Towards Computational Quality Management for Automatically Generated Adaptive Work Instructions in Industry 5.0

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***Abstract*—Industry 4.0 focused on digitalization to make machines work together effectively. Industry 5.0 will put more emphasis on the human worker, whose cognitive abilities and adaptability are invaluable to the factory of the future. We expect a lot from the Operator 5.0 in terms of skills and knowledge, hence research on cognitive assistance systems that can help manage the cognitive load by providing automated digital instructions and production information is highly relevant. To achieve a certain standard, we look at previous work on instruction quality and put it into perspective with insights from UX and instructional design. We argue, that many frameworks lack an objective measure to evaluate and monitor instruction quality. However, assistance systems in Industry 5.0 are designed to generate instructions automatically and adapt them to changes in real-time. Hence, the systems need a way to verify the quality of the produced instructions in order to work effectively and avoid errors. Focusing on assembly tasks, we first identify responsibilities for quality issues by assigning them to different components of an assistance system, before identifying initial objective metrics for the system to rely on.**

***Index Terms*—Industry 5.0, work instructions, assistance systems, quality management**

I. Introduction

The manufacturing industry is undergoing a significant transformation driven by advancements in automation, artificial intelligence, and Industry 4.0 as well as 5.0. Among other factors, this transformation is marked by increasing complexity in manufacturing machines and factories, according to Mark, Rauch, and Matt [1]. This has major implications for the future worker. Romero, Bernus, Noran, *et al.* [2] coined the term ”Operator 4.0”, which is a framework of eight possible scenarios. Each one describes how the previous technological developments affect the human worker. For instance, the ”smarter operator” scenario has the worker thrive on the vast amount of information available through smartphones, personal assistants, and computers. While the ”healthy operator” scenario sees the worker utilizing wearable devices to track the physiological status and the ”super-strength operator” scenario imagines workers using exoskeletons to provide more ”strength” to the user. Thorvald, Berglund, and Romero [3] conclude that the future human worker must interact effectively with diverse technologies, manage large amounts of information, transfer knowledge seamlessly between virtual and physical environments, and take responsibility for their own and their colleagues' ongoing skill development. According to Mark, Rauch, and Matt [1], the future role of the human operator is that of a knowledge worker, with skill requirements approaching those of engineers. Burggräf, Dannapfel, Adlon, *et al.* [4] further emphasize the importance of adaptability and cognitive abilities for workers in this context. Moreover, the evolution of Industry 4.0 towards Industry 5.0 is expected to further enhance human-machine collaboration. Maddikunta, Pham, B, *et al.* [5] state that Industry 5.0, in its current form, is about the collaboration of the “unique creativity of human experts” and “powerful, smart, and accurate machinery”. They further detail that Industry 5.0 will significantly increase manufacturing efficiency and enable constant monitoring. In addition, repetitive tasks are meant to be done by robots or machines, while the cognitive tasks are assigned to humans. Finally, they claim that the production processes will be automated to a large degree, since real-time data of the machines will be available to capable human experts [5]. Ultimately, the goal is to leverage real-time data to create a complete, seamless digital representation of the production plant, including the workstations and even the worker. To achieve this, the workplace of the future should be adaptive, in order to accommodate for mass personalization as well as the individuality of the worker.

To address these challenges, digital instructions and assistance systems have emerged as a promising solution. Mark, Rauch, and Matt [6] define worker assistance systems as technical tools that support workers without replacing them, enhancing their tasks without posing risks. These systems not only provide real-time guidance but also serve as valuable training tools, as noted by Yigitbas, Sauer, and Engels [7]. The implementation of such systems aims to achieve several key goals, as outlined by König and Winkler [8]:

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- Ensure quality
- Increase productivity
- Improve ergonomics
- Control variance

Despite these visions for the future of manufacturing, many factories continue to rely on traditional paper-based instructions, which presents several challenges. Tsutsumi, Gyulai, Takács, *et al.* [9] highlight the inefficiencies of paper-based methods, which require expertise, lead to time loss, and strain memory. These limitations often result in operators neglecting instructions and relying on their knowledge [10].

We argue that an assistance system designed for Industry 5.0 needs to be able to create high quality work instructions automatically, as it reacts to real-time data created by the overall infrastructure.

Designing an assistance system and consequently rolling it out to the shop floor is a complex project. It needs to be ensured that the assistance system is properly connected to the necessary infrastructure and it needs to be tested on pilot stations to gather feedback from workers via user studies. The results of the user study inform the next iteration and so on. We acknowledge that a human-centric design philosophy is vital, especially for assistance systems that are to be used by human workers, however, we argue that there are some objective measures a high-quality instruction should adhere, too. Moreover, an assistance system that is supposed to create work instructions automatically, needs more specific guidelines than a human curator. "Make it easy to understand", is already a fuzzy request, even for a human, but an automated system needs well-defined, measurable rules. Objective measurements of work instructions that do not rely on user surveys would also speed up the iterative design process as the success can be evaluated by the achieved metrics of the system. Traditionally, systems use an experimental setup to track metrics like "assembly time, mental workload, and error rates"[11]. Gelec and Lindenlaub [12] used eye-tracking to assess the human behavior at an assistance system, which is an approach that is gaining traction. We argue that objective measurements would ensure minimum standards, even as the technologies or media used to provide work instructions may change. Similarly, objective metrics make it easier to compare different systems or even the very same system over different iterations. Finally, objective measures in addition to subjective measures may yield synergistic effects, like recognizing patterns of these different metrics. We acknowledge that large language models may handle the "fuzziness" of such a request, but even so we argue that there is a need to create metrics that can actually reflect how well the instruction fits within the criteria given, to act as a "failsafe" and return the work instruction for adjustment back to the system for refinement if it fails set thresholds of some metrics. In the next section (Section II) we will first cover the related work in order to deduce possible objective metrics of work instructions. Still, there is certainly a need to strike a balance between objective and subjective metrics. Chen, Paas, and Sweller [13] argue that the objectivity of objective measures is already a flawed characteristic to begin with, as the receiver of information is the variable that defines the level of complexity of information, due to the subjective nature of complexity. Therefore, in Section III we will map attributes of work instructions to the different entities of the assistance system, including the user, so that we can grasp which attributes actually benefit from objective metrics. Section IV will include a short summary and recommendations for future research aimed at validating our approach.

II. Related work

A. *Types of assistance systems*

Worker assistance systems can be categorized into three groups, based on the area of assistance they are aiming at. These categories are informational, physical, and cognitive [8]. Sensory assistance systems are able to sense important characteristics of the work and in turn provide directions, based on the sensor input. Physical assistance systems support the worker on a physical level. This might be a direct personal assistance, such as an exoskeleton that helps the worker handle larger weights, or an accompanying robot carrying tools. Finally, there are cognitive assistance system, which primarily act to reduce the cognitive load of the worker by enhancing "the key phases of human information processing systems" [12]. When a worker interfaces with a digital instruction system, the worker may not need to think about the next steps, because the digital instructions are provided. Therefore, the worker can focus more resources on the individual operations.

B. *Cognitive load theory*

Cognitive load theory (CLT), which was proposed in 1988 by Sweller [14], is the underlying scientific idea behind the latter kind of system. The general idea of CLT is building on the substantial difference between long-term memory and working memory. Long-term memory describes the kind of knowledge that has been consolidated, either by means of emotional impact [15] or over time through repetition [16]. Working memory describes the cognitive system that can hold information for a limited amount of time and/ or at a limited capacity. For instance, most people can recall 7 digits, when presented with a long sequence of digits [17]. This capacity can be increased through practice or by using mnemonic techniques, like chunking [18]. Chunking describes the process of summarizing a few smaller items into one larger item. The sequence 1-9-8-1-7-4-7 might be chunked into two items (the year 1981 and Boeing 747) instead of the individual seven items. Planning, problem-solving, and creativity are examples of tasks that are associated with working memory. Transferred to work instructions, novice workers might initially need step-by-step instructions, while over time they learn to chunk common sequences and a single instruction may thus cover more complex operations. CLT itself focuses specifically on the constraints of working memory and distinguishes in the context of learning three different types of cognitive load:

- **Intrinsic load** - inherent to the complexity of the material.

- **Extraneous load** - related to the way the material is presented.
- **Germane load** - inherent to the process of actively “constructing” knowledge.

Based on this distinction, in a teaching context the goal is to minimize extraneous load, while managing the intrinsic load based on the learner’s proficiency and maximize the germane load, as it is associated with the actual learning process. For an assistance system the extraneous load is especially important as the way digital instructions are presented are the key characteristic that can relieve the perceived cognitive load. In the context of an assistance system, the intrinsic load is inherent to the operation that the worker is supposed to do next. Germane load does not really apply to assistance systems, as performance assistance is the goal in opposition to traditional ”learning”. Learning can still occur; however, it is usually considered to be incidental rather than intentional, since the worker is not expected to recall any information later on. Assistance systems do borrow from instructional design as well as user experience (UX) design. As pointed out before, assistance is different from learning, therefore it is important to critically reflect, whether instructional design insights should actually be applied to the assistance system in question.

C. Relevant UX and instructional design principles

Mayer’s principles for multimedia learning [19] are well-cited and grounded in cognitive load theory. The principles are based on three assumptions. People perceive information through two different channels, one for processing auditory information and a second one for visual information. Presenting auditory information via assistance systems is actually somewhat tough, as the shop floor environment is quite noisy to begin with and workers are expected to listen up. Moreover, Mayer assumes people have limited-capacity to process information at any one point in time. Finally, he argues that a learner should be actively engaged with the content to be learned to achieve better results. Examining each of the twelve principles is beyond the scope of this paper, therefore we pick out the more relevant ones for our argument. The ”multimedia principle” is the very first principle on the list and states that learners learn best when provided a combination of words and pictures. This might be somewhat relevant, as this is supposed to benefit the processing of information, a goal we also strive for with assistance systems. The ”segmenting principle” states there are better learning outcomes when students can control the pace. This is not feasible on a shop floor, because the tact times are not based on each new worker. The ”coherence principle”, which states that unnecessary information should be excluded for better learning outcomes, and the ”signaling principle”, which states that vital information should be highlighted in a way to draw attention, are valuable ideas, in particular for assistance systems.

A valuable framework for the UX design of information systems was created by Nielsen and Mack [20]. They came up with 10 usability heuristics, many of which are also relevant to assistance systems, as they are information systems, too. The system status should be visible. There should be a match between the system and the real word, which means that words and pictures that are based in the real world are much more effective than internal ones. This is the inherent logic for a ”pencil” icon, to equip a form of digital pencil. User control and freedom is a less important principle for assistance systems. The idea is that users often perform actions by mistake, hence there should be a sort of emergency exit, similar to the possibility to ”exit without saving”. The notion that there is a need for explicit error messages is relevant for maintenance personnel, but may be less relevant to the worker. On the other hand, the ”consistency and standards” principle directly relates to findings from [21] and [22] which we will discuss further below. The principle ”recognition rather than recall” is linked to CLT as the memory burden of the user should be reduced. The principle ”Aesthetic and minimalist” design states that unnecessary information should be excluded from interfaces. This principle is very similar to Mayer´s ”coherence principle”. These frameworks are cornerstones in their respective fields and share some foundational assumptions. However, as pointed out before, assisting is in some important aspects different from learning or teaching.

D. Designing assistance systems

The distinction between learning and assisting raises the question of how assistance systems should be designed to effectively support workers. Bartolomei, Barravecchia, Mastrogiacomo, *et al.* [23] propose a promising framework for establishing rules for how work instructions in an assistance system could be created based on the assembly features of a task and which media formats are suited best for each assembly feature. Holland and Bronsvoort [24] introduced the “taxonomy of assembly features” in 2000, which serves as the foundation of the framework of Bartolomei, Barravecchia, Mastrogiacomo, *et al.* [23]. On the level of mapping the ideal assistance systems to a specific task and a user group, Mark, Rauch, and Matt [1] introduced a systematic methodology. They devised nine categories of workers (i.e. elder worker, unexperienced worker) and mapped a total of 23 issues, which either need to be addressed or not to each user group. For instance, an elder worker has the issues of hearing and seeing adequately, hence an assistance system needs to account for that. They further looked at all possible forms of assistance systems and gave each assistance system a score for each of the 23 issues based on how well the system is suited to address this issue. This proposed methodology assumes that one can calculate which of the issues need to be addressed at the workstation, also considering the group of workers, and then calculate the best assistance system for the given scenario.

E. Optimizing work instructions

Beyond optimizing assistance systems based on task requirements and worker profiles, it is also essential to consider the quality of the work instructions provided to ensure effectiveness and usability. Low quality work instructions may reduce the efficiency of an operator, despite the growing capabilities expected from one. In order to build high quality work instructions, we first need to focus on avoiding bad work instructions. Haug [21] identified a total of 15 potential quality problems that may affect work instructions. Haug defined work instructions as "instructions delivered in both verbal form (words, communicated orally or in writing) and non-verbal form (pictures, images, models, gestures, etc.)". Palmqvist, Vikingsson, Li, *et al.* [22] drew from Haug's framework and other previous work [25], [26] and synthesized six critical attributes for improving usability in assembly instructions. These attributes are **relevance**, **timeliness**, **correctness**, **accessibility**, **completeness** and **format**. They used the gathered information as the basis for nine statements that guided the evaluation of work instructions:

- display information clearly
- contain relevant content
- does not contain any difficult terms
- easy to understand
- can be interpreted fast
- support the understanding of work tasks
- support daily work
- support standardized work
- show ergonomic guidelines

While they offer valuable insights into how a work instruction should look like, both frameworks fail to provide any specific means to assess and evaluate work instructions on an objective level. In the following section, we want to add to these works, by conceptualizing ways to actually measure these qualities and guidelines objectively.

III. Towards Computational Quality Management of Instructions

The TwinMaP project focuses on improving the quality and adaptability of work instructions in industrial assembly environments. Instead of viewing the instruction system as an isolated entity, our approach recognizes that work instructions exist within a broader operational framework, where multiple stakeholders interact. To improve instructional quality, we define a pipeline that incorporates three key entities:

- **operation reasoner** - The decision-making component responsible for generating a valid work plan as basis for instructional content.
- **instruction planner** - The adaptive optimization unit that refines instructions based on worker-specific needs. It ensures that instructions are tailored to the operator's skill level, cognitive capacity, and task complexity.
- **presentation layer** - The interface for delivering instructions, including both textual guidance and 2D/3D visualizations. It determines how information is structured and presented.

By recognizing these entities, our approach enables a structured mapping of instruction quality issues to their respective areas of responsibility. This ensures that optimization efforts and quality problems target the right aspect of the instruction pipeline, depending on their origin in the system architecture.

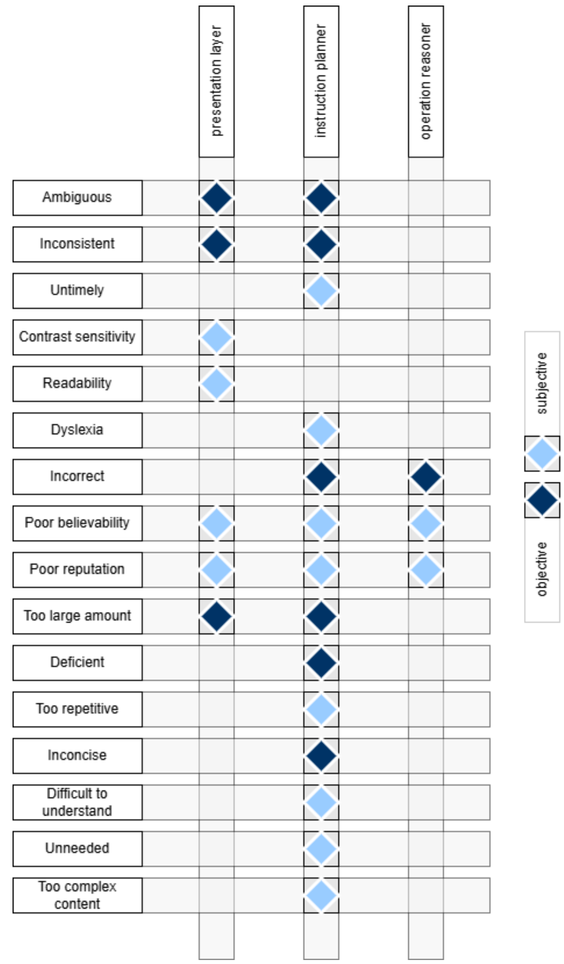

Fig. 1. The figure illustrates the identified instructional challenges (measurable either objectively or subjectively) and maps each to one of the three system components responsible for the instructional challenge

We argue that Haug's framework is a valuable starting point for our considerations in regard to quality problems and respective potential metrics for the assistance system to calculate. Hence, we will go through the relevant quality problems one by one (Fig. 1). It should be noted that we disregard potential technical problems, like 3D models not loading, slow internet speeds and so on. This is more of an general requirement. An **ambiguous** textual instruction arises when an instruction is phrased in a way that leaves room for interpretation. For instance, the instructions "Tighten the screw appropriately" begs the questions on which particular screw to use and what "appropriately" actually means. This kind of wording can create confusion for the operator, leading to misinterpretation, slower task execution, and potential errors. This issue is closely related to **inconsistency**, as ambiguity may also results from a lack of uniform terminology, vocabulary, and phraseology across different instructions. Nielsens Usability Heuristics further emphasize that consistency in language enhances the UX. To identify and quantify inconsistency in the presentation layer, various computational metrics can be employed. Perceptual similarity [27] and Structural Similarity

Indices (SSIM) [28] can be used to detect discrepancies in instructional design by analyzing the visual structure of text-based instructions. On a textual level, cosine similarity embeddings [29] can assess linguistic consistency, ensuring that different instructions for the same action maintain uniform phrasing. To prevent or mitigate ambiguity and inconsistency, several strategies can be implemented:

- Implementing a controlled vocabulary that ensures consistent terminology across all instruction sets.
- Using standardized sentence structures to maintain clarity in procedural steps.
- Providing inline clarifications for potentially ambiguous terms, especially for novice users.
- Restricting free-text input by offering predefined action choices and structured text elements, minimizing the risk of inconsistent phrasing.
- Using a trained model to generate uniform text suggestions from free-text inputs, ensuring that all instructions adhere to a predefined linguistic standard.

The timing of presented information is critical in industrial worker assistance systems. Even when an instruction is technically correct, its effectiveness depends on when and how it is delivered. **Untimely** presentation occurs when instructions are shown either too early, too late or in a way that disrupts the natural workflow of the worker. This issue affects both the textual and the visual components in the presentation layer. Untimely presentation can occur when the 3D model revealing future steps prematurely, irritating the operator with irrelevant information at the time and making it difficult for the worker to focus on the immediate task. This can result in misplaced attention and slower task execution. Therefore, instructions should be synchronized with task progression, ensuring that both textual and 3D visual instructions appear only when relevant. Progressive disclosure should be used in 3D models preventing distractions from future steps. Beyond cognitive overload, other accessibility barriers must be addressed to ensure that instructions are usable for all workers. Factors such as visual impairments (e.g., color blindness, **contrast sensitivity** issues), reading difficulties (**readability**), or **dyslexia** can impact a worker's ability to efficiently process instructions. Implementing contrast-aware design, alternative text formats, and customize font sizes can enhance accessibility for diverse user needs. The system should allow workers to set individual preferences, like visual accessibility options, while persistently storing these settings to automate future adaptation.

Ensuring the correctness of instructions is a fundamental responsibility of the operation reasoner and instruction planner. Errors in instructions — whether caused by manual planning, outdated data, or incorrect interpretation of system-generated plans - can lead to inefficiencies, mistakes, or safety risks. **Incorrect** instructions directly impact trust in the assistance system, affecting both **believability** (worker confidence in the instruction) and **reputation** (long-term reliability perception). To assess trust in the system, usage tracking can provide valuable insights. Monitoring whether and how frequently operators rely on the assistance tool can indicate confidence in its reliability. A decrease in engagement or frequent overrides of suggested instructions may signal trust issues. To enhance trust and reliability, planning systems must:

- Verify data accuracy by cross-referencing existing databases, machine data, and expert knowledge before instructions are issued.
- Introduce validation mechanisms that allow for expert review, historical instruction comparisons, and automatic plausibility checks.
- Provide traceability for instructions, showing sources of information and allowing workers to report discrepancies in real time.

Worker-related instruction issues require an iterative, user-centered approach, as their resolution depends on adapting instructions to the worker's expertise, cognitive capacity, and interaction behavior. Unlike general instruction quality problems, which can be optimized based on established UX and instructional design principles, these issues demand dynamic personalization, ensuring efficiency with low cognitive load.

A key challenge is balancing instruction payload, as **too large amount** of information can overload both experts and novices, while too little information may lead to a **deficient** instruction. The instruction planner, responsible for adaptive individual optimization, e.g. by chunking, should ensure that optimized instructions are not that **repetitive** and **inconcise** like their original versions, focusing on delivering only the necessary information for the task at hand.

Issues such as content that is **difficult to understand** can be objectively assessed using readability metrics like the Kincaid Grade Level [30], though adapted for the industrial context. Similarly, whether an instruction is **unneeded** is often a subjective perception, as what is redundant for an expert may be essential for a novice. These subjective issues are classified accordingly in our system, as depicted in Fig. 1, where instruction-related quality problems are distinguished between objective and subjective aspects.

While subjective issues require worker-specific adaptation, activity monitoring helps identify patterns that indicate potential problems. For instance, tracking "continue" or "skipping time" during instruction execution can reveal whether certain steps are consistently skipped, suggesting that they may be perceived as unnecessary. Likewise, extended interaction time on specific steps may indicate excessive complexity (**too complex content**). Such data-driven insights, combined with direct user feedback, allow the system to iteratively refine and personalize instructions.

IV. Conclusion

In this paper we explained the vision for Industry 5.0 and how assistance systems are vital for integrating the future worker into the factory of the future. More specifically, we looked at existing frameworks on work instruction quality and built on these previous works to map potential quality problems of work instructions to the components of an assistance system that affect these issues. Additionally, in our effort to propose metrics that can actually be used to objectively and automatically assess instructional problems, we categorized the issues into the categories "objective" and "subjective". This categorization helped us identify the specific problems that are a problem of adaptation or a general problem. Finally, we actually proposed ways to prevent and mitigate different instructional problems. It is difficult to come up with ways to assess the subjective measures. These kinds of metrics need yet to be developed. Possible research could look into the validity of expert reviews for assessing these subjective qualities or real-time worker feedback. One may also include an additional performance monitoring layer within the assistance system. The proposed approach to systematically manage the quality of automatically generated work instructions, while built on previous works from different fields (i.e. UX design, linguistics), remains purely theoretical as of now. In a next step, we plan to actually integrate the proposed metrics and insights into an assistance system and study the potential merits of the approach outlined in this paper.

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