2020].

In this thesis, the DSR methodology is applied to create an artifact, which is a framework to select the matching cognitive assistance system for a given maintenance task. It should be capable of creating relevant benefits, considering the task's properties. To match these requirements, the environmental needs must be analyzed and sorted (i.e., Relevance Cycle).

For the development of this artifact, a systematic literature review is used as a knowledge base (i.e., Rigor Cycle). Therefore, Scopus is utilized to determine the important literature based on specific keywords regarding the main research question by using the following search string:

("cognitive assistance ") AND (("Production "OR "Maintenance "OR "Assembly "OR "Manufacturing ")

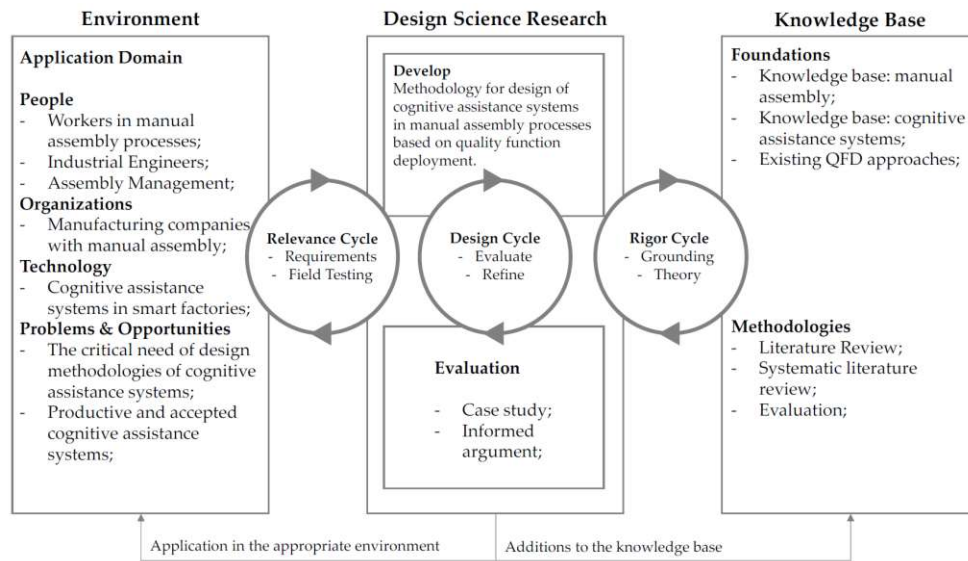


Figure 1.1: Design science framework [Pokorni et al., 2022]
- adapted from [Hevner et al., 2004]

Based on this knowledge, the artifact has been developed and evaluated (i.e., Design Cycle). The evaluation uses an illustrative, qualitative case that proves the functionality. The aim here is to pick a cognitive assistance system for one illustrative task based on the framework's recommendation and develop it. Ultimately, the artifact should lead to selecting a cognitive assistance system that enhances a given task's efficiency and quality.

1.4 Structure of work

The graph (figure 1.2) provides an overview of the structure of this thesis. It starts with a short background chapter (Chapter 2), which explains the historical background, the need for cognitive assistance, and the methods of cognitive task analysis. In Chapter 3, a systematic literature review to summarize the state-of-the-art knowledge in this field is conducted to create a classification of the existing systems and provide an overview of existing matching frameworks. In Chapter 4, a framework is developed to select a proper cognitive assistance system for specific tasks to improve the key performance indicators of the maintenance process. This framework is evaluated in Chapter 5 with a qualitative case. Chapter 6 concludes the outcomes of the thesis and gives suggestions for future work.

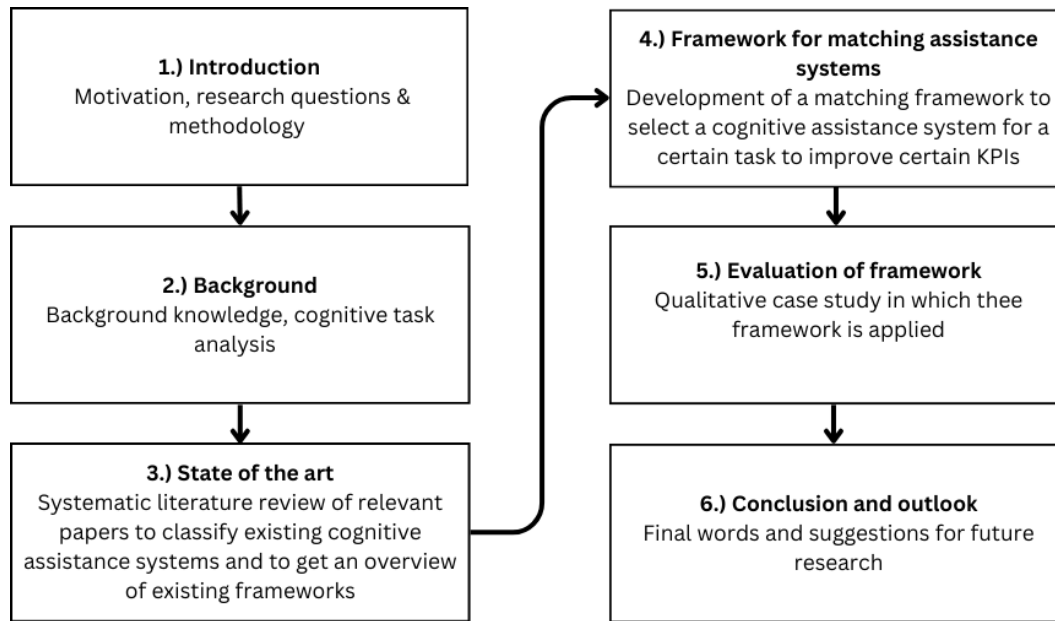


Figure 1.2: Structure of work

CHAPTER 2

Background

2.1 Transformation to human-centered production

In the past century, the vision of fully automated factories was a primary driver of research. Despite several innovations, such as the microprocessor and computer-integrated manufacturing (CIM), which focused on technology aspects, several attempts to create fully automated, unpeopled factories have failed [Nelles et al., 2016]. On the contrary, research started to focus on how to take advantage of the capabilities and competence of human workers in cyber-physical systems [Nelles et al., 2016].

2.1.1 Industry 4.0

Modern human-centered production originates in the vision of Industry 4.0, which aims to ensure the competitiveness of the German industry [Kagermann et al., 2013]. First published in 2013, Industry 4.0 describes the implementation of the Internet of Things (IoT) and services into manufacturing [Kagermann et al., 2013]. Therefore, the authors state the following:

“In the future, businesses will establish global networks that incorporate their machinery, warehousing systems and production facilities in the shape of Cyber-Physical Systems (CPS). In the manufacturing environment, these Cyber-Physical Systems comprise smart machines, storage systems and production facilities capable of autonomously exchanging information, triggering actions, and controlling each other independently.” [Kagermann et al., 2013]

The idea of Industry 4.0 is to create intelligent products, processes, and procedures using various interconnected IT systems [Kagermann et al., 2013]. McKinsey & Company names four disruptive technologies which are drivers of Industry 4.0 [McKinsey & Company, 2022]:

1. **Connectivity, data, and computational power:** cloud technology, blockchain, sensors
2. **Analytics and intelligence:** machine learning and artificial intelligence
3. **Human-machine interaction:** virtual reality (VR), augmented reality (AR), robotics and automation
4. **Advanced engineering:** additive manufacturing, renewable energy, nanoparticles

Industry 4.0 encourages vertical and horizontal integration to create highly customizable products [Kagermann et al., 2013]. Even though the paper first mentions the adopted role of human workers, it focuses on automated factories [Kagermann et al., 2013]. In response to the German population's demographic shifts, it suggests that in the future, employees will control the factory from the outside in virtual and mobile workplaces [Kagermann et al., 2013]. Consequently, there is a high demand for highly skilled workers trained through upskilling and reskilling [McKinsey & Company, 2022]. Even though automation takes a significant part of Industry 4.0, the original vision also suggests a shift towards a more human-centered perspective:

“Through Industrie 4.0, we will also enable a paradigm shift in human-technology interaction. It will be machines that adapt to the needs of human beings and not vice versa. Smart industrial assistance systems with multi-modal user interfaces will bring digital learning technologies directly into the workplace.” [Kagermann et al., 2013, p.19ff.,36]

2.1.2 Human-cyber-physical systems and Operator 4.0

Over the years, the original Industry 4.0 concept, which focused on automation, had developed toward a more human-centric perspective [Romero et al., 2016]. This development is covered by the term “Human-cyber-physical production systems” [Romero et al., 2016]. These human-cyber-physical systems are defined in the following way:

“Systems engineered to (a) improve human abilities to dynamically interact with machines in the cyber- and physical- worlds using ‘intelligent’ human-machine interfaces, using human-computer interaction techniques designed to fit the operators’ cognitive and physical needs, and (b) improve human physical-, sensing- and cognitive capabilities, using various enriched and enhanced technologies (e.g., using wearable devices).” [Romero et al., 2016]

Ansari et al. state that human-cyber-physical production systems “[...] aim to deeply interact and collaborate with humans towards achieving a common goal (e.g., reducing failure rate in assembly activities) rather than only providing services or assistance to facilitate human jobs” [Ansari et al., 2018].

While human-cyber-physical production systems and human-centricity are essential parts of Industry 4.0, the European Commission published a paper that covers the

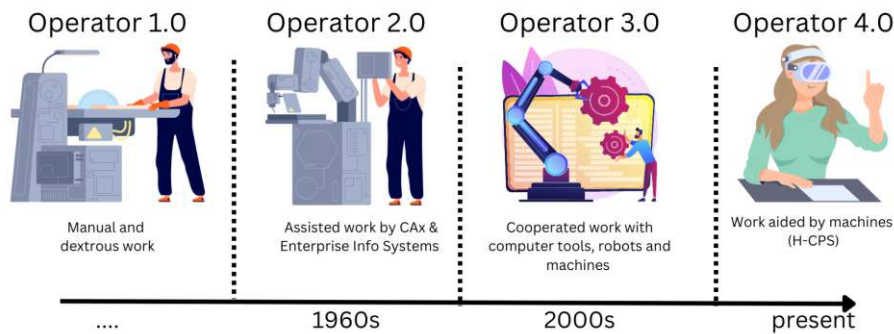


Figure 2.1: Evolution of operators
adapted from [Romero et al., 2016]

weaknesses of Industry 4.0 about current challenges such as climate change, the COVID-19 pandemic, and social problems [European Commission, 2022]. Consequently, they introduced the term Industry 5.0 to emphasize a new approach towards a more human-centered production perspective [European Commission, 2022]. On the other hand, the Association Industry 4.0 of the Federal Ministry of Economic Affairs and Climate Action criticizes the term “Industry 5.0” because it suggests that it contains new content and that the fourth industrial revolution is complete [Association Industry 4.0, 2024]. Following this opinion, this thesis will not use the term Industry 5.0.

The paradigm shift towards human-centricity and human-cyber-physical systems in Industry 4.0 correlates with the Operator 4.0 concept by Romero et al. [Romero et al., 2016]. The operator is seen as “smart and skilled” and performs work aided by machines. His capabilities are expanded by using technological means instead of robots [Romero et al., 2016]. Therefore, the design philosophy relies on adaptive production systems with a focus on the enhancement of the sensory, cognitive, and physical capabilities of the operator [Romero et al., 2016].

Assessing the definition of cognitive assistance systems, cited in sections 1.1 and 2.2.1, cognitive assistance systems are part of these human-cyber-physical systems as they represent intelligent human-machine interfaces that improve the cognitive capabilities of human operators. Finally, one can state that these systems are required to implement the Industry 4.0 vision successfully [Romero et al., 2016].

2.2 Cognitive assistance systems

2.2.1 Definition

Human-centered cyber-physical production systems and Operator 4.0 concepts directly lead to workers needing sensory, cognitive, and physical assistance. With a focus on cognitive assistance systems, Pokorni et al. state that these systems define the interaction of humans and machines in cyber-physical systems [Pokorni et al., 2022]. Operators

will face significant difficulties working with increasingly sophisticated interconnected machines without these systems [Pokorni et al., 2022]. Regarding their importance, it is essential to deduce a clear definition of the term “cognitive assistance systems,” starting from a general definition of assistance systems. The authors Mark et al. define these workers’ assistance systems in the following way:

“[...] technical systems that support the worker during manufacturing or assembly work tasks without replacing him, without overruling him, and without posing any danger to the worker.” [Mark et al., 2021]

For a more specific definition, which also pays attention to the interactive aspect, Trotha et al. introduced the term “advanced assistance system“, which can be summarized in the following way [Trotha et al., 2018]:

“An advanced assistance system is an interactive interface that encapsulates complexity, increases the acting capability of the user, and therefore allows better usage of the plant.” [Späker et al., 2021]

These worker’s assistance systems can be generically divided into cognitive, sensorial, or physical systems [Romero et al., 2016]. The following table presents examples of each of them:

N°	Sensorial Systems	Physical Systems	Cognitive Systems
1	Eye Tracking	Exoskeleton	Augmented Reality
2	Motion Sensing	Collaborative Robot	Virtual Reality
3	Safety Glove	Back Support	Head Mounted Display

Figure 2.2: Examples of assistance systems
[Mark et al., 2021]

Regarding the cognitive capabilities of Operator 4.0, Romero et al. refer to the work of Carroll and state that [Carroll, 1993]:

“A cognitive capability is the operator’s capacity and ability to undertake the mental tasks (e.g., perception, memory, reasoning, decision, motor response, etc.) needed for the job and under certain operational settings“ [Romero et al., 2016].

Summarizing all these definitions, one can define cognitive assistance systems as interactive technical systems that support the operator while doing mental tasks required to fulfill a specific job. Thus, they reduce the complexity and increase the worker’s capabilities without replacing or overruling him. This definition is similar to that of Pokorni et al.,

who define cognitive assistance systems in the following way:

“Cognitive assistance systems are technical systems that process information and support humans in performing their tasks, enhancing the worker’s capabilities. These systems provide the worker with the right knowledge and information in the right way and at the right time and can also comprise alarms of hazards, notifications, automatic intervention, documentation, and control of the correct execution of work tasks in the assembly system.”
[Pokorni et al., 2022]

The following chapters use the abbreviation “CAS“ for cognitive assistance systems.

2.2.2 Constraints of human cognition

Mühlbradt criticizes that CAS are often selected based on organizational and technical considerations while disregarding constraints of human cognition [Mühlbradt, 2022]. This leads to systems being often developed past the actual requirements.

To avoid this situation, Mühlbradt suggests the evaluation of human constraints [Mühlbradt, 2022]. These constraints can be derived from two different causes: Firstly, constraints can be caused by a lack of training and are, therefore, changeable [Mühlbradt, 2022]. Secondly, constraints can be caused by human nature and are not changeable, which requires using cognitive assistance [Mühlbradt, 2022].

These constraints can be aggregated into three types [Mühlbradt, 2022]:

1. Limits of “speed“: how fast can information be processed
2. Limits of “capacities“: how much information can be handled in a certain situation
3. Limits of “reliability“: How accurate is the processing of information

2.3 Maintenance

2.3.1 Definition and overview

The DIN 31051, which is a norm about the fundamentals of maintenance, defines the term maintenance in the following way:

“Combination of all technical, administrative, and management measures during the life cycle of a unit, which serves to maintain or restore it to its functional condition so that it can perform the required function.”
[Deutsches Institut für Normung, 2019]

According to the norm, maintenance consists of four different measures :

1. “Servicing: Measures to delay the reduction of the available wear margin
2. Inspection: Measures to detect and assess the actual state of a unit

3. *Repair: Physical measures to restore the function of a faulty unit*
4. *Improvement: Combination of all technical and administrative measures to increase reliability and/or maintainability and/or safety of a unit without changing its original function“ [Deutsches Institut für Normung, 2019]*

Historically, maintenance has evolved from reactive maintenance, which only responds to occurred failures, towards prescriptive maintenance, which uses many different sensors, data sets, and AI to prescribe a certain maintenance measure [Sahli et al., 2021]. All the development steps can be seen in Figure 2.3.

Like the evolution of Industry 1.0 to Industry 4.0, maintenance is commonly categorized into four stages, starting at Maintenance 1.0 up to Maintenance 4.0 [Arkadiusz and Jasiulewicz - Kaczmarek, 2019].

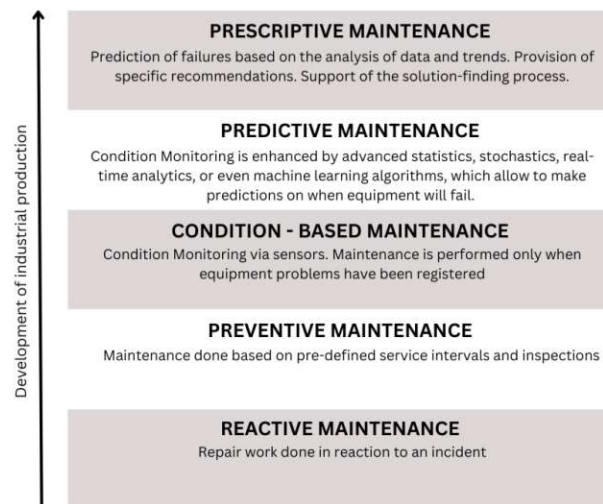


Figure 2.3: Classification of maintenance stages [Arkadiusz and Jasiulewicz - Kaczmarek, 2019]

At the beginning of the industrial age, it was sufficient to limit maintenance to the faults that had already happened [Arkadiusz and Jasiulewicz - Kaczmarek, 2019]. Machine operators mostly carried out these jobs, relying on their knowledge. Later, as machines became more complex, Maintenance 2.0 started to become professionalized and was regularly carried out by separate departments in the form of inspections and service intervals (“Preventative Maintenance”) [Arkadiusz and Jasiulewicz - Kaczmarek, 2019]. With the rise of automation and more complex systems, requirements for maintenance got more profound and led to Maintenance 3.0, which relied on a Condition-Based Maintenance (CBM) approach [Arkadiusz and Jasiulewicz - Kaczmarek, 2019]. For the first time, monitoring data was used on a large scale to identify anomalies before failures [Arkadiusz and Jasiulewicz - Kaczmarek, 2019]. In reaction to Industry 4.0 with its vi-

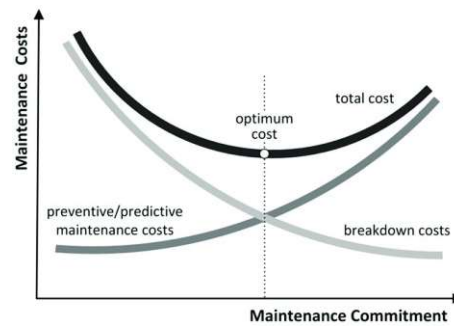


Figure 2.4: Maintenance costs [Netto et al., 2020]

sion of smart factories and its Cyber-Physical Production Systems (CPPS), research and manufacturers currently establish Maintenance 4.0, which enforces a shift towards prescriptive maintenance, called PriMa, through the automation of knowledge-based support systems and the usage of large amounts of heterogeneous data [Ansari et al., 2019].

Matyas describes two main goals of maintenance activities [Matyas, 2018]. Firstly, the maximization of reliability and safety, and secondly, the minimization of costs and maximization of profits [Matyas, 2018]. At this point, considering the four maintenance measures mentioned in the DIN 31051, we find that there are two different drivers for the costs of maintenance: Firstly, the prices for any preventive measures (service, inspection, improvement) and secondly, the costs for breakdowns (repairment costs, downtimes). Considering this, effective cost-based maintenance must ensure finding the right moment for its measures [Choubey et al., 2019] and [Netto et al., 2020].

Looking at Figure 2.4, it is essential to mention that these curves vary for each machine. Consequently, if a machine causes high breakdown costs, predictive measures must be used more than in the opposite case. Therefore, each machine and production facility requires a maintenance strategy matching the specific requirements.

2.3.2 Maintenance standard process

Matyas states that the standardization of maintenance processes is a crucial factor for lean maintenance [Matyas, 2018]. The suggested model (figure 2.5) includes eight steps and allows the description of all possible maintenance activities [Matyas, 2018]. It also separates value-adding from supportive activities.

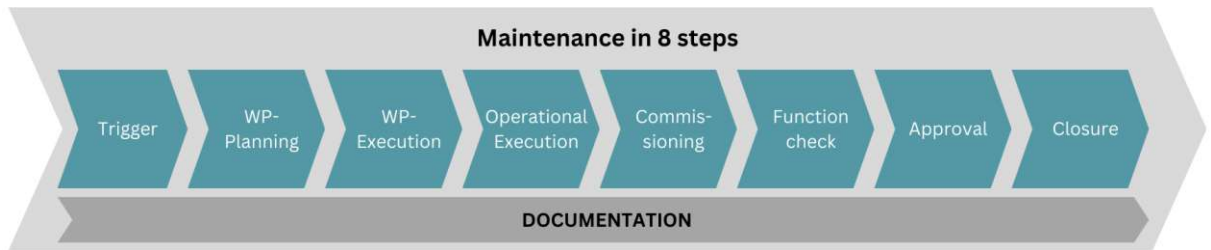


Figure 2.5: Standard maintenance process [Matyas, 2018]

The standard process contains 8-steps [Matyas, 2018]:

1. Trigger

Start event: Occurrence of a malfunction/planned maintenance activity

In this step, all relevant information required for the work- preparation and execution is collected, and measures are deducted.

End event: Necessary measures are determined

2. Work Preparation (WP)-Planning

Start event: Necessary measures are determined

Planning of personal, material, equipment, and execution date.

End event: Completed work order

3. Work preparation (WP)-execution

Start event: Completed work order

Planned resources are issued, the area is unlocked, and obstructive parts are removed for an unobstructed execution of the maintenance measures. The step is finished when the system is ready for the actual maintenance tasks.

End event: Preparation finished

4. Operative execution

Start event: Preparation finished

Planned activities of the work order are conducted. This step is the only value-adding step and the process's core step.

End event: Planned maintenance measures are conducted

5. Commissioning

Start event: Planned maintenance measures are conducted

Commissioning includes evaluating the components before the start-up and the actual start-up of the systems.

End event: System is ready for service

6. Function check

Start event: System is ready for service

The conducted activities are evaluated concerning their quality. Afterward, they are noted in the plant book and an accompanying document.

End event: Function confirmed/ Function not confirmed

7. Approval

Start event: Function confirmed

The release transfers the viewing unit to the user's area of responsibility.

End event: Approval granted/Approval not granted

8. Closure

Start event: Approval granted

Includes reporting and logging, disposal of consumables, and the closure of the work order. Future measures are derived, and the maintenance plan gets updated.

End event: Completed work order

2.3.3 Key Performance Indicators - (KPI)

According to Matyas, key performance indicators (KPIs) are “*condensed information about technical and economic facts in figures.*” [Matyas, 2018]. They provide a concise and objective picture of the current situation and are important for decision-making [Matyas, 2018]. As the impact of CAS needs to become measurable, KPIs are highly important for developing the framework. Even though numerous different KPIs exist in the maintenance field, some of the most common KPIs are presented here. These are separated into “performance metrics,” which are objective and measurable, and “perception metrics,” which represent the feelings and perceptions of the worker (cf. table 2.1).

Table 2.1: Example of KPIs

Performance metrics	
Speed	How much time is required for the maintenance task? [Burggräf et al., 2020a] and [Shin et al., 2021]
Error rate	How many errors occur during the execution of the maintenance task? [Haslgrübler et al., 2018] and [Burggräf et al., 2020a]
Safety	How many accidents are caused by this (sub)-task?
Maintenance cost intensity	Ratio of maintenance costs and production costs

Labor cost share	Ratio of maintenance labor costs against the total maintenance costs [Matyas, 2018]
Surplus work	Ratio of activities still to be carried out against craft capacity per day [Matyas, 2018]
Perception metrics	
Worker relief	Reduction of cognitive load and stress of worker [Reisinger et al., 2018] and [Ulmer et al., 2023]
Flexibility	Ability to adapt to new situations, products, and variants with the least possible efforts [Burggräf et al., 2020a]

2.4 Classification of maintenance tasks

Matyas states (cf. section 2.3.2) that each maintenance process can be described within a standard process, which consists of 8 steps [Matyas, 2018]. This standard process covers the maintenance process, such as an inspection or a repair, and consists of numerous tasks [Matyas, 2018]. To find a proper assistance system, it is important to classify the various tasks, and understand the basic cognitive activities of a task, and evaluate the activities that need the most assistance. The following distinguishes maintenance tasks between physical and cognitive tasks, routine vs. non-routine tasks, social vs. individual tasks, and mobile vs. stationary tasks.

Physical tasks vs. cognitive tasks

First, a distinction must be made between physical and cognitive tasks. While movements and sensorial abilities characterize physical tasks, cognitive tasks concern mental activities [Cimini et al., 2023]. Nonetheless, most tasks are not distinctive but a mixture of physical and cognitive activities.

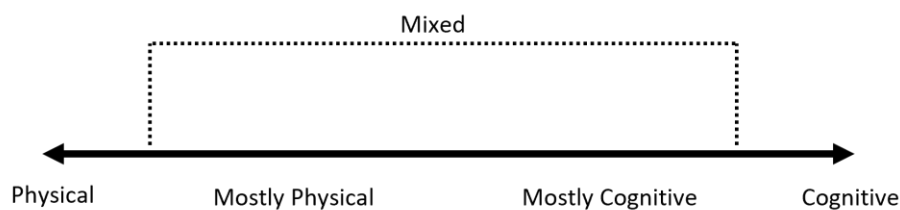


Figure 2.6: Cognitive vs. physical tasks

Routine vs. non-routine tasks

Another distinction can be made between routine and non-routine tasks. According to Cimini et al., a routine task is an activity that is performed following programmed rules [Cimini et al., 2023]. It can be broken down into repeating certain types of work

without any significant changes over time, making it easy to standardize and optimize [Cimini et al., 2023]. Untrained and inexperienced workers and computers can easily carry out these tasks, as the activities are logically ordered and can be translated into simple operations [Cimini et al., 2023].

On the contrary, non-routine tasks do not have any well-defined procedures and are often abstract. These tasks involve analytical capabilities, intuition, and problem-solving skills. These tasks can not be translated into simple operations and must be carried out by experienced workers [Cimini et al., 2023].

Individual vs. social tasks

Social tasks involve a high level of social interaction and are carried out by multiple operators [Frey and Osborne, 2017]. Consequently, these tasks require teamwork, strong social cohesion, and teamwork [Frey and Osborne, 2017]. The number of people involved essentially sets the complexity of the task and limits the scope of technical replacement and support [Frey and Osborne, 2017]. On the contrary, individual tasks are carried out by a single operator and can, therefore, easily be supported by computers [Cimini et al., 2023] and [Frey and Osborne, 2017].

Mobile tasks vs. stationary tasks

The task's mobility describes where the task is carried out. Stationary tasks are carried out in fixed workplaces, which means that the equipment is stationary and allows the usage of advanced technologies, machines, and computer systems. On the contrary, mobile tasks are performed outside fixed workplaces with mobile equipment, and operators are often limited regarding using CAS. Even though the mobility of the task is not relevant to the matching function, it is crucial to consider these aspects for the selection of the hardware components of the system.

It is worth noting that this work focuses on routine and individual tasks since the number of tasks in maintenance is high and ranges from minor inspections up to highly complex operations with dozens of people involved (e.g., repairment of windmill, inspection of water turbine, etc.).

2.5 History of modern task analysis

According to the Oxford Dictionary, a task is “*a piece of work that someone has to do*” [Oxford Dictionary, 2023b]. This definition delivers a comprehensive understanding and includes almost all human activities. Therefore, Hollnagel suggests extending this definition to “*functions or activities that must be carried out to achieve a specific goal*” [Hollnagel, 2012]. Because of this extension, task analysis generally involves what people must do to achieve a specific goal. In other words, task analysis deals with “who does what and why.”


















	Search		Inspect
	Find		Pre-Position
	Select		Release load
	Grasp		Transport empty
	Transport loaded		Rest for overcoming fatigue
	Position		Unavoidable delay
	Assemble		Avoidable delay
	Use		Plan
	Disassemble		

Figure 2.7: Therbligs according to [Gilbreth and Gilbreth, 1919]

Several attempts at searching general all-purpose components that describe each task failed in the past. Nonetheless, it is essential to mention the work of Frank Bunker Gilbreth, who first categorized tasks by the usage of 17 different basic motions, which he called therbligs (figure 2.7) [Hollnagel, 2012] and [Gilbreth and Gilbreth, 1919].

The field of task analysis has its roots in the early 1900s when Frederick W. Taylor first studied human performance in the work environment in a scientific way (“Scientific management approach”) [Proctor and Van Zandt, 1994], and [U.S.NRC., 2020] and [Taylor, 1911]. Taylor found that tasks could be described as a sequence of actions and motions, such as the therbligs [Taylor, 1911]. These could be described as “Sequential Task Organization” [Hollnagel, 2012].

However, due to an increase in the complexity of tasks in the 1950s, the increasing capabilities of machines, and the higher number of cognitive tasks, the sequential task organization reached its limits, as people often had to perform multiple activities at the same time [Stanton, 2006]. Additionally, Taylor’s scientific management approach had shortcomings, as it fails to consider the psychological aspects of work [Hackman and Oldham, 1980]. Nowadays, only a few tasks are considered sequential; as an example, Hollnagel mentions the world of cooking (figure 2.8), in which most recipes represent a simple sequence of actions [Hollnagel, 2012].

In contrast, the most sophisticated tasks can be described via a hierarchical approach. As a reaction to increasingly complex tasks, Miller developed a task analysis model in which main tasks could be split into subtasks [Miller, 1953]. This implied a specific hierarchy of tasks, although it was not a prominent feature of his method [Hollnagel, 2012]. Building on this, Annett et al. developed the hierarchical task analysis (HTA) [Annett and Duncan, 1967] and [Annett et al., 1971]. Due to its generic nature, it allows for the analysis of any task

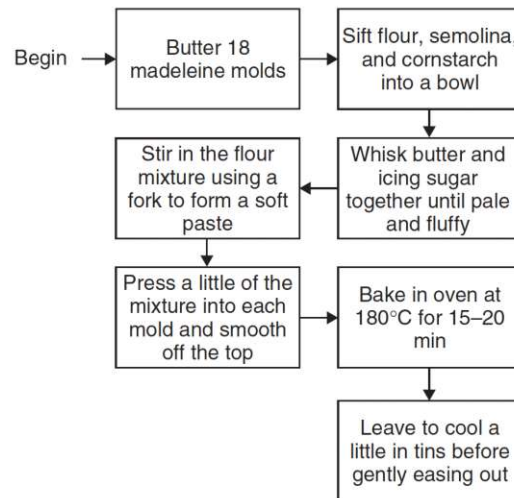


Figure 2.8: Example of a sequential task [Hollnagel, 2012]

in any field. The HTA clearly defines that one or many tasks serve to achieve a goal, while each task can be hierarchically broken down into subgoals. While doing so, the level of hierarchies and details are not fixed and can be chosen individually [Ergonomics, 1998]. The following graph (figure 2.9) from Hollnagel shows an example in the case of a bank withdrawal at an ATM [Hollnagel, 2012].

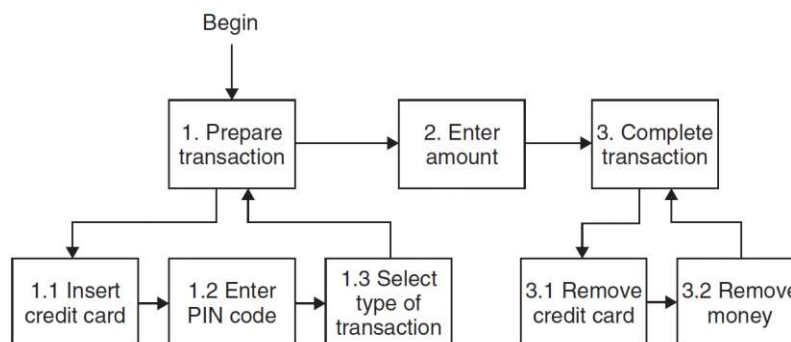


Figure 2.9: Example of a hierarchical task [Hollnagel, 2012]

In this example (figure 2.9), the upper level shows the main tasks and their order to reach the goal, while the first level of subtasks gives more detailed descriptions for each task [Hollnagel, 2012]. These could be, of course, extended to a further degree. At this point, Hollnagel mentions that finding the correct detail to describe a task is not always trivial and should be based on the specific application of the analysis [Hollnagel, 2012].

The significant advantage of the HTA is its capability to include cognitive tasks in the analysis [Annett, 2004]. According to this, the HTA method is suitable for correctly

describing various maintenance tasks. To do so, first, the data of the different maintenance tasks must be collected. Therefore, several methods exist, such as activity sampling, structured interviews, field observations, or verbal protocols. Additionally, techniques such as “think aloud” protocols and introspection (assuming that others will do the same as you) can be used to get information about cognitive tasks. After the collection of the data, the information must be aggregated and sorted in a proper way to describe the process [Hollnagel, 2012].

2.5.1 Cognitive task analysis

To find the matching CAS for a given maintenance task, it is necessary to understand which parts of the task need cognitive assistance most. To decide whether cognitive assistance is needed for specific (sub)-tasks, Strengé and Schack found two different approaches: First, a static estimation about whether assistance is required, which might be based on statistics about error frequency or the generally expected need for assistance [Strengé and Schack, 2023]. Secondly, a dynamic analysis detects user signals that can be measured using sensors such as eye tracking or electrocardiography (EEG) [Strengé and Schack, 2023].

The following paragraphs will focus on the first, the static approach, using the methods of cognitive task analysis and workload classification suggested by Knisely et al. [Knisely et al., 2021]. The process is the following:

1. Traditional task analysis: Break down the task into a set of basic actions that are necessary to achieve a goal
2. Cognitive task analysis: Assign observable and non-observable cognitive basic actions to all steps of the task using Bloom’s and Harrow’s taxonomies
3. Validate the decomposition and find actions that need cognitive assistance the most

Bloom’s cognitive taxonomy

To describe cognitive tasks adequately, Bloom and Krathwohl found six non-observable cognitive skills sorted by their increasing cognitive complexity [Bloom and Krathwohl, 1956] (figure 2.10). That means that each succeeding level requires the skills of the prior levels. Even though this taxonomy was created for an educational purpose, its usage is helpful in cognitive task analysis. In 2001, Anderson and Krathwohl revisited the original taxonomy and made a few changes in the alignment used in this work [Anderson and Krathwohl, 2001].

1. Remember: Recall knowledge and basic concepts
2. Understand: Interpretation of information
3. Apply: Implement what was learned in the remember and understand phases
4. Analyze: Decomposing the system into composite parts and examining those parts

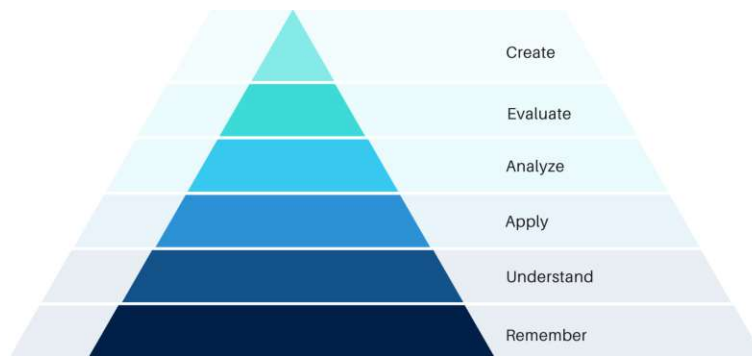


Figure 2.10: Bloom's taxonomy [Anderson and Krathwohl, 2001]

5. Evaluate: Make judgments based on criteria and standards
6. Create: Produce new or original work

Harlow's psychomotor taxonomy

Contrary to Bloom's taxonomy, Harlow's taxonomy focuses on observable actions sorted by their complexity but also considers non-observable sensorial actions such as perception (figure 2.11) [Harlow, 1972].

1. Reflexive movements: Movements induced without learning caused by stimuli
2. Fundamental movements: Movement patterns that build on reflexive movements
3. Perceptual abilities: Interpretation of sensory information about oneself and the environment
4. Physical abilities: Functional characteristics of the body such as strength, endurance, or agility
5. Skilled movements: Complex movements that require training
6. Non-discursive movements: Movements and gestures required for communication

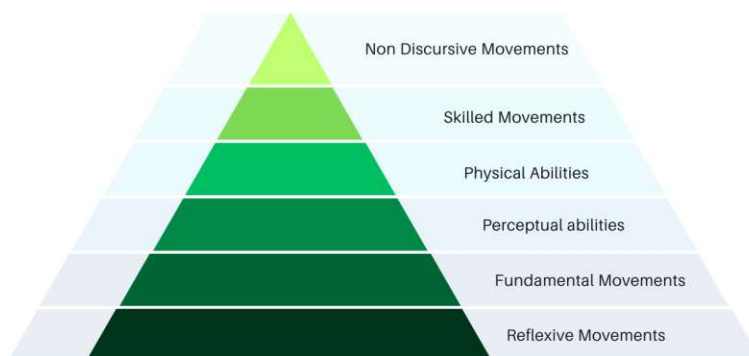


Figure 2.11: Harlow's taxonomy [Harlow, 1972]

Assistable cognitive actions

Harrow's and Bloom's taxonomies provide a solid base to categorize human tasks properly to understand the workload and complexity. Nonetheless, not all actions of Harrow's taxonomy can be supported by cognitive assistance; only "perceptual abilities" are covered by CAS. Table 2.2 summarizes the basic cognitive actions that CAS can assist.

Taxonomy	Action
Bloom	Remember
	Understand
	Apply
	Analyze
	Evaluate
	Create
Harrow	Perceptual abilities

Table 2.2: Actions that CAS can assist

CHAPTER 3

State-of-the-Art

As the field of CAS is still evolving, many solutions, definitions, and examples exist. To get a foundation for the matching framework, it is important to get an overview of the state of the art in the field of cognitive assistance. Therefore, a systematic literature review is conducted to analyze all relevant papers in this field. The following chapter guides through this process, closes with a classification of the CAS, and states existing matching frameworks.

3.1 Motivation and method

3.1.1 Methodology

According to Rowley and Slack, the systematic literature review (SLR) is defined as “*a summary of a subject field that supports the identification of specific research questions*” [Rowley and Slack, 2004]. In this master thesis, SLR is used as a knowledge base to support the development of the matching artifact. The SLR methodology is based on vom Brocke et al., which follows five consecutive steps (figure 3.1) [vom Brocke et al., 2009].

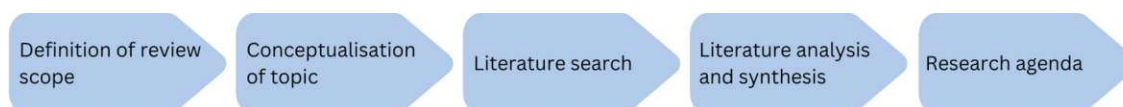


Figure 3.1: Consecutive steps of systematic literature review
[vom Brocke et al., 2009]

Stage I sets the scope of the literature review. Vom Brocke et al. suggest the taxonomy of Cooper, which is comprised of six categories (table 3.1) [vom Brocke et al., 2009] and [Cooper, 1988]. This stage sets the frame for the following literature research. While coverage and perspective are mutually exclusive, others can be combined. Stage II aims

Focus	Research outcomes Research methods Theories Applications
Goal	Integration Criticism Central issues
Organisation	Historical Conceptual Methodological
Perspective	Neutral representation Espousal of position
Audience	Specialised scholars General scholars Practitioners/Politicians General public
Coverage	Exhaustive Exhaustive and selective Representative Central/pivotal

Table 3.1: Taxonomy of literature reviews [Cooper, 1988]

to conceptualize the topic, provide an overview of the existing knowledge, and serve to find adequate keywords and filters. In Stage III, the database is queried using keywords and filters to find articles and papers that match the topic and research question. In addition, a backward and forward search can be utilized to complement the coverage of the topic. In Stage IV, relevant articles will be read and analyzed to synthesize the knowledge base and answer the research question. Additionally, the SLR should set the foundation for future research, which is called Stage V [vom Brocke et al., 2009].

Vom Brocke et al. argue that the documentation of the SLR research is highly important to deliver comparable results and allows further research on the topic [vom Brocke et al., 2009].

3.1.2 Literature review

According to the SLR methodology of vom Brocke et al., discussed in section 3.1.1 the SLR follows the five suggested stages (figure 3.1) [vom Brocke et al., 2009]:

Stage I sets the scope (table 3.2) for the following SLR according to the taxonomy of Cooper (table 3.1) [Cooper, 1988].

Stage II aims to provide an overview of the topic and the existing knowledge to find keywords for the literature review. Therefore, the Background (cf. chapter 2) introduces CAS and their relevance in the maintenance field. According to this knowledge base and the objective of finding a classification of CAS, the following keywords were selected for the SLR:

Focus	Research Outcomes Theories Applications
Goal	Integration
Organisation	Conceptual
Perspective	Neutral representation
Audience	General scholars Practitioners
Coverage	Exhaustive and selective

Table 3.2: Cooper taxonomy for SLR

“Cognitive Assistance“ AND (“Production“ OR “Maintenance“ OR “Assembly“ OR “Manufacturing“)

Since the field of cognitive assistance is entirely emerging and closely tied to the rise of Industry 4.0, the period is set from 2013 up to 2023. Furthermore, only articles and conference papers written in English are included.

In **Stage III**, the search string above was applied to Scopus, which resulted in 269 search results. Scopus was selected as it is one of the biggest abstract and citation databases, covering millions of peer-reviewed entries and providing an intuitive search engine. Afterward, the papers were filtered by title and abstract to remove papers that did not match the topic and research question. The remaining 107 papers were split into papers of high, mid, and low relevance according to the following criteria:

High relevance:

- Papers focusing on CAS in the maintenance and repair
- Papers that deal with specific CAS
- Papers aiming to classify CAS

Medium relevance:

- Papers focusing on CAS, especially for manufacturing, assembly, and production
- Papers regarding the design of CAS

Low relevance:

- Physical assistance systems
- Papers focusing on the impacts of CAS (Ergonomics)
- Papers focusing on CAS in training
- Papers focusing on software development for CAS

3. STATE-OF-THE-ART

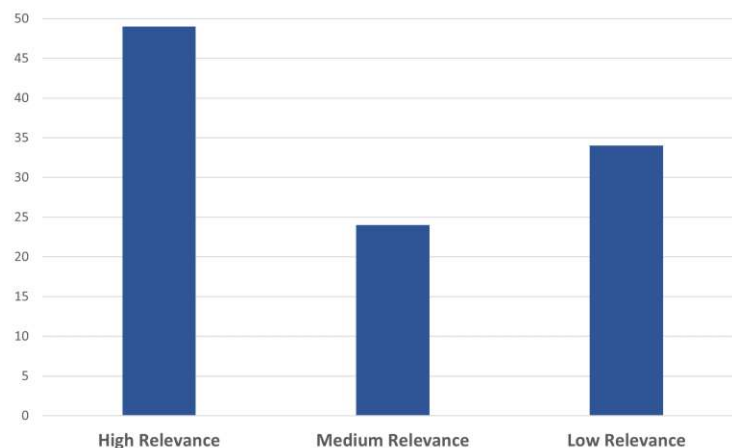


Figure 3.2: Filter by relevance

After applying this criterion to the papers, 49 papers were classified as highly relevant. After considering the accessibility of the papers, 45 papers were chosen as the foundation of the SLR (figure 3.3). A list of the results can be found in Table A.1.

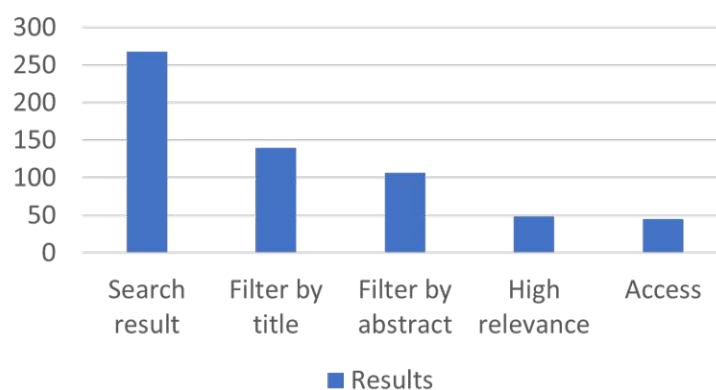


Figure 3.3: SLR filtering

In **Stage IV**, the papers are described first in a descriptive analysis and later in a content analysis. The descriptive analysis overviews the various papers, authors, and countries. The content analysis aims to extract relevant knowledge from the papers to create the classification of CAS. Therefore, a list of all relevant technologies was made (table A.1) and sorted by groups and attributes.

Finally, **Stage V** makes proposals for future research. The results and the lack of knowledge are summarized in section 3.4 and set the base for the development of the artifact in the following chapters.

3.1.3 Descriptive analysis

Publications per year

Plotting the documents over the publication year (figure 3.4) shows that most of this research has been done since 2017. As cognitive assistance is a pretty rising topic, it can be assumed that the up-to-dateness of the knowledge is limited, therefore, follow-up research in this field is suggested in the following years.

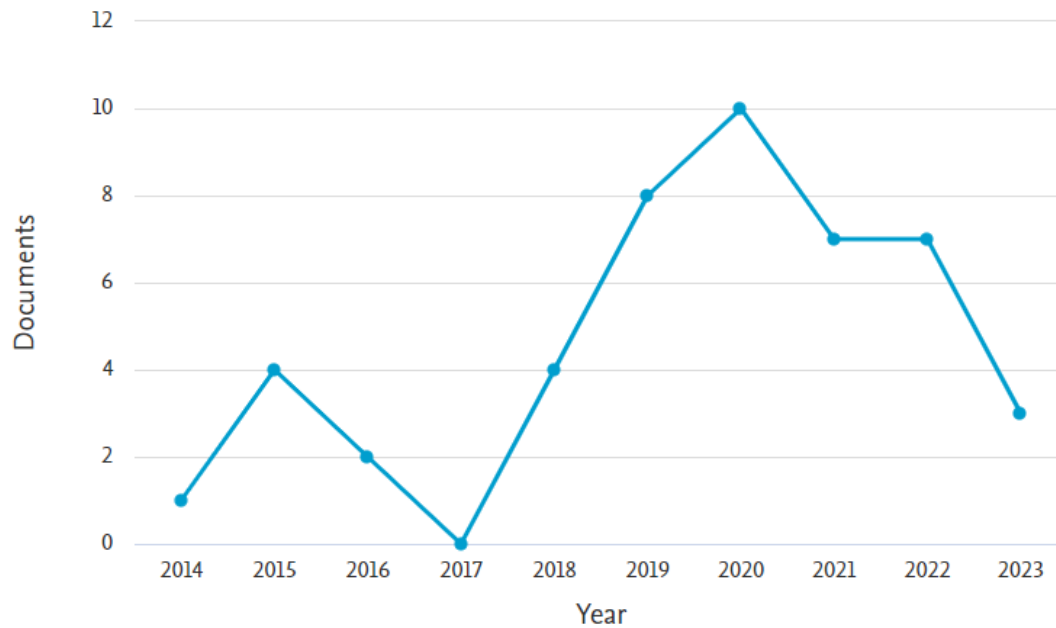


Figure 3.4: SLR - Papers per year

Publications per author

Counting the number of authors results in 148 researchers, of which 22 published more than one paper. Most often, Mark, B.G., Rauch, E. and Matt, D.T. are found as authors with five publications each (figure 3.5).

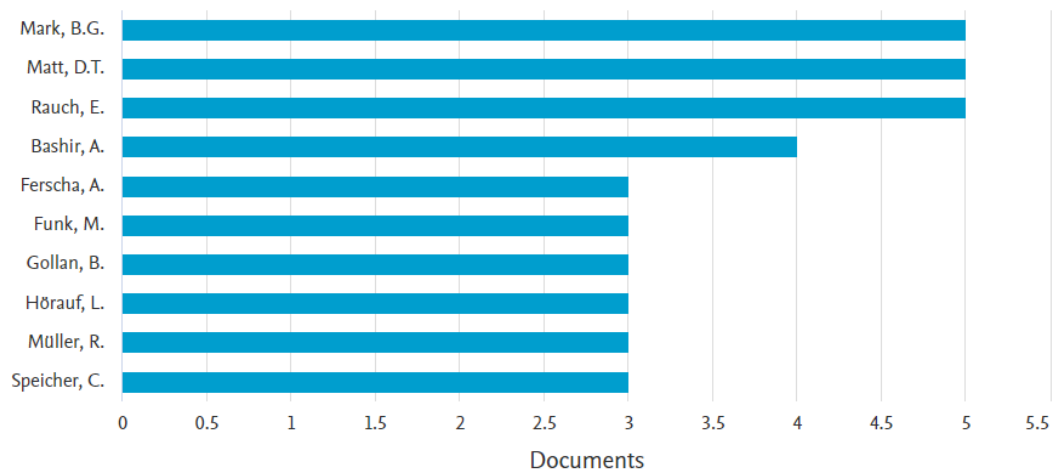


Figure 3.5: SLR - Papers per author

Publications per country

Regarding the papers per country (figure 3.6), Germany appears to be leading in this field with 25 publications, followed by Austria with 7 and Italy with 5 publications. This gives an insight into the importance of Industry 4.0 research and the research in the field of cognitive assistance in Central Europe, compared to other regions.

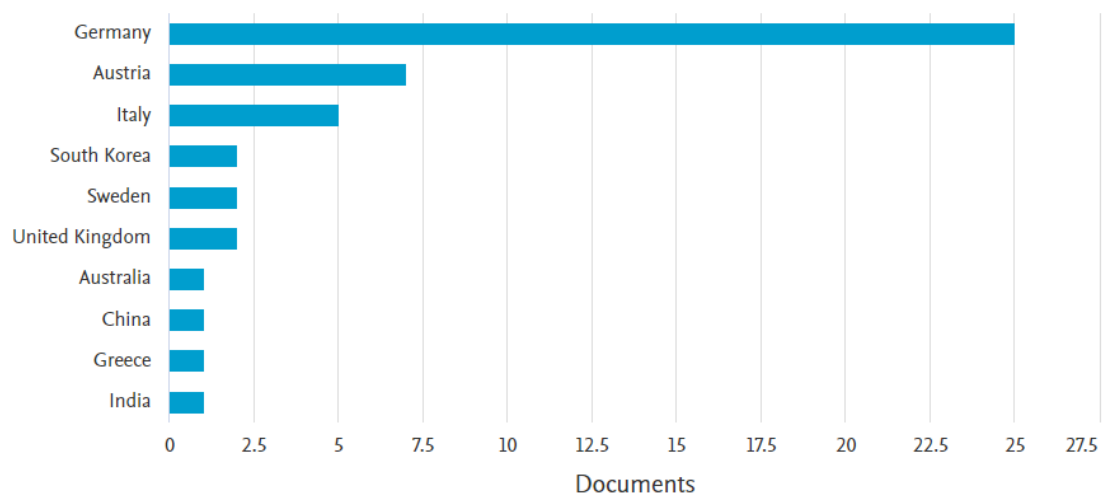


Figure 3.6: SLR - Papers per country

3.1.4 Content analysis

The content analysis should answer how the great variety of combinations of CAS can be sorted and classified to generate the matching artifact. The difficulty lies in infinite combinations of software, hardware, and sensors, each leading to another CAS. Therefore,

it is crucial to create upper categories that are mutually exclusive but include all variations. In the first step, the 46 papers were sorted by their purpose (table 3.3). Therefore, six categories were introduced:

1. **Practical development of CAS:** Papers, which present specific and practical examples of CAS. Eversberg and Lambrecht conducted a case study comparing digital work instructions with augmented reality and paper-based documents [Eversberg and Lambrecht, 2023]. Redzepagic et al. developed a monitoring system that automatically measures deviations and informs workers about faults using augmented reality [Redzepagic et al., 2020]. Shin et al. undertook an experiment with an AI-based predictive maintenance system, where endoscopic images are used for bearing fault detection of windmills, while Müller et al. described assistance systems that detect faults in the rework area [Shin et al., 2021], [Müller et al., 2019b] and [Müller et al., 2018]. Funk and Schmidt tested in-situ projectors in assembly situations [Funk and Schmidt, 2015]. Park et al. developed a deep-learning-based assistance system that uses image recognition and provides information using a wearable augmented reality system [Park et al., 2020]. Gerdenitsch et al. evaluated the user acceptance of a head-mounted device [Gerdenitsch et al., 2021]. Gurevich et al. designed a system using projection and augmented reality, allowing remote collaboration between a worker and an assistant [Gurevich et al., 2015]. Similarly, Fleck et al. developed a tele-assistance using augmented reality that supports workers during maintenance operations [Fleck et al., 2020]. Simonetto et al. conducted a case study with projected augmented reality systems, while Jungwirth et al. and König et al. conducted practical research on augmented reality systems [Simonetto et al., 2021], [Jungwirth et al., 2019] and [König et al., 2019]. Meanwhile, Aehnelt and Urban experimented with smartwatches on the shop floor [Aehnelt and Urban, 2014].
2. **Frameworks and design principles for CAS:** These papers describe design principles and guidelines for developing CAS. Haslgrübler et al. presented a conceptual framework for implementing CAS [Haslgrübler et al., 2018]. Reisinger et al. presented a concept for automated data-driven reconfiguration of digital assistance systems [Reisinger et al., 2018]. Meanwhile, Burggräf et al. evaluated design parameters that affect the adaptability and adaptivity of worker assistance systems [Burggräf et al., 2020b]. Similarly, Ramakrishnaraja et al. wrote about design principles for industrial mixed reality systems [Ramakrishnaraja et al., 2020]. Müller et al. researched how to introduce CAS in dynamic environments, such as the rework area [Müller et al., 2019a]. The paper of Pokorni et al. covers the design of CAS based on the quality function deployment method [Pokorni et al., 2022]. Hoffman and Fecteau wrote about introducing decision assistance tools in maintenance [Hoffman and Fecteau, 2023].
3. **Theoretical models:** Papers, which discuss theoretical foundations of CAS, such as artificial intelligence or software development. For example, Bleser et al. deal

with the algorithms and sensor networks that are used for CAS [Bleser et al., 2015]. Illankoon and Tretten developed a theoretical model on how to improve maintenance decision support systems [Illankoon and Tretten, 2021]. Merkel et al. created functions to make a need-based selection of the systems [Merkel et al., 2019]. Aehnelt and Bader published their paper to formalize and automate the processing of background knowledge in information assistance systems [Aehnelt and Bader, 2015]. Gollan et al. did theoretical research on how to fuse multiple sensors in industrial assistance systems [Gollan et al., 2018]. The paper of Wellsandt et al. covers the question of how to improve the interaction between computers and humans in predictive maintenance systems [Wellsandt et al., 2021].

4. **Human factors and CAS:** Improving the usability, ergonomics, and acceptance of CAS. Ulmer et al. did research on how to create human factor-aware assistance systems by using gamification and hardware modularisation [Ulmer et al., 2023]. In their paper, Mark et al. categorize CAS according to their various user groups [Mark et al., 2019]. The work of Mühlbradt focuses on psychological aspects and the cognitive constraints of humans, while Yang et al. wrote about the influences of augmented reality systems on performance and the cognitive load of workers [Mühlbradt, 2022] and [Yang et al., 2019]. Quandt et al. presented a human-centered design process for CAS [Quandt et al., 2022].
5. **Evaluation and comparison of CAS:** Practical evaluation of CAS in the field. Klapper et al. conducted a study to evaluate the current use of CAS in today's factories [Klapper et al., 2020]. The work of Burggräf et al. is a study with 132 participants to find the opportunities and obstacles of adaptive assistance systems in assembly systems [Burggräf et al., 2020a]. Eversberg and Lambrecht evaluated digital work instructions with augmented reality versus paper-based documents in a case study and found that the repair task can be completed faster and with a lower perceived workload [Eversberg and Lambrecht, 2023]. Similarly, Zigart and Schlund did a literature review to evaluate augmented reality technologies in manufacturing [Zigart and Schlund, 2020]. Funk et al. conducted a study to assess the effectiveness of assistance systems for manual assembly work [Funk et al., 2019]. Also, Funk et al. compared various assistance systems - in-situ projection, head-mounted displays, tablets, and paper instructions- in assembly [Funk et al., 2016]. A similar study by Rodriguez et al. compares paper instructions with digital glasses in assembly [Rodriguez et al., 2021]. Büttner et al. compared head-mounted displays and in-situ projection in assembly [Büttner et al., 2016]. Müller et al. evaluated a tablet-based maintenance assistance system [Mueller et al., 2020]. Mark et al. conducted a study to evaluate the impact of projection-based assistance systems in assembly processes [Mark et al., 2020].
6. **Classifications of CAS:** Attempt to sort and classify multiple CAS. Mark et al. conducted a systematic literature review to create an overview of the state-of-the-art of CAS [Mark et al., 2021]. Another work by them builds on

the prior research and creates a classification of the various assistance systems [Mark et al., 2022a]. Finally, they use this knowledge to create a selection methodology for CAS [Mark et al., 2022b].

Table 3.3: Papers by purpose

Purpose of Paper	Source
1. Practical development of CAS	[Eversberg et al., 2022], [Redzepagic et al., 2020], [Shin et al., 2021], [Funk and Schmidt, 2015], [Park et al., 2020], [Gerdenitsch et al., 2021], [Gurevich et al., 2015], [Simonetto et al., 2021], [Jungwirth et al., 2019], [Aehnelt and Urban, 2014], [Konig et al., 2019], [Fleck et al., 2020], [Müller et al., 2019b], [Müller et al., 2018]
2. Frameworks and design principles for CAS	[Haslgrübler et al., 2018], [Reisinger et al., 2018], [Burggräf et al., 2020b], [Müller et al., 2019a], [Ramakrishnaraja et al., 2020], [Pokorni et al., 2022], [Hoffman and Fecteau, 2023]
3. Theoretical Models	[Bleser et al., 2015], [Illankoon and Tretten, 2021], [Merkel et al., 2019], [Aehnelt and Bader, 2015], [Gollan et al., 2018], [Wellsandt et al., 2021]
4. Human factors and CAS	[Ulmer et al., 2023], [Mark et al., 2019], [Mühlbradt, 2022], [Quandt et al., 2022], [Yang et al., 2019], [Bocklisch et al., 2022]
5. Evaluation and Comparison of CAS	[Klapper et al., 2020], [Burggräf et al., 2020a], [Eversberg and Lambrecht, 2023], [Funk et al., 2019], [Zigart and Schlund, 2020], [Funk et al., 2016], [Rodriguez et al., 2021], [Mueller et al., 2020], [Mark et al., 2020], [Büttner et al., 2016]
6. Classifications of CAS	[Mark et al., 2022a], [Mark et al., 2022b], [Mark et al., 2021]

At this point, mentioning existing classification attempts in the papers is crucial. First, Mark et al. described a classification of CAS shown in (figure 3.7) [Mark et al., 2019]. Even though this classification covers most systems and, therefore, serves the purpose of matching them with different user groups, this category does not include all variations of CAS. It is thus not usable for matching with maintenance tasks.



Figure 3.7: CAS - Classification according to [Mark et al., 2019]

Secondly, Mark et al. made an SLR-based classification of worker assistance systems, which also includes a classification of CAS (figure 3.8) [Mark et al., 2021]. This classification is also cited in [Mark et al., 2022a] and [Mark et al., 2022b]. Even though it delivers an exhaustive list of available technologies, the classification does not cover whole systems. For example, augmented reality is usually combined with another technology, such as a tablet or a head-mounted display.

1. Augmented Reality	8. Smart Scan Glove	14. Projector
2. Mixed Reality	9. Smartphones	15. Monitor
3. Virtual Reality	10. In-Situ Projection	16. Pictorial Instructions
4. Tablet	11. Laser Projection System	17. Voice Control
5. Visual Computing System	12. Portable Computer	18. AI Based Intelligent Personal Assistant
6. Projection-based Assistance	13. Computer Assisted Instructions (CAI)	
7. Head Mounted Display		

Figure 3.8: CAS - Classification according to [Mark et al., 2021]

Therefore, this SLR attempts to create an upper-level grouping. The multiple technologies mentioned in the papers were extracted in (table A.1) to make an overview of the various topics.

3.2 Classification of CAS

3.2.1 Components

As a starting point for the classification, each cognitive assistance system can be broken down into its main components: sensors, software, databases, and interaction devices. Sensors create a link to the outer world, then software processes the information using existing data from databases, and finally, the output is presented to the user on his interaction device.

Sensors

Sensors serve as input for the CAS and create a link to the outer world. Therefore, the right choice of sensors according to the environment is crucial for the whole system's

performance [Gollan et al., 2018]. According to Gollan et al., sensors need to create an awareness of the situation and therefore have to be I) selected carefully, II) be capable of handling considerable amounts of data, III) be able to work combined with other sensors and IV) should allow the proper interpretation of psycho-physiological states [Gollan et al., 2018]. At this point, it is essential to mention that an enormous number of sensors have been invented, which means that the following list (figure 3.9) does not claim to be exhaustive but covers all technologies mentioned in the papers of the SLR.

- | | |
|----------------------------|-----------------------|
| 1. Eye tracker | 7. GPS |
| 2. Physiological Sensor | 8. Microphone |
| 3. RGB-D Sensor (Kinect) | 9. Scanner |
| 4. RFID | 10. Weighting Machine |
| 5. Camera | 11. Gyroscope |
| 6. Inertial Measuring Unit | |

Figure 3.9: CAS - Sensors

Software

The software of the CAS serves as a “brain,” which compares information from the outer world collected by sensors and data stored in databases and then creates the user output (f.e. as a Virtual Reality Simulation or checklist). Due to simplicity, the software can be distinguished between traditional software and software based on artificial intelligence and machine learning.

- | | |
|-------------------------|-------------------------|
| 1. Traditional Software | 2. AI/ML Based Software |
|-------------------------|-------------------------|

Figure 3.10: CAS - Software

Database

The database serves as a knowledge base for the assistance system and is usually on a server. It keeps all the relevant information, such as media files, documentation, and maintenance information [Reisinger et al., 2018].

Interaction devices

Interaction devices are technologies that directly interact with the user and provide him with the output of the assistance service. Therefore, its choice is crucial for the later success and acceptance of the assistance, as it stands in a close relationship with the user [Reisinger et al., 2018].

- | | |
|-------------------------|------------------|
| 1. Head Mounted Display | 6. Smart Glasses |
| 2. Headset | 7. Projection |
| 3. Tablet/ Handhelds | 8. Display |
| 4. Laptop | 9. Touchscreen |
| 5. Smartwatch | 10. Speakers |

Figure 3.11: CAS - Interaction devices

3.2.2 CAS

Using the knowledge of the main components of CAS, it is possible to identify the main combinations of these. The name “CAS” includes the word “systems,” which means, according to the Oxford Dictionary, “*a group of things, pieces of equipment, etc. that are connected or work together*” [Oxford Dictionary, 2023a]. According to this, CAS combine multiple components to assist operators while working. As infinite variations exist, it seems more practical to work with groupings than with a list that names specific systems. The following list presents an overview of the most cited and most prominent CAS groups found in the SLR :

- **Augmented reality (AR):** Real-world with information overlay, but limited interaction (tablet, smartphone) [Speicher et al., 2019] (cf. section 3.2.3)
- **Mixed reality (MR):** “Strong AR”: Virtual elements are integrated into the environment and can be manipulated by the user in an interactive way (Apple Vision Pro, Microsoft HoloLens) [Speicher et al., 2019] (cf. section 3.2.3)
- **Virtual reality (VR):** The user experiences a fully virtual view while wearing a headset (Oculus Rift, Meta Quest) [Speicher et al., 2019] (cf. section 3.2.3)
- **Projection-based assistance (Projection):** Technical system that projects e.g. instructions manuals into the workplace [Mark et al., 2021]
- **Computer-assisted instructions (CAI):** Computer device with a monitor or headset to give, e.g., instruction manuals [Mark et al., 2021]
- **AI-based assistant:** Artificial intelligence that helps the operator while interacting with computers or machines (ChatGPT, Google Bard, Siri) [Mark et al., 2021]
- **Maintenance decision support (MDS):** Artificial intelligence and software, which supports monitoring and decision-making tasks in maintenance [Illankoon and Tretten, 2021]

3.2.3 Attributes

To get more clarity about the various possible systems, attributes describe these various systems more precisely.

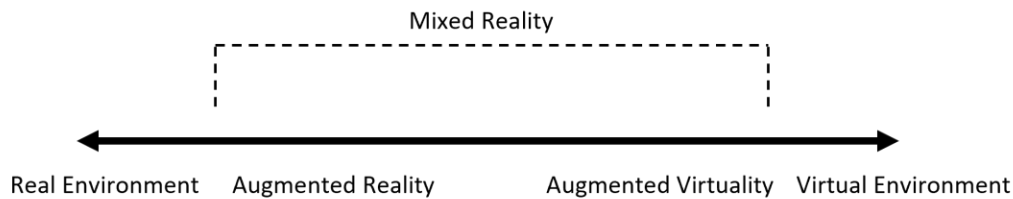


Figure 3.12: Virtual continuum [Milgram et al., 1994]

Functionality

Aehnelt and Bader suggest putting CAS into five different groups of functionalities [Aehnelt and Bader, 2015]:

1. **Raising awareness:** Providing the operator with information on relevant states, events, and occurrences, which are important for the planning or execution of his task
2. **Guiding:** Providing information about complex procedures and step-by-step instructions
3. **(Execution) Monitoring:** Collecting data to monitor the correct execution of maintenance tasks
4. **Documenting:** Support of documentation during and after the task execution
5. **Guarding:** Protect workers from overload by balancing load levels

Additionally, for the context of maintenance tasks, two more groups can be defined:

6. **Training:** CAS, which supports the operator in the training of maintenance operations
7. **Condition Monitoring:** Collecting and analyzing machine parameters to give well-timed maintenance suggestions to minimize costly engine failures and downtimes (cf. Predictive Maintenance, section 2.3.1).

Virtual continuum

In the context of CAS, terms such as “Augmented Reality“, “Mixed Reality“ or “Virtual Reality“ are often used with different meanings. This is usually caused due to marketing reasons and fluid transitions between various technologies. Nonetheless, it is essential to define these terms clearly to make classifications later on. As a starting point, the virtual continuum by [Milgram et al., 1994], shown in Figure 3.12 gives a hint about the scientific understanding of these terms.

According to Milgram et al., the real environment is “...consisting solely of real objects, and includes whatever might be observed when viewing a real-world scene either directly in person, or through some kind of a window, or via some sort of a (video) display...”

[Milgram et al., 1994]. In contrast, the virtual environment is completely simulated to an extent in which virtual objects appear 'real'. In between lies mixed reality, which includes any technology blending the real and visual environment. In this definition, augmented reality augments the real environment with some virtual elements, while augmented virtuality adds a few real objects into a virtual environment.

In contrast, Skarbez et al. revisited the virtual continuum 27 years later and found that a completely virtual environment would not be limited to visual impressions but instead include all basic exteroceptive senses, such as sight, hearing, touch, smell, and taste [Skarbez et al., 2021]. Therefore, only an environment like in the movie "Matrix", where a person's sensory organs are disconnected from their brain, could be defined as entirely virtual. Consequently, as seen in Figure 3.13, all systems, including VR, fall into the mixed reality spectrum [Skarbez et al., 2021].

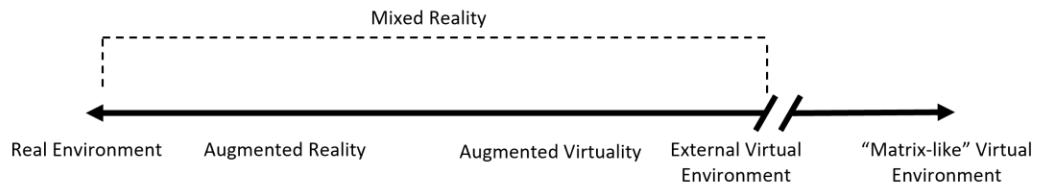


Figure 3.13: Virtual continuum according to [Skarbez et al., 2021]

However, other researchers and companies have different definitions for these terms, which makes it important to find a working definition for this paper. Therefore, the following definitions will be used in this work (figure 3.14):

1. **Reality:** Solely real objects, observed viewing the real-world (Displays, In-Situ Projection) [Milgram et al., 1994]
2. **Augmented Reality:** Real world with information overlay, but with limited interaction (Tablet, Smartphone) [Speicher et al., 2019]
3. **Mixed Reality:** "Strong AR": Virtual elements are integrated into the environment and can be manipulated by the user in an interactive way (Apple Vision Pro, Microsoft HoloLens) [Speicher et al., 2019]
4. **Virtual Reality:** The user experiences a fully virtual view while wearing a headset (Oculus Rift, Meta Quest) [Speicher et al., 2019]

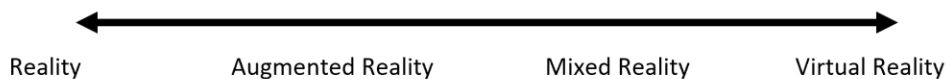


Figure 3.14: Working definitions used in this paper

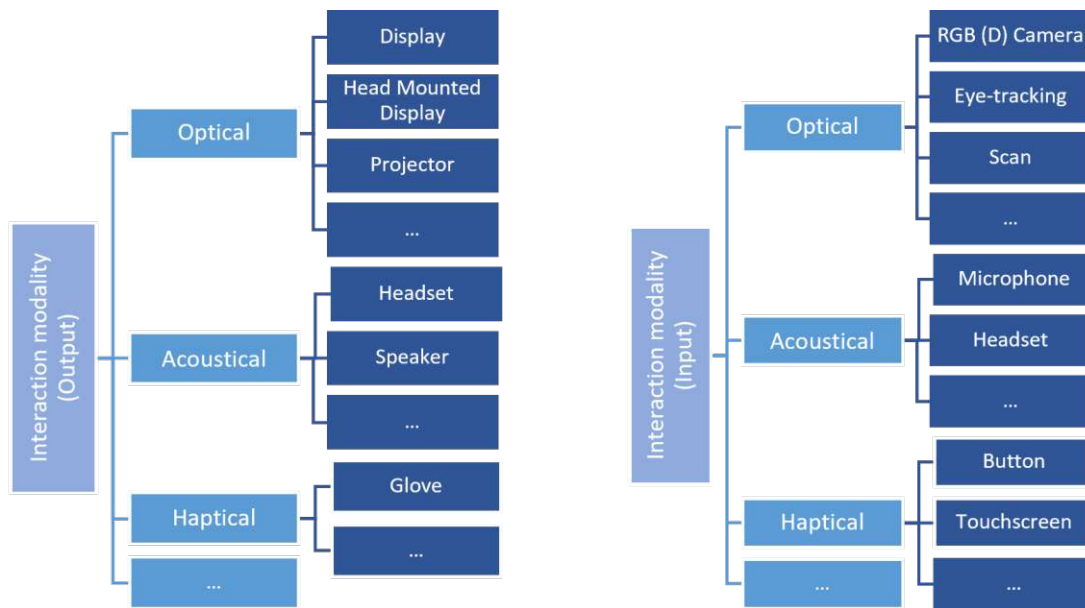


Figure 3.15: Interaction modality for the output [Pokorni et al., 2022]

Adaptability and adaptivity

According to Loch et al., it is crucial to distinguish between adaptability, which the user initiates, and adaptivity, which is undertaken by the system [Loch et al., 2018]. In this context, adaptability means that users can change the systems at their discretion, but at the cost of a higher operating effort [Burggräf et al., 2020b]. On the contrary, adaptive systems automatically adapt to changing environmental conditions or user characteristics [Burggräf et al., 2020b]. Compared to adaptable systems, adaptive systems do not require manual effort and are, therefore, easier to operate [Burggräf et al., 2020b].

Interaction modality

The interaction modalities describe the system and define how the interaction with the assistance system is ensured [Pokorni et al., 2022]. Therefore, they have to be defined for the output and input of the system (figure 3.15).

Mobility

Sensors and interaction devices mentioned above can be classified by mobility status. Figure 3.16 shows a division of interaction devices and sensors between mobile and stationary, based on weight and size. If tasks are carried out mobile, battery energy supply must be ensured. Of course, mobile systems can be used in a stationary context.

Mobile	Stationary
Sensors	
1. Eye tracker 2. Inertial Measuring Unit 3. GPS 4. Camera 5. Scanner 6. Physiological Sensor 7. Scanner 8. RFID 9. Gyroscope	1. RGB-D Sensor 2. Weighting machine
Interaction devices	
1. Head Mounted Display 2. Headset 3. Tablet/Handhelds 4. Laptop 5. Smartwatch 6. Smartphone 7. Smart Glasses	1. Projection 2. Display 3. Speakers

Figure 3.16: CAS - Mobile vs. stationary

3.2.4 Examples of classified CAS

The following examples should provide an overview of the classification scheme provided in the previous section. Therefore, random examples from the papers with practical examples (table 3.3) were selected to evaluate the identified classes presented in section 3.2.2. Each system must be submitted within this list to prove its completeness. Additionally, the attributes and components are listed to describe the system clearly.

Example 1: Mixed reality system with deep learning

The first system evaluated presented by Park et al. is a mixed reality system (according to CAS systems presented in section 3.2.2 and the working definition of mixed-reality in section 3.2.3) [Park et al., 2020]. The system consists of the following components, according to section 3.2:

Interaction device	Smart glass like HoloLens
Sensors	RGB-D Sensor, inertial measuring unit
Database	Information processed by the trained model in real-time running on a server
Software	AI/Deep learning-based image recognition

Table 3.4: CAS: Components of example 1

According to the mobility, all components allow mobile usage as long as the HoloLens is

connected to the server. The system's main functionality is the provision of guidance, but it also supports training and raising awareness. To do so, an RGB-D sensor scans the surrounding objects of the worker, the usage of inertial measuring units, and gyroscopes. The information is then processed by deep learning-based image recognition, which detects relevant objects and provides guidance on the worker's smart glass. The worker sees the real object, enriched with interactive information about the tools, positions, the object, and the next working steps [Park et al., 2020].

Example 2: Smartwatch assistance

The second system, by Aehnelt and Urban, is a computer-assisted instruction (CAI) system (according to CAS systems presented in section 3.2.2), with the following components [Aehnelt and Urban, 2014]:

Interaction device	smartwatch (main), display
Sensors	gyroscope, inertial measuring unit, GPS
Database	-
Software	traditional software

Table 3.5: CAS: Components of example 2

The suggested system is stationary and situated in reality (according to section 3.2.3), as it uses stationary displays to support the worker. Nonetheless, the main component, the smartwatch, is highly mobile. Therefore, the system can be easily adapted for mobile usage. The smartwatch serves as the interaction device and allows the user to control the information provided by the other displays. Additionally, the smartwatch informs the worker about incidents or new work tasks. The main functionalities of this CAS are guiding and raising awareness. Based on the information provided, the system has limited learnability, as it uses traditional software and can adapt to the worker's conditions to prevent mental overloads.

Example 3: Projection-based assistance

The third system was developed by Funk and Schmidt and is a projection-based assistance system (according to CAS systems presented in section 3.2.2), with the following components [Funk and Schmidt, 2015]:

Interaction device	projector
Sensors	RGB-D camera
Database	-
Software	AI/Deep learning-based image recognition

Table 3.6: CAS: Components of example 3

The suggested system is stationary and situated in reality (according to section 3.2.3), as all the objects are observed while viewing a real-world scene. The system's functionalities are raising awareness, guiding, training, and execution monitoring. To do so, the system's camera detects relevant objects, and the projector highlights positions where action is required. The system's learnability is high, as an experienced worker can easily train it by demonstrating the workflow. The paper does not give any hints about the adaptivity and adaptability of the system.

3.3 Matching algorithms: State-of-the-Art

As CAS are still emerging technologies, most papers in this field have been published in recent years. Some researchers have already tried to answer the question of how to select the right assistance system for a specific use case.

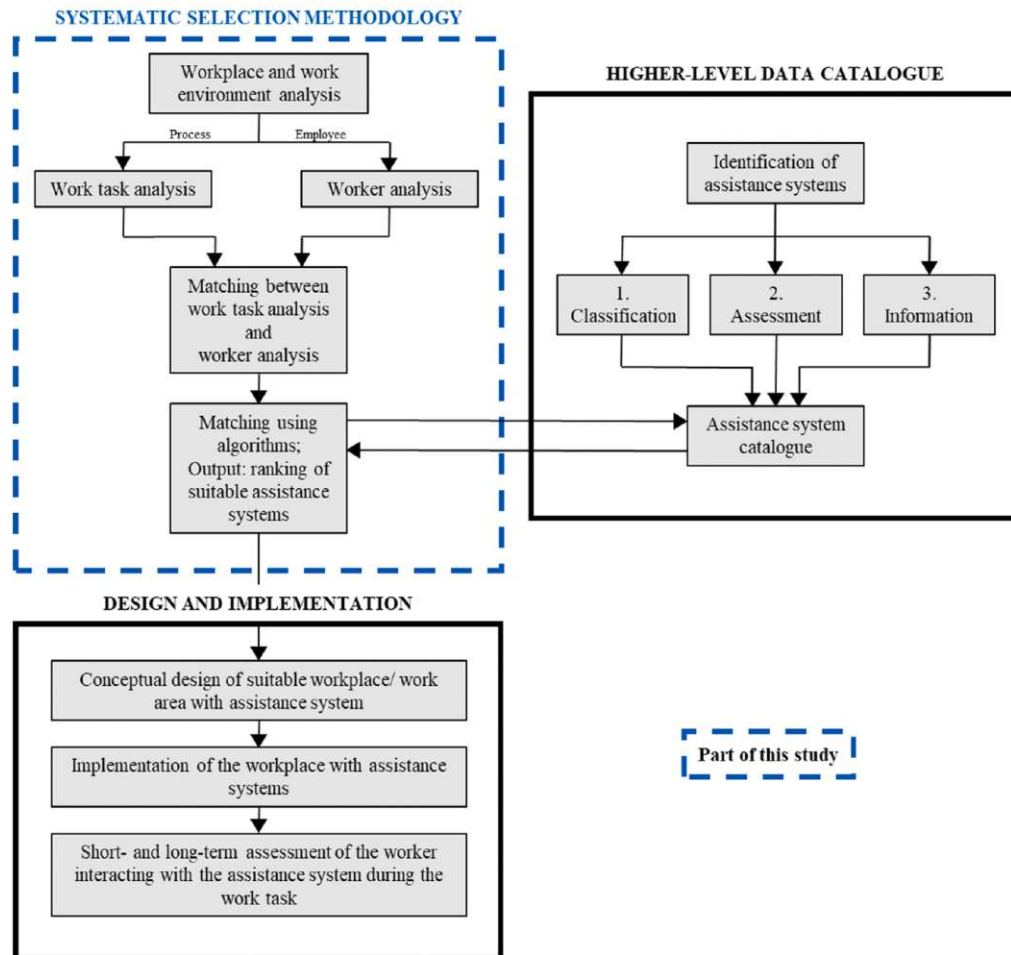


Figure 3.17: Selection methodology from [Mark et al., 2022b]

First, Mühlbradt et al. published a paper with a selection framework based on cognitive constraints [Mühlbradt, 2022]. Secondly, Mark et al. created a matching function that connects CAS with different user groups, such as migrant, elderly, or flexible workers [Mark et al., 2019].

Nonetheless, the closest work was published by Mark et al., which matches a CAS with worker requirements and a specific task [Mark et al., 2022b]. The selected approach can be seen in Figure 3.17. The matching starts with a work task analysis, in which the task is classified via 23 different attributes such as technical knowledge, creativity, learning ability, ability to hear, or logical thinking. All of these attributes R_i are sorted in a vector \vec{a} and are rated between 0 “not needed“, 0.5 “partly needed“ and 1 “needed“, taking regard to the requirements of a specific task. Afterward, the worker analysis defines another vector \vec{b} with values between 0 “no help needed“ and 5 “maximum help needed“ for each attribute N_i .

The following vector \vec{a} represents the task’s requirements, while vector \vec{b} represents the need for assistance by the worker [Mark et al., 2022b].

$$\vec{a} = \begin{bmatrix} R1 \\ R2 \\ R3 \\ \dots \\ R23 \end{bmatrix} \quad (3.1)$$

$$\vec{b} = \begin{bmatrix} N1 \\ N2 \\ N3 \\ \dots \\ N23 \end{bmatrix} \quad (3.2)$$

The component-wise multiplication (\odot) of \vec{a} and \vec{b} results in vector \vec{c} , which rates the need for assistance for each attribute [Mark et al., 2022b].

$$\vec{c} = \begin{bmatrix} R1 \\ R2 \\ R3 \\ \dots \\ R23 \end{bmatrix} \odot \begin{bmatrix} N1 \\ N2 \\ N3 \\ \dots \\ N23 \end{bmatrix} = \begin{bmatrix} RN1 \\ RN2 \\ RN3 \\ \dots \\ RN23 \end{bmatrix} \quad (3.3)$$

Then, in the last step, the vector \vec{c} is multiplied by matrix \mathbf{M} , which contains a rating of ability to support the 23 actions for each assistance system (figure 3.18) [Mark et al., 2022b]. In this context, 0 means “assistance system can not provide any support“, while 10 stands for “maximum support“ [Mark et al., 2022b]. The classification of the assistance systems is based on a systematic literature review and was done in a separate work [Mark et al., 2021] and [Mark et al., 2022b]. The authors state that rating the different assistance systems is part of an ongoing study, which will be released soon [Mark et al., 2022b].

$$\vec{t} = \mathbf{M} \times \vec{c} = \begin{bmatrix} AS1_{A1} & \dots & AS1_{A23} \\ \vdots & \ddots & \vdots \\ ASn_{A1} & \dots & ASn_{A23} \end{bmatrix} \times \begin{bmatrix} RN1 \\ RN2 \\ RN3 \\ \dots \\ RN23 \end{bmatrix} = \begin{bmatrix} AS1 \\ AS2 \\ AS3 \\ AS4 \\ \dots \\ ASn \end{bmatrix} \quad (3.4)$$

Vector \vec{t} includes a score for each assistance system. Therefore, the system with the highest score matches the given specifications and requirements the best. In this case, assistance system number two would be the preferable choice [Mark et al., 2022b].

In summary, the mathematical model seems to be a sound way to consider the task's characteristics, the worker's requirements, and the assistance system's capabilities.

3.4 Summary

The systematic literature review provides a good starting point for the design and development of the matching algorithm in the following chapter. Evaluating the different technologies mentioned in the literature led to the insight that an all-embracing classification is a research gap. Thus, most of the existing groupings, such as in Figure 3.8, lack mutual exclusiveness. For this purpose, the clustering of the systems in this paper aims to satisfy this criterion (cf. section 3.2.2). Each system comprises four components: sensors, software, a database, and an interaction device.

To describe the systems even more precisely, attributes such as mobility, position in the virtual continuum, functionality, interaction modality, adaptability, and adaptivity can be used (cf. section 3.2.3). To illustrate the classification, section 3.2.4 presents some examples.

Finally, a state-of-the-art analysis of the existing matching algorithm was conducted. It found that there are only two selection methodologies in the literature. Firstly, a paper by Mühlbradt et al. presents a selection methodology based on cognitive constraints. Secondly, the work of Mark et al. includes a matching algorithm to select the right assistance system for different user groups [Mark et al., 2022b]. Even though this algorithm is easy to use, it does not aim to improve the KPIs of the given task. Nonetheless, it will be the starting point for the matching algorithm developed in the following chapter.

ASSISTANCE SYSTEM	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23
<i>Wearable Lifting/Holding Aid</i>	0	0	0	0	8	8	0	0	0	0	0	0	0	0	0	0	0	0	0	7	4	0	0
<i>Ergonomic Manual Workplaces</i>	0	0	0	4	0	0	0	0	0	0	2	0	3	0	0	0	0	0	0	5	8	0	0
<i>Collaborative Robot</i>	0	0	0	8	9	9	0	0	0	0	0	0	0	0	0	0	0	0	0	8	5	0	0
Cognitive Assistance Systems																							
<i>Augmented Reality (AR)</i>	9	5	0	0	0	0	6	5	4	4	5	5	0	4	0	3	2	3	7	0	5	6	5
<i>Virtual Reality (VR)</i>	9	3	0	0	0	0	7	5	4	5	4	6	0	5	0	3	3	6	2	0	2	7	3
<i>Mixed Reality (MR)</i>	9	3	0	0	0	0	8	5	3	3	4	4	0	3	0	3	2	5	2	0	2	6	1
<i>Visual Computing System</i>	0	0	0	0	0	0	3	0	0	0	0	0	2	0	0	0	0	0	5	0	3	0	9
<i>Projection-Based Assistance System</i>	6	4	0	7	0	0	7	8	3	5	8	8	0	7	0	4	5	0	10	0	4	3	9
<i>Smart Scan Glove</i>	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	2	8	0	0
<i>Smart Phone</i>	3	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	1	3	0
<i>In-situ Projection</i>	0	7	0	4	0	0	5	4	4	4	3	3	0	3	0	3	2	2	3	0	5	6	3
<i>Laser Projection System</i>	0	6	0	0	0	0	0	0	0	5	7	6	0	7	0	4	4	0	8	0	7	6	0
<i>Portable computer</i>	2	0	0	0	0	0	0	0	0	3	0	0	0	2	0	0	0	3	2	0	1	4	0
<i>Computer Assisted Instructions (CAI)</i>	0	0	0	0	0	0	4	0	3	4	4	2	0	3	0	3	2	0	4	0	4	5	0
<i>Pictorial Instruction</i>	0	0	0	0	0	0	0	0	0	2	2	5	0	4	0	0	2	0	5	0	0	5	4
<i>Voice Control</i>	0	9	0	0	0	0	0	0	0	0	0	0	4	0	0	4	0	0	0	0	4	3	0

Figure 3.18: Rating for each assistance system [Mark et al., 2022b]

Framework for matching CAS

This chapter aims to develop a matching function that suggests which CAS to select for specific tasks and KPIs.

4.1 Design and development of framework

The framework of Mark et al. provides a good starting point for the matching function [Mark et al., 2022b]. The matching function needs to be adapted so that it allows KPIs to be considered. Furthermore, the authors use different classifications of CAS and work tasks. Therefore, the model must be adapted to maintenance task requirements. The suggested algorithm (cf. figure 4.1) is based on the work of Mark et al. with some adaptations to the objectives of this work [Mark et al., 2022b].

The selection framework starts with a cognitive task analysis of the selected task. It is then broken down into its cognitive basic actions (cf. table 2.2). Then, using the knowledge of the previous step, the cognitive basic actions are rated according to their share of the overall task.

Afterward, one or more KPIs of the task to be improved are selected. In the next step, each cognitive basic action is rated according to its influence on the KPIs. For example, “perception“ might greatly influence the error rate, while “create“ has only a small impact on the task’s speed.

Multiplying the rating of the share and the rating of the influence on the KPIs results in a rating of the need for assistance for each cognitive basic action. Finally, the cross-product of the rating of the need for assistance for each cognitive basic action and the capabilities of each CAS to support these cognitive basic actions results in the rating of the CAS for the given task.

4. FRAMEWORK FOR MATCHING CAS

For a better understanding of the process, each step of the process will be explained in more detail in the following.

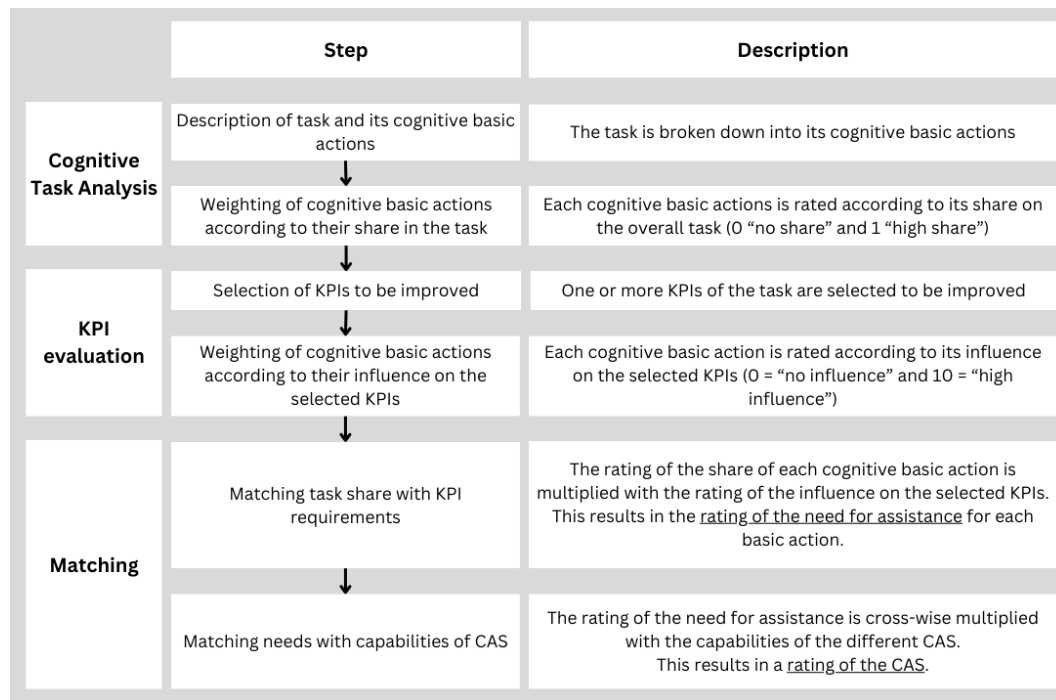


Figure 4.1: Matching framework

Description of task

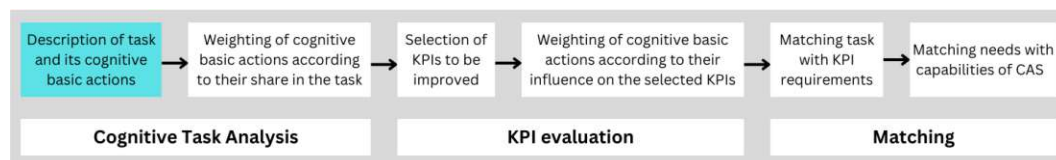


Figure 4.2: Matching framework - step 1

The first step of the framework is a precise description of the task and its cognitive actions using Hallow's and Bloom's taxonomies (cf. table 2.2). To illustrate this step, a simple monitoring task from Knisely et al. was selected [Knisely et al., 2021]. In this task, the operator monitors a system until he receives an alert or indication to fulfill a procedure. The operator executes the procedure and monitors the response of the system. A sequential task analysis, shown in Figure 4.3, provides a good starting point for a more detailed analysis [Knisely et al., 2021].

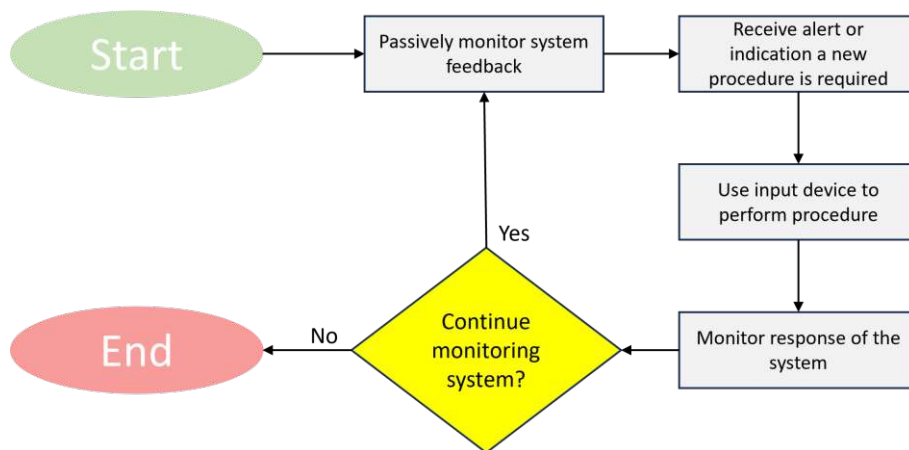


Figure 4.3: Sequential task analysis of monitoring task [Knisely et al., 2021]

Afterward, the task is broken down into its basic actions. Each step of the task is then listed in a row of a table. Then, the proper cognitive basic action from table 2.2 gets assigned to each step. The row remains blank if a step consists of a physical basic action. For example, table 4.1 breaks down the monitoring task of Knisely et al. [Knisely et al., 2021].

Task	Action
1.) Detect alert	
1.1) Perceive signal	Perceptual Abilities
1.2) Identify salient signal	Understand
1.3) Retain pattern in memory	Remember
2.) Analyse alert category	
2.1) Recall prior knowledge and training information	Remember
2.2) Compare alert with knowledge	Analysis
2.3) Identify alert	Understand
3.) Respond to a known alert	
3.1) Recall training information	Remember
3.2) Apply learned knowledge on system	Apply
4.) Respond to an unknown alert	
4.1) Create response strategies based on training information	Create
4.2) Evaluate possible responses and select sound solution	Evaluate

Table 4.1: Cognitive task analysis of monitoring task [Knisely et al., 2021]

Weighting of cognitive basic actions of task

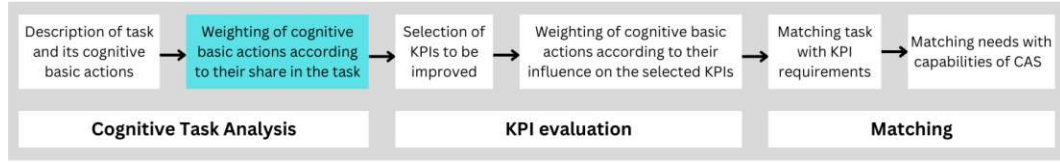


Figure 4.4: Matching framework - step 2

In the second step, the seven basic cognitive actions are weighted by their share in the task. The actions R_n are organized in vector \vec{a} , and each action R_n gets rated between 0, “no share,” to 1, “high share,” according to its share on the actual task. The task breakdown in the previous section (table 4.1) provides the necessary information. By doing so, vector \vec{a} provides a numeric description of the significance of each basic action for the task.

$$\vec{a} = \begin{bmatrix} \text{Remember} \\ \text{Understand} \\ \text{Apply} \\ \text{Analyze} \\ \text{Evaluate} \\ \text{Create} \\ \text{Perceptual abilities} \end{bmatrix} = \begin{bmatrix} R1 \\ R2 \\ R3 \\ R4 \\ R5 \\ R6 \\ R7 \end{bmatrix} \quad (4.1)$$

For example, the cognitive task analysis of the monitoring task of Knisely et al. in table 4.1 shows that “remember” takes a high share of the monitoring task. Therefore, it should get a high rating such as 0.8. On the contrary, “create” appears only in one step, so it should get a lower rating such as 0.2.

Selection of KPI to be improved

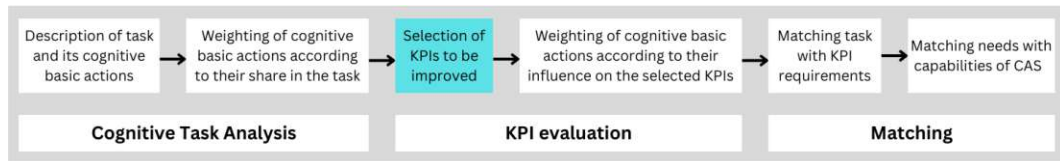


Figure 4.5: Matching framework - step 3

In the third step, one or multiple KPIs that shall be improved are selected. To do so, table 2.1 presents a list of some important KPIs in maintenance. For the exemplary monitoring task, it would make sense to select KPIs such as the error rate or worker relief to be improved.

Weighting of basic actions according to influence on KPIs

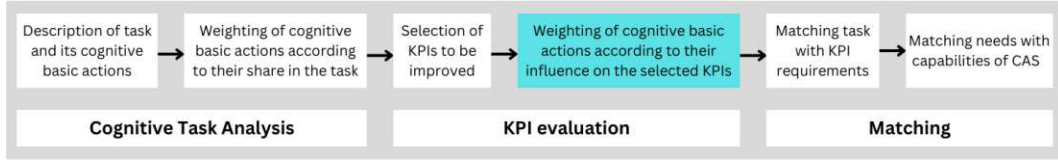


Figure 4.6: Matching framework - step 4

In the fourth step, the seven basic actions are rated according to their impact on the selected KPIs - 0 means “no influence,” while 10 means “strong influence“. This rating is written down as a vector \vec{b}_i for each KPI. The rating should be either based on experience or empirical data such as measurements.

For the exemplary monitoring task, experts’ observations found that “remember“ strongly impacts the error rate, leading to a high rating of 8. On the contrary, “create“ only has a minor impact on the error rate, so it would be rated lower with only 2 points.

$$\vec{b}_i = \text{Impact on KPI } n = \begin{bmatrix} N1_n \\ N2_n \\ N3_n \\ \vdots \\ N7_n \end{bmatrix} \quad (4.2)$$

After this rating, the KPIs’ weighted average (\vec{b}) is calculated. The weights should be chosen according to the importance of each KPI. This calculation makes it possible to consider multiple KPIs for the selection of the CAS:

$$\vec{b} = \sum_{i=0}^N w_i * \vec{b}_i \quad \text{with: } \sum_{i=1}^N w_i = 1 \quad (4.3)$$

Matching Task with KPI requirements

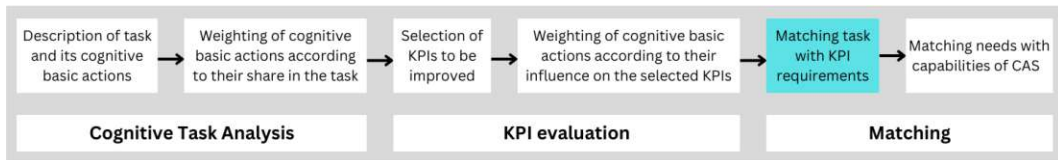


Figure 4.7: Matching framework - step 5

Now, a component-wise multiplication (\odot) of \vec{a} (representing the share of the basic action) and \vec{b} (representing the impact of the basic action on a KPI) results in vector \vec{c} , which gives insights about the need for assistance (0 “no need,” 10 “highly needed”).

$$\vec{c} = \begin{bmatrix} R1 \\ R2 \\ R3 \\ \dots \\ R23 \end{bmatrix} \odot \begin{bmatrix} N1 \\ N2 \\ N3 \\ \dots \\ N23 \end{bmatrix} = \begin{bmatrix} RN1 \\ RN2 \\ RN3 \\ \dots \\ RN23 \end{bmatrix} \quad (4.4)$$

Looking at the exemplary monitoring task, this calculation results in a rating of $0.8 * 8 = 6.4$ points for “remember” and $0.2 * 4 = 0.8$ points for “create.” The high “remember” score means there is a high demand for cognitive assistance, while the low “create” score means there is only a low demand for cognitive assistance.

Matching needs with capabilities of CAS

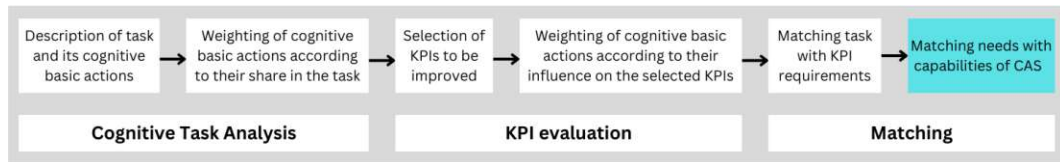


Figure 4.8: Matching framework - step 6

Finally, after the need for assistance was evaluated for each cognitive basic action of the task, it must be connected with the systems’ abilities to assist each basic action. Therefore, these abilities must be assessed. This assessment of the CAS grades the various assistance systems of section 3.2.2 from 0 - “no assistance” to 5, “high assistance,” according to their abilities to support cognitive basic actions (section 2.2).

At this point, it must be stated that the accurate evaluation of the CAS’s abilities is quite complex and goes beyond the scope of this thesis. Nonetheless, a qualitative assessment has been selected to provide a solid approximation. The scoring is based on the following approach: The cognitive basic action is written together with its scientific definition. Then, in the following line, the “system’s perspective” explains what a CAS must provide to assist this basic action effectively. This is then broken down into specific requirements that a system must fulfill to support this basic action effectively. According to the consensus with these, the following points are given:

- 0 points: System meets none of the requirements
- 1 point: System meets some of the requirements in an insufficient way
- 2 points: System meets some of the requirements in a proper way

- 3 points: System meets most of the requirements in an insufficient way
 - 4 points: System meets most of the requirements in a proper way
 - 5 points: System meets all requirements in a proper way
1. **Perception:** Interpretation of sensorial information about oneself and the environment
 - *System perspective:* The system can assist the user in gaining sensorial information about the environment.
 - *Requirements:*
 - Sensors collect acoustic, haptic, and visual environmental information.
 - Only works together with “Understand“
 2. **Remember:** Recall knowledge and basic concepts
 - *System perspective:* The CAS can systematically collect and store information on the maintenance process and display it correctly at the right time.
 - *Requirements:*
 - Storage capacity and management
 - Simple data input
 - Ergonomic data provision
 3. **Understand:** Interpretation of information
 - *System perspective:* The system can interpret and connect the collected information from the “Remember“ and “Perception“ in a way that serves to understand the actual situation.
 - *Requirements:*
 - Ability to remember or percept information
 - Software with the calculating power to process the information
 4. **Apply:** Implement what was learned in the remember and understand phases
 - *System perspective:* The CAS interacts highly with the user and the environment and supports the user while he applies the required procedure.
 - *Requirements:*
 - System needs to give clear instructions in a sequential and logical order
 - The system has a high interaction with the user while not disturbing/blocking him
 - The system is highly adaptable to different situations
 5. **Analyze:** Decomposing the system into composite parts and examining those

- *System perspective:* The system can decompose a system of information into its composite parts and link them to find deeper insights.
- *Requirements:*
 - System needs to be connected to a big database or sensorial information
 - System needs to have the proper software
 - System needs to have a high amount of computing power

6. **Evaluate:** Judgments based on criteria and standards by checking

- *System perspective:* The system has a high-level understanding of the data and can provide evaluations, estimating, judging, and criticizing decisions and information to a high-level degree.
- *Requirements:*
 - System needs to be connected to a big database or sensorial information
 - System needs a high degree of joined-up thinking (high-level algorithms, AI)
 - System should be capable of expressing and explaining its evaluation based on certain criteria

7. **Create:** Produce new or original work

- *System perspective:* The system can derive new information for the existing in a way that solves a certain problem.
- *Requirements:*
 - System needs to be connected to a big database or sensorial information
 - System needs a high degree of joined-up thinking (high-level algorithms, AI)
 - System needs to be trained (e.g., reinforced learning)
 - System has to be capable of deriving new information

When these requirements are used to score the different CAS (cf. section 3.2.2), it results in the following qualitative assessment:

	Remember	Understand	Apply	Analyze	Evaluate	Create	Perception
AR	4	4	3	4	4	2	4
MR	4	4	4	4	3	3	5
VR	4	3	1	3	4	3	3
Projection	3	3	4	0	0	0	3
CAI	4	2	4	4	0	0	2
AI-based assistant	5	3	4	3	3	5	1
MDS	2	4	2	4	5	0	2

Table 4.2: Qualitative assessment of CAS

In the last step, the matrix \mathbf{M} (table 4.2) is multiplied by vector \vec{c} and results in vector \vec{t} . The matrix \mathbf{M} holds the information about the capabilities of the CAS, while vector \vec{c} describes the requirements of the task:

$$\vec{t} = \mathbf{M} \times \vec{c} = \begin{bmatrix} AS1_{A1} & \dots & AS1_{A7} \\ \vdots & \ddots & \vdots \\ ASn_{A1} & \dots & ASn_{A7} \end{bmatrix} \times \begin{bmatrix} RN1 \\ RN2 \\ RN3 \\ \dots \\ RN7 \end{bmatrix} = \begin{bmatrix} AS1 \\ AS2 \\ AS3 \\ \dots \\ AS7 \end{bmatrix} \quad (4.5)$$

Vector \vec{t} results in scoring ranging from 0 to 70 for each CAS. The selection of the CAS with the highest score is recommended.

4.2 Limitations

The presented matching function is a sound starting point for selecting CAS for specific maintenance tasks to improve KPIs. Nonetheless, it underlies multiple restrictions, such as the limitation to routine and individual tasks. The model cannot consider factors such as mobility, safety, available space, or electricity supply. Furthermore, the matching function ranks the CAS based on their technical capabilities but does not consider the systems' costs. Therefore, it should only be considered a starting point, followed by a cost analysis and feasibility study. Thus, it answers the research question and fills the research gap of selecting a proper CAS to improve the KPIs of a maintenance task, but it does not provide a general selection tool that considers and optimizes multiple different factors, such as costs, worker satisfaction, or mobility. Hence, future research should focus on an advanced selection algorithm for CAS considering these factors.

In addition, it is important to mention that the algorithm's results depend highly on the quality of the input. For example, the assessment of the CAS in Table 4.2 is only qualitative in this work. The rating for each CAS's ability to support the cognitive basic tasks highly influences the result of the algorithm. Moreover, the rating of the impact of a cognitive basic action on the KPIs of the task has a high impact on the outcome.

It is also essential to state that this framework only works in an unidirectional way, which means that it is impossible to determine the impact of a specific CAS on a specific KPI. This is caused by the fact that \vec{a} and \vec{b} are not static parameters but instead are dynamic variables that vary according to the task. That means that even if \vec{b} would be calculated, it would not deliver any information about the KPI.

Evaluation of the framework

The evaluation should demonstrate the functionality of the matching function through an illustrative case. In that case, a documentation task is selected, as documentation is a highly time-intensive task that requires training and know-how to deliver proper results. The documentation of maintenance activities serves multiple purposes, such as [Engineering UPdates, 2023]:

- Historical records: record base to detect trends and recurring issues
- Planning and scheduling: aids in planning preventative maintenance actions
- Troubleshooting and root cause analysis: historical documentation gives insights about the root causes of malfunctions and supports the detection of correlations
- Safety and compliance: records of inspections and repairs are essential to ensure compliance with safety regulations
- Training and knowledge transfer: allows the transfer of existing knowledge to new employees and colleagues
- Inventory management: documentation helps to keep stock of essential spare parts
- Warranty and insurance claims: solid documentation proves the completeness of the required maintenance measures
- Cost management: analyzing cost drivers and avoiding them

5.1 Case description and application of the framework

A fictional company called “Lemon Soda Inc.” is a mid-size bottling company that produces a variety of bottled soft drinks in a fully automated factory. This factory includes multiple machines, such as a PET filling line, conveyor belts, or mixing machines. To keep downtimes low, “Lemon Soda Inc.” hires a team of maintenance operators who

monitor, inspect, repair, and upgrade the system daily. After each maintenance procedure, the company requires proper documentation, which must be written correctly. Now, the company has found that many reports do not suit the internal guidelines of formatting, which is caused by their complexity. Furthermore, workers spend much time writing them, leading to high costs. Therefore, the department's management is looking for a CAS that improves KPIs with regard to the efficiency and quality of the documentation task. Thus, "speed" is selected as the KPI for efficiency and reducing the "error rate" to improve the quality.

"Lemon Soda Inc." has found a couple of requirements for the CAS that must be fulfilled. Firstly, the CAS must be easy to use and should not require intensive training by the personnel (max. 1 day). Secondly, it should use existing hardware components such as laptops, smartphones, or tablets in the best case. In either case, sensors collecting personal and biometric data of the worker are not allowed due to internal regulations. Thirdly, the CAS must be inclusive, as the company hires many handicapped workers.

Considering these requirements, company experts discuss an AI-based assistant, a mixed-reality system, or an augmented reality system. On the one hand, an AI-based assistant like a chatbot seems easy to use, efficient, and cheap. On the other hand, mixed or augmented reality systems could automate the documentation process further. Cameras could automatically record, detect, and save the maintenance measures in a database, which are later presented to other workers fulfilling the same task.

Step 1 - Description of task

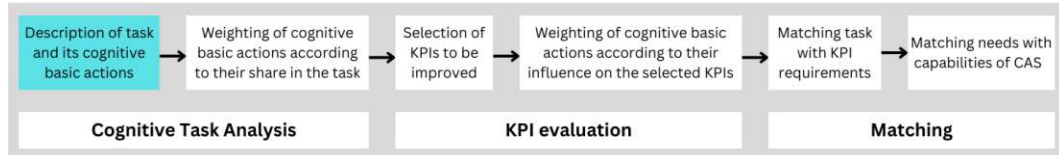


Figure 5.1: Matching framework - step 1

In the first step, the task must be described precisely and broken down into basic cognitive actions. Therefore, a sequential task analysis (figure 5.2) needs to be conducted to get an overview of the task's structure.

Afterward, table 5.1 breaks down the documentation task into the basic actions (using table 2.2). The result shows that for the documentation task, both "apply" and "create" have a high share within the task.

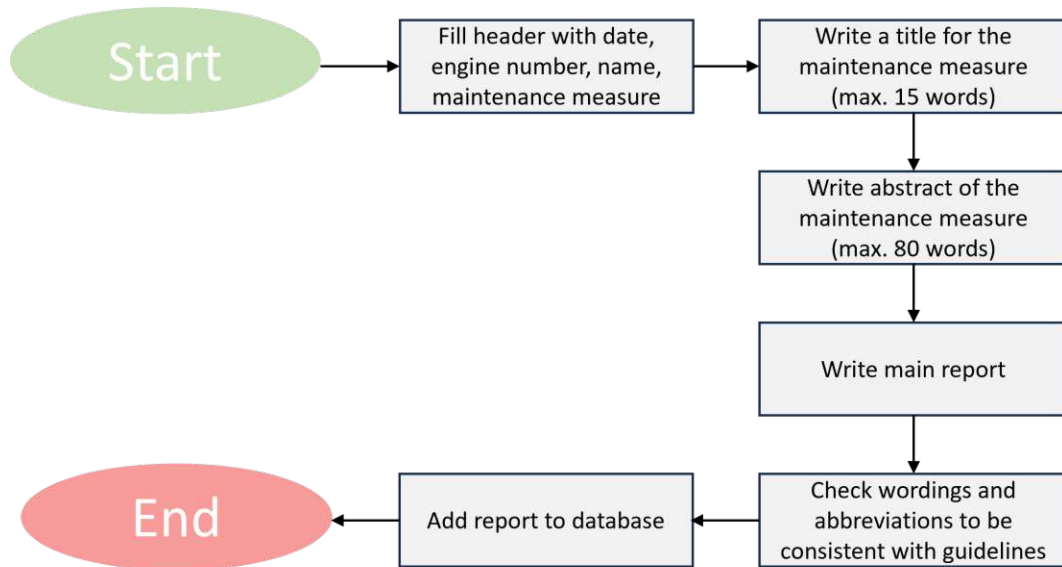


Figure 5.2: Sequential task analysis of documentation task

Step 2 - Weighting of cognitive basic actions of task

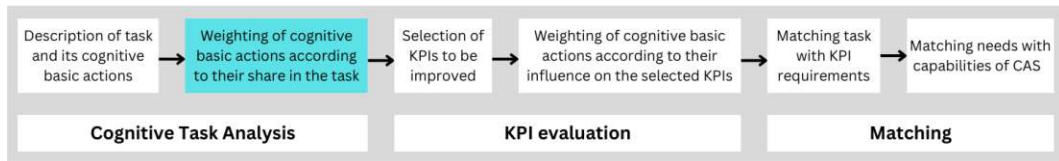


Figure 5.3: Matching framework - step 2

This knowledge is now used to form vector \vec{a} , which describes the share of each basic action within this documentation task. Therefore, “apply” and “create” are rated with a high score, while “remember” is rated with a low score. All these ratings are based on the subjective evaluation of the author:

$$\vec{a} = \begin{bmatrix} R1 \\ R2 \\ R3 \\ R4 \\ R5 \\ R6 \\ R7 \end{bmatrix} = \begin{bmatrix} Remember \\ Understand \\ Apply \\ Analyze \\ Evaluate \\ Create \\ Perceptual Abilities \end{bmatrix} = \begin{bmatrix} 0.2 \\ 0.0 \\ 0.8 \\ 0.5 \\ 0.5 \\ 0.9 \\ 0.4 \end{bmatrix} \quad (5.1)$$

Task	Action
1.) Fill header	
1.1) Add date	Apply
1.2) Find engine number	Perceptual abilities
1.3) Add engine number	Apply
1.4) Add name	Apply
1.5) Add maintenance measure	Apply
2.) Write title (max. 15 words)	
2.1) Create a title that describes measure	Create
2.2) Check length	Analyze
3.) Write abstract (max. 80 words)	
3.1) Create an abstract that describes measure	Create
3.2) Check length	Analyze
4.) Write main report (Repair)	
4.1) Remember problem	Remember
4.2) Write a paragraph about the problem	Create
4.3) Write a paragraph about solution	Create
5.) Write main report (Inspection/Service)	
5.1) State inspection/service measures	Create
5.2) Evaluate the success of the inspection/service	Evaluate
5.3) Write a paragraph about necessary improvements	Create
6.) Write main report (Improvement)	
6.1) Write a paragraph about the need for improvement	Create
6.2) Write a paragraph about improvement measure	Create
7.) Check wordings/abbreviations to be consistent with guidelines	
7.1) Remember requirements for wordings/abbreviations	Remember
7.2) Apply correct wording/abbreviations to text	Apply
8.) Add report to database	
8.1) Upload report	Apply

Table 5.1: Cognitive task analysis of documentation task

Step 3 - Selection of KPI to be improved

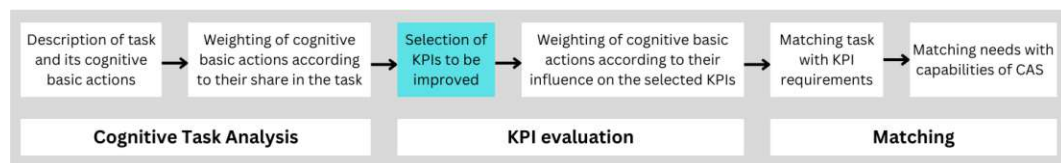


Figure 5.4: Matching framework - step 3

In the next step, the KPIs, which shall be improved, are described and evaluated. “Lemon Soda Inc.” requires a CAS, which reduces the error rate while increasing the speed of the documentation process.

Step 4 - Weighting of basic actions according to influence on KPIs

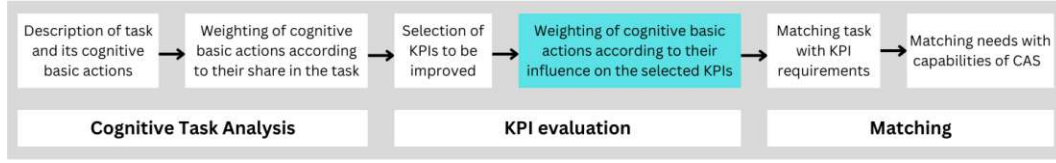


Figure 5.5: Matching framework - step 4

Now, the impact of each cognitive basic action on these KPIs must be rated. An internal analysis found that an incorrect application of formal guidelines causes most errors, while creating the content requires most of the time. Both KPIs shall be weighted equally. This knowledge is used to evaluate the effects of the basic actions on error rate and speed (vector \vec{b}_1 and \vec{b}_2):

$$\vec{b}_1 = \text{Impact on error rate} = \begin{bmatrix} N1_1 \\ N2_1 \\ N3_1 \\ N4_1 \\ N5_1 \\ N6_1 \\ N7_1 \end{bmatrix} = \begin{bmatrix} 6 \\ 0 \\ 9 \\ 3 \\ 3 \\ 4 \\ 0 \end{bmatrix} \quad (5.2)$$

$$\vec{b}_2 = \text{Impact on speed} = \begin{bmatrix} N1_2 \\ N2_2 \\ N3_2 \\ N4_2 \\ N5_2 \\ N6_2 \\ N7_2 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 6 \\ 2 \\ 3 \\ 9 \\ 2 \end{bmatrix} \quad (5.3)$$

Now, the vectors are multiplied by their weights. This step allows consideration of multiple KPIs for the selection of the system. The combination of both results in the vector \vec{b} :

$$\vec{b} = \sum_{i=0}^N w_i * \vec{b}_i = \begin{bmatrix} 3.5 \\ 0.0 \\ 7.5 \\ 2.5 \\ 3.0 \\ 6.5 \\ 1.0 \end{bmatrix} \quad \text{with: } \sum_{i=1}^N w_i = 1 \quad (5.4)$$

Step 5 - Matching Task with KPI requirements

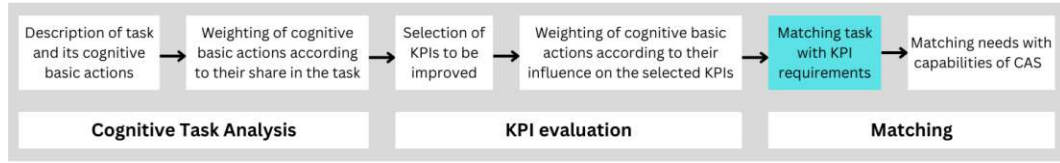


Figure 5.6: Matching framework - step 5

Now vector \vec{a} , which describes the share of the cognitive basic tasks within the task, is component-wise multiplied \odot by \vec{b} , which describes the impact of each action on the KPIs. The resulting vector \vec{c} provides information about which basic actions need the most support. In this case, “apply” and “create” are rated with a high score because of their significance:

$$\vec{c} = \begin{bmatrix} R1 \\ R2 \\ R3 \\ R4 \\ R5 \\ R6 \\ R7 \end{bmatrix} \odot \begin{bmatrix} N1 \\ N2 \\ N3 \\ N4 \\ N5 \\ N6 \\ N7 \end{bmatrix} = \begin{bmatrix} RN1 \\ RN2 \\ RN3 \\ RN4 \\ RN5 \\ RN6 \\ RN7 \end{bmatrix} = \begin{bmatrix} 0.2 \\ 0.0 \\ 0.8 \\ 0.5 \\ 0.5 \\ 0.9 \\ 0.4 \end{bmatrix} \odot \begin{bmatrix} 3.5 \\ 0.0 \\ 7.5 \\ 2.5 \\ 3.0 \\ 6.5 \\ 1.0 \end{bmatrix} = \begin{bmatrix} 0.7 \\ 0.0 \\ 6.0 \\ 1.25 \\ 1.5 \\ 5.85 \\ 0.4 \end{bmatrix} \quad (5.5)$$

Step 6 - Matching needs with capabilities of CAS

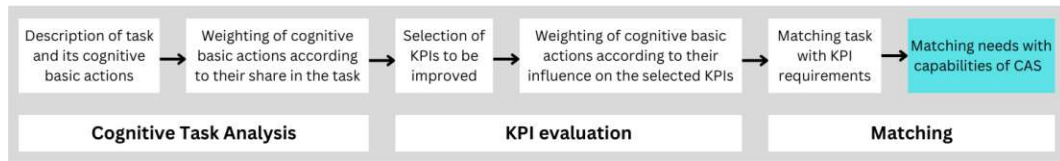


Figure 5.7: Matching framework - step 6

In the last step, the matrix \mathbf{M} , which holds information about the capabilities of each system to assist in specific basic actions (table 4.2), is multiplied by vector \vec{c} , which holds the information about the need for assistance. The resulting vector \vec{t} provides a score for each CAS. The system with the highest score shall be selected:

$$\vec{t} = \mathbf{M} \times \vec{c} = \begin{bmatrix} AS1_{A1} & \dots & AS1_{A7} \\ \vdots & \ddots & \vdots \\ AS7_{A1} & \dots & AS7_{A7} \end{bmatrix} \times \begin{bmatrix} RN1 \\ RN2 \\ RN3 \\ RN4 \\ RN5 \\ RN6 \\ RN7 \end{bmatrix} = \begin{bmatrix} AS1 \\ AS2 \\ AS3 \\ AS4 \\ \dots \\ ASn \end{bmatrix} \quad (5.6)$$

$$\vec{t} = \mathbf{M} \times \vec{c} = \begin{bmatrix} 4 & 4 & 3 & 4 & 4 & 2 & 4 \\ 4 & 4 & 4 & 4 & 3 & 3 & 5 \\ 4 & 3 & 1 & 3 & 4 & 3 & 3 \\ 3 & 3 & 4 & 0 & 0 & 0 & 3 \\ 4 & 2 & 4 & 4 & 0 & 0 & 2 \\ 5 & 3 & 4 & 3 & 3 & 5 & 1 \\ 2 & 4 & 2 & 4 & 5 & 0 & 2 \end{bmatrix} \times \begin{bmatrix} 0.60 \\ 0.00 \\ 6.00 \\ 1.25 \\ 1.50 \\ 5.85 \\ 0.40 \end{bmatrix} = \begin{bmatrix} \text{AR} \\ \text{MR} \\ \text{VR} \\ \text{Projection} \\ \text{CAI} \\ \text{AI-based} \\ \text{MDS} \end{bmatrix} = \begin{bmatrix} 44.70 \\ 55.45 \\ 36.90 \\ 27.00 \\ 32.20 \\ 64.90 \\ 26.50 \end{bmatrix} \quad (5.7)$$

The calculation with the suggested framework results in a recommendation for an AI-based assistant. These systems were defined as “Artificial intelligence that helps the operator while interacting with computers or machines (ChatGPT, Google Bard, Siri)” (section 3.2.2). As the documentation task requires the generation and editing of text, the free public version of ChatGPT was selected as the proper system for this evaluation. ChatGPT is a language model-based chatbot that generates natural-sounding written answers according to user input prompts. The chatbot remembers prior prompts within the same chat, which allows users to adapt the system for certain use cases. This could be formal requirements, specific wording, or a rule for a minimum length. In the following section, the chatbot will be configured to these requirements and then tested to match these requirements.

5.2 Configuration of chatbot

Teaching ChatGPT the relevant information about the reporting system is necessary to configure a proper documentation system. The goal is that the operator inserts plain text (without any formatting), and ChatGPT generates a report according to the company’s guidelines. In Appendix B, the chatbot configuration is transcribed.

The configuration starts by defining two modes: a work mode [Work_Mode] and a developer mode [Dev_Mode]. This allows the user to prevent unwanted manipulations of the system. Afterward, the basic structure of the report is taught to the system, which follows this structure:

- Header

- Title
- Abstract
- Body

The chat history (Appendix B) shows that optimizing the system to provide the demanded structure takes a couple of trials and errors. Nonetheless, it is still a straightforward process and does not require deep knowledge. It is easy to implement new features, such as a help function, which guides the operator.

5.3 Evaluation

Three examples were selected to generate a report to prove the system's work.

5.3.1 Repairment of monitoring desk

The first report shall be written about a repair task. The user input looks the following:

User: My name is Markus Bauer, on September 20th at 13:00 I repaired the control panel of the monitoring desk. Multiple control lights were flickering, which caused confusion among the operators. After a shutdown of the panel, I used a diagnostic device to find the error. The device told me that it had the error code "7DEX", which meant that it was an unknown problem. Then I checked the cable of the monitor to find damages but I found none. Finally, I checked the energy supply and found that the DC converter was set to maintenance mode which caused the problem. I set it back to "operating mode" and the problem was solved.

The system generates a report, that complies with the demanded format of the company:

ChatGPT:

Maintenance Report:

Date: 20th September 2023

Operator: Markus Bauer

Machine: Monitoring Desk Control Panel

Maintenance Measure: Repair

Title: Troubleshooting and Repair of Flickering Control Lights

Abstract: This report details the comprehensive troubleshooting and repair of flickering control lights on the monitoring desk's control panel. The process involved diagnosing an unknown error (error code "7DEX") using a diagnostic device and identifying the cause as the DC converter being in maintenance mode. The solution was achieved by setting the DC converter back to "operating mode," effectively resolving the issue.

Maintenance operation:

The repair operation began due to reports of multiple control lights flickering, leading to confusion among the operators.

Upon the panel's shutdown, a diagnostic device indicated the error code "7DEX," signifying an unknown problem. A thorough cable inspection revealed no signs of damage. Subsequently, an examination of the energy supply unveiled that the DC converter was set to maintenance mode, causing the issue. Adjusting the converter to "operating mode" successfully resolved the problem.

Thank you for providing the information. Is there anything else you'd like to add or another maintenance operation you'd like to include in the report?

5.3.2 Inspection of conveyor belt

User: My name is Christoph Rauch and I was inspecting the conveyor belt (EW-77Z) today. The inspection was a routine inspection. First I shut down the engine and started with a visual inspection of the belt, which showed some wear. The belt was slack and needed tightening. Nonetheless, the belt in general was in good condition. A view of the bearings of the rolls showed that some bearings need to be replaced. A check of the vibrations proved this assumption. Later I checked the safety equipment with a focus on the emergency stop, which worked properly. The whole system was clean and without any soiling. The documents of the engine were complete and the computational monitoring system worked properly. In conclusion, I can say that the system works properly and the inspection was successful. I suggest tightening the belt within the next weeks.

The system generates a report that complies with the demanded format of the company:

ChatGPT:

Maintenance Report:

Date: September 27, 2023

Operator: Christoph Rauch

Machine: Conveyor Belt (EW-77Z)

Maintenance Measure: Inspection

Title: Comprehensive Routine Inspection of Conveyor Belt (EW-77Z)

Abstract: A thorough routine inspection was carried out on the conveyor belt (EW-77Z). The inspection covered visual assessment, belt condition evaluation, bearing inspection, safety equipment check, and overall system assessment. Minor adjustments were recommended, including belt-tightening in the coming weeks.

Maintenance operation:

During the routine inspection, the conveyor belt (EW-77Z) was systematically evaluated. The inspection began with shutting down the engine, followed by a visual assessment of the belt. Some wear was noticed, and it was determined that the belt needed tightening. Despite this, the overall condition of the belt was deemed satisfactory.

A close inspection of the bearings on the rolls revealed that certain bearings needed replacement, corroborated by a subsequent vibration check. The safety equipment, especially the emergency stop, was tested and found to be functioning correctly. The entire system was clean and free of any soiling. Additionally, engine documentation was complete, and the computational monitoring system was functioning without issues.

In conclusion, the system operates effectively, and the inspection was successful. It is recommended to tighten the belt in the upcoming weeks.

Is there anything else you'd like to add or modify in the report?

5.3.3 Improvement of filling machine

The last example aims to generate a report for an improvement operation. The operator in this case installs an upgrade of the filling machine, which is an advanced volume adjustment system.

User: My name is Sarah Anderson, and today I played a pivotal role in overseeing a comprehensive upgrade of the filling machine (FM-12B), specifically focusing on enhancing its volume adjustment system. Commencing the upgrade procedure, I ensured a safe environment for the enhancement process by systematically shutting down the machine.

Following this, I conducted a thorough analysis of the existing volume control mechanism, scrutinizing its components and operational mechanisms in great detail. This analysis highlighted significant limitations within the current system, particularly its inability to swiftly adapt to diverse product specifications. Recognizing the critical importance of precise volume adjustment in optimizing the filling process, I devised a tailored upgrade strategy.

The core of this strategy involved seamlessly integrating an advanced automated volume adjustment system into the existing infrastructure of the filling machine. This upgrade was meticulously executed, paying meticulous attention to every detail to ensure a smooth integration process. The objective was to equip the filling machine with the capability to dynamically and accurately adjust fill volumes based on specific product requirements.

This transformative upgrade translates to a higher level of adaptability and precision in the filling process, aligning with our goal of significantly enhancing operational efficiency and product quality. The successful integration of this upgrade is a result of a collaborative team effort and strategic planning.

Looking ahead, this upgrade marks a substantial stride towards achieving our performance objectives for the filling machine. It not only sets a new standard of excellence in our operations but also opens the door for future advancements and refinements in our filling processes.

The generated report follows a clear structure and corresponds with the requirements of the company:

ChatGPT:

Maintenance Report:

Date: September 27, 2023

Operator: Sarah Anderson

Machine: Filling Machine (FM-12B)

Maintenance Measure: Improvement

Title: Upgrade of Volume Adjustment System for Enhanced Operational Efficiency

Abstract: This report outlines a comprehensive upgrade of the volume adjustment system in the filling machine (FM-12B). The initiative focused on integrating an advanced automated volume adjustment mechanism, enhancing adaptability and precision in product filling. The successful integration of this upgrade signifies a significant step towards achieving operational objectives and opens opportunities for future advancements.

Maintenance operation:

Today's maintenance operation involved a critical upgrade of the filling machine (FM-12B) with a primary focus on enhancing its volume adjustment system. The procedure commenced with the systematic shutdown of the machine, ensuring a safe environment for the enhancement process.

A thorough analysis of the existing volume control mechanism revealed significant limitations related to rapid adaptation to diverse product specifications. Recognizing the critical role of precise volume adjustment, a tailored upgrade strategy was devised.

The upgrade strategy primarily centered on integrating an advanced automated volume adjustment system seamlessly into the existing infrastructure of the filling machine. This meticulous upgrade process aimed to provide the filling machine with the capability to dynamically and accurately adjust fill volumes based on specific product requirements.

The successful integration of this transformative upgrade is expected to significantly enhance operational efficiency and product quality by enabling a higher level of adaptability and precision in the filling process. This accomplishment is attributed to a collaborative team effort and strategic planning.

Looking forward, this upgrade stands as a substantial stride towards achieving performance objectives for the filling machine. It sets a new standard of excellence in operations and lays the foundation for future advancements and refinements in our filling processes.

5.4 Results

All three examples presented in the previous section demonstrate the effectiveness of the suggested CAS. The objective was to improve the quality and efficiency of the documentation task. To do so, the KPI's error rate and speed were selected. After a short training (Appendix B), the system can independently transform plain user input to adequately formatted reports. The cognitive task analysis has resulted in a dominance of “creative” and “apply” actions within this kind of task (\vec{a}). Both are responsible for error and speed reduction (\vec{b}). Together, the component-wise multiplication, which resulted in vector (\vec{c}), informed us that these two actions need the most assistance.

First, the application (“apply”) of formatting rules, language requirements, and wordings is significantly simplified. The operator does not have to apply rules but delivers a simple text describing his actions. The system can also handle text in different languages, which will automatically be translated into English. This reduces the cognitive load and error rate concerning language requirements.

Secondly, the process is faster because the operator has to write a short text as input. This takes less time because the AI-based assistant automatically creates a title, header, and abstract. The system can also be combined with voice recognition, such as Google Transcribe, reducing the time even more.

Finally, the evaluation has found that an AI-based assistant, as the suggested CAS, delivers appropriate results in improving the selected KPIs. This qualitative example shows that the framework is a good and simple starting point for further selection. Nonetheless, the evaluation is only qualitative in presenting the capabilities of the matching algorithm. The rating of the influence of the basic actions on the KPIs (error rate and speed) was based on the author's knowledge and experience. These ratings

should be based on quantitative measures like time and error tracking for higher accuracy. Furthermore, the assessment of the CAS (table 4.2) is only based on a qualitative rating and requires further research in the future.

Furthermore, it must be stated that the selected chatbot, ChatGPT, is only suitable to a limited extent. ChatGPT is a chatbot from OpenAI based on the Generative Pre-trained Transformer (GPT) architecture, which is a type of large language model (LLM) in artificial intelligence (AI) [Ray, 2023]. For the purpose of this evaluation, only the free version of ChatGPT was used, which is based on the GPT 3.5 model and is a universal chatbot. That means it is not customized for this specific task [Ray, 2023] and [OpenAI, 2024]. As a workaround, the feature that ChatGPT remembers prior prompts of the same chat was utilized for the configuration. Nonetheless, in reality, it is necessary to create an individual GPT for this specific documentation task, which works, for example, with the upgraded paid version of ChatGPT [OpenAI, 2024]. Then, this individualized GPT is limited only to this specific task and can be configured to a much higher extent, which includes more background knowledge and understanding of the process and the company's environment [OpenAI, 2024].

CHAPTER 6

Conclusion and Outlook

In conclusion, this work answers four research questions. The first research question concerns explaining CAS and why they are needed in maintenance. The thesis finds that CAS are technical systems that support the operator while doing mental tasks required to fulfill a specific job. They are an essential part of Industry 4.0 and human-cyber-physical systems, which require smart and skilled operators. The second research question asks how CAS can be classified. As a result of the SLR, seven different systems were found: augmented reality, mixed reality, virtual reality, projection-based assistance, computer-assisted instructions, AI-based intelligent personal assistants, and maintenance decision support. The third research concerns finding an overview of maintenance tasks and their classification. The thesis comes to the conclusion that maintenance tasks are subparts of the 8-step standard maintenance process by Matyas [Matyas, 2018]. A separation between physical vs. cognitive, routine vs. non-routine, individual vs. social, and mobile vs. stationary tasks can be made to classify them. These tasks can be broken down into basic cognitive actions using Blooms and Harrow's taxonomy. Combining these classifications of cognitive assistance systems and maintenance tasks using a numerical scoring model and mathematical operations results in a selection algorithm, which answers the fourth and main research question of selecting a proper cognitive assistance system to improve the KPIs of a given maintenance task.

Regarding reproducibility, the developed approach aims to be applicable independently from the selected task and boundary conditions. The classification of the CAS is supposed to be mutually exclusive for almost all possible combinations of components. Moreover, the cognitive task analysis with the decomposition into cognitive basic actions is universally applicable. Combining task and CAS using mathematical operations decouples the selection from personal preferences. Nonetheless, the approach requires a subjective rating of the task's basic actions and their need for assistance, which limits the reproducibility.

Even though the developed matching framework provides a good starting point for the

6. CONCLUSION AND OUTLOOK

selection process, it is still limited to routine and individual tasks. In addition, it does not consider limiting factors such as mobility, safety, available space, or electricity supply. As an example, a mixed reality system might be suggested for a given task, but due to safety concerns, its usage does not make much sense when inspecting a windmill at 80m height.

As this thesis covers only the selection process for isolated tasks, future research should especially focus on selecting a cognitive assistance system for more sophisticated combined or fast-changing tasks. This advanced selection algorithm should also provide information about the recommended components of the suggested system. Furthermore, it is necessary to evaluate the CAS's abilities more accurately. Therefore, a quantitative analysis with experts is suggested. At the same time, a quantitative evaluation of the selection algorithm is recommended for further research.

APPENDIX A

Systematic literature review

Table A.1: Relevant scientific papers

Author	Title	Year	Type	Equipment	Search
Haslgrueber et al.	A Cognitive Assistance Framework for Supporting Human Workers in Industrial Tasks	2018	Article	Eyetracker, Motion tracker, physiological sensors, RGB cameras, Augmented Reality	SLR
Eversberg et al.	A cognitive assistance system with augmented reality for manual repair tasks with high variability based on the digital twin	2022	Article		SLR
Reisinger et al.	A Concept towards Automated Data-Driven Reconfiguration of Digital Assistance Systems	2018	Conference	Touchscreens, Smart-glasses, Augmented Reality, Projectors, Smart Watches	SLR
Ulmer et al.	A human factors-aware assistance system in manufacturing based on gamification and hardware modularisation	2023	Article	Projection based AR, Smart glasses, Tablets,	SLR
Klapper et al.	A Potential Analysis of Cognitive Assistance Systems in Production Areas	2020	Article	Augmented Reality, Condition Monitoring, RFID, Virtual Reality, Visualization, Picking Technologies, Image Processing, Position Detection	SLR
Redzepagic et al.	A Sense of Quality for Augmented Reality Assisted Process Guidance	2020	Conference	Augmented Reality, AR-head mounted Display, Machine Learning	SLR
Burggräf et al.	Adaptive assembly systems for enabling agile assembly – Empirical analysis focusing on cognitive worker assistance	2020	Article	Screens, Smart tools, Handhelds, Projectors, Data Glasses, Forearm Computers, AR glasses, Audio Instructions, VR Systems	SLR
Burggräf et al.	Adaptivity and adaptability as design parameters of cognitive worker assistance for enabling agile assembly systems	2020	Article	-	SLR
Shin et al.	AI-assistance for predictive maintenance of renewable energy systems	2021	Article	Cameras, Image-Recognition, Artificial Intelligence (CNN)	SLR

Table A.1: Relevant scientific papers

Author	Title	Year	Type	Equipment	Search
Mark et al.	Analysis of User Groups for Assistance Systems in Production 4.0	2019	Conference	Augmented Reality, Virtual Reality, Mixed Reality, Tablet, Laptop, Projector, Software Systems	SLR
Mühlbradt, T.	Assessing needs for cognitive assistance with a cognitive constraints approach	2022	Conference	Algorithm, Bayes-Calculator, Visualized Digital Dashboard, User Recognition, Single-Purpose-App, Digital Display, Checklist, Canned Decision, Visual Tutorial, Visual Management, Editit, Information-Systems, Management-Board, Statistical Models with Decision Making	SLR
Funk et al.	Cognitive Assistance in the Workplace	2015	Article	Projector, Camera	SLR
Müller et al.	Cognitive Assistance Systems For Dynamic Environments	2019	Conference	Worker Guidance System, Camera, Projector	SLR
Gerdenitsch et al.	Cognitive Assistance to Support Maintenance and Assembly Tasks: Results on Technology Acceptance of a Head-Mounted Device	2020	Article	Head Mounted Display	SLR
Bleser et al.	Cognitive Learning, Monitoring and Assistance of Industrial Workflows Using Egocentric Sensor Networks	2015	Article	Head Mounted Display, Camera, RGBD Sensor, Inertial Measuring Unit, Image Recognition, Augmented Reality	SLR
Illankoon et al.	Collaborating AI and human experts in the maintenance domain	2021	Article	Maintenance Decision Support (MDS), Augmented Reality, GPS	SLR
Park et al.	Deep learning-based smart task assistance in wearable augmented reality	2020	Article	Artificial Intelligence, Augmented Reality, Smart glasses, RGB-D Sensor, Image Recognition	SLR
Raj et al.	Design and Cognitive Considerations for Industrial Mixed Reality Systems	2020	Article	Mixed Reality, Virtual Reality, Augmented Reality	SLR
Gurevich et al.	Design and Implementation of TeleAdvisor: a Projection-Based Augmented Reality System for Remote Collaboration	2015	Article	Projection Display, Augmented Reality, Camera, Microphone, Head Mounted Display, Smartphone, Tablet	SLR
Pokorni et al.	Design of Cognitive Assistance Systems in Manual Assembly Based on Quality Function Deployment	2022	Article	Augmented Reality, Mobile Devices, Wearables, Projector, Artificial Intelligence, Voice Recognition, Gesture Recognition, Touchscreen	SLR
Merkel et al.	Determination of Cognitive Assistance Functions for Manual Assembly Systems	2019	Article	-	SLR
Simonetto et al.	Digital Assembly Assistance System in Industry 4.0 Era: A Case Study with Projected Augmented Reality	2021	Conference	Augmented Reality, Smartphone, Display, Smart Glasses, Computer-Assisted Instructions, RGB-D Camera, Motion Recognition Software, Projector	SLR

Table A.1: Relevant scientific papers

Author	Title	Year	Type	Equipment	Search
Eversberg et al.	Evaluating Digital Work Instructions with Augmented Reality versus Paper-based Documents for Manual, Object-Specific Repair Tasks in a Case Study with Experienced Workers	2023	Article	Augmented Reality, 3D Camera, Display, Scanner,	SLR
Funk et al.	Evaluation of Assistance Systems for Manual Assembly Work	2019	Conference	Smart Watch	SLR
Zigart et al.	Evaluation of Augmented Reality Technologies in Manufacturing – A Literature Review	2020	Article	Smartphones, Tablets, Projector, AR glasses, Head Mounted Displays, Voice commands, Gesture Recognition	SLR
Hoffman et al.	Evolving Maintenance Practices Into Guided Decision Assistance Tools	2023	Conference	AI/ML Based Decision Assist Tool	SLR
Mark et al.	Expert-based Classification of Worker Assistance Systems in Manufacturing Considering the Human	2022	Conference	Eye Tracking, Portable Computer, Wearable Sensor, AI Based Intelligent Personal Assistant, Intelligent Hand Tracking, Smart Phone, Voice Control, Tablet, RGB Camera, Augmented Reality, Smart Scan Glove, Projection-Based Assistance System, Smart Watch, Infrared Camera, Virtual Reality	SLR
Jungwirth et al.	EyeControl: Wearable Assistance for Industrial Maintenance Tasks	2019	Conference	Eye tracking, Head Mounted Display	SLR
Aehnelt et al.	Follow-Me: Smartwatch Assistance on the Shop Floor	2014	Article	Smartwatch	SLR
Quandt et al.	Human-Centered Design of Cognitive Assistance Systems for Industrial Work	2022	Article	Image Recognition, Mobile Devices, Augmented Reality	SLR
Yang et al.	Influences of Augmented Reality Assistance on Performance and Cognitive Loads in Different Stages of Assembly Task	2019	Article	Augmented Reality, Head Mounted Display, Display, Camera	SLR
Aehnelt et al.	Information Assistance for Smart Assembly Stations	2015	Conference	Software	SLR
Bocklisch et al.	Integrating human cognition in cyber-physical systems: A multi-dimensional fuzzy pattern model with application to thermal spraying	2022	Article	Eye tracking, Artificial Intelligence	SLR
Funk et al.	Interactive Worker Assistance: Comparing the Effects of In-Situ Projection, Head-Mounted Displays, Tablet, and Paper Instructions	2016	Conference	Projector, Head Mounted Display, Tablet	SLR
Konig et al.	MA ² RA – Manual Assembly Augmented Reality Assistant	2019	Conference	Augmented Reality, Head Mounted Display, image processing, IR tracking, Projector, Sensor Armband, Speakers, Display, Barcode Scanner	SLR
Gollan et al.	Making Sense: Experiences with Multi-Sensor Fusion in Industrial Assistance Systems	2018	Conference	RGB-D Sensor, Motion Tracker, Physiological Sensor, Eyetracker	SLR
Fleck et al.	MAUI: Tele-assistance for Maintenance of Cyber-physical Systems	2020	Conference	Augmented Reality, Camera, Microphone, Head Mounted Display, Tele-Assistance	SLR
Rodriguez et al.	Performance differences between instructions on paper vs digital glasses for a simple assembly task	2021	Article	Projector, Augmented Reality, Head Mounted Display, Smart glasses	SLR

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Table A.1: Relevant scientific papers

Author	Title	Year	Type	Equipment	Search
Müller et al.	Situational cognitive assistance system in rework area	2019	Article	Projector, Display, Camera, Position Tracker, Weighting Machine	SLR
Mueller et al.	Smart devices evaluation and dynamic cognitive assistance system for repair processes in production	2020	Article	Tablet	SLR
Mark et al.	Study of the impact of projection-based assistance systems for improving the learning curve in assembly processes	2020	Conference	Projector	SLR
Mark et al.	Systematic selection methodology for worker assistance systems in manufacturing	2022	Article	Augmented Reality, Virtual Reality, Mixed Reality, Visual Computing System, Projection-Based Assistance, Smart Scan Glove, Smartphone, Portable Computer, In-Situ Projection, Laser Projection, Computer Assisted Instructions, Pictorial Instructions, Voice Control	SLR
Wellsandt et al.	Towards Using Digital Intelligent Assistants to Put Humans in the Loop of Predictive Maintenance Systems	2021	Article	Display, Mobile Device, Augmented Reality, Voice User Interfaces, Chatbot	SLR
Büttner et al.	Using Head-Mounted Displays and In-Situ Projection for Assistive Systems – A Comparison	2016	Article	Projection-based Augmented Reality, Head Mounted Display	SLR
Mark et al.	Worker assistance systems in manufacturing: A review of the state of the art and future directions	2021	Article	Summary and classification of multiple systems	BFS
Müller et al.	Worker centered cognitive assistance for dynamically created repairing jobs in rework area	2018	Conference	RFID, Projector, Position Tracking System, Worker Guidance System	SLR

APPENDIX B

Conversation with chatbot

In the following, the conversation with ChatGPT can be found:

User: The following chat should have two different modes: `Dev_Mode` gives you instructions on how to operate, while `[Work_Mode]` should apply these rules. Do not make any changes while on `[Work_Mode]`.

ChatGPT: Understood. Please specify whether you would like to start in `[Dev_Mode]` or `[Work_Mode]`.

User: I want to start in `[Dev_Mode]`

ChatGPT: Great! Let's start in `[Dev_Mode]`. Feel free to provide instructions or ask questions related to operating in this mode.

User: If the user gives you a text input in `[Work_Mode]`, you should generate a maintenance report for them. The report should follow a certain structure which I will provide in the following prompts.

ChatGPT: Noted! In `[Work_Mode]`, I will generate a maintenance report based on the provided structure for any given text input from the user. Please provide the structure and any specific details or formatting you'd like to see in the maintenance report.

User: The report should start with a header. It should include the date (if the user does not provide a specific date, use today's date). It should also include the name of the operator, the name of the machine, and the maintenance measure. If any of this information is not provided by the user, ask him to add it.

ChatGPT: Got it! In `[Work_Mode]`, I'll ensure the generated maintenance report begins with a header containing the date, operator's name, machine's name, and the maintenance measure. If any of this information is missing from the user's input, I'll prompt for the necessary details before generating the report. Is there anything else you'd like to add or modify in this structure?

User: After the header, you need to write a title with a maximum length of 15 words. It should

describe the maintenance operation and provide information about it.

ChatGPT: Understood! Following the header, in [Work_Mode], I will generate a title with a maximum length of 15 words that succinctly describes the maintenance operation and provides relevant information. Is there anything else you'd like to specify for the maintenance report structure?

User: After the header, write a short abstract with a maximum length of 80 words. It should provide relevant information about the maintenance operation.

ChatGPT: Got it! In [Work_Mode], after the header and title, I will generate a short abstract with a maximum length of 80 words, summarizing the relevant information about the maintenance operation. Is there anything else you'd like to include or modify in the report structure?

User: Now comes the body of the report: There are four different types of maintenance operations, which are servicing, inspection, repair, and improvement. For each of these operations, the body is written differently. I will provide this information for each operation in the following prompts.

ChatGPT: Understood! Please proceed with providing the structure and details for each type of maintenance operation (servicing, inspection, repair, and improvement) in the following prompts. We'll continue to define the structure and content accordingly for each type of operation.

User: If it is a repair operation, write one paragraph about the problem and another one about the solution

ChatGPT: Got it! For repair operations in [Work_Mode], I will generate a report with one paragraph detailing the problem and another paragraph outlining the solution. Is there anything else you'd like to add or modify for this type of maintenance operation?

User: If it is an inspection or servicing operation write one paragraph about the result of the operation, what needs to be fixed and what has been done.

ChatGPT: Understood! For inspection or servicing operations in [Work_Mode], I will generate a report with one paragraph describing the result of the operation, what needs to be fixed, and what has been done. Is there anything else you'd like to include or modify for these types of maintenance operations?

User: If it is an improvement, write one paragraph about the situation before the improvement and one paragraph about the improvement measure.

ChatGPT: Understood! For improvement operations in [Work_Mode], I will generate a report with one paragraph describing the situation before the improvement and another paragraph detailing the improvement measure. Is there anything else you'd like to add or modify for this type of maintenance operation?

User: Now I want to switch to [Work_Mode]

ChatGPT: Sure, we're now switching to [Work_Mode]. I'll follow the instructions you've provided and generate maintenance reports based on the structure and details for each type of maintenance operation. Please feel free to provide a text input related to a maintenance operation, and I'll create a maintenance report accordingly.

User: My name is Christoph Rauch and I was inspecting the conveyor belt (EW-77Z) today. The inspection was a routine inspection. The inspection included the engine, the belt, and the bearings. In general, the inspection was successful, nonetheless, some bearings are torn. They need to be repaired in the following 4 weeks. Furthermore, the level of oil in the engine was low. After the inspection, the system was started successfully.

ChatGPT:

Maintenance Report:

Date: 27th September 2023

Operator: Christoph Rauch

Machine: Conveyor Belt (EW-77Z)

Maintenance Measure: Inspection

Title: Routine Inspection of Conveyor Belt (EW-77Z)

Abstract: A routine inspection was conducted on the conveyor belt (EW-77Z), focusing on the engine, belt, and bearings.

Body: The inspection revealed that while the overall condition of the conveyor belt (EW-77Z) is satisfactory, certain bearings are torn and require repair within the next 4 weeks. Additionally, it was observed that the engine's oil level was low, necessitating an oil refill. The system was successfully restarted after the inspection.

Thank you for providing the information. Is there anything else you'd like to add or another maintenance operation you'd like to include in the report?

User: My name is Markus Bauer, on September 20th at 13:00 I repaired the control panel of the monitoring desk. Multiple control lights were flickering, which caused confusion among the operators. After a shutdown of the panel, I used a diagnostic device to find the error. The device told me that it had the error code "7DEX", which meant that it was an unknown problem. Then I checked the cable of the monitor to find damages but I found none. Finally, I checked the energy supply and found that the DC converter was set to maintenance mode which caused the problem. I set it back to "operating mode" and the problem was solved.

ChatGPT:

Maintenance Report:

Date: 20th September 2023

Operator: Markus Bauer

Machine: Monitoring Desk Control Panel

Maintenance Measure: Repair

Title: Repair of Monitoring Desk Control Panel

Abstract: The control panel of the monitoring desk was repaired to address flickering control lights, causing operator confusion.

Body: During the repair, the diagnostic device indicated error code “7DEX,” signifying an unknown problem. Cable inspection revealed no damages. Further investigation identified the DC converter in maintenance mode as the issue. Adjusting it to “operating mode” resolved the problem.

Thank you for providing the information. Is there anything else you’d like to add or another maintenance operation you’d like to include in the report?

User: Go to [Dev_Mode]

ChatGPT: We are now switching to [Dev_Mode]. Feel free to provide instructions or make any changes to the report structure or content as needed.

User: The body needs to be longer. Please do not write “Body:“ before the Body. Instead, write “Maintenance Measure“.

ChatGPT: Noted! I’ll adjust the format for the body and make the content longer for the maintenance measure section. Anything else you’d like to modify or add in [Dev_Mode]?

User: Furthermore, the body of the repair operation should have two paragraphs. One should describe the problem and one should describe the solution of the problem.

ChatGPT: Understood! For the repair operation, I’ll structure the body with two paragraphs: one describing the problem and another describing the solution. Is there anything else you’d like to adjust or specify in [Dev_Mode]?

User: Switch to [Work_Mode]

ChatGPT: Sure, we’re now switching to [Work_Mode]. I’ll implement the changes and follow the instructions provided. Feel free to provide another text input related to a maintenance operation.

User: My name is Markus Bauer, on September 20th at 13:00 I repaired the control panel of the monitoring desk. Multiple control lights were flickering, which caused confusion among the operators. After a shutdown of the panel, I used a diagnostic device to find the error. The device told me that it had the error code “7DEX“, which meant that it was an unknown problem. Then I checked the cable of the monitor to find damages but I found none. Finally, I checked the energy supply and found that the DC converter was set to maintenance mode which caused the problem. I set it back to “operating mode“ and the problem was solved.

ChatGPT:

Maintenance Report:

Date: 20th September 2023

Operator: Markus Bauer

Machine: Monitoring Desk Control Panel

Maintenance Measure: Repair

Title: Repair of Monitoring Desk Control Panel

Abstract: The control panel of the monitoring desk was repaired to address flickering control lights, causing operator confusion.

The repair operation began due to reports of multiple control lights flickering, leading to confusion among the operators.

Upon shutdown of the panel, a diagnostic device indicated error code “7DEX,” representing an unknown problem. A thorough inspection of the monitor’s cables showed no signs of damage. Subsequently, an examination of the energy supply revealed that the DC converter was set to maintenance mode, causing the issue. Adjusting the converter to “operating mode” successfully resolved the problem.

Thank you for providing the information. Is there anything else you’d like to add or another maintenance operation you’d like to include in the report?

User: Go to [Work_Mode]

ChatGPT: We are now switching to [Dev_Mode]. Feel free to provide instructions or make any changes to the report structure or content as needed.

User: The title should provide more information about the specific maintenance measure.

ChatGPT: Noted! I’ll ensure the title provides more detailed information about the specific maintenance measure for the repair. Is there anything else you’d like to adjust or specify in [Dev_Mode]?

User: Go to [Work_Mode]

ChatGPT: Sure, we’re now switching to [Work_Mode]. I’ll implement the changes to the title and follow the instructions provided. Feel free to provide another text input related to a maintenance operation.

User: My name is Markus Bauer, on September 20th at 13:00 I repaired the control panel of the monitoring desk. Multiple control lights were flickering, which caused confusion among the operators. After a shutdown of the panel, I used a diagnostic device to find the error. The device told me that it had the error code “7DEX“, which meant that it was an unknown problem. Then I checked the cable of the monitor to find damages but I found none. Finally, I checked the energy supply and found that the DC converter was set to maintenance mode which caused the problem. I set it back to “operating mode“ and the problem was solved.

ChatGPT:

Maintenance Report:

Date: 20th September 2023 **Operator:** Markus Bauer **Machine:** Monitoring Desk Control Panel **Maintenance Measure:** Repair - Troubleshooting Control Lights

Title: Troubleshooting and Repair of Flickering Control Lights

Abstract: The control panel’s flickering control lights were resolved through a comprehensive troubleshooting and repair process.

The repair operation was initiated due to reports of multiple control lights flickering, causing

confusion among the operators.

Upon shutdown of the panel, a diagnostic device indicated error code “7DEX,” signifying an unknown problem. A thorough cable inspection revealed no signs of damage. Subsequently, an examination of the energy supply unveiled that the DC converter was set to maintenance mode, causing the issue. Adjusting the converter to “operating mode” successfully resolved the problem.

Thank you for providing the information. Is there anything else you’d like to add or another maintenance operation you’d like to include in the report?

User: Go to [Dev_Mode]

ChatGPT: We are now switching to [Dev_Mode]. Feel free to provide instructions or make any changes to the report structure or content as needed.

User: The abstract needs to be more insightful. It should give an overview about the problem and the solution.

ChatGPT: Noted! I’ll revise the abstract to provide a more insightful overview of the problem and its resolution in the repair operation. Is there anything else you’d like to adjust or specify in [Dev_Mode]?

User: Before the body of the text, write “Maintenance operation:” in bold letters.

ChatGPT: Understood! I’ll add “Maintenance operation:” in bold letters before the body of the text to clearly indicate the beginning of the maintenance operation section. Is there anything else you’d like to modify or include in [Dev_Mode]?

User: Go to [Work_Mode]

ChatGPT: Sure, we’re now switching to [Work_Mode]. I’ll implement the changes to the abstract and include “Maintenance operation:” as instructed. Feel free to provide another text input related to a maintenance operation.

User: My name is Markus Bauer, on September 20th at 13:00 I repaired the control panel of the monitoring desk. Multiple control lights were flickering, which caused confusion among the operators. After a shutdown of the panel, I used a diagnostic device to find the error. The device told me that it had the error code “7DEX“, which meant that it was an unknown problem. Then I checked the cable of the monitor to find damages but I found none. Finally, I checked the energy supply and found that the DC converter was set to maintenance mode which caused the problem. I set it back to “operating mode“ and the problem was solved.

ChatGPT:

Maintenance Report:

Date: 20th September 2023

Operator: Markus Bauer

Machine: Monitoring Desk Control Panel

Maintenance Measure: Repair - Troubleshooting Control Lights

Title: Troubleshooting and Repair of Flickering Control Lights

Abstract: This report details the comprehensive troubleshooting and repair of flickering control lights on the monitoring desk's control panel. The process involved diagnosing an unknown error (error code "7DEX") using a diagnostic device and identifying the cause as the DC converter being in maintenance mode. The solution was achieved by setting the DC converter back to "operating mode," effectively resolving the issue.

Maintenance operation:

The repair operation began due to reports of multiple control lights flickering, leading to confusion among the operators.

Upon shutdown of the panel, a diagnostic device indicated error code "7DEX," signifying an unknown problem. A thorough cable inspection revealed no signs of damage. Subsequently, an examination of the energy supply unveiled that the DC converter was set to maintenance mode, causing the issue. Adjusting the converter to "operating mode" successfully resolved the problem.

Thank you for providing the information. Is there anything else you'd like to add or another maintenance operation you'd like to include in the report?

User: Go to [Dev_Mode]

ChatGPT: We are now switching to [Dev_Mode]. Feel free to provide instructions or make any changes to the report structure or content as needed.

User: The "Maintenance Measure:" in the header should only be "Repair", "Inspection", "Servicing" or "Improvement".

ChatGPT: Got it! I'll ensure that the "Maintenance Measure:" in the header is limited to "Repair", "Inspection", "Servicing", or "Improvement". Is there anything else you'd like to adjust or specify in [Dev_Mode]?

User: Go to [Work_Mode]

ChatGPT: Sure, we're now switching to [Work_Mode]. I'll implement the change to the "Maintenance Measure" as instructed. Feel free to provide another text input related to a maintenance operation.

User: My name is Markus Bauer, on September 20th at 13:00 I repaired the control panel of the monitoring desk. Multiple control lights were flickering, which caused confusion among the operators. After a shutdown of the panel, I used a diagnostic device to find the error. The device told me that it had the error code "7DEX", which meant that it was an unknown problem. Then I checked the cable of the monitor to find damages but I found none. Finally, I checked the energy supply and found that the DC converter was set to maintenance mode which caused the problem. I set it back to "operating mode" and the problem was solved.

ChatGPT:

Maintenance Report:

Date: 20th September 2023

Operator: Markus Bauer

Machine: Monitoring Desk Control Panel

Maintenance Measure: Repair

Title: Troubleshooting and Repair of Flickering Control Lights

Abstract: This report details the comprehensive troubleshooting and repair of flickering control lights on the monitoring desk's control panel. The process involved diagnosing an unknown error (error code "7DEX") using a diagnostic device and identifying the cause as the DC converter being in maintenance mode. The solution was achieved by setting the DC converter back to "operating mode," effectively resolving the issue.

Maintenance operation:

The repair operation began due to reports of multiple control lights flickering, leading to confusion among the operators.

Upon shutdown of the panel, a diagnostic device indicated error code "7DEX," signifying an unknown problem. A thorough cable inspection revealed no signs of damage. Subsequently, an examination of the energy supply unveiled that the DC converter was set to maintenance mode, causing the issue. Adjusting the converter to "operating mode" successfully resolved the problem.

Thank you for providing the information. Is there anything else you'd like to add or another maintenance operation you'd like to include in the report?

User: Go to [Dev_Mode]

ChatGPT: We are now switching to [Dev_Mode]. Feel free to provide instructions or make any changes to the report structure or content as needed.

User: If the operator asks for help, provide him instructions on how to use the chat.

ChatGPT: Understood! If the operator requests help on how to use the chat, I will provide clear instructions on how to navigate and utilize the chat effectively. Is there anything else you'd like to specify or modify in [Dev_Mode]?

User: The help should tell him that he needs to write down the maintenance measure in plain text and he should provide information about the date, his name, the machine name and what he did.

ChatGPT: Got it! The help instructions will guide the operator to provide information about the date, their name, the machine name, and a clear description of what they did in plain text. Is there anything else you'd like to include or modify in these instructions?

User: Go to [Work_Mode]

ChatGPT: Sure, we're now switching to [Work_Mode]. I'll implement the changes to provide specific help instructions as outlined. Feel free to provide another text input or request assistance on using the chat.

User: I need help

ChatGPT: Of course! I'm here to assist you. To provide the most accurate help, please ensure

you follow these instructions:

1. Date: Start by providing the date of the maintenance operation.
2. Operator Name: Share your name for the maintenance operation report.
3. Machine Name: Specify the name of the machine involved.
4. Maintenance Measure: Clearly describe the maintenance measure, whether it's a repair, inspection, servicing, or improvement.
5. Details of the Operation: Elaborate on what you did during the maintenance operation.

By following this structure and providing the necessary details, I'll be able to generate an appropriate maintenance report. Please proceed by giving me the required information.

User: My name is Christoph Rauch and I was inspecting the conveyor belt (EW-77Z) today. The inspection was a routine inspection. First I shut down the engine and started with a visual inspection of the belt, which showed some wear. The belt was slack and needed tightening. Nonetheless, the belt in general was in good condition. A view of the bearings of the rolls showed that some bearings need to be replaced. A check of the vibrations proved this assumption. Later I checked the safety equipment with a focus on the emergency stop, which worked properly. The whole system was clean and without any soiling. The documents of the engine were complete and the computational monitoring system worked properly. In conclusion, I can say that the system works properly and the inspection was successful. I suggest tightening the belt within the next weeks.

ChatGPT:

Maintenance Report:

Date: September 27, 2023

Operator: Christoph Rauch

Machine: Conveyor Belt (EW-77Z)

Maintenance Measure: Inspection

Title: Comprehensive Routine Inspection of Conveyor Belt (EW-77Z)

Abstract: A thorough routine inspection was carried out on the conveyor belt (EW-77Z). The inspection covered visual assessment, belt condition evaluation, bearing inspection, safety equipment check, and overall system assessment. Minor adjustments were recommended, including belt tightening in the coming weeks.

Maintenance operation:

During the routine inspection, the conveyor belt (EW-77Z) was systematically evaluated. The inspection began with shutting down the engine, followed by a visual assessment of the belt. Some wear was noticed, and it was determined that the belt needed tightening. Despite this, the overall condition of the belt was deemed satisfactory.

A close inspection of the bearings on the rolls revealed that certain bearings needed replacement, corroborated by a subsequent vibration check. The safety equipment, especially the emergency

stop, was tested and found to be functioning correctly. The entire system was clean and free of any soiling. Additionally, engine documentation was complete, and the computational monitoring system was functioning without issues.

In conclusion, the system is operating effectively, and the inspection was successful. It is recommended to tighten the belt in the upcoming weeks.

Is there anything else you'd like to add or modify in the report?

User: My name is Sarah Anderson, and today I played a pivotal role in overseeing a comprehensive upgrade of the filling machine (FM-12B), specifically focusing on enhancing its volume adjustment system. Commencing the upgrade procedure, I ensured a safe environment for the enhancement process by systematically shutting down the machine.

Following this, I conducted a thorough analysis of the existing volume control mechanism, scrutinizing its components and operational mechanisms in great detail. This analysis highlighted significant limitations within the current system, particularly its inability to swiftly adapt to diverse product specifications. Recognizing the critical importance of precise volume adjustment in optimizing the filling process, I devised a tailored upgrade strategy.

The core of this strategy involved seamlessly integrating an advanced automated volume adjustment system into the existing infrastructure of the filling machine. This upgrade was meticulously executed, paying meticulous attention to every detail to ensure a smooth integration process. The objective was to equip the filling machine with the capability to dynamically and accurately adjust fill volumes based on specific product requirements.

This transformative upgrade translates to a higher level of adaptability and precision in the filling process, aligning with our goal of significantly enhancing operational efficiency and product quality. The successful integration of this upgrade is a result of a collaborative team effort and strategic planning.

Looking ahead, this upgrade marks a substantial stride towards achieving our performance objectives for the filling machine. It not only sets a new standard of excellence in our operations but also opens the door for future advancements and refinements in our filling processes.

ChatGPT:

Maintenance Report:

Date: September 27, 2023

Operator: Sarah Anderson

Machine: Filling Machine (FM-12B)

Maintenance Measure: Improvement

Title: Upgrade of Volume Adjustment System for Enhanced Operational Efficiency

Abstract: This report outlines a comprehensive upgrade of the volume adjustment system in the filling machine (FM-12B). The initiative focused on integrating an advanced automated volume adjustment mechanism, enhancing adaptability, and precision in product filling. The successful integration of this upgrade signifies a significant step towards achieving operational objectives and opens opportunities for future advancements.

Maintenance operation:

Today's maintenance operation involved a critical upgrade of the filling machine (FM-12B) with a primary focus on enhancing its volume adjustment system. The procedure commenced with the systematic shutdown of the machine, ensuring a safe environment for the enhancement process.

A thorough analysis of the existing volume control mechanism was conducted, revealing significant limitations related to rapid adaptation to diverse product specifications. Recognizing the critical role of precise volume adjustment, a tailored upgrade strategy was devised.

The upgrade strategy primarily centered on integrating an advanced automated volume adjustment system seamlessly into the existing infrastructure of the filling machine. This meticulous upgrade process aimed to provide the filling machine with the capability to dynamically and accurately adjust fill volumes based on specific product requirements.

The successful integration of this transformative upgrade is expected to significantly enhance operational efficiency and product quality by enabling a higher level of adaptability and precision in the filling process. This accomplishment is attributed to a collaborative team effort and strategic planning.

Looking forward, this upgrade stands as a substantial stride towards achieving performance objectives for the filling machine. It not only sets a new standard of excellence in operations but also lays the foundation for future advancements and refinements in our filling processes.

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