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DEEP QUALITY MODELS TO IMPROVE THE LOW CHARACTERISTICS BASED INTELLIGENT SYSTEMS

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ABSTRACT:

We look at the things that make it hard to define the requirements for artificial intelligence systems (AIS) and check them before they are built or updated. Harmonizing definitions and making a hierarchy of AIS characteristics is very important for regulating the development of standardization techniques and tools, as well as for evaluating and providing requirements during the creation and implementation of AIS. In addition to describing the whole construction process, the main results are a meta-model for specifying quality models for AI systems, reference elements about relevant views, entities, quality properties, and measures for AI systems based on existing research, an example instantiation of a quality model for a real-world industrial use case, and lessons learned from applying the construction process. The goal of this paper is to understand, categorize, and evaluate critically the quality models that are already in place for AI systems, software, and parts.

Keywords: Intelligent System, Quality models, Harmonization, Instantiation.

INTRODUCTION:

Intelligent manufacturing is becoming more and more intelligent to industrial societies, especially since the rise of industry 4.0, in which most industrial tasks will be done by robots with intelligence. Since digital change is getting bigger every day. Not only are manufacturing societies used to speed up the development of manufacturing systems, but they are also used to improve the systems' functionality, flexibility, usability, and ability to work with other systems. For each manufacturing function, different methods and approaches are made to keep the level of intelligence

ISSN- 2394-5125 VOL 8, ISSUE 04, 2021

up. This is because the operations done within the scope of the function are different. This is also true for quality operations. Since so many years, people have thought about putting AI into quality systems. Computer vision and artificial intelligence, for example, can be used well to keep an eye on quality in a lot of different situations. As the quality of many things made in factories is determined by how big they are and what they look like on the outside, computer vision technology is mostly used to replace human eyes. This was appealing to the manufacturing community because it was cheap. It has been shown over and over again that automated machine vision systems can use statistical analysis methods and also look at the shape and surface of a quality to figure out how good it is. In the age of Industry 4.0, the success of manufacturing systems will depend a lot on how well they can run operations on their own. This can be made sure by using artificial intelligence in the design of some manufacturing systems. A general system that might have some characteristics of intelligent manufacturing systems. Manufacturing systems face a lot of problems because they have to deal with a wide range of products and services that require very complicated operations. For example, customization is a very important feature that customers want in goods and services. There seem to be a number of unique needs like this one for manufacturing systems to meet the need for change that is already there. Now, it's clear that just giving the manufacturing system the flexibility it needs isn't enough for a proper transformation. The whole supply chain will take part. On the other hand, operations and systems that don't need people to run them make them more competitive and make it harder for people who don't know how to create the required autonomy.

Since artificial intelligence, information technology, and robots with good sensors are the technologies that make up advanced manufacturing systems that can solve these problems, manufacturers should put in a lot of time and effort to learn about and try out these technologies in their work. In other words, the manufacturers may need to use intelligent equipment and lean principles. This means they need to make sure their manufacturing hardware is as productive and effective as possible, cut down on waste (such as scraps, overtime, costs, etc.), shorten cycle times, and increase output. Intelligent equipment should not only be able to use AI and machine learning, but it should also be able to process big data collected from a certain number of sensors in different roles. This is so that equipment, processes, services, and products can be

ISSN- 2394-5125 VOL 8, ISSUE 04, 2021

managed in a proactive way. To make intelligent systems in this way, you need to use advanced information and manufacturing technologies to maintain intelligence, reconfigurability, interoperability, reusability, and flexibility. A survey that lists the different needs of agent-based intelligent manufacturing systems in particular. Note that intelligent manufacturing requires certain types of technologies to make sure that the manufacturing equipment is as intelligent as possible. Internet of Things, Cyber-Physical Systems, Cloud Computing, Big Data Analytics, Learning Events, Creating Immediate Responses to Unexpected Changes, etc. will be needed to keep the required level of smartness. Note that AI-enhanced sensors, decision-making systems that use big data analytics, and advanced materials should all be integrated into the production life cycle and be used to drive it. It looks like the level of intelligence of manufacturing systems will have a lot to do with how competitive they are. In particular, manufacturers will focus on using the data integration capabilities of information systems, intelligent decision making and reasoning (cognitive evaluation) over the available data, showing the results of the cognitive process through dashboards and interactive visual analytics, using smart sensor technologies, and so on. For a manufacturing system, being able to process real-time data from machines and do intelligent analysis on that data by using AI technologies makes it possible to predict and understand critical events and solve problems right away, before they cause any dangerous or wasteful situations. This feature of manufacturing systems lets the machine do predictive maintenance and make manufacturing suits that work well.

The first step in making a recommender is to define the problem that the recommender is meant to solve and test the assumption that a recommender can give useful suggestions to the developer who is having the problem. We use the term "framing the problem" to describe the things that happen during this phase. The definition of a software engineering recommender in the introduction gives us a place to start looking into the problem and solution that a recommendation engine is trying to solve. When thinking about making a recommender, the task and setting in which it will be used must be very clear. One more thing to think about is who the recommender is for: developers or end users. The idea of a "targeted task" by a recommender refers to a developer's specific goal at a certain time, such as implementing a feature that was given to them in the source code.

ISSN- 2394-5125 VOL 8, ISSUE 04, 2021

Even though a developer always knows what the current task is, it might not be written out in the code. The context of a recommender is the information and tool environment in which the task is done, such as the source code and other artifacts that are available and the set of tools that can be used to do the work. The context also shows the steps the developer took to finish the task. This helps define when a recommender can give information and what that information is: Most of the time, beginners have very different information needs than experts. Frequent proposals may be helpful for the first group, but the second group often doesn't like being stopped in the middle of their work to be told things they already know. On the other hand, visual system manipulations seem to be getting harder and harder in manufacturing sites, especially since the introduction of 5G. Being able to try out manufacturing operations in a virtual world and make digital copies of them makes it easier for designers to find out and predict the effects of new business models, new technology implementations, and smart decision making. It's important to remember that technological progress and "disruptive" technologies improve companies a competitive edge and make it possible to build systems that are better than traditional automation systems. On the other hand, intelligent manufacturing operations and the ability to process data in real time make it possible to predict possible failures before they happen and to spot any oddities. This could lead to more preventive maintenance and less downtime and broken machines. In this way, quality management in an integrated manufacturing environment is very important to keep manufacturing competitive.

LITERATURE REVIEW

Perkusich et al. (2020) recently defined AI4SE as a set of SE techniques that "explore data (from digital artifacts or domain experts) for knowledge discovery, reasoning, learning, planning, natural language processing, perception, or helping to make decisions." AI4SE was made because of how quickly software systems and, as a result, SE tasks are getting bigger and more complicated. Wherever software engineers couldn't think of anything else to do, "automatable" methods were looked into. While looking for answers, the SE community noticed that a number of SE tasks can be written as data analysis (learning) tasks and can therefore be helped by ML algorithms, for example. Concerning software engineering, the goal was to look at the

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problems and practices that come up during model creation by looking at how developers could benefit from using or changing the standard workflow to machine learning.

Barenkamp et al., 2020, used a systematic review of previous research and five qualitative interviews with software developers. The results of the study are broken down into different areas of software development. Major AI achievements and future possibilities include: (a) using algorithms to automate time-consuming, routine tasks in software development and testing, such as bug hunting and documentation; (b) doing structured analyses of large datasets to find patterns and new information clusters; and (c) doing systematic evaluations of these datasets in neural networks. AI speeds up development, cuts costs, and makes things work better. Automation in software engineering is better than the AI we have now, which depends on structures made by humans and mostly just copies itself. AI tools can help developers think of new ideas.

The way M.Ulan (2021) put together the data for this study is clear, realistic, and easy to understand. With this method, quality model and metric-based software quality assessment is reliable and can be done over and over again. Probabilities are given for good and bad quality based on all of the software artifacts that can be seen. Validation was based on both theory and evidence. The quality of the information, how easy it is to fix bugs, and how accurate the information is were all looked at. With the help of software visualization, the usefulness of aggregation for multivariate data and the effects of different aggregation methods were evaluated. Lastly, the author looked at how MCR could be used in the real world and used that to rate real-world options. The author used machine learning, made a benchmark using regression problems, and tested how well the overall result matches the truth and represents the input variables. Our method is accurate, sensitive, and makes it easier to make decisions based on more than one factor. Our method can be used as an unsupervised predictor that doesn't need to know the truth.

Koneru et al (2021) Recommendation systems are becoming more and more important to business transactions, sales, and general success. The focus of this survey is on recommendation systems and how they are used. Depending on what an organization needs, a recommender system can have different parts and

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characteristics. This study shows design criteria and the most important parts of a recommender system. There are a few well-known ways of doing things that are looked at. In the end, showed people from the film, music, and online shopping industries how to recommend movies. The goal of the survey is to give people a broad understanding of the situations where certain recommender systems are useful.

RESEARCH METHODOLOGY

This section gives you a framework for making an integrated, intelligent quality system. The main goal of this framework is to set up activities that require a lot of knowledge to make sure quality and continuous improvement. This, in turn, calls for a system for tracking and evaluating performance. The proposed framework is based on meeting business goals, which must be in line with the goals of the processes..

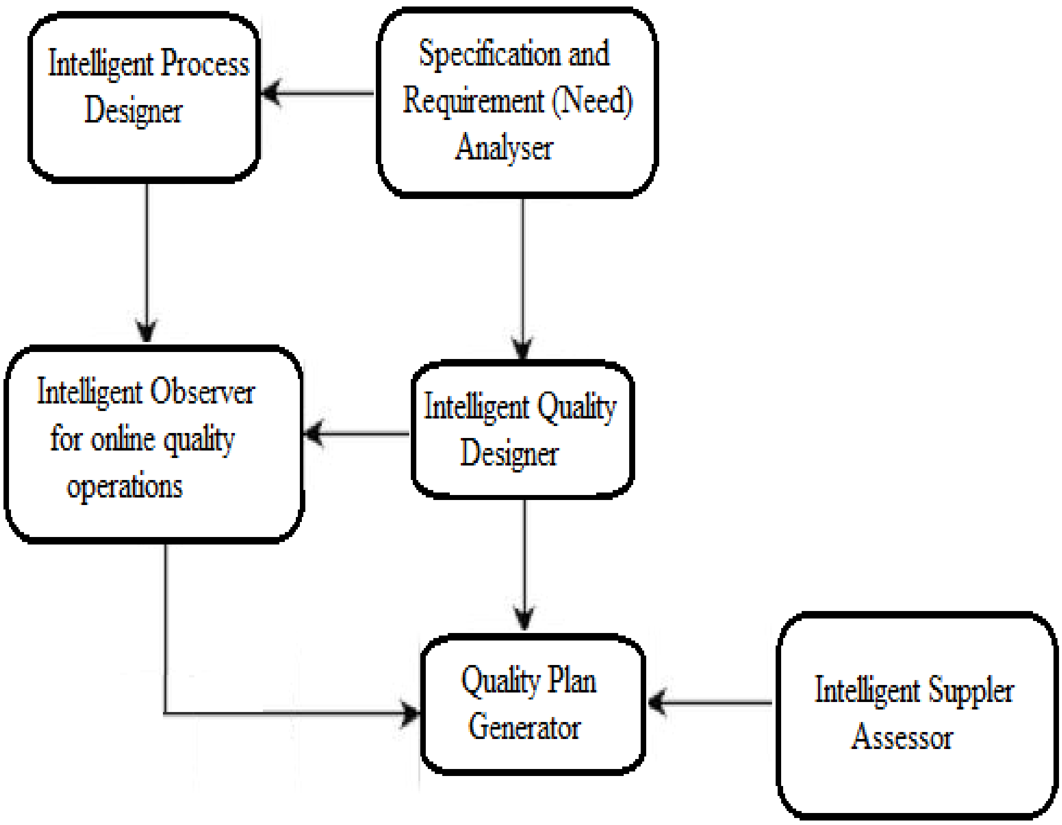

Figure 1. Architecture Framework

ISSN- 2394-5125 VOL 8, ISSUE 04, 2021

Note that intelligent tools can help with quality management in a number of ways, as shown below.

• Any manufacturing system's quality policies and goals could be helped by intelligent tools that help set up the right quality plans and standards.

• Knowledge about quality management could be stored in knowledge bases and used to make decisions about quality. How well the system works will depend on how well the relevant knowledge sets are learned and used.

• Data from different sensors could be collected and analyzed so that the process could be monitored in real time to make sure it meets quality standards.

Design and operational reliability (the ability to do a specific job), availability (the ability to keep working), maintainability (the ability to be fixed quickly and easily), and safety (the ability not to hurt people, the environment, or any assets) analysis (SARM) could be done in a smart way to make sure that products or systems have the right engineering characteristics. SARM has been shown to be good at finding, analyzing, evaluating, preventing, verifying, and fixing system flaws and risks. Intelligent tools could make it easier and faster to do these analyses, which would be good for the business.

The process specification and the product specification are two parts of specification analysis. These things should work well together. Intelligent systems should be able to align and compare a set of predefined requirements (called a "specification match") and intelligently analyze those requirements to come up with a full set of specifications that can be used to design processes correctly so they can run according to a plan. This could be done with the help of fuzzy logic and expert systems. Machine learning systems can also help agents improve process and product specifications and come up with the best designs.

Quality function deployment (QFD) is a good way to use customer needs to shape product specifications. Supporting this function with intelligent tools could make it possible to automatically predict product quality based on what customers want. This data would also be used to make plans for design and production. When customer demand changes, which happens most of the time, the effect on manufacturing can be figured out. Because of this, intelligent QFD can also be used during the

ISSN- 2394-5125 VOL 8, ISSUE 04, 2021

manufacturing process. Intelligent tools like fuzzy logic would help with things like adding new requirements, taking away an existing one, or changing the design attributes.

If you look at the costs of quality, you might learn something useful about how well quality-related operations work. The quality management process could be made better with the help of a cost-benefit analysis. Deterioration and sampling costs, as well as the cost of inspection and control systems for specific products with specific attributes or specifications. Intelligent cost analyzers can gather cost data and come up with real costing and pricing strategies that don't hurt the quality of the products or services but make them more appealing. Analyzer may come up with some suggestions for improving quality.

ANALYSIS & RESULTS

This part shows how the review was analyzed and what the results were. Figure 2 shows how many studies were chosen to look at the quality of AI models based on their level. Most AI quality models were published at the system level and software level (five papers each). At the level of AI parts, there were no papers about quality models.

Figure 3 shows the common characteristics of quality found in a few studies of AI quality models for software and systems. Privacy and security are the most talked about quality characteristics in the studies that were chosen.

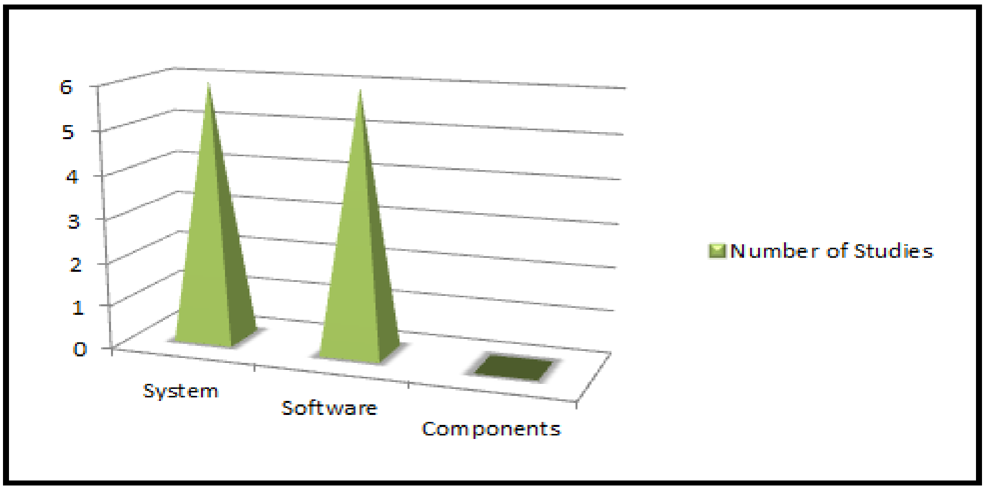

Figure 2. Quality Models by levels

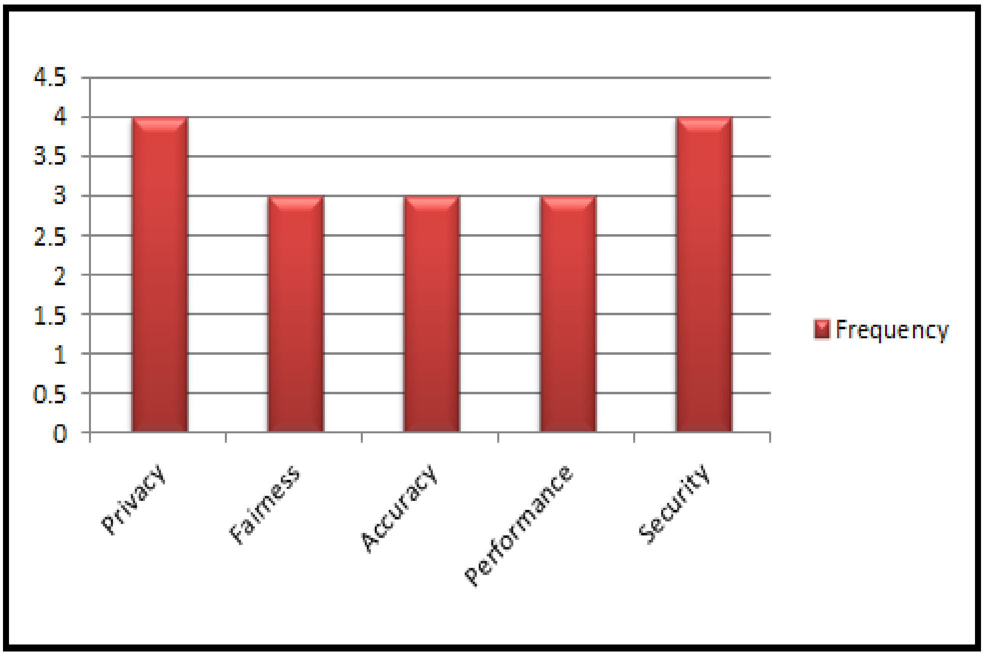

Figure 3. Quality Characteristics Frequency

Based on the SMS done for this study, only a few good AI software models have been suggested. But the empirical evaluation was only done with a small number of experts, and the rest of the studies were not included. Also, research on quality models or standards in AI software doesn't get as much attention as it does in traditional systems. The quality characteristics that the AI software quality models come up with are not enough. They only suggested a few quality characteristics and left out a lot of others. In the research literature, there is still a need for more complete quality models or standards for AI software, along with empirical tests to see if the proposed quality characteristics are acceptable and useful. Also, because each software paradigm is different, each one needs its own software quality model. For example, so far, we've talked about quality models for traditional software, object-oriented software, service-oriented software, and component-based paradigms. The AI and ML software paradigm is different from the AI and ML software component paradigm because the components in the AI and ML software paradigm are not clear.

CONCLUSION

Intelligent quality management is getting a lot of attention in the manufacturing world because it offers many ways to improve the quality of both products and services. Agent-based systems, knowledge-based systems, computer vision, and intelligent

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inspection systems have all been shown to be able to keep the quality of manufacturing systems and their outputs high. With the help of intelligent system generation technologies, real-time monitoring and failure prediction systems, real-time observation through visual inspection, data analysis and visualization of information that drives evidence-based decision making, and integration of manufacturing systems along the entire supply chain and manufacturing life cycle could be done very well. This, in turn, makes it easier for manufacturing systems to keep getting better and better so that the end product is of higher quality. There may be a lot of ways for manufacturers to make fully automated quality systems that can do some things on their own. This makes it more likely that the traditional quality system will change into a smart production system, especially if the digitization process is seen as one of the most important strategic goals.

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