CHALMERS

Evaluating the possible applications of social robots in the manufacturing industry

A guide in what aspects to consider in implementation of cognitive agents

Bachelor thesis in Mechanical engineering

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A review regarding the possible use of social robots in the manufacturing industry

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1 Introduction

The increasing use of automation in organisations and production systems generates a need for further research and development of strategies for complimentary technology as well as models for such applications and implementations to better interact the human with automated systems (Fereidunian, Lucas & Lesani et al 2007). Social robots are primarily used in interaction-heavy fields of application in comparison to industrial robots, and the benefits or possible ramification of a broader use not yet fully investigated (Scheutz 2012). Additionally, while service robots are becoming an increasingly large portion of the robotics market there is a notable lack of frameworks and methods for how to actually use and prioritise technology and its features for human-centred use. Looking to existing and future needs requires a subsequent outline for organisations to use as insight into what aspects of service robots, intelligent automation or virtual agents they could utilise (Belanche Casaló, Flavián & Schepers 2019).

To evaluate the possible implementation of social robots in the technical industry there is need to investigate what concepts would be viable at all and which could have a beneficial effect in a production system or organisation. The foundation for this is previous research in fields relevant to social robots such as levels of automation, game-based learning and Human-Robot Interaction (HRI). The framework for implementation investigates possibilities offered by HRI, concepts of knowledge management and implementation of innovation. Implementing social robotics is a major undertaking in the industry today and has mainly reached other fields such as the educational system, healthcare and customer service. It is therefore important to try and map the most important factors for a theoretical framework in a technical industry using what has been established so far and what can be improved and added to make it a viable alternative to existing solutions in a production environment. By looking at in what way companies are already using this technology and its benefits and need for improvement, we can assess what function and features are important in various aspects of use.

In summary, we try and navigate what features of a social robot can play a role in selected areas of the technical industry and production line. The features of a social robots investigated are based on a Furhat robot, consisting of a conversational AI (Conversational User Interface

– CUI), adaptable facial features and speaker voice as well as a camera for gaze following behaviour. We categorize the manufacturing industry into common roles of a production line and evaluate possible concepts through those. The framework for eventual concepts is made up of research of previous implementations as well as management of innovation.

1.1 Glossary

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1.2 Purpose and research questions

This analysis aims to give a comprehensive overview of the potential use of social robots in technical organisations with a clear emphasis on roles within the manufacturing industry. It aims to evaluate the opportunities to implement social robots in assisting operators with the hopes of laying out groundwork for evaluating benefits of cognitive agents in a production setting, such as improving work environment and enabling faster and more flexible learning. Possible areas of implementation are introduced as well as concepts for the production line, both in today's environment and moving into Industry 4.0.

The questions this study aims to investigate is:

Q1a: What market is there today for social robots and what factors matters most in implementation?
Q1b: Can social robotics be utilised in the integration of operators and Industry 4.0?
Q2: What aspects of a manufacturing organisation are most likely to benefit from implementation of social robotics?
Q3: What potential concepts could be introduced in production - utilising function and features of a social robot?

1.3 Scope and limitations

The considerations are regarding what previously mentioned features are used in what manner, separately or in combination, and for what reason they are applied to that specific context. This includes possibly using game-based learning for cognitive task assistance, as well insights generated by research of already developed Furhat robots and their constructed interfaces. The generated framework will work as a mapping of existing structures, ideas and concepts relevant to the field. An evaluation in terms of an analysis will propose important factors to consider in implementing social robots, and recommendations for how to generate concepts. It will not begin to describe detailed suggestions of how to test the generated concepts, which will be subject to further study by programming a Furhat robot and conducting said tests and experiments. It will mainly work as a theoretical framework of guidelines as to where social robotics can be of use in an industry that have not yet adopted much of this technology.

The social robot that serves as an example of technology in this paper is a Furhat robot, and while other social robots may be mentioned or briefly discussed, they are not subject to the evaluation conducted in the analysis.

Furthermore the analysis is not specified to any one particular company or structure but aims to suggest a framework than can be developed, extended and adapted to suit various needs of organisations. An unexpected limitation of the proposed concept generation was the inability to create proof of concepts using the SII Innovation Labs own Furhat robot, due to the current Covid-19 pandemic of 2020, disrupting accessibility to the robot and other relevant associations. A more theoretical approach was adopted to hopefully enable easier mapping of creating concepts and functionality when again gaining access to the technology.

2 Theoretical framework

The framework constructed is considered background and a foundation for the analysis of possible implementations. It is divided into two parts, a literature review and an overview of the relevant methods for implementation of innovation.

2.1 Literature review

The following review is a contextual overview to illustrate the most interesting aspects of social robotics, their use and potential. This is a very complex subject that includes very multidisciplinary requirements, and so the following review is by no means exhaustive but aims to give sufficient background to better understand actual and possible functionality of social robotics and related fields.

2.1.1 Knowledge management

Knowledge is understanding or having information about a particular thing or study and the value of accessing and applying it have become increasingly important in organisations and their information sharing in a more competitive industry. The structures of such systems where knowledge is to be created, transferred and applied are many and varied and should be treated as complex systems and is most relevant when based upon resources applied to the particular field of interest (Alavi and Leidner, 2001). Knowledge management (KM) is today a popular concept to evaluate and create frameworks for, yet there is not a great deal of research regarding KM in a manufacturing industry (Gunasekeran and Ngai, 2007). It would also be distributed in an organisation over several levels and areas of work, such as networks, processes and information technology available (Gunasekeran and Ngai, 2007). According to Gunasekeran and Ngai, there are at least two important areas that becomes increasingly significant in terms of KM in a manufacturing context, namely network technologies and local databases. This basically constitutes the actual body of knowledge in the organisation and the way it is allocated. Other influencing factors to consider would be human-centred ones, such as culture and any individuals own knowledge and the amount of information not translated from the minds of operators into a system (Lin, 2002). Additionally, there are generally speaking two categories when discussing KM: explicit and tacit knowledge. Explicit knowledge is something that is possible to record and have a coherent way of being communicated through documentation. Tacit knowledge being the more difficult one to map, since its largely dependent upon the person in question and the individuals unique learning through trial and error and constitutes of mental structures developed over time (Lin, 2002).

A recurring format for overviewing the type of content within KM is dividing the material into where or when it is gathered, processed or used. An example of this is a categorization made by Marc Demarest 1997, where there are four platforms to view KM – discerning knowledge, choosing a container, dissemination and the use made of the knowledge (application). It is described as a company’s knowledge economy and being tacit or shared but takes shape throughout the entirety of the organisation – such as anything from materials, to processes and organisational management.

2.1.1.1 Knowledge sharing and knowledge transfer

To be able to further distinguish between what part of knowledge belongs to what process or area, there is also knowledge sharing and knowledge transfer to consider when discussing information resources of an organisation.

The actual exchange of information is of high value, since documentation and application have no significant importance on their own in terms of managing and utilising the knowledge (Cabrera and Cabrera, 2002). Knowledge sharing can also be described as a connector between the knowledge of the individual and that of the organisation as a whole (Hendriks, 1999). Since the potential benefits are very recognised and an increasingly popular strategy to increase competitiveness in a company, many are keen to develop easily adaptable systems to better source the individual's knowledge in an area. One of the issues that have been recognised in attempting this is that a lot of the sought-after knowledge is in the shape of tacit knowledge and therefore considered much harder to access (Riege, 2005).

When handling knowledge in these terms there are more traditional ways of approaching its management such as if the documentation process is performed manually by classical tools like pen and paper or a standard computer interface, as compared to approaches proposed and used in Industry 4.0 that aims to utilise adaptive robots and cyber physical systems (Ustundag and Cevikcan, 2017). The concepts implemented in Industry 4.0 require a much greater infrastructure of communication and connectivity to function in the desired manner. This is due to it being largely based on the Industrial Internet of Thing, cloud computing, embedded systems (cyber physical systems), supporting technologies as well as automation and additive manufacturing (Ustundag and Cevikcan 2017; Lee, Bagheri and Kao 2014).

2.1.1.2 Knowledge management in manufacturing industry

Since KM can include quite different areas and function in very different ways depending on what subject is referred to and where and when it was being looked at (Gunasekeran and Ngai 2007), it is important to further develop methods better adapted to a specific industry's need.

In manufacturing, organisations are choosing to adopt a more KM-focused structure for the processes involved, both regarding internal and external relationships to better manage data and information (Gunasekeran and Ngai 2007). According to Fast-Berglund et al (2018) there are challenges to overcome in the manufacturing industry in terms of the management of deep-set knowledge and experience.

The same would be true for the operators managing the resources of knowledge within an organisation or production line, with the variance in people's way of exchanging knowledge needing to be acknowledged in the way to structure new and improved systems to utilise competence through robots and digital systems (Li, Fast-Berglund and Paulin 20XX).

2.1.2 Industry 4.0

Some of the globally leading nations of manufacturing - Germany, France, US, Japan and China – have each drafted extensive plans for the structure and implementation of intelligent automation helped by their governments (Statista, In-depth: Industry 4.0, 2019).

Industry 4.0 is on its own a vast concept with several interesting and complex sub-divisions. It aims to integrate automation and digital solutions further into production through the use of artificial intelligence and a system of sensors and computers who enables the machines and operators to be connected to the Internet of Things (IoT) (Rauch, Linder and Dallasega 2020). The interconnected system – primarily connected to IoT- go under the common name of Cyber-physical systems (CPS) and constitute much of the intended infrastructure of Industry 4.0 (Rauch, Linder and Dallasega 2020). One theory of the evolution of Industry 4.0 presents two options, a techno-centric system versus an anthropo-centric one. It refers to in which way CPS will work, either with technology dominating and determining structures, while the other would mean that operators will still be mainly in focus with CPS as a support system instead (Fantini, Pinzone and Taisch 2020).

Many components are required when constructing a system like Industry 4.0, and while there are several technologies and key aspects, many agree upon five important categories of technology; Additive Manufacturing, Artificial Intelligence (AI), Robotics, Internet of Things (IoT), and Augmented and Virtual Reality (AR and VR) (Statista, In-depth: Industry 4.0 2019). Where to place factories is also facing a shift, seeing as proximity to the consumer is becoming a priority. Probably the main difference, however, lies in the strategies and infrastructure of the system in terms of digitalising and creating flexibility throughout the production process, primarily using connectivity to build CPS. This translates into reduced costs and new revenue (Statista, In-depth: Industry 4.0 2019).

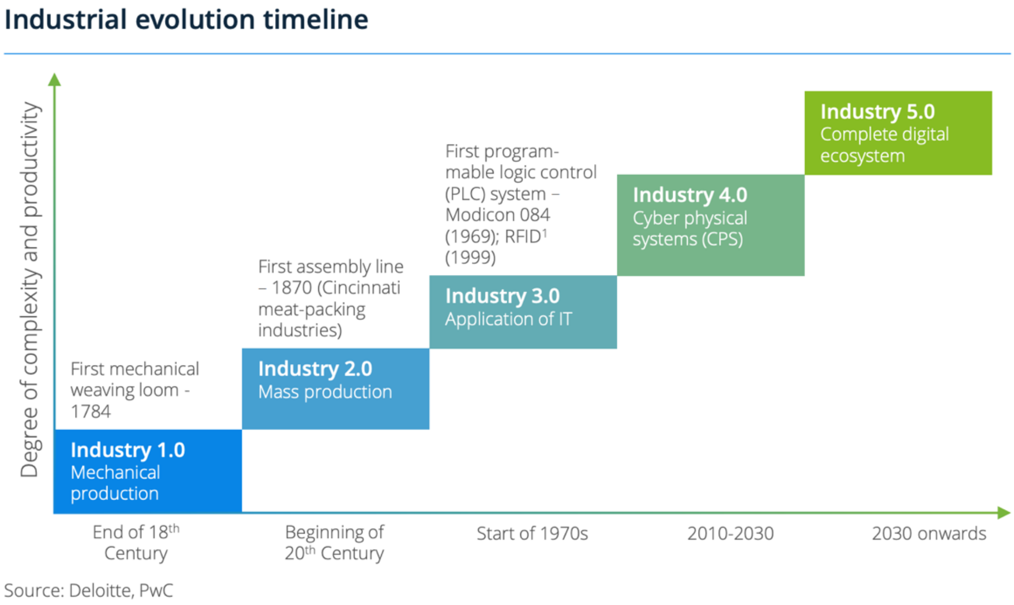


Figure 1 Chart describing the timeline of Industrial evolution to degree of complexity. Source: Deloitte, PwC (2019)

2.1.3 Operators in the technical industry

Simply intending to improve an already functional system can instead result in operators experiencing the system as more difficult due to unfamiliarity (Zhang et al 2017). In discussing improving control rooms of a nuclear power plant, Zhang et al claims that despite intentions to make the interface or integration easier, operators create strong mental models on the way the original system works and can instead be very difficult to adapt to new technology. The implementation could therefore instead become an unproductive hindrance in how they perform their work. For the integration to be successful it should not be introduced without a well-rounded understanding of the system to avoid causing unnecessary issues and errors for the operators.

Within the concept of Industry 4.0 there is the equivalent concept of Operator 4.0, which encompasses the competence to effectively navigate the cyber-physical systems and more complex human-machine environment (Romero et al 2016). One of the challenges in the implementation of Industry 4.0 would be the efficient integration of both new systems and a broader range of worker, with different competence, skill and possibly background both in training and culture which calls for a social perspective as well as a technical one (Romero et al 2016).

Human operators maintain a vital role within production systems, and challenges that come with managing the workforce in an increasingly automated environment are varied. One such significant challenge is to integrate aging operators and apprentices in smart factories and high-tech systems, as well as an increasingly diverse workforce (Ruppert et al 2018).

The differences in how operators will work between todays production systems and the ones of Industry 4.0 are not easily predicted, but there are suggestions in what they can consist of.

2.1.3.1 Cognitive automation strategy for Operator 4.0

Seeing as Operator 4.0 will come to perform many different tasks, the need for a flexible worker is increased. Fast-Berglund, Mattson, Li and Thorvald (2020) created a strategy for this reason, one created to support cognitive assignments in manufacturing for the operator called cognitive automation strategy. The strategy has three steps:

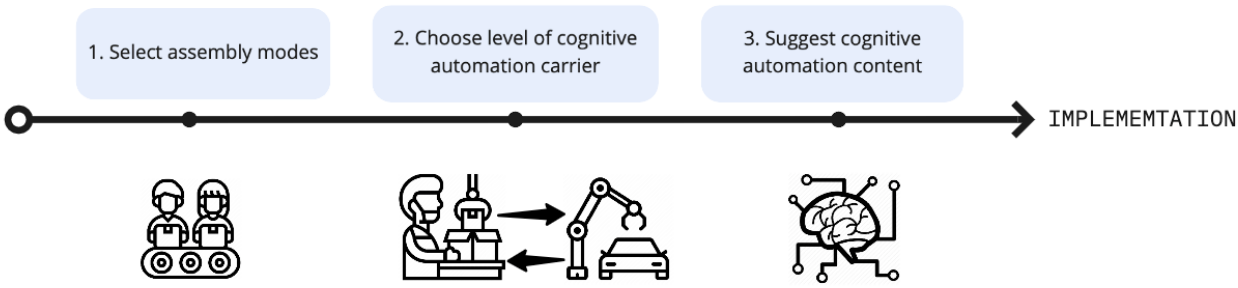


Figure 2 Illustration describing the process of a cognitive automation strategy

It's based upon the interaction of human-machine interface and while many solutions in CPS are driven by technology and innovation, this could help bridge the gap between that technology and its operators and optimise processes. The aim of which is expressed as "suggest and form a strategy that enhance operator cognition by (a) moving between assembly modes, and (b) supporting knowledge levels and cognitive processes." In addition to those definitions, the research question that was asked to shape the strategy was "how cognitive automation solutions can be designed to support Operator 4.0 in complex assembly" (Mattson, Fast-Berglund, Li & Thorvald 2020).

In step one, selecting assembly modes, there are three modes selected to be of particular interest for Operator 4.0, namely *Learning, Operational* and *Disruptive* – referred to as L-O-D (Mattson, Fast-Berglund, Li & Thorvald 2020).

Connected to these assembly modes are divisions of knowledge, such as what type of knowledge is most relevant or active during what mode. The levels of knowledge are then called *skill-based, rule-based* or *knowledge-based behaviour.*

Skill-based behaviour is considered more automated and intuitive – requiring very little active effort after the intention is made up. It is considered unconscious and is similar in nature to tacit knowledge, knowledge and skill such as bicycle riding as well as skills similar in nature to craftmanship (Mattson, Fast-Berglund, Li & Thorvald 2020). Rule-based behaviour is more conscious and requires an active access to information in the shape of stored rules from previous learning experiences. Signs in the surroundings is typically an activator for such behaviour in the way of association (Mattson, Fast-Berglund, Li & Thorvald 2020). Knowledge-based behaviour on the other hand is the decision-making process when faced with a previously unknown situation that requires problem-solving and is often expressed in conceptual terms.

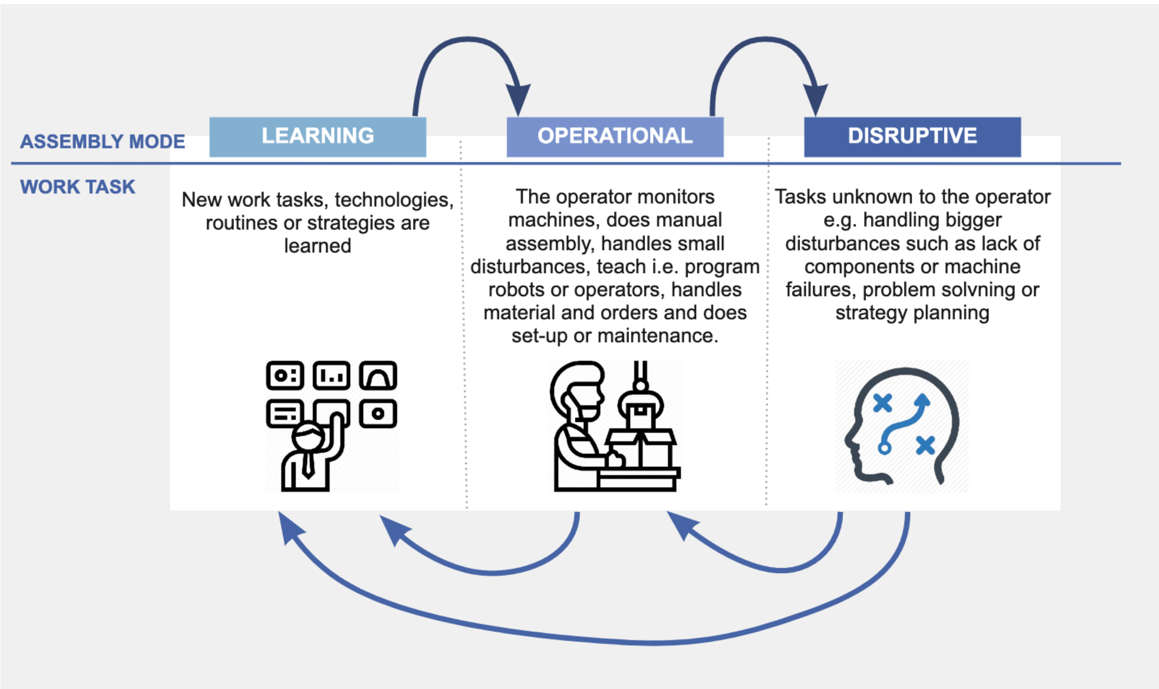


Figure 3 Figure showing the different assembly modes with descriptions of each mode. Movement beteween the modes are represented by arrows. Original figure created by the quoted authors Mattson, Fast-Berglund, Li & Thorvald 2020

These different categories of thinking are relevant when determining what approach is more of use in the various assembly modes, like in what context certain aspects of learning or information is better suited. These connections are illustrated below:

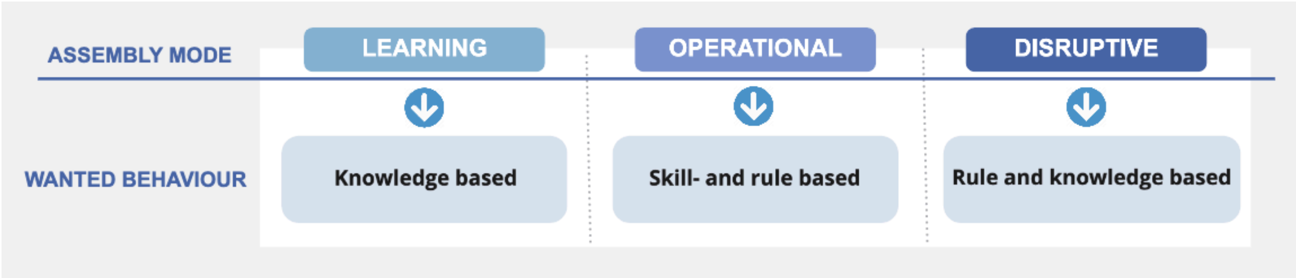


Figure 4: Illustration the assembly modes in respect to wanted behaviour for cognition. Original figure created by the quoted authors Mattson, Fast-Berglund, Li & Thorvald 2020

Cognitive processes are divided up into two different kinds, intuition and reasoning. Intuition is the quick and easy information and subsequent assessment while reasoning while reasoning is rational, more considered and analytic. The fit into the different modes are dependent upon what quality of cognition has the highest value for the described tasks (Mattson, Fast-Berglund, Li & Thorvald 2020).

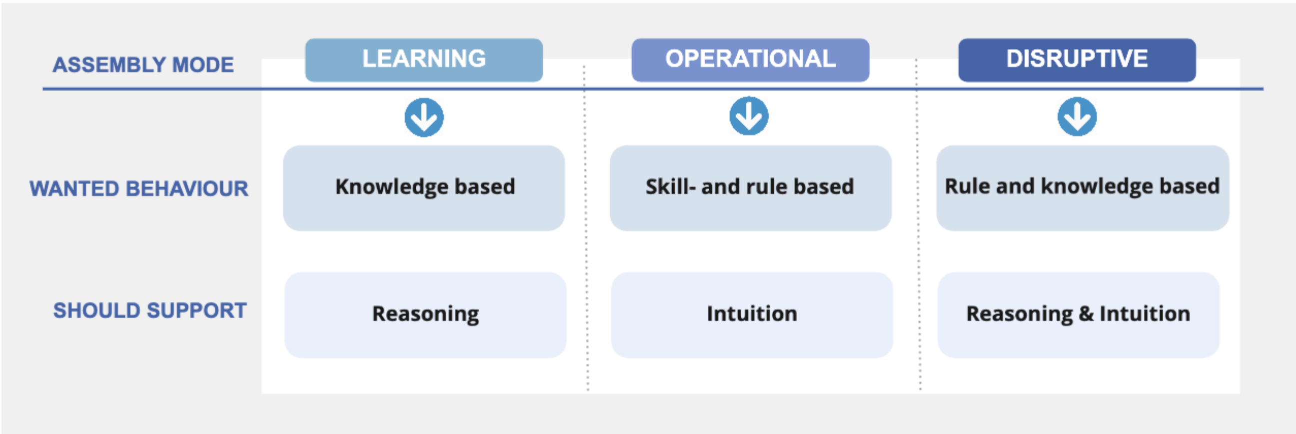


Figure 5: Illustration of what cognitive processes to be suppirted in what category. Original figure created by the quoted authors Mattson, Fast-Berglund, Li & Thorvald 2020

The cognitive automation levels being created are described in the following table:

Table 1
Cognitive automation levels ranging from 1 to 7, description (Frohm et al., 2008) and examples.

Cognitive automation level	Description	Example
1 Totally manual	The user creates his/her own understanding for the situation, and develops his/her course of action based on his/her earlier experience and knowledge	Users earlier experience and knowledge
2. Decision giving	The user gets information on what to do, or proposal on how the task can be achieved	Work order
3. Teaching	The user gets instruction on how the task can be achieved	Checklists, manuals
4. Questioning	The technology questions the execution, if the execution deviate from what the technology consider being suitable	Verification before action
5. Supervision	The technology calls for the users' attention, and direct it to the present task	Alarms
6. Intervene	The technology takes over and corrects the action, if the executions deviate from what the technology consider being suitable	Thermostat
7. Totally automatic	All information and control is handled by the technology. The user is never involved	Autonomous systems

Figure 6 : Table describing automation level. Original figure created by the quoted authors Mattson, Fast-Berglund, Li & Thorvald 2020

Which is then used to determine what level of cognitive automation is more common and of use in what category of task:

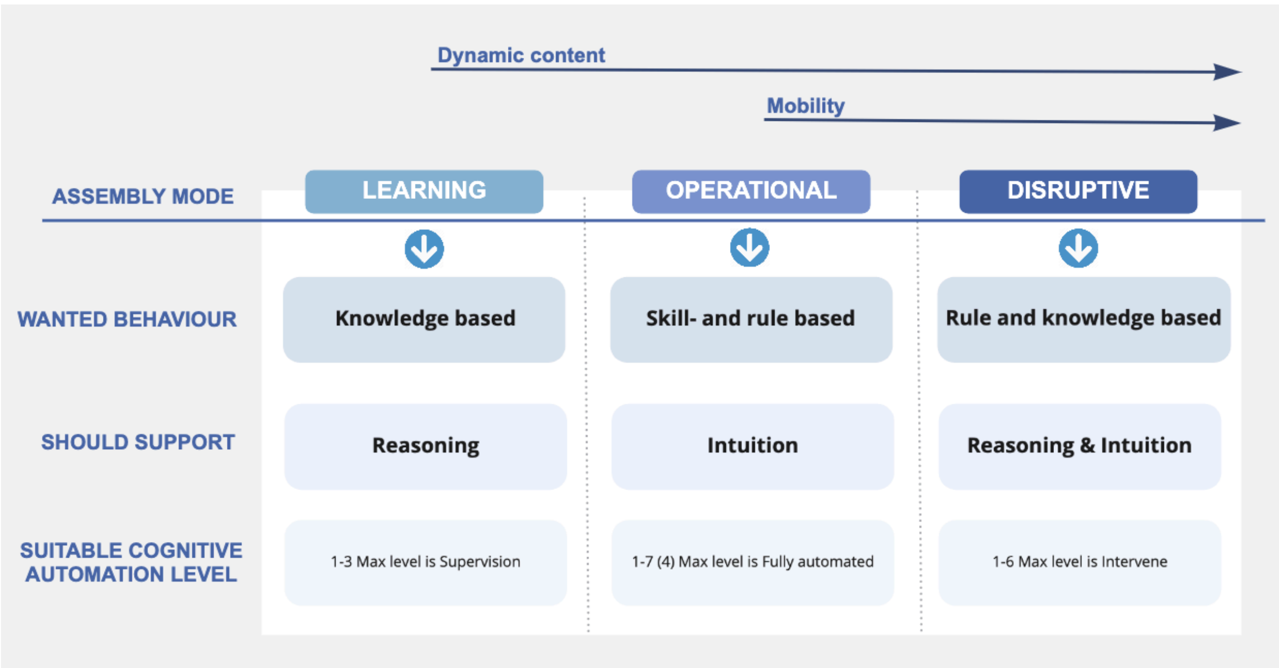


Figure 7: Completed figure describing the cognitive automation strategy. Original figure created by the quoted authors Mattson, Fast-Berglund, Li & Thorvald 2020

This constitutes the framework created to answer the question of "*how can cognitive automation solutions be designed to support Operator 4.0 in complex assembly?*", meant to enable an easier navigation when faced with a larger number of different tasks in a production context. This will also include a multitude of systems according to Industry 4.0, and thus gives operators a better comprehension of what is required for a task to be able to better place support for it (Mattson, Fast-Berglund, Li & Thorvald 2020).

2.1.3.2 Operator emotion assessment

Mattson, Li, Fast-Berglund and Gong (2017) gives insight into how one could measure the emotional response to situations and design of a complex final assembly station. The comfort and well-being of an operator is of great importance moving into Operator 4.0, both from a social perspective and one looking to performance of operation. Mattson et al (2017) used various devices, mostly consisting of different sensors made for specific data, and real-time measurements to discern the weighting of emotion. The data consisted of parameters such as blood volume pulse, heart rate, breathing activity and brain activity (Mattson, Li, Fast-Berglund and Gong 2017).

When achieving something called flow, an operator is considered more content while also performing better, and to maintain such situations where it is possible to achieve a work-flow there are two strategies: (1) adapt the work to encourage work flow, with rules, clear goals, feedback and control and (2) provide training and learning opportunities for operators to perfect skills and set manageable goals (Mattson, Li, Fast-Berglund and Gong 2017). To match the flexibility needed in Industry 4.0 and the increasing level of automation, cognitive automation needs to be taken into consideration to be able to provide an attractive workplace as well as a healthy production (Mattson, Li, Fast-Berglund and Gong 2017).

In addition to the well-being of operators influencing the quality of their work, overall productivity is also shown to be poorer when the workplace grows more dynamic and presents shorter time for learning with an increase of variance in products (Shafer, Nembhard & Uzumeri 2001). This is due to operators being reassigned more often and not becoming skilled enough at each task in assembly, which eventually effects overall productivity. Overall productivity can be translated into lost output, higher cost and poorer competitiveness for the organisation. The experienced workers actually get better at both learning quickly, but at the same time also a higher rate of forgetting due to the high-paced changes (Shafer, Nembhard & Uzumeri 2001).

When looking at what parameters were evident to affect worker learning and worker forgetting, they found that if *variance* among workers was vital for not underestimating its effects, in comparison to measuring only *central tendencies* (Shafer, Nembhard & Uzumeri 2001). This is due to worker heterogeneity, that diversity within personal and human factors makes the workforce harder to impose standardize processes upon with similar results. They could also, however, in their own study show that the heterogeneity and variance in time it took to learn a task resulted in an improved system performance with better output. The correlation between getting a higher score at being proficient at a task came from when a worker spent more time at one specific station, that also means it takes longer between stations for workers in rotation and subsequently makes it easier to forget a previously remembered strategy or method (Shafer, Nembhard & Uzumeri 2001).

2.1.4 Social robots

According to Duffy (2000) a social robot can be described as “A physical entity embodied in a complex, dynamic, and social environment sufficiently empowered to behave in a manner conductive to its own goals and those of its community”. Another definition by Dautenhahn and Billard (1999) reads: “Social robots are embodied agents that are part of a heterogeneous group: a society of robots or humans. They are able to recognize each other and engage in social interactions, they perceive histories (perceive and interpret the world in terms of their own experience), and they explicitly communicate with and learn from each other.” A third viewpoint from Breazeal (2002) is: “a sociable robot is able to communicate and interact with us, understand, and even relate to us, in a personal way. It is a robot that is socially intelligent in a human-like way”.
The main difference in classifying a robot as social is in both its ability to interact with a human in a meaningful way, and for it to be to some degree anthropomorphised – the qualities that makes humans ascribe human-like properties to technology (Duffy 2003). With its expansion and increasing use, the diversity in who can and who will use social robots increases and therefore calls for continued development of its flexibility in user friendliness – making it adaptable to culture, language and social background (Culley and Madhavan 2013). Social robots have the ability to different degrees see to the user’s individual needs both through its own programming and the user’s projection of personality from interaction with an anthropomorphised robot as well as growing increasingly personalised due to the use of AI (Duffy 2003). However, the effect of anthropomorphism and simulated facial features is well established, yet still limited due to no broader system yet engineered to reflect a wide enough library of cues and reactions (Chen et al 2018).

Breazeal (2003) notes that an important difference in how automation of robots change in regard to their intended environment. The most common type normally focuses on improving a task and working separately from a human such as working in a hostile environment or when performing a dangerous task. This would include high-speed automated systems in production. There are robots who perform easy tasks and work near humans or with very little contact, such as automated vacuum-cleaners or automated lawn mowers. The last category of interactive robots intends to fill a gap of assistance and partnership with humans and share the environment in which they work through frequent exchange of actions and/or instruction (Breazeal 2003). When referring to the most efficient ways of communication a social interface would assumedly be the preferred one, due to its potential for flexibility and learning. Cues in social communication most importantly includes facial expression, gestures, gaze direction and voice (Breazeal 2003).

Further definitions of social robots are either based on function or situation or a combination of the two:

Classification of social robot, by author	**Description**
Socially evocative (Breazeal 2003)	Social robots who relies on the way humans anthropomorphise and does not actually play a large part of exchange, but creates reaction by emoting
Social interface (Breazeal 2003)	Social robots that utilises communication cues similar to humans to model social human behaviour, considered shallow models or representation
Socially receptive (Breazeal 2003)	Foremost based on imitation and able to adapt skills to some degree. More interactive than for social interface yet not able to seek out contact on their own
Sociable (Breazeal 2003)	Advanced model of cognition and sociability that performs an active exchange of interaction with humans. Independent motivation and goals.
Socially situated (Fong, Nourbakhsh and Dautenhahn 2003)	Social robots situated in an environment where interaction with its surroundings is made possible. Can distinguish between cognitive agents and inanimate objects
Socially embedded (Fong, Nourbakhsh and Dautenhahn 2003)	Social robots that are situated in a social environment, interact with agents and/or humans, structurally

	connected with the setting and somewhat aware of human interaction models
Socially intelligent (Fong, Nourbakhsh and Dautenhahn 2003)	Social robots that show a clear connection to human interaction and social models, with a thorough understanding of cognitive functions and social competence

2.1.4.1 Social robots and Human-Robot Interaction (HRI)

Human-Robot Interaction, HRI, is a field dedicated to combining psychology, cognitive science, artificial intelligence, computer science, social sciences, robotics, engineering and human-computer interaction (Dautenhahn 2007). While the field of HRI is a well-established one, there is considerable challenges in drawing definite conclusions due to its complex nature (Dautenhahn 2007). Worth noting also is the issue of human-robot interaction needing new sets of knowledge and systems due to it – while having similarities - still being quite different from human-human interaction or that with a computer interface (Dautenhahn 2007). According to Al Moubayed et al (2012) recreating the dynamics of a human face in a social robot creates better possibilities for understanding and communication, but also constitutes a major challenge due to the complexity of such a simulation. Humans gather much information from interaction with a face and different features can give insight to things such as speech and intonation as well as affect and attention (Al Moubayed, Beskow, Skantze & Granström 2012). // There are several documented phenomena regarding the way we perceive a robot, an anthropomorphised one, amongst others two called the Uncanny Valley effect and the Mona Lisa effect. The Uncanny valley (*add definition) // There are suggestions that the Uncanny Valley effect is not only applicable to the physical manifestation of a anthropomorphic robot, but that minute changes in expression could influence how willing the user is to trust the robot in question, and can have a greater effect on perception than previously thought (Mathur and Reichling 2015). The trust in a cognitive agent/robot is of great importance and still subject to much research due to it being a very layered and complex concept (Cullet and Madhavan 2013)

Human social characteristics are not easily described or categorised, but to measure the level of interaction and effective communication there are some aspects to use as guidelines in HRI according to Fong et al (2003), namely:

- Express and/or perceive emotions
- Communicate with high-level dialogue
- Learn/recognize models of other agents
- Establish/Maintain social relationships
- Use natural cues (gaze, gestures, etc.)
- Exhibit distinctive personality and character
- May learn/develop social competencies

The use of social robots is varied with further adaptations to come, developed with the common assumption that humans prefer to interact with machines in as similar a way as with other humans (Fong, Nourbakhsh and Dautenhahn 2003). Scheutz (2012) argues while there have been demonstrations in health benefits of social robots, referring to applications in the health industry, there is also a risk of inflicting emotional distress onto a user.

There is a lack of research in regard of how workers or operators experience the work with robots, and what effect it has on their work environment moving forward (Sauppé and Mutlu 2015). In a study attempting to change that, workers perception of a collaborative robot in a human-robot work cell in different manufacturing plants were measured through ground theory. Operators, management and maintenance were all represented and did show a difference respectively in perception of a collaborative robot at a workstation. The operators mainly thought of the relationship with the robot as humanlike while maintenance and management viewed it more as a tool or equipment. Operators also ascribed the collaborative robot more humanlike characteristics such as personality and intent. More emotional connections were also described by operators (Sauppé and Mutlu 2015).

Another important concept with HRI is that of joint attention. Joint attention is really a human-human interaction that there is hoping to emulate to improve collaboration with human-robot teams (Pereira, Oertel, Fermoselle, Mendelson & Gustafson 2019). Joint attention is a way of creating social cues and with subtle hints using gaze, mimics and expressions to communicate in a faster and more natural way. The underlying function that enables this is called Visual Perspective Taking and is the ability to see the surroundings from a perspective of another, enabling the experience of more accurately perceiving the others attention. A reason to strive for a well-functioning Visual Perspective Taking is the optimising of time when interacting with a robot, say in performing a task. In a study performed by Pereira, Oertel, Fermoselle, Mendelson & Gustafson (2019) this was explored, in way of simulating what they call responsive joint attention. The aspects taken into consideration was gaze direction, speech and actions during a real-time cognitive task – this one consisting of solving puzzles. A system was created for gaze behaviour in connectivity to speech alongside object tracking that allowed for the robot to know where attention was with each move. There was also a function of hints and feedback where the robot could give a verbal hint in combination with looking towards where the placement should be. This was an example of multimodal cues and successful joint attention with the participants (Pereira, Oertel, Fermoselle, Mendelson & Gustafson 2019).

2.1.5 Virtual assistants and their technologies

The concept of using the natural spoken language as a way of communicating with a computer interface has been around for several decades, but not until a few years back has it become developed enough to serve its intended function. The recent decades success in the area is mainly due to the progress in speech technology, dialogue modelling and CPU capacity (McTear 2002).

There are a great many different spoken dialogue systems, depending on what specific technology is being used and how it's applied. Several aspects of how such a system is constructed is relevant for its function and can be divided into: speech recognition, language understanding, dialogue management, communication with external system, response generation and speech output. All of these carry different weight depending on what the system is designed for or intended to do (McTear 2002).

According to Këpuska and Bohouta (2018), interactive conversational systems are the fastest growing area in AI. They list the largest actors within that technological field such as Microsoft's Cortana, Apple's Siri, Amazon Alexa, Google Assistant and Facebook's M. These are commonly referred to as VPA's – Virtual Personal Assistants with the main purpose of providing interaction with its system through conversation as similar as possible to one like human-human.

AI is undoubtably one of the most hyped-up technologies of the last decade and since it mimics human cognition its applications are numerous. According to studies presented in *Educause Horizon Report 2019*, there is still scepticism regarding AIs application within education, but seeing trends where organisations are increasingly positive to implementing it as well as school-age children will at a very high rate enter a job market consisting of types of work that might not exist yet. According to the same report, the personalisation, assistive qualities and analytics of artificial intelligence makes it very relevant within education – especially when it comes to personalisation for students' own needs (Educause Horizon Report 2019).

Thanks to the major developments over the last few years in natural language processing (NLP), many have been using engines with such systems to create virtual assistants, most in the shape of conversational AI in various digital devices in assistance service (Educause Horizon Report 2019). The obvious advantages being hands-free use of network connectivity and assistance as well as convenience for a larger part of a population, allowing older users a more natural interface as well as people with disabilities. Chatbots have also already been used in many assistive scenarios, no least for educational purposes for students or workers in training. The capability of these depend on the frequency of users as well as diversity of user input and is getting increasingly better seeing as more data is collected and made available. One obstacle for making this more globally accessible than today lies in recruiting talent, especially for making the systems equally efficient in multiple languages, others include gender bias and creating potentially harmful gender stereotypes (Educause Horizon Report 2019).

AR/VR add*

2.1.6 Furhat robot

There are a fair few social robots on the market today, but the Furhat robot has gained a widespread recognition due to its demonstration of function within several fields of work (Furhat 2019). The robot itself consists of a computer platform combined with microphones, onboard camera, projector, speakers and the mask that constitutes the robots face. One of its main features is the ability of adapting the robot seemingly endlessly, as the image of the face is back projected and can be customised to a significantly high degree. Not only is the interface itself easily customised but the platform is able to connect to other tools, such as software developed for a specific function or expansion of features. It also supports approximately 40 languages (Furhat 2020).

Applications of the Furhat robot within research:

Human-Robot Interaction (HRI) – the interplay between a human and robot and what parameters play a role in what manner. A very broad field with complex components.

Conversational Agents – Artificial intelligence being used to generate conversations as similar or fluent as possible in imitation of human-human conversational skill.

Cognitive development – various applications within the field of cognition, includes both learning and task management, applications to understanding attention span and improving everyday environment for example elderly or autistic children.

Expressive characters – bringing popular characters in the entertainment industry, such as comic book characters or anime, into the three-dimensional world by adapting the robot to its looks and characteristics for interaction with people.

Human communication/perception – includes ways of investigating in what way psychology, language and other social cues.

Innovation labs – combining new technologies and breaking science to explore further possibilities of social robots

Teaching – using the human-like interface to motivate learning and add assistance to existing teaching tools

The arts – artists aiming to engage people in emotional ways by conversation and interaction

Applications of the Furhat robot within business / Developed concepts:

TNG – The worlds first unbiased interviewer
Duetsche Bahn – Multilingual travel assistant
Merck – Pre-screening medical robot
Bandai Namco – bringing animated characters to life
Stockholms stad – robot teaching assistant
Eilab – robots for psychotherapy training

A Furhat robot has many of its advantages based upon the fact that it is so flexible to use and modify to a specific purpose. In HRI research, there are arguments for the importance of things such as head movements, facial clues of expression and gaze interaction – something that the Furhat robot has cooperated into its user interface (Al Moubayed, Beskow, Skantze & Granström 2012). There are other findings that implies that human-like gestures performed by a robot can increase its likeability and perception of human likeness (Salem, Eyssel, Rohlfing, Kopp & Joublin 2013), which the robot "Pepper" utilises amongst other features (SoftBank robotics 2020), and which the Furhat robot in extension does not have at the time being due to the lack of other parts than the neck and face. However, since the Furhat robot is easily adapted to new systems and tools through its original platform, there are concepts that can be created with additional embodiment such as arms and mobility-solutions through combining different robotic solutions (Åsa Fasth-Berglund et al 2018).

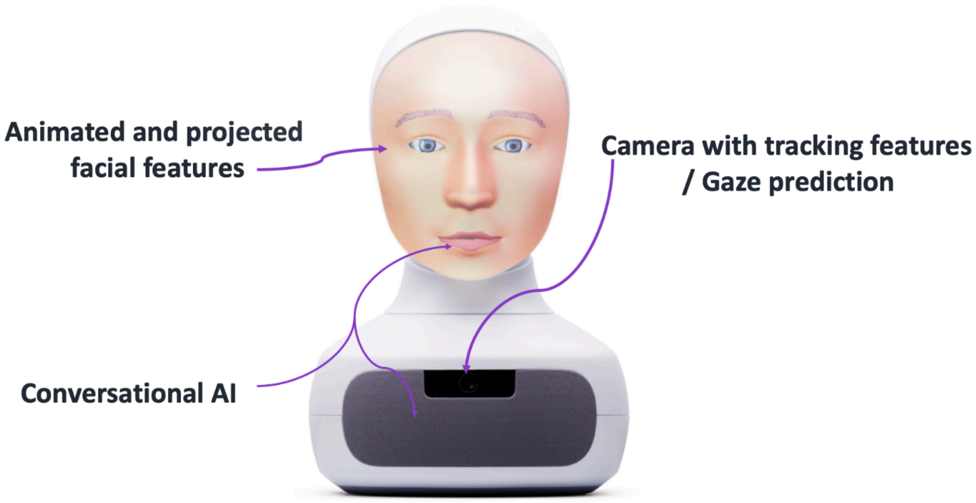


Figure 8: Picture of a Furhat robot with arrows describing the baseline features for function. Source unedited picture: Furhat.com

2.1.7 Game-based learning and gamification

A well-established connection has been made between motivation and playing games. This has in turn been used to further evaluate to what extent and through what parameters game-based-learning can be applied in various fields of research and work (Richter, Raban & Rafaeli 2015). The concept of "gamification" was presented by the industry following this connection, a collective expression for describing the use of elements of gaming in traditionally non-gaming systems to increase user engagement and motivation (Richter, Raban & Rafaeli 2015).

One application of great interest would be that of knowledge sharing, and the increase of such through the use of gamification (Richter, Raban & Rafaeli 2015; Deterding, Khaled et al. 2011).

Fraser, Papaioannou and Lemon (2018) introduced a new form of communication system in a role-playing game between the user and a Non-playable character (NPC) due to the previous way felt unnatural and could break immersion for the user. It came together through trials in the 2017 Amazon Alexa Challenge (Alexa Prize, Amazon 2017) where they wanted to increase the emotional engagement for the user by adding an "emotion model" with the help of IBM Watson's Tone Analyser to create an emotion score for the NPC and measure the users engagement using a Likert scale of user enjoyment. Using the emotional model for the NPC made the users score the interaction higher and spend more time engaging in conversation with the NPC (Fraser, Papaioannou and Lemon 2018).

The nature of user engagement lies in the response-function of an interface, which is only different kinds of feedback. In this case, we refer to feedback in a social context, such as reaction and conversation. It is well-established that when sufficient feedback is offered, the object learns more easily and quickly (Hounsell 2003).

A Pepper robot was used to implement a gamified approach to motivate patients for rehabilitation purposes after suffering a stroke. The system is referred to as a gamified robotic system. The research they used and they themselves stresses very clearly for such a system to be sufficiently personalized, both the design of the HRI and the task itself (Polak, Bistritsky, Gozland and Levy-Tzdek 2019). Again, the feedback was considered of great importance by the participants, seeing it as a reward for taking part of the task and a clear frame of reference on the status of their performance (Polak, Bistritsky, Gozland and Levy-Tzdek 2019).

There are several categories of motivation as well, such as intrinsic, social and extrinsic. Extrinsic rewards are common to associate with gamification, that includes badges, bars, levels and points. Intrinsic is more akin to self-fulfilment, the sense of accomplishment and belonging. The social aspect is the one related to group-dynamics and peer influence, wanting to take part and comparing involvement to others (Richter, Raban & Rafaeli 2015). There are also parts of Goal setting theory that can have a great impact on task performance in terms of motivation and engagement. Self-efficiency is the perceived ability to perform a certain task and can have a major influence in how a person chooses to act or involve oneself in activities aka motivation (Richter, Raban & Rafaeli 2015). High self-efficiency typically translates into accepting more challenging tasks, a higher degree of perseverance and quicker recovery if making a mistake.

There is also something to be mentioned of educational games and come in many varieties and forums and has recently become more relevant in from a knowledge sharing perspective. Based upon the premise of that learning is more efficient when performing an activity and using existing structures, a study found that master students that performed a game meant to highlight benefits and challenges of knowledge transfer did experience a quicker learning curve compared to only theorising on the subject (Stenholm, Bergsjö and Catic 2019).

2.2 Application of innovation

There are many schools of managing innovation, and it changes with a global climate and trends in society. However, there are a few methods that allow for insight into how innovation is introduced into industry and to explain the challenges and mentality surrounding such products, two of them outlined here.

2.2.1 Gartners hype cycle

A frequent method to review the real value and potential of a product is the visualisation called Gartner hype cycle. It is a tool to see where in development a product is, how it might evolve over time and describes different phases from innovation to deployment (Gartner 2020). The standard curve used looks like this:

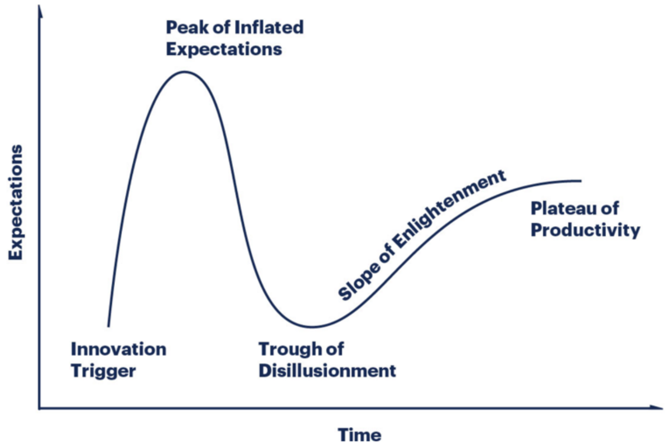


Figure 9: Typical Gartners hype cycle. Source: Gartner.com

The y-axis represents Expectations while the x-axis represents Time. *Innovation trigger* is what sparks the technological revolution in what the product intends to do while the product is still in testing and development. *Peak of inflated Expectations* is when the scales balance out, and the initial hype of over-promise has been met with poor results or failures. A lot is decided in this is phase whether or not to continue on with pushing the product. *Trough of Disillusionment* that follows is the lack of faith in the product after setbacks and failed attempts in either achievement of technology or market implementation. Only if the product can prove to early adopters that the product reaches the set goals will investments resume. *Slope of Enlightenment* on the other hand, is where understanding about the true potential and benefits become clearer and more realisable. Often accompanied by more companies wanting to approach the market of the product with second- or third-generation products but the industry is still not convinced of the long-term viability. Finally, at the *Plateau of Productivity*, is where mainstream adoption happens, and the product is commercially viable (Gartner 2018).

Since many products, strategies and innovations can be described in this manner it is a well-documented pattern. However, since the applications are so broad, there are additional categories to divide innovations into to be able to better compare markets and products. The categories of time are as follows: “Less than two years”, “two to five years”, “five to ten years”, “more than ten years” and “obsolete before plateau” (Gartner 2018).

Why it is used: The Gartner hype cycle is by no means a sure prediction of the lifecycle of innovation, but may lead to great insights and bring a lot of opportunities by being able to compare and estimate with similar products or chain of events. They also highlight what they call traps regarding this model and divides them up into four categories: adopting too early, giving up too soon, adopting too late or hanging on too long (Gartner 2018).

2.2.2 Diffusion of Innovation

A technique used for product diffusion is Diffusion of Innovation. It describes the progression for when a product is introduced and adapted into a market and is measured in what time is required and over categories of what is called adopters (Crawford 2014 p 290). The categories for these are commonly referred to as innovators, early adopters, early and late majority and laggards (Crawford 2014). The system of Diffusion of innovation can further be divided up into four key elements, namely innovation, communication channels, time and the social system (Mahajan, Muller and Bass 1990). The modelling of such is dependent upon the products ability to be embraced by the early categories, since they can then significantly influence to what extent the later categories will adopt the product or technology. A common way of assessing the early categories willingness to adopt a product is to look at similar products and their diffusion curve, something that can be difficult with very cutting-edge technology or innovative products but a guideline in assessing market strength nonetheless (Crawford 2014).

In terms of durable goods, such that don't expire or are consumed rapidly, there is a model known as the Bass model that calculates probability for different categories for sales of a product at a later point in time (Crawford 2014). The estimation is explained by:

$$\boxed{s(t) = pm + [q - p]Y(t) - \left(\frac{q}{m}\right)[Y(t)]^2}$$

p is initial trial probability
q is a diffusion rate parameter
m is the total number of potential buyers
Y(t) is the total number of purchases by time *t*

The Bass model is of value for, amongst other things, forecasting market behaviour in adopting technology (Crawford 2014). Through this type of forecast, the potential for long-term sales, time of peak sales and magnitude of said peak. The forecasts predictive qualities have been adapted and applied to various fields and types of products. One such application was forecasting the advancement of Facebook, which would traditionally not be considered as goods, but followed the same patterns of innovators and their influence on the following categories of adopters (Crawford 2014).

3 Methodology

This is a broad-spectrum analysis of a fairly new field and the approach for investigating possible implementation is therefore also broad range with only selected sections explored in more depth. Those are selected based upon previous research and active social robots today. It is intended to be able to be understood by someone familiar with manufacturing processes and automation but with no particular expertise.

3.1 Literature review

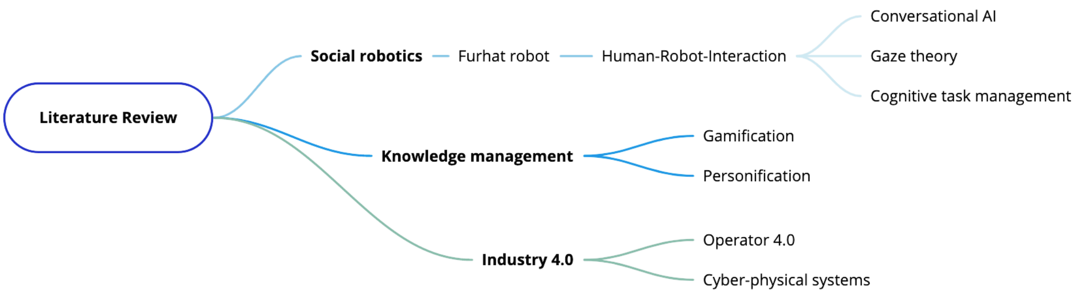


Figure 10: Mind map describing researched topics

The literary review of this analysis is the backbone for the research questions and plays a very important role thanks to the amount of areas of research social robots touch upon. Some of the most important topics relevant to implementing social robotics can be found in the studies previously conducted and proposed even if they don't specifically focus on implementation or manufacturing, seeing as the field of HRI has many various applications. An overview in the shape of a mind map in the beginning of each chapter to illustrate what aspects are covered. The areas on where to focus research and evaluation in using a social robot (Furhat robot) was given through the previous work of the SII Innovation lab that has possession of a Furhat robot and where studies on embodied automation, tacit knowledge and HRI have been conducted and frequently researched. Therefore, the material that constitutes the review can

be found to have been discovered in the following ways:
- Recommended research from SII Innovation Lab and their own previously conducted research, primarily regarding Operator 4.0 and embodied automation
- Search through academic databases using keywords and specific additions for narrowing down results. Keywords and other parameters used are specified below.

Keywords: *Social robot, Human-Robot Interaction, Industry 4.0, Operator 4.0, Embodied automation, Knowledge management, Game-based learning, Cognitive agents, Collaborative robot, Virtual agents, Furhat robot*
Add-ons: *Learning, manufacturing, assembly, psychology*

Articles and studies dated older from before 1990 have been excluded due to a rapidly changing field regarding robotics and automation as well as gamification, yet no time limit was implemented in topics such as knowledge management or psychology since those tend to be more consistent over time by a slower rate of change.

3.2 Implementing innovation

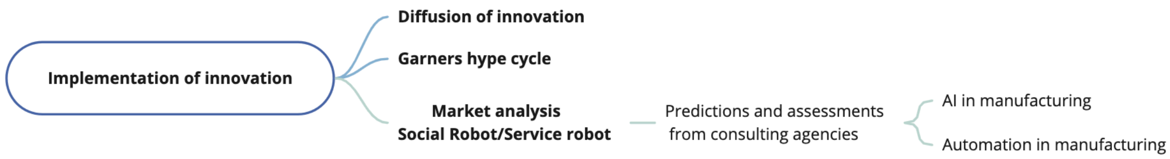


Figure 11: Mind map illustrating researched topics

Innovation is a curious thing to market since it carries more unknowns with it than previously tried products or their improvements. Since it’s a very dynamic field, there are few methods proven to be fairly accurate in either predicting the market or looking at historically significant cases, but some have great value in describing how innovation is connected to psychology and actions of market leaders. Two of these being used here is *Diffusion of Innovation* and *Gartners hype cycle.* They are both described and accounted for in chapter 2.

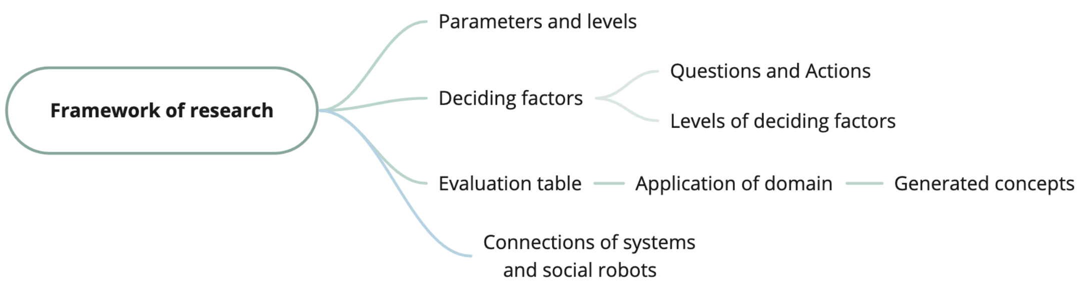
3.3 Market analysis

Social robots are a fairly small part of the robotics market as of yet and the distinctions between subcategories of service robots and consumer robots is not always easily made. However, in this analysis, the main focus has been social robots to adhere to the limitations specified for the intended scope. Since the social robot we base the interface on is a Furhat robot, its features will also be explored as separate functions such as conversational AI, expressions of humanoid robots and gaze theory to explore the very similar markets to a more complex robot in search of ways of application.

The market analysis of social robots and their distinguishing features is divided up into two sections. The first one is a background-section covering the most reported challenges of the field as well as prominent actors on the current market. The second one is one investigating the current implementations in the field of social robots according to research, financial reports and material provided by manufacturers of social robots – perhaps most importantly Furhat robotics.

Statista statistics database have been frequently consulted for reports in usage, finance and perception regarding social robots and virtual assistants. Other companies are listed when resources they've provided are being used.

3.4 Framework of research



The material presented intends to serve as the foundation for possible concepts and conclusions moving forward is presented through both a literary review and a collection of innovations projects, in theory and current statistics. Together, it aims to give insight into what has been done in this field and in relation to this field at this point in time, as well as what can be interpreted as contributory knowledge and future research.

To generate concepts of implementation the main aspects will be (i) Nature of function (ii) Features utilised for function (iii) Additions: cross-sectional technologies/connection to CPS. To help with this, the concept presented by Mattson et al (2020) concerning cognitive automation strategy in complex assembly will be used to better place where social robot can be of assistance in a cognitive process in assembly. The L-O-D model helps explain both what features and what functions could be relevant in performing tasks and supporting an operator and is therefore very relevant in evaluating implementation. Assembly is not a standardised process in any one company but has enough similar elements to propose similar ways of integration. The features being evaluated in each context as features of a social robot is based upon the main aspects of the Furhat robot namely; Conversational AI, Gaze tracking and Personalisation (Individualisation/Level of anthropomorphism). The feature of being able to build an application around the social robot and its purpose will be described as add-ons and extensions. Possible concept regarding other aspects of the manufacturing organisation will be based upon other market uses in other industries today, together with research investigating HRI and CPS. The weighting of features is based upon how important that specific feature is for the function of that specific application. *The assumption being made is that the social robot can function at a high enough level so that each feature is well-enough developed for the desired function (works the way its intended) - and that* ***suitability*** *for implementation is the varying factor.* It is therefore interpreted as a scale of *feature relevant to application* where a low score says the function is not very dependent upon that particular feature. The higher score of the mean value of the feature score, the more suited a social robot (Furhat robot) would be for that application.

The framework of research consists of X figures and the associated analysis. It is derived from the literary review and the market analysis and serves as a guideline in what aspects are most relevant to consider when wanting to implement social robotics in an organisation. It also gives suggestions for how this can be structured and evaluated and should be treated as the theoretical evaluation is describes. It is important to note that the validity of the methodology of the framework of research would be much higher if the weighting of features in the evaluation is performed by experts in the field.

4 Market analysis

A recurring and increasingly important issue with automation of the industry lies in the loss of jobs for workers (Rauch, Linder and Dallasega 2020). Up to over 40% of jobs in manufacturing and construction is at risk of being replaced by automated alternatives and calls for better utilisation of existing skills within a workforce (Statista 2028, PwC).

Another challenge for manufacturers to overcome is that the production market needs to adapt to increasingly more varied demands of buyers and consumer, creating a greater need for flexibility of the production (McKinsey & Company Discussion Paper 2017).

The field of social robots is, as is already stated, a fairly new one since the technology required for a well-enough functioning interaction did not exist until only the last couple of decades. Technology that drives social robots forward into industries are typically AI, sensors and continuous improvement in batteries. The robots are expected to be present in many different domains and interact with humans in ways of assistance and conversation (KPMG, Social Robots 2016).

Categories of robots are not completely agreed upon, but for this purpose we use KPMGs definitions: Industrial and Service robots. Industrial are the ones responsible for the larger part of automation primarily in factories and production such as car manufacturing etc. Service robots have two subdivisions of professional and personal depending on which application they are created for and features given priority. Service robots are also the most common ones seeing as all automated vacuum-cleaners and lawnmowers classifies as such – which makes up for a large part of the total amount of robots (KPMG, Social Robots 2016) – as well as it being in general more diverse than the industrial robots. According to International Federation of Robotics (IFR): Statistical Department Executive Summary World Robotics 2019, more than 750 companies were at the time in the industry of producing such robots (which here includes social robots) and conducting related research. Loup Ventures: International Federation of Robotics expects a significant increase in the market of social and entertainments robot according to a prediction reaching into 2025, when they expect the market to be worth an estimate of over two billion US dollars. Their numbers are shown in the figure below:

SOCIAL AND ENTERTAINMENT ROBOTICS OUTLOOK

	2015	2016	2017E	2018E	2019E	2020E	2021E	2022E	2023E	2024E	2025E	2015 -2025 CAGR
Social & Entertainment Robots												
Units Sold (M)	1.70	2.13	2.60	3.12	3.67	4.22	4.85	5.58	6.14	6.75	7.43	**15.9%**
ASPs	$588	$518	$466	$429	$399	$372	$348	$326	$306	$289	$273	**-7.4%**
Market Value (B)	$1.00	$1.10	$1.21	$1.34	$1.46	$1.57	$1.69	$1.82	$1.88	$1.95	$2.03	**7.3%**
Total Units Sold (M)	**1.7**	**2.1**	**2.6**	**3.1**	**3.7**	**4.2**	**4.9**	**5.6**	**6.1**	**6.8**	**7.4**	**15.9%**
Y/Y	*29.0%*	*25.0%*	*22.5%*	*20.0%*	*17.5%*	*15.0%*	*15.0%*	*15.0%*	*10.0%*	*10.0%*	*10.0%*	
Total Mkt Value (B)	**$1.0**	**$1.1**	**$1.2**	**$1.3**	**$1.5**	**$1.6**	**$1.7**	**$1.8**	**$1.9**	**$1.9**	**$2.0**	**7.3%**
Y/Y	*5.3%*	*10.0%*	*10.3%*	*10.4%*	*9.3%*	*7.2%*	*7.5%*	*7.8%*	*3.4%*	*3.7%*	*4.0%*	

Source: Loup Ventures, International Federation of Robotics

Figure 12: Social and entertainment robotics outlook. Soruce: Loup Ventures, IFR, Statista (2017)

Since much of the progress of social robots are driven by the further development of AI, the breakthroughs being made there creates new opportunities faster than before - something IFR considers to boost the market over the next few years. However, as more applications appear and developers come to market, the cost of producing will become lower and subsequently lower the cost of robots and increase competition, which affects the monetary value estimation of the industry. Not only is a large increase expected in both market value, areas of application and units sold, they also believe there will be a considerable difference in that social robots will constitute a much larger part of sold service robots than before (compared to domestic robots/professional robot domain), due to the increased use of social applications new technology enables. The categories themselves will need to be redefined also, seeing as more social robots may well be applied in the household as well in similar function as virtual agents, made possible by the increased quality and accessibility of sensors and cloud-based technology (Loup Ventures: International Federation of Robotics 2017).

4.1 AI and Automation in Manufacturing

Having truly escalated in capabilities over the last decade, AI is a vital piece of intelligent automation. A study conducted by MIT in 2016 told of up to 85% higher productivity with teams of both humans and robots as opposed to teams of one or the other (Statista, In-depth: Industry 4.0 2019).

According to McKinsey & Company Discussion Paper 2017, the magnitude of change within the manufacturing industry due to AI and automation will force many actors on the market to possibly redesign entire supply-chains and plant designs. The benefits of real time optimisation are many and can be easily imagined in systems that are very dependent on each component, operator and process to work as well as possible. They list some of these benefits in the following manner: shorter development cycles, greater engineering efficiency, prevent faults and unnecessary repairs, increase safety by automation, reduce inventory costs and optimise prices.

Communication is also mentioned as something that directly affects revenue and output. Seeing as most communication and documentation are manual today, it can create discrepancies between the levels of an organisation and not be subject to good enough review when reporting and results or structures of tasks and processes. One way to minimise loss due to poor communication is to introduce advanced analytics, for prediction purposes and identifying pileups. Today this is done using historic data, either collected by the company or from several, to implement deep learning networks for said purposes. What would make a great difference, however, is the ability to base those on real time data, which is one of the key points of a Smart Factory (Industry 4.0). It is also mentioned that there could be great use of virtual agents in this scenario to, being connected to the IoT and a real time data stream they could notify the correct outlets on relevant analytics, material, inventories, energy consumption and bottlenecks (McKinsey & Company Discussion Paper 2017).

Inefficiencies are all common trademark of a production that has not been optimised or continuously kept up to date and can amount to billions of dollars (US dollars) yearly. Again, analytics and deep learning can have a major impact on registering relevant data before any problem arises, avoiding unnecessary stops and failures in an assembly line. This is meant to be in combination with collaborative robots and AGV's. Virtual agents would be used to flatten the learning curve, reduce errors in assembly and cognitive tasks as well as instruct and interact through various means throughout the factory (McKinsey & Company Discussion Paper 2017).

In discussing the implementation of AI and CPS, it is also clearly stated that manufacturers would need to invest heavily in operators training, competence development and knowledge management. Not only is this relevant with all new technologies, but especially so within most manufacturers, seeing as the workforce will only get increasingly diverse, as well as most of the workers (96%) are over 30 years old and might not have been exposed to very new technologies in operation (McKinsey & Company Discussion Paper 2017).

Deloitte insights: Automation with Intelligence (2019) also claims automation is the great and important change in the industry, and that robots are to be welcomed, not feared. They conducted extensive interviews with over 500 company leaders spread over 26 countries regarding automation strategy and implementation, as well as the operators in the organisation. The organisations involved were of various fields of work.

While many of the participating companies said they were expecting to see a much larger return due to increased work capacity – up to 27%- there did not seem to be a very large number of those who'd actually proposed any plans for the integration between machine, robots and operators in a new, automated system. Only about one third claimed to have investigated the matter (Deloitte: Automation with Intelligence 2019).

The investigation by Deloitte also showed certain qualifiers for success when choosing to implement automated technologies. They divided them up into six important factors:

1. A total implementation within all levels of an organisation, both as a strategy and functional operations.
2. Combines Robot Process Automation (RPA) and Artificial Intelligence (AI) into what Deloitte calls Intelligent Automation – which is the same as general interconnectivity between digital resources and automation technology in a Cyber-physical system.
3. All technology and its subsequent required infrastructure are all in place when adopting an automated approach in the organisation. This also includes clear guidelines for conduct as well as cybersecurity.
4. Well-developed definitions of processes and procedures.
5. Value-orientated productivity with a deep organisational understanding about how to create value.
6. A clear simplification of all systems, in efforts to lower costs.

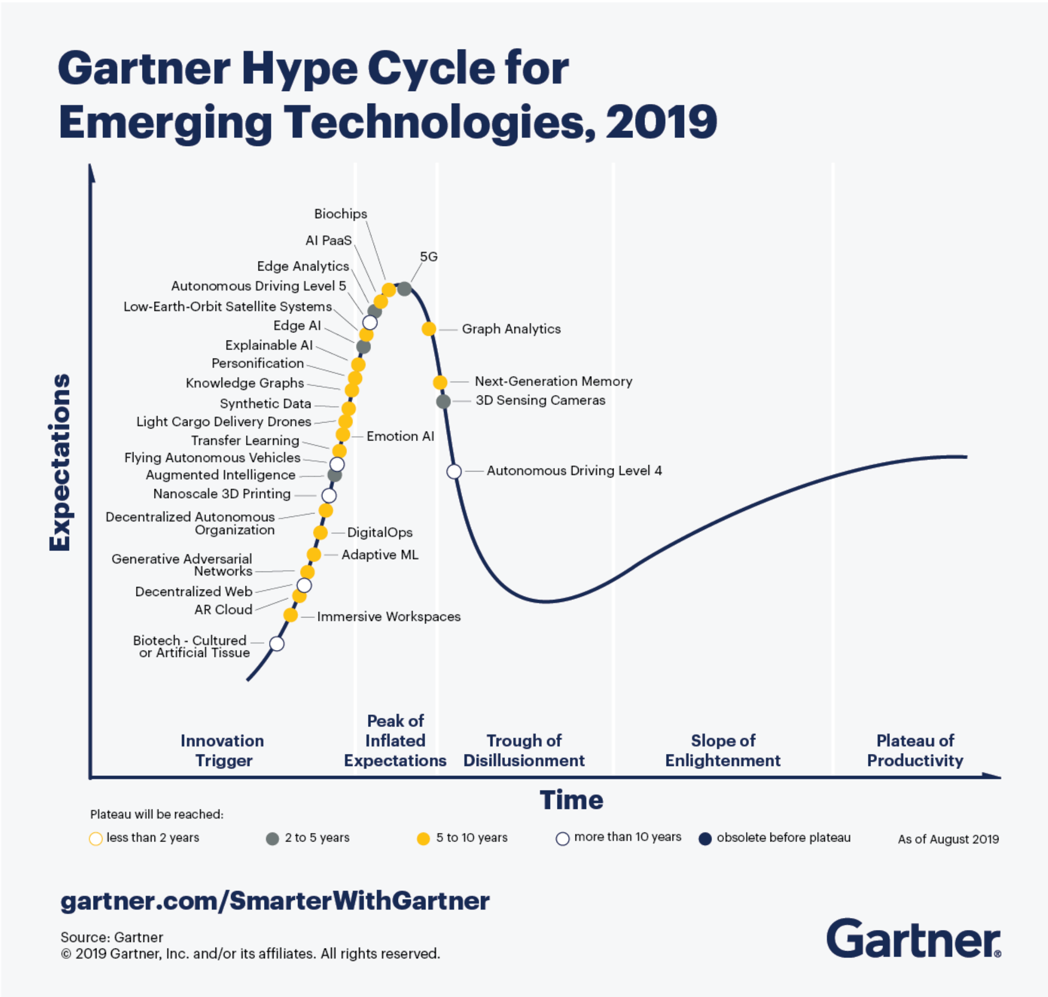
Among the early adopters of the group, some had implemented parts of a Cyber-physical system, such as RPA or AI separately but not as an overall concept for the company, and they showed markedly lower revenue (8.5% increase in revenue as compared to 2.9 %). One of the difficulties companies faced when trying to find ways of implementing AI, however, was the lack of talent to be acquired for development and application. One solution could be to place larger weight on training management, staff and operators to better interact and work with the new systems, allowing people to learn in cooperation and allowing the technologies to be better suited and optimised to the organisations purpose (Deloitte: Automation with Intelligence 2019).

Deloitte refers to this shift in industry as "*The age of with*", meaning humans now cooperate and utilise automation and machines in a new and more intelligent way, sharing more similarities and a higher working cognition in the assistance of human work. This includes how organisations view automation and the technologies it consists of, and in what way – and by what means, it will interact with the human elements of a company. Another aspect that was noted to be lacking in the investigation, was that where organisations did offer retraining of operators and staff it was almost always after the fact of the new system already being put in use. A more efficient way would probably be to prevent failures and faults in a system and the well-being of workers by making the training of new roles and tasks a priority when the system has been decided upon (Deloitte: Automation with Intelligence 2019).

Voice of the Workforce is another survey Deloitte performed in Europe among companies that automated their business, with a focus on the workers experience and abilities. Of those taking part, amounting of 15 000 workers around Europe, 65% believed they need significantly improved IT- skillset to be considered employable in the age of automation (Deloitte: Voice of the Workforce in Europe 2018). Yet according to what retraining has had to have been done in organisations after introducing automated systems, it's very uncommon to have to utilise greater technical and/or data-skills. Mainly the skills needed for keeping the workforce up to date is much more in line with "process skills", which is to say critical thinking and cognitive tasks involving more creative thinking as well as both simpler and more complex problem-solving. Apart from being a completely different challenge to meet, it is also a clear difference in consequence of implemented automation and CPS-systems. Like previously mentioned* there is greater need now to invest in in-house talent and capacity to really maximise output and use from new technological systems (Deloitte: Automation with Intelligence 2019).

In addition to benefits related to investing within an organisation in existing workforce, it also showed that workers were more supportive of the new technology when it was being implemented rather than when it was being planned, Deloitte seems firm in believing that workers will become more and more positive towards intelligent automation as it grows more common, and especially if systems are more efficiently adapted to utilise their capabilities and retraining offered at an early stage. Automation will instead of competing with human capabilities act as a complement, and instead enable workers to develop more human-centred qualities such as imagination and curiosity as well as emotional and social intelligence (Deloitte: Automation with Intelligence 2019).

4.2 Gartner hype cycle for relevant technologies



Actors on the market today and their applications

Health industry
Entertainment industry
Educational system
Customer Service
Scandit
Eyeware
Knightscope
Furhat Robotics
Faception
Intuition Robots
TNO
Mobsya

5 Analysis

The analysis is based upon information compiled through the literature review and market analysis. It describes the **Parameters and Levels**, **Deciding Factors** and framework in the form of an **Evaluation table** of possible areas of implementation. Important to note is that many factors can be similar in nature, interchangeable, possible to combine and have various ways of evaluation and this is not meant to exclude any of those possibilities, but merely show a way of overviewing important factors in an emerging field of application.

5.1 Areas of implementation

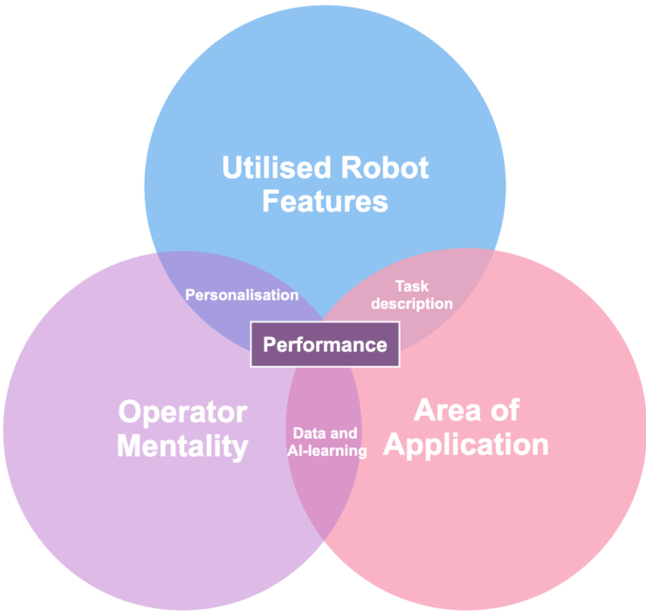


Figure 13: Venn diagram showing the interaction between parameters for consideration in implementing social robotics

Looking at an assembly line, there are a multitude of ways for layout and structure and is most commonly adjusted to the organisation's specific logistics. A big part of assembly is in general consisting of several tasks to assemble components together in a final product with varying degrees of complexity and is referred to as final assembly or complex final assembly (Mattson 2013). The level of complexity as well as the ability for cognitive thinking to handle a task is dependent upon the design and the operator. The need for human capacity is greater in such a context where complexity increases, seeing as it's the human flexibility that enables problem solving (Heilala and Voho 2001). According to Schleich, Shcaffer and Scavarda (2007), the best way of improving a task in final assembly is to enable the operator to perform better, which leads to fewer errors, higher quality, faster processes, better work environment, quick changeovers and lower cost.

It is considered very common practice to instruct the execution of a task through written instructions, something that is still the most prevalent in manufacturing organisations but seemingly gives way to interactive technologies such as VR and AR (Statista, Industry 4.0 2019).

5.2 Deciding factors

Illustrations of the levels of a system's *deciding factors*, in which what variables change depending on organisational need, when creating new systems or deciding on implementation:

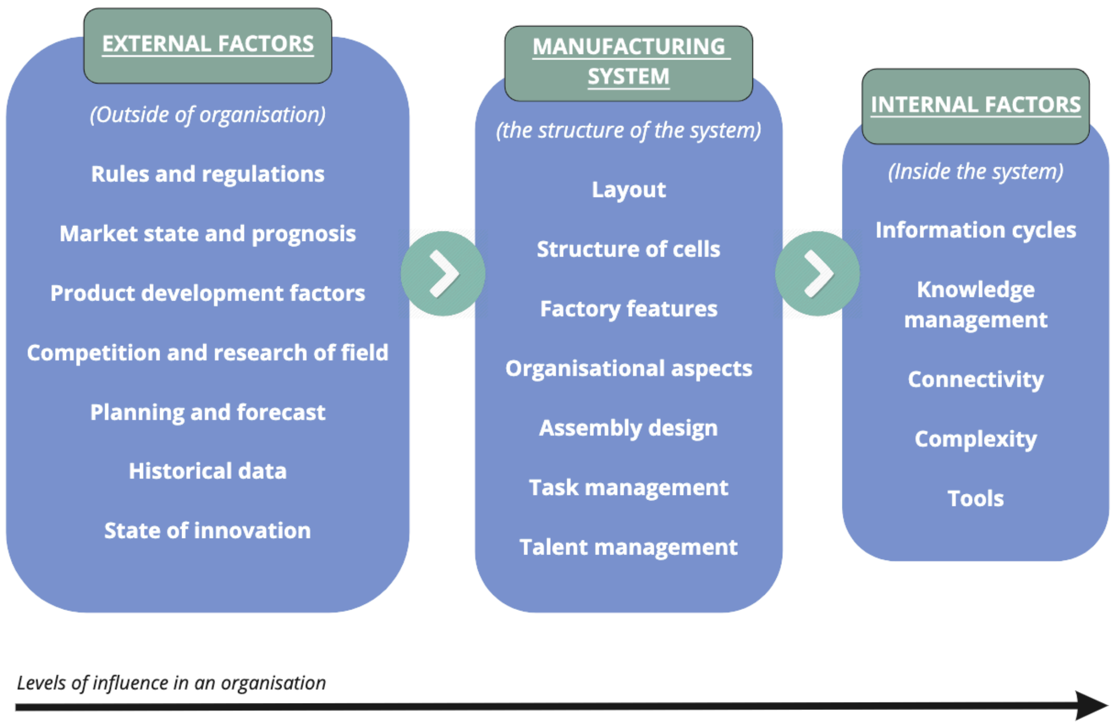


Figure 14: Deciding factors for implementation of processes and procedures in technical organisations

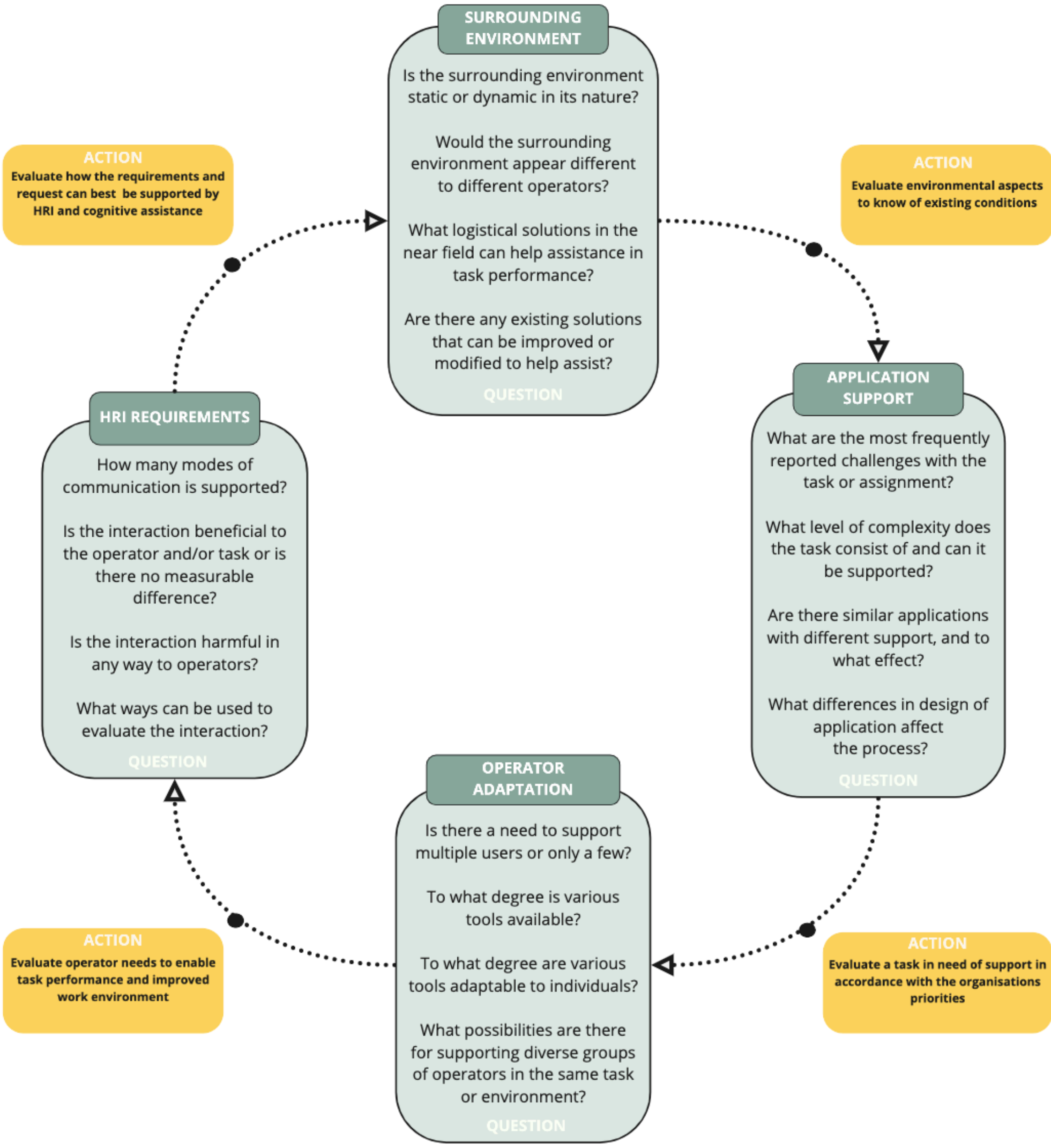


Figure 15: Framework describing Actions and Questions to consider when evaluating implementation of social robotics/cognitive agents

5.3 Evaluation table for social robots in manufacturing

The following table is an overview of where in a manufacturing environment social robot could be implemented and *what features could be more or less useful* in the given context.

APPLICATION OF DOMAIN	KEY FUNCTION	FEATURES UTILISED	WEIGHTING OF FEATURE	REQUIRED EXTENSION	PLACEMENT IN L-O-D	POSSIBLE ADD-ON APPLICATION
1 COMPLEX FINAL ASSEMBLY	Cognitive task assistance, Feedback	Gaze tracking Personalisation Conversational AI	4 5 5	Task configuration system (programming task)	Learning and Operational	Gamification, Alternate system connection (VR, AR)
2 QUALITY CONTROL	Scan and Feedback	Gaze tracking Personalisation Conversational AI	5 3 4	Task configuration system (programming task)	Learning and Operational	Gamification, Alternate system connection (VR, AR), QR-codes, Additional cameras
3 MAINTENANCE	Supervision and Feedback	Gaze tracking Personalisation Conversational AI	3 2 4	Connectivity to IoT	Operational and Disruptive	Display for HMI
4 MACHINE OPERATION	Supervision, Scan and Feedback	Gaze tracking Personalisation Conversational AI	5 2 4	Connectivity to IoT	Learning and Operational	Alternate system connection (VR, AR), Display for HMI
5 INVENTORY AND ANALYTICS	Information processing and delivery	Gaze tracking Personalisation Conversational AI	1 2 5	Connectivity to IoT	Operational and Disruptive	Connectivity to Cyber-phsyical systems
6 OPERATOR TRAINING	Cognitive task assistance, Feedback	Gaze tracking Personalisation Conversational AI	4 5 5	Task configuration system (programming task)	Learning and Operational	Gamification, Alternate system connection (VR, AR)

Figure 16: Table showing concepts evaluated for implementation in a manufacturing context

Explanation of table parameters:

The categories of evaluation are chosen based upon the theoretical framework in combination of features derived from base functions of a Furhat robot. Most of these categories can be subdivided into multiple levels on their own, which are mentioned throughout this section, but the framework for evaluation can simply be extended to serve those categories as well. Weighting should again be considered in such cases to ensure the functions of whatever social robot is being evaluated as to properly gauge the actual use of each function and making sure what features are relevant in what context. The integration with greater cyber-physical systems will also mean many more aspects to consider in implementation, yet the framework serves as a foundation and could be applied whether in terms of a larger or smaller scope.

Application of Domain: The parameter describing area of work or job description. Can in itself be consisting of many subdivisions and smaller tasks, but simply focuses on different aspects of the manufacturing organisation in general. Subdivisions to be evaluated can be each task in themselves within one area of application, such as actions per assembly.

Key function: What the social robot would be intended to do in the described assignment, in terms of role or most distinguished purpose. The different key functions described here is:
- Cognitive task assistance: the ability to assist in highly cognitive assignments in a meaningful way, may very well demand a multimodal approach such as facial expressions and verbal assistance though voice and projection.
- Feedback: for the operator or process to improve and the exchange to have learning qualities, feedback would be introduced as a key function to reduce time for learning task and improving problem solving abilities in users. Feedback is the verbal approval or dismissal of an action or idea, or similar response to a performance. Feedback in this case is not only assumed to be performed verbally but by facial features and gaze interaction as well. For the purpose of these applications, feedback can be both the encouragement of progress and effort as well as hints and guidance to an improved process.
- Scan: The ability to scan for things lies in the camera function. The camera is not only functional for gaze interaction but for more traditional tasks as well. Scanning is a feature used in a Furhat robot called Petra whose application is developed by the medical organisation Merck, made for pre-screening people for diseases (Furhat 2020). The success of Petra also shows it is possible to create a reliable interface who can scan assembled components – parts marked with QR-codes would be an efficient way of doing so – and to act as a resource at work also in terms of scans for health. Health in manufacturing context can mean many things, and something that is always incredibly relevant to the field are injuries. Ergonomically poor tasks and performance can lead to work-related injuries for operators and implementing already existing structures into a digital system that can scan and provide feedback could be a way to reduce those risks.
- Supervision: Does not mean control of task performance, but a more observing and mobile

role for the robot. Should be able to have well-developed spacial reasoning to be able to properly assess aspects relevant to the work.
- Information processing and delivery: Function very similar to existing virtual agents, with capacity to handle large amount of real time data and status of the production system.

Features utilised: Three main three features used have been identified by using the Furhat robot as the desired robot to implement. The weighting per application can be understood through the following figures and explanation:

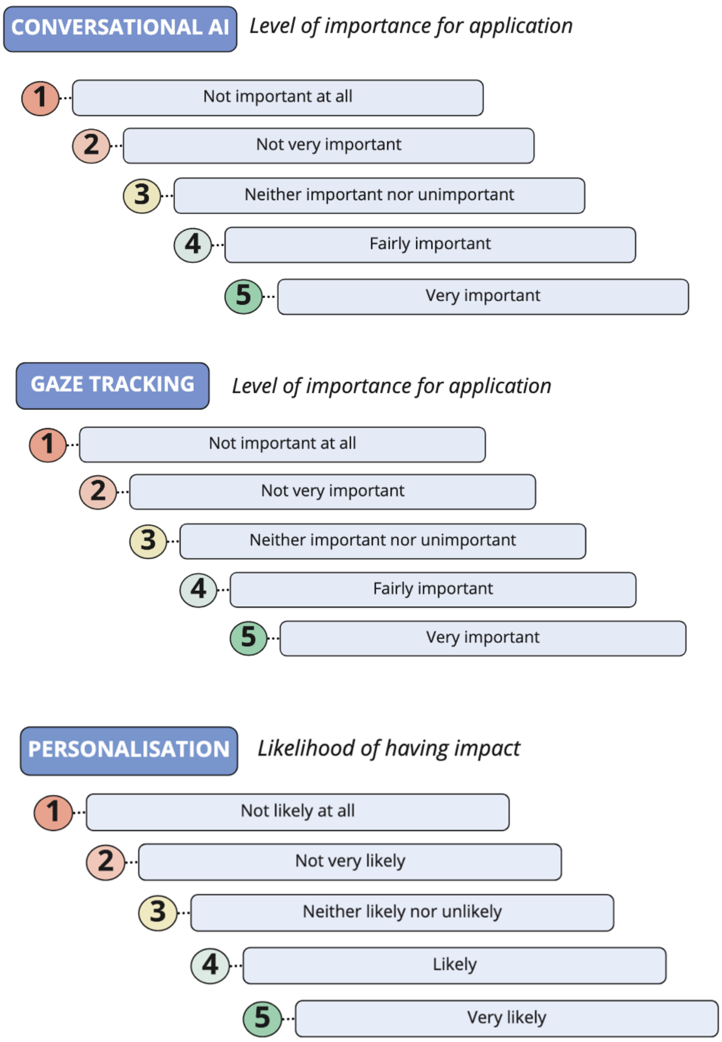


Figure 17: Explainations of weighting systems values

The weighting of features is based upon how important that specific feature is for the function of that particular application. *The assumption made is that the social robot can function at a high enough level, with each feature is well-enough developed for the desired function, and that suitability for implementation is the varying factor.* It is therefore interpreted as a scale of *feature relevant to application* where a low score says the function is not very dependent upon that particular feature. The higher the mean value is of the feature score, the more suited a social robot (Furhat robot) would be for that application.

The weighting conducted here is through the research performed in line and scope of this project. In extending the evaluation framework for organisations the weighting would be less bias if performed by a panel of experts in relevant fields and subjects.

Required Extension: Category for technology or asset need to be available for key function to be realisable. For example talent, in terms of the required competence for programming software of developing applications – such as programming a task or entering suitable feedback and instruction. It could also be the system in a larger sense, where Internet of Things is needed to stay up to date with real time data or input. Possible subdivisions are dependent upon what area of application is being evaluated and to what extent – namely if any or how many tasks or actions of a task is being looked at.

Placement in L-O-D:
Based upon the cognitive automation strategy by Mattson et al (2018), applications and functions can be placed in accordance to the categories presented there – Learning, Operational and Disruptive. This is not used as a definite scale, but a guideline to where most of said applications or areas of work would be found in said model. Since Learning is mostly connected to reasoning it can be more easily programmed than intuition, but operational is here included since the connection between these regarding tacit and explicit knowledge is evident though difficult to measure what specific function has what effect.

Possible add-on application:
Social robots, and the Furhat robot, is created with the intention to be a tool or a central figure to larger systems. This could be new technological features such as more detailed scanning and recognitive structures or a multitude of other sensors to measure various parameters in manufacturing. Connectivity to other platforms of communication could be easily imaginable, where combinations of Virtual Reality-technology or Augmented Reality-technology would enable operators in primarily the Learning and Operational categories. The levels of knowledge related to the L-O-D model, can be of use when designing the role of the robot in question. There is also theory meaning that skill-based knowledge, such as tacit knowledge,

might be transferable using intelligent agents such as this (Fast-Berglund et al. 2018). HMI-displays can help visualise information in combination with verbal communication. Game-based learning, like gamifying an operational system to motivate users to either log hours of practice/increased skill, enter instructions or data and encourage AI-learning could also be used in engaging operators.

Other add-on applications not discussed here includes more monitoring sensors for emotional assessment of operators. These are presented in the literary review and can be considered an example of sensory feedback used to assess health and well-being of operators, focusing on different aspects depending on what value is measured. It is not in the evaluation itself due to being possible to apply to any interaction with a social robot.

5.4 Domain evaluation

1. *Complex Final Assembly*:

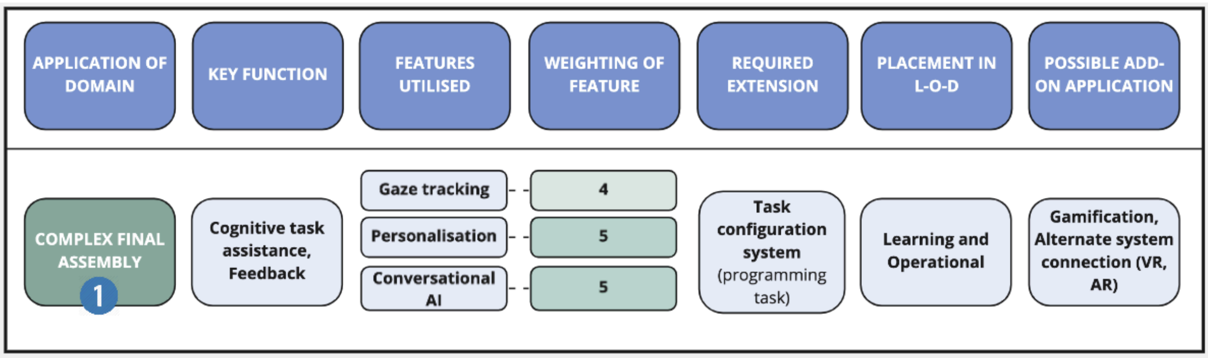


Figure 18: Complex final assembly table

Like previously mentioned, this is an aspect of assembly where human factors have a big impact in comparison than many others. The higher variety of products the greater need for flexibility, and therefore an assumable increase in complexity (Mattson 2013). Therefore there is a significant need for cognition and problem-solving abilities for an operator, no less looking to the development of the manufacturing industry with its increased demand for flexibility of its workers (Romero et al 2016). To use the social robot as a cognitive assistant has been demonstrated through experiments conducted – see Pereira et al (2019) on Joint attention.

Prioritised in complex assembly would be abilities that help the robot better understand its surroundings and the operator's skill-level and intent. To engage the operator all three features are important, seeing as it's human-like behaviour that encourages interaction (Al Moubayed 2012).

To have an intelligent assistant be of use in task assistance in complex assembly such as this, there is a need for talent within programming to ensure a functional framework adapted to the task and organisation (Krüger, Lien & Verl 2009). In terms of placement for an intelligent assistant - in this case a social robot - assignments where flexibility is required are significantly more relevant than simply pick-and-place, yet too large a variety can be difficulty to create a system for effective cognitive assistance (Krüger, Lien & Verl 2009). This might be helped however with connectivity to a larger CPS and IoT and evaluated through the suggested frameworks.

Weighted score:

$$Mean\ of\ importance\ of\ features: \frac{4 \times 5 \times 5}{3} = 33.33$$

2. *Quality Control:*

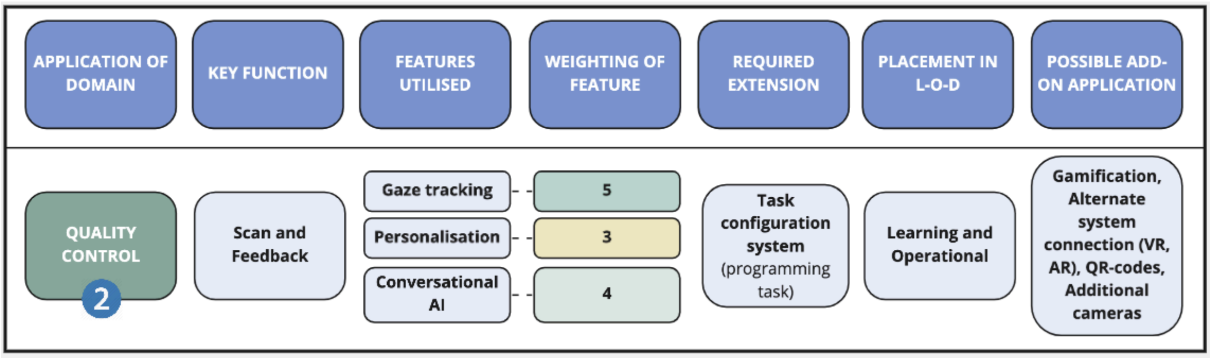


Figure 19: Quality control table

One of the more common stations in a production system is Quality Control (QC) where the product is subjected to examination to ensure that it is up to the desired standard. The organisation decides what level that is as well as how it is conducted and by what method. Common practice is manually inspecting and testing a product while documenting results afterwards or simultaneously. The key function here would be the use of a scanning-function in combination with the ability to verbally document aspects of the process, as well as provide feedback as to mistakes or actions to improve the process.

Already, a new take on QC using AR is gaining traction, where operators takes a picture of an assembled part and can directly compare it to an AR-overlay so that one can immediately tell if it's not correctly assembled (Statista, Industry 4.0 2019). This is used by Porsche for example, and the plan is to connect those cameras in the assembly to the cloud where a database can provide real-time feedback and instructions for modification if necessary (Statista, Industry 4.0 2019). This could work well having a social robot being connected to both cameras and the cloud, providing instant feedback.

$$Mean\ of\ importance\ of\ features: \frac{5 \times 3 \times 4}{3} = 20$$

3. *Maintenance:*

APPLICATION OF DOMAIN	KEY FUNCTION	FEATURES UTILISED	WEIGHTING OF FEATURE	REQUIRED EXTENSION	PLACEMENT IN L-O-D	POSSIBLE ADD-ON APPLICATION
MAINTENANCE 3	Supervision and Feedback	Gaze tracking	3	Connectivity to IoT	Operational and Disruptive	Display for HMI
		Personalisation	2			
		Conversational AI	4			

Figure 20: Maintenance table

Also, the concept of Maintenance is become more and more digitalised, where machine learning and its developed algorithms make predictions incredibly accurate and avoids long runs of downtime due to unforeseen failures (Statista, In-depth: Industry 4.0 2019). Maintenance is becoming a more developed area seeing as various solutions to conduct it remote and get faster feedback have become a closer reality with the digitalisation of factories (Masoni et al 2017). The ways to do so varies and is of course dependent upon what the system looks like as well as what data is documented and analysed. However, looking to the structure of Industry 4.0, some suggestions of improvement rely on AR-technologies.

The gaze-tracking would be one of the more important features, not specifically to that purpose but because of the operators need to fully view the machine or process to be able to determine the scope of the damage or detail of fault. This does require the camera (as well as microphone to communicate if there are issues with the technology) to be of quite high performance (Masoni et al 2017), something that can be conceivable in a connection to a social robot in terms of a supervisory role. Another system proposed by Sipas, Alexopoulos, Xanthakis and Chryssolouris (2016) involves regarding maintenance as a CPS on its own, where the main goal would be to properly utilise the data that is offered through documenting the processes and interaction of humans, machine and parts. This is called context-awareness and revolves around the ability to determine what situation requires what data in support of the system. This could be helped by an AI system, learning both the specific system requirements for sorting data, as well as being able to adapt to different operators preferences of presenting information – less in ways of personalisation but more in the actual selection of information and in what way or order it would work best, depending on the individual operators needs and interaction with the agent.

In the context-aware system there are multiple ways to actually sort the data, mainly through the use of apps for different purposes with servers dedicated to support-functions from such as database and frameworks for offering instructions, forms and feedback (Sipas, Alexopoulos, Xanthakis and Chryssolouris 2016).

The social robot would need to be able to distinguish between operators as well as have the ability to be connected to multiple cameras, have some auditory function to record events as well as great communication skills for feedback and instruction. Connectivity to the IoT would be a reuirement for the data to be recorded, processed and offered in return – as well as working together with sensors.

$$Mean\ of\ importance\ of\ features\colon \frac{3 \times 2 \times 4}{3} = 8$$

4. *Machine Operation*

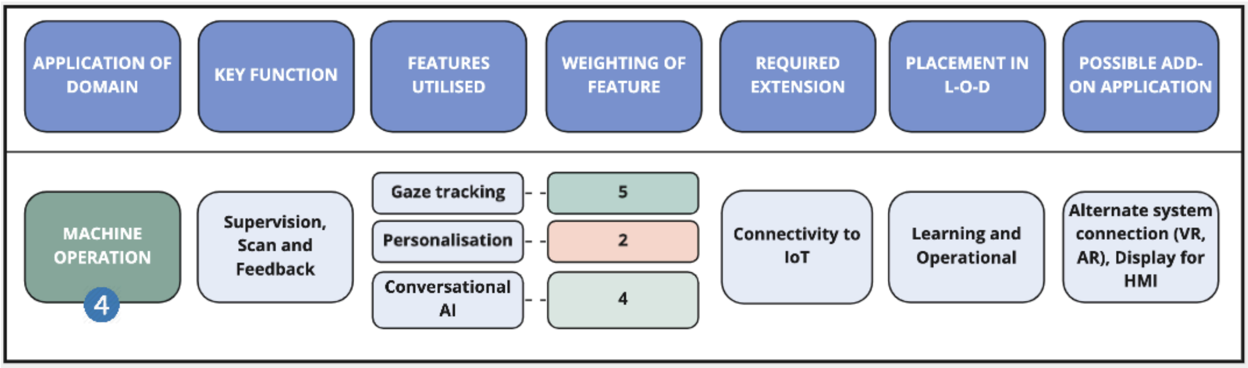


Figure 21: Machine operation table

Machine operation stretches over the entire manufacturing plant floor, seeing as any action involving handling machinery or tools in the manufacturing environment can classify as such. Here it is referred to as primarily a substitute of a manual in combination with a supervisory role for monitoring the execution of a task. The monitoring itself would require a high level of quality camera and spacial recognition, especially in terms of safety requirements both in handling of machines and tools as well as to avoid injuries from poor execution to oneself and others. Poor handling can of course also affect the state of the equipment and can be taken into consideration from a cost-perspective also. This is described as the key function Scan and is what is the social robot would do in terms of determining health and status of an operator. Similar functions have already been developed in a Furhat robot named Petra by the medical company Merck, that has the ability to screen for three common health issues (Merckgroup 2019). Creating frameworks for ergonomics in the same manner in machine operation might be able to identify – and primarily rectify by real-time feedback – work-related injuries and strain in operators.

$$Mean\ of\ importance\ of\ features: \frac{5 \times 2 \times 4}{3} = 13.33$$

5. *Inventory and Analytics*

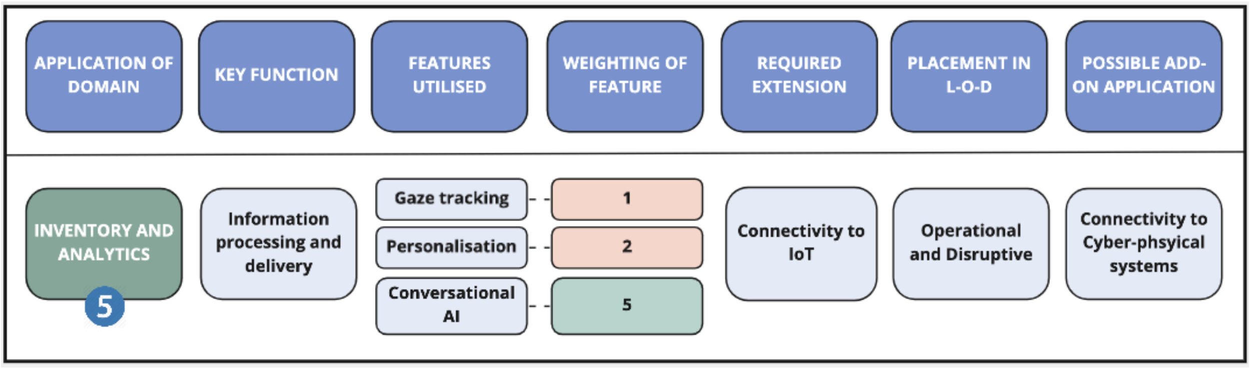


Figure 22: Inventory and analytics table

Mentioned frequently in relation to CPS, is the need for a practical mode of process and communication of the organisations data. This would be a connector of systems through multiple sensors and aids throughout a system. The camera used in a social robot such as a Furhat would be very limited in collecting large amounts of data but could instead be connected to a larger network - although the benefits of interactive gaze and recognition would might not have any other benefits in comparison to cameras in regular use.

To illustrate, Unmanned Aerial Vehicles (UAV) have been made popular in manufacturing as well by being able to track multiple systems simultaneously, and have already used for inventory tasks by use of scanners and such Frameworks for this might include UAVs, ground stations, tags such as barcodes or QR-codes, AR-technology and operator input (Fernández-Caramés, Blanco-Nova, Suárez-Albela and Fraga-Lamas 2018). The ground station in such systems could take shape of a social robot, or be complemented by such, to encourage operator input and real-time diagnostics.

$$Mean\ of\ importance\ of\ features: \frac{1 \times 2 \times 5}{3} = 3.33$$

6. *Operator training*

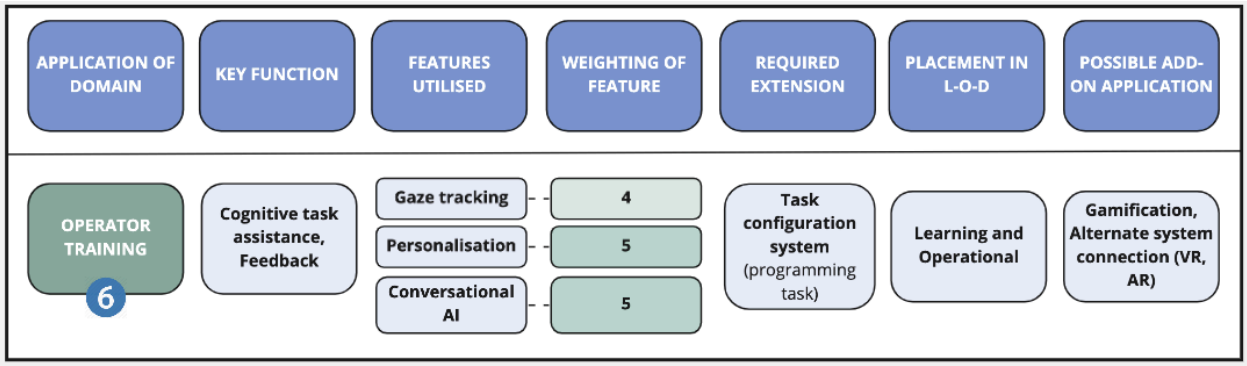


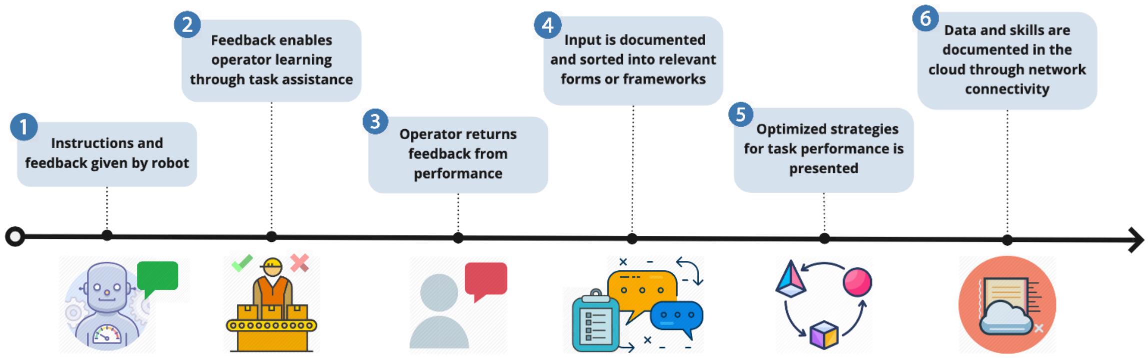
Figure 23: Operator training table

Something very central to topics such as this, is that one of the challenges with digitalising manufacturing organisations and moving into Industry 4.0 is the need to encourage further skill-development for operators and enable greater flexibility for task performance by flattening the learning curve (Shafer, Nembhard & Uzumeri 2001). The call for not only assistance in cognitive tasks but also ability to adapt and adjust the instructions and delivery to a more diverse work force does make a great fit for a social robot with features such as the Furhat robot. Unfortunately, HRI within manufacturing and industrial environments are not very well-explored but shows great promise in terms of benefitting operators in task-performance in a production line (Bahn, Rea, Young and Sharlin 2015). Seeing as the demography and diversity of the workforce is very likely to become more varied as well as a generational shift in operators happening (see section XX), introducing social aspects to learning might become vital to maintaining an efficient transfer of knowledge between operators and between operators and organisation. Since much of the skills and knowledge in the manufacturing is intuitive and documented and communicated through written channels (Fasth-Berglund et al 2018), much of the knowledge of the workforce is continuously lost in both shift of jobs as well as when not given enough time to learn each task – resulting in forgetting skills more quickly (Shafer, Nembhard & Uzumeri 2001).

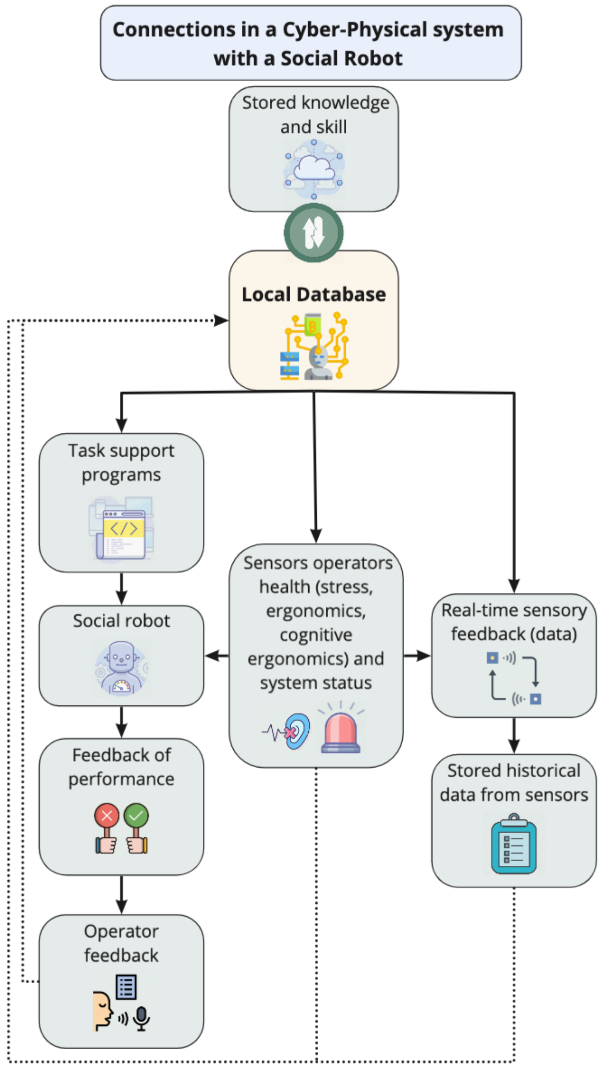
$$Mean\ of\ importance\ of\ features: \frac{4 \times 5 \times 5}{3} = 33.33$$

5.5 Social robots applied in a socio-technical system

In collecting and documenting knowledge:



Social robots and connectivity in a cyber-physical system:



5.6 Humanizing an increasingly automated production line

It is a widespread belief that automation will result in a major loss of jobs in the manufacturing sector (McKinsey & Company Discussion Paper 2017). Other analysis claims that it is not a loss of jobs, but merely a shift in what and where they'd be (Statista, In-depth: Industry 4.0 2019). A trend that seems to be recognised by most though, is the change in demography regarding the workforce, primarily in age and cultural variety. According to Deloitte's 2018 survey reviewing the changing workforce of Europe, "The voice of the workforce", if the trend of people working for longer in life continues on there might be a significant shift in that organisations will have a large part of workers (approximately 38%) that are 50 years or above. The survey also tells of the motivation to continue work, even after the standard age of retirement, and showed that older workers are not opposed to working even later in life, with various alternatives to either continue on as full-time or explore other options that still enables being able to work but in different circumstances, such as self-employment or part-time. Even though companies and organisations today have not in general made any strategy to more closely review or use information regarding workers motivation and skill set in relation to their age, it would seem to become much more important moving forward. Employing older workers and keeping their skill within the industry might be a great advantage and would encouraging a review of policy and motivational tools to help such initiatives (Deloitte, European Workforce Survey 2018). The results shown from the survey also presented various factors ranked for different ages of workers, to map what aspects of employment was most attractive and what could make them differ in priority, leading to insights regarding what approach management could have to further encourage motivation and job satisfaction. Job security and monetary compensation was the main factors for workers when considering motivation, but there are large portions of the workforce in various age groups that wished for well-defined goals, responsibility, possibilities to broaden skills and growth opportunities. All told it seemed that variation was evident across any workforce due to preferences, background and age – thus a more adaptable managerial strategy should be adopted to maximise worker motivation (Deloitte, European Workforce Survey 2018, p 12). Considering the prognosis for the workforce of production and manufacturing with its increased diversity and shift in age distribution, prioritising learning and teaching skills, sustaining both tacit and explicit knowledge is likely to become a competitive advantage to organisations and it would need to utilise more tools for engagement that are adaptable to various groups.

In terms of attitude towards social robots, which is very relevant when discussing operators and implementation, much can vary as well depending on things like culture, age, gender and level of education (de Graaf and Allouch 2013). In measuring attitudes and user perception of a robot its possible to divide certain aspects of HRI into categories as well, such as utilitarian factors and hedonic factors. Utilitarian factors focus on how useful and easy to use the robot in question is and is based upon the perception of users. In this domain, according to de Graaf and Allouch (2013), much of the research on HMI in relation to HRI indicates that the perception of how easy the robot is to use or operate, the more useful it also appears to the user in strong correlation. This in itself affects the general attitude towards the robot. The same correlation was found regarding perceived *adaptability*, which influences perceived usefulness, enjoyment, attitude towards use and use intention (de Graaf and Allouch 2013). They go on to explain that the collective material on this suggest that *a robot's ability to adapt its behaviour to the users preferences and personality can improve acceptability*. This very clearly supports the theory that operators would be more motivated and/or engaged for using a social robot if its adaptable to different users – both in function and personalisation. Aside from usability in terms of utilitarian factors, there is also hedonic factors that more imply the intrinsic motivation in accepting the robot by emotional response, such as enjoyment and attractiveness. Enjoyment of using the robot and physical appearance of the robot are the most important aspects for engaging a user in regard to hedonic variables (de Graaf and Allouch 2013). Social presence of a robot also plays a central role as to the Intention of use, based upon a model presented to measure acceptance of an assistive social robot (Heerink, Kröse, Ever and Weilinga 2009). Mentioned in studies regarding acceptance and use of social robots is the abbreviation TAM – Technology Acceptance Model – that was put forth by Davis in 1986, consisting of parameters of perceived usefulness and perceived ease of use of computer systems that have shown great psychometric quality value. When comparing the variables in studies (perceived usefulness and perceived ease of use), it showed that usefulness was clearly more strongly correlated to usage than ease of use (Davis, 1989). So not only needs the social robot be appealing enough and adaptable enough to motivate use, but also useful enough in what function it claims to perform, to increase its usage and perceived usefulness. Stated by Davis (1989), it's a logical connection seeing as one would more easily forgive a system for being more or less difficult to use, compared to a system that does not serve a useful purpose. The foundation for which, evaluation of possible implementation is highly relevant for, presented earlier in this analysis.

6 Conclusion

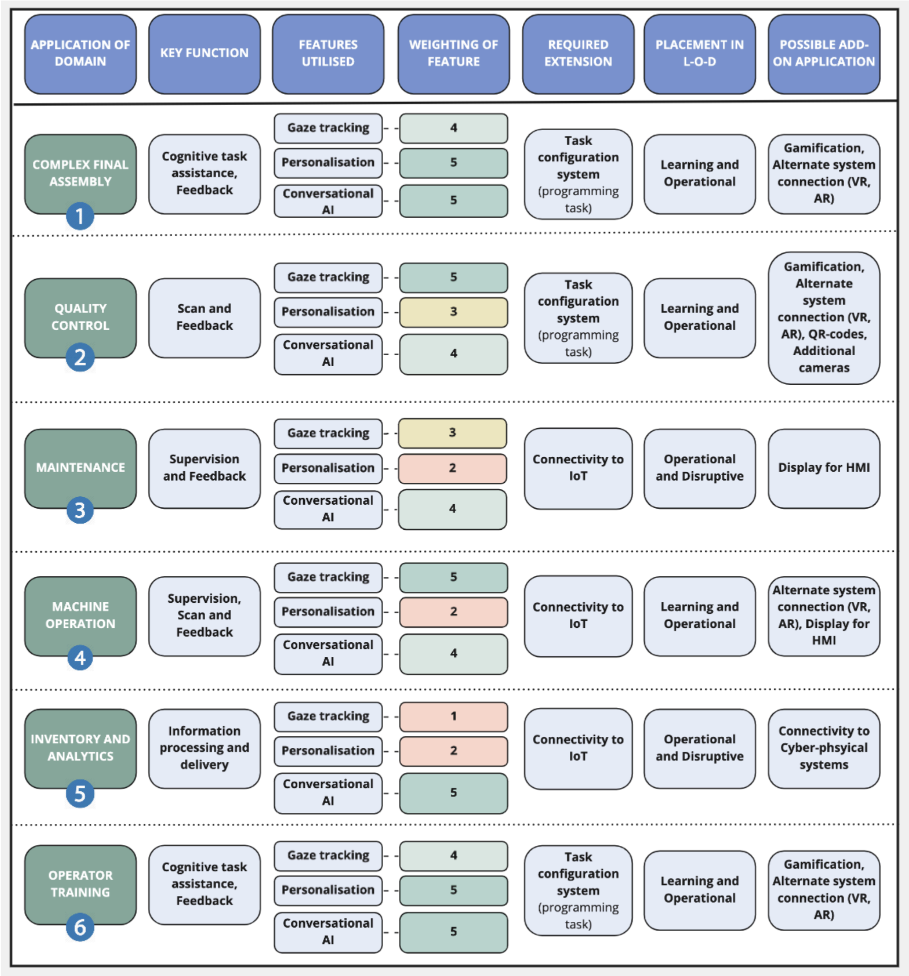
There is a definite call for technology and solutions that enable connectivity in production systems. Structures that enable learning skills and problem solving have can come in the form of virtual assistants as well as social robots, and further research is needed to properly determine what aspects are of more use in specific situations. Learning and managing skills within and in connection to an organisation is central and looking to Operator 4.0 and the increasing use of cyber-physical systems there is space for interaction between operator and the automated system through technology such as social robot. This can prove to be useful in terms of motivating users within the organisation to practice cognitive tasks for flattening the learning curve for new tasks or assignments by providing feedback and advice during processes such as assembly or quality control. There is also promise - though admittedly notoriously difficult to measure – in motivating operators to more easily and naturally share their knowledge and skill, and by more closely mimicking human interaction by using more detailed face projection and the ability to adapt the robot to a desired demographic.

Through a literary review that describes the outline of several topics relevant for social robotics and the utilisation of a Furhat robots features, a lot of the studies conducted suggested more potential research for how social robots are perceived in different environments, through different actions and in terms of different users. There is not sufficient groundwork done yet for implementation of social robots in the technical industry, seeing as the market research suggests a large gap between expectations for Industry 4.0 and cognitive agents, compared to actual strategies and systems developed. In terms of assisting operators, social robots show a lot of promise. The anthropomorphisation allows for an engaged interaction and the ability to make the exchange suitable for different demographics and to some extent different tasks, it opens up possibilities in the manufacturing factory. This is evaluated through a proposed framework consisting of five categories for six *Applications of Domain*. The framework itself simply suggests what areas are beneficial to explore and ways to evaluate features in terms of function for each area. It could be modified to suit various organisations depending on interest of implementation.

Another point of the analysis is to shine a light upon what specific features would be beneficial for interaction in a task in comparison to the more commonly adopted virtual assistants. Virtual assistants by way of conversational AI is already in large use in assistive situations through connectivity to the internet – most often used in hands-free situations for looking up information online, but by anthropomorphised agents these can serve more complex functions through gaze and spacial reasoning, as well as feedback and sensory connections. The three baseline functions of a Furhat robot is evaluated in context of each application, and through the weighting each total score for to what extent features are utilised decides how suitable a social robot with such function would be in that context. The two applications that received the highest total score were *Complex final assembly* and *Operator training* out of the six proposed areas. The scoring of both was approximately 33 out of 42 for utilisation of features, so that creating a program, application, platform or framework through a Furhat robot would utilise its particular function. No lower limit was set to determine how high a score was required, which is something that could be adapted when having performed live tests and evaluation scores for how well it aligns with the framework presented. However, the two concepts with the highest scores are supported through the literary review well enough to develop proof of concepts for further evaluation.

The validity of these results is only reliable to the extent of this paper, with the basis of a literary review and market analysis. To improve the validity one would advantageously research relevant facilities and organisations, adapt the framework and evaluate through proof of concept with a wide enough range of participants. Adapting the framework would constitute a process following the suggested steps of evaluating implementation: Parameters and levels, Deciding factors and Evaluation table.

Add-on applications are also suggested, backed by the research suggested in the literary review on knowledge management, Operator 4.0 and gamification. It is suggested through the concepts related to application of domain to where these add-ons could provide value. Suggested combinations, as well as all six concepts, can be seen in the Evaluation table:



Finally, it is reasonable to assume that a cognitive agent – preferably a social robot functioning at "socially embedded" level – working to assist operators at Learning and Operational levels is of use to the manufacturing organisation. Connectivity mapping and creating applications that enable documentation and task assistance is very relevant to the field and especially so moving into Industry 4.0. It should focus on being *useful* and with a fairly high level of *adaptation* to be engaging enough for operators today, and an increasingly diverse workforce in the future. This could lead to a flatter learning curve in a more flexible and varied production with higher output for the organisation. It could also serve as a central point for documenting skills and knowledge of operators, provide broader training and learning opportunities in a system as well as supporting different levels of knowledge and cognitive processes. It should be noted however, that not all applications would make use of the highly interactive interface of a social robot but can instead provide assistance through other types of virtual agents. Further research is required to continuously evaluate systems for suitability of robot technologies.

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A note of caution regarding anthropomorphism in HCI agents

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