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Towards an ontology to capture human attributes in human-robot collaboration

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Abstract
A core predicate of Industry 5.0 (I5.0) is the integration of human, environmental and social factors with new technologies. The integration of collaborative robots offers increased productivity but raises questions on safety and how robots can respond to varying cognitive and physical attributes. This paper discusses the significance of structured ontologies in managing complex information for proactive, safe, and productive human-robot collaboration. The paper highlights the future work to be undertaken to ensure the safe and fluid integration of humans and robots within I5.0.

Keywords: ontology, human-robot collaboration, human behaviour

1. Introduction

The use of Industry 4.0 (I4.0) methods and tools across the manufacturing sector is continually growing and broadly encompasses Cyber-Physical Systems and Industrial Internet of Things (Vogel-Heuser and Hess, 2016). The focus is on integrating computational tools with physical manufacturing systems, such as a robot or machine tool. Whilst I4.0 is still progressing in both the research and industrial communities; work has also focused on developing Industry 5.0 (I5.0), the next iteration (Xu *et al.*, 2021). I5.0 evolves the concepts in I4.0 that are primarily data and computational tools focused and integrates human, environmental, and social aspects to enable new approaches that go beyond physical systems, synergistically bringing humans and machines together.

A key factor of I5.0 is the use of collaborative robots, where it is envisaged that there will be a closer relationship between the human and robot. Human-robot interaction (HRI) allows the human and robot to share the same environment and communicate, but without direct contact. Human-robot collaboration (HRC), as shown in Figure 1., allows there to be direct contact between the human worker and robot, so that skills, competence, and resources are shared during collaborative tasks (Li *et al.*, 2023). Within HRC, both the human and robot must communicate their intents and goals to successfully work together and dynamically adapt to each other's movements and plans. With HRC comes many potential benefits in productivity and efficiency as robots can take over repetitive and risky tasks, allowing the human to focus on tasks that require a level of dexterity the robot cannot meet (Maurtua *et al.*, 2017). However, this can bring up difficulties in safety when robots and humans work in proximity in the same environment; fatal accidents can occur due to faulty sensors and robot malfunctions. It is also challenging to establish trust between the human and robot whilst also enabling robots to respond appropriately to unpredictable situations involving human workers. Within this type of collaborative working approach there are many different data streams; from the robot's kinematic structure to the human operator's fluctuating behaviour and changes in environmental conditions.

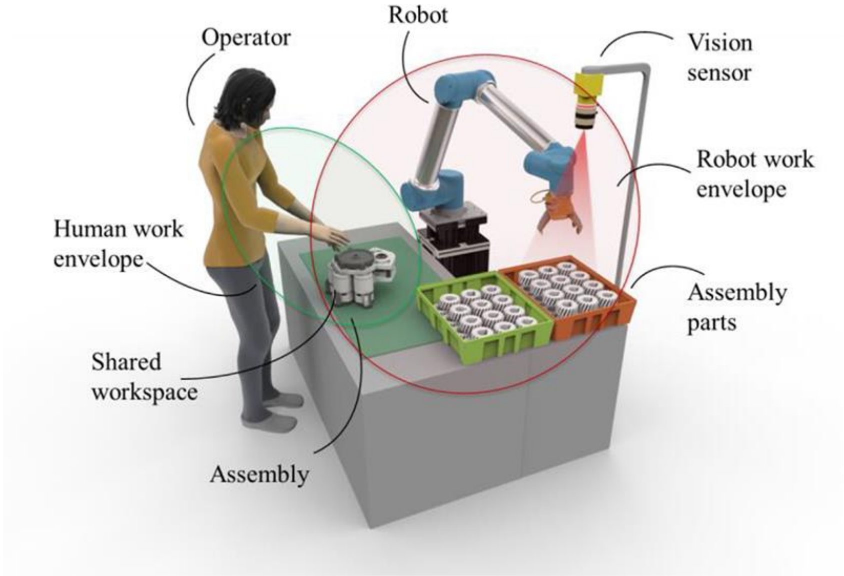

Figure 1. Human-robot collaborative assembly (Malik and Bilberg, 2019)

As the level of data becomes richer, variable, and more complex, structured methods are needed to manage it for effective decision making (e.g., when a worker should do a particular task). Information modelling techniques are typically used to enable data management, clustering, fault finding and connectivity between different systems within a common production map. These can consist of knowledge and data maps developed using, for example, XML, UML, Express G and other formalised, hierarchical data mapping methods (Martin-Guillerez *et al.*, 2010).

An ontology is a way to structure knowledge within a system and provides a common vocabulary for different systems, processes, and actors (Prestes *et al.*, 2013). It can represent the hierarchy of different concepts, or objects, and store any possible relationship between different 'things' within the whole system. This can also improve information sharing between various components of different systems.

As we begin to see the emergence of I5.0 and the coupling of humans and robots for a new type of work force and production facility, this brings the challenge of managing a myriad of complex information and data to ensure that human-robot collaboration can be proactive, safe, and highly productive. Aspects such as human behaviour, cognition and emotion need to be studied in detail, establishing the relationships between these aspects and all other parts of the system. For example, links between human cognitive or physical load and the capabilities of the worker needed to be established to determine task allocation and achievement.

This paper investigates the recent advancements in manufacturing ontologies to facilitate human-robot collaboration, which is the core focus of the EU H2020 Fluently project (Fluently, 2022). HRC in this case will involve a human operator interacting with a collaborative robot arm to perform manufacturing tasks, such as an assembly process, where the previous scenario involved only a human performing these tasks. The robot is introduced into the workplace with the aim to improve efficiency and reduce the load on the human. Now the human must adapt to the different style of working, but there should also be consideration on how the robot will need to adapt to the human working alongside.

We investigate how abstract human concepts can be represented within an ontology. Whilst the ontology structure works well to show taxonomical structure of concepts it may not lend itself well to the more emotional and social aspects of a human's behaviour. However, these are important considerations when the human is working in close proximity to the robot, so that the robot can adapt to potential unexpected human behaviour and learn over time the best working strategies.

The paper is organised as follows. Firstly, in Section 2, upper ontologies and those within the manufacturing domain are reviewed, along with exploring the cognitive and physical aspects of the human in a collaborative environment. In Section 3, the development of an ontology for HRC is outlined. The work is discussed in Section 4 and conclusion and future work are presented in Section 5.

2. Background

2.1. Ontologies within manufacturing

Large and complex systems need structured methods to ensure that relationships and connections between components and entities can be correctly mapped, linked and modelled. Here, an ontological approach can show how different objects (e.g., machine tool, fixture, tool, etc.) are involved in particular tasks and decision making. An ontology is a level beyond a taxonomy for a system, which is a way to show the classification hierarchy of a system, as it describes the relationships, constraints, and rules in more depth (Prestes *et al.*, 2013). This information is represented in a way that computer software can interpret and reason over the knowledge represented, for example in robot path planning applications (Gayathri and Uma, 2018). The core components of an ontology are classes, relations, and axioms. Classes represent the different types of entities, or things, that the ontology is meant to describe. Relations show how different classes can be associated to each other. Axioms are statements that define the relationships between concepts and their properties in a formal way.

General upper ontologies are often used as a base structure to develop more specific domain focused ontologies, such as those geared towards manufacturing systems and HRC. One of the most common upper ontologies used in new ontology development is the Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE), designed to capture the basic concepts, properties, and relations which underly natural language and human common sense (Masolo et al., 2003). DOLCE Ultra Lite (DUL) is a simplified, less abstract, and more practical version of DOLCE for use in real-world applications (Gangemi, 2010).

KnowRob is an ontology-based knowledge processing system designed to enable robots to reason about the world and perform complex tasks; it can bridge the gap between vague task descriptions and the detailed information needed to perform those tasks (Tenorth and Beetz, 2013). It takes some upper-level ontology concepts from DUL. The Ontology for Collaborative Robotics and Adaption (OCRA) (Olivares-Alarcos et al., 2022) is compliant with KnowRob, therefore has inherited the use of the DUL upper ontology. OCRA focuses on addressing the uncertainty and safety constraints that are introduced with use of a collaborative robot in an industrial task.

The Suggested Upper Merged Ontology (SUMO) is another commonly reused upper ontology (Niles and Pease, 2001). Manufacturing process (MPRO) ontology is built using aspects of the SUMO ontology as its foundation, focusing on classes and properties specific to manufacturing processes, such as assembly processes (Bruno, 2015). The Core Ontology for Robotics and Automation (CORA) is also designed using SUMO as a foundation and is the IEEE standard for this area (Prestes et al., 2013). Collaborative CORA (CCORA) extends the CORA ontology to include concepts related to HRC.

Umbrico et al. (2020, 2022) developed the SHAREWORK architecture to represent HRC within collaborative cells. This is where robots and operators collaborate at different cognitive and physical levels and can communicate seamlessly. The main modules for this architecture are the knowledge base, task planning, action and motion planning, and human-system interaction. The knowledge base module contains the Sharework Ontology for Human Robot Collaboration (SOHO), which is built on top of CORA (which relies on SUMO) and SSN, with DOLCE as a foundational layer.

The ontologies discussed here have a low-level inclusion of HRC aspects, as discussed by David et al. (2023) who focused on the inclusion of agent capabilities in human-robot assembly tasks by introducing a mixed-reality interface. To develop an ontology that is representative of HRC, where the human and robot undertake joint tasks, more consideration is needed for human aspects. The following sections build on the state-of-the-art ontologies detailed here and propose the addition of the 'human data'.

2.2. Human representation within human-robot collaboration

For humans and robots to work seamlessly and effectively, task planning requires flexibility to take account of the stochastic nature of the human. There are multiple external effects that can influence every aspect of the process. Most notably the cognitive and physical state of the human and how they exist and interact with the robot and environment. Working closely with a robot can be stressful for the human, which can affect the productivity and quality of tasks. Stress can thus affect the humans emotional/cognitive state and potentially affect physical capabilities. Therefore, for HRC to be introduced into the workplace, an understanding of the workers mental and physical state whilst performing certain tasks with or without the collaborative robot is required (Gervasi *et al.*, 2023).

There can also be issues pertaining to trust in the system. If robots are introduced into workplaces that already have established workflows, this can bring uncertainty and a lack of trust in the performance. For example, Trauer et al. (2022) mention the lack of trust in new technologies leads to slow adoption and that trust is a vital component in complex, unstable and uncertain situations. Trust links directly to the human's emotional state and physical safety. Specific strategies to improve safety, such as adjusting robot speed and design can greatly improve trust in working with robots (Maurtua *et al.*, 2017). Gualiteri et al. (2022) performed a trial where participants had to interact with a cobot for a collaborative assembly task. This was to examine cognitive variables such as trust, usability, frustration, perceived enjoyment, acceptance, stress, and cognitive workload. As expected, the workers performance and cognitive variables improved as the trial developed.

Human metrics, such as cognitive and physical load, stress, and other emotional indicators, can gain insight into how the human may behave and what their capabilities may be for certain tasks. Cognitive load in relation to performing a task is the amount of mental effort or processing capacity (Skaramagkas et al., 2021). This is commonly measured using self-reporting subjective measures or from physiological data such as heart rate variability (HRV), eye blink rate, skin conductance and electroencephalography (EEG). Physical load concerns how forces can affect the body (Winkel and Mathiassen, 1994). This measure can also be determined through self-reporting on how particular tasks affected the workers body, which can include commenting on difficulty in manipulating heavy objects or working in an awkward posture. This can also be measured from physiological data; including heart rate and energy metabolism (Zhao et al., 2010). Excessive cognitive and physical loads can lead to failures that affect work performance. Studies into these metrics include either self-reporting using scales such as, the NASA Task Load Index (TLX) (Hart and Staveland, 1988), or the use of sensors to objectively measure and gain health data that could link to cognitive or physical load.

Gervasi et al. (2023) examine how experience gained through HRI affects the user experience in conjunction with different configuration factors, such as robot speed and proximity to the robot workspace. They consider results from both self-reporting and physiological sensors, including Electrodermal activity (EDA) and heart data through PPG with a non-invasive biosensor wristband. Perceived safety was found to be negatively affected by increase of robot speed and if the human couldn't control the task execution time, but this generally improved as the human became more familiar with working with the robot. Buerkle et al. (2022) focus on improving collaborative tasks between the human and robot by implementing a human sensor framework which uses subjective, objective and physiological metrics.

Cognitive and physical performance of the human during HRC tasks improves as the human spends time with a collaborative robot or using other technologies. The human is consistently evolving at a rate that will be individual for each worker. Attributes such as experience, age, training, etc. can influence task performance, so these need to be accounted for.

Considering the ontology representation of these human attributes; most will not be able to be defined explicitly within the format. For objective and physiological metrics, relationships can be defined along with the correct data, but there are often no concrete thresholds to determine when the exact onset is or the level to which they will significantly impair the worker (Vanneste *et al.*, 2021).

In addition to using sensors to attempt to record aspects such as cognitive and physical load to determine a human's status, recording/monitoring human emotion has also been considered to adapt working style based on how the human may be feeling. Studies examining how emotions can be recognised in real time primarily involve artificial intelligence (AI) methods for facial expression recognition. For example, convolutional neural networks trained on datasets of facial images which are then used in real time with cameras and face tracking technologies (Chiurco et al., 2022). Although, these can run into problems due to camera positioning or the face being obscured with safety equipment or parts during operations. Additionally, there could be problems such as the workers neutral face being classified as an emotion such as, anger, fear, sadness.

In the area of ontology development, there have been a few ontologies focused on the representation of human emotions including more in-depth human attributes represented in a human-robot situation. Gil et al. (2015) developed the Emotions ontology (EmotionsOnto) to describe detection and expression systems related with emotions and additionally represent the contextual and multimodal elements. The OntPercept ontology, developed by Azevedo et al. (2020) focuses on social robotics, where research is focused on models allowing robots and humans to interact naturally. Another emotion ontology, EMONTO, is used to store semantic information obtained from social robots that can detect emotions (Graterol *et al.*, 2021). Their proof-of-concept study showed that integrating speech-to-text and algorithms for emotion detection with the ontology had promise. Emotion is complex and there are different theories regarding how it is classified (Gyrard and Boudaoud, 2022). Therefore, compared to metrics such as cognitive and physical load, emotion is found to have a less obvious impact on the performance of tasks in HRC and is more difficult to directly measure and relate to other aspects.
The next section builds on the current literature in encapsulating and representing human attributes within an ontological framework.

3. Development of an ontology for human-robot collaboration

3.1. Ontology structure

The ontology described here is based on the structure of pre-existing upper ontologies. As mentioned in the literature, building an upper ontology from scratch is complicated and unnecessary (David *et al.*, 2023). Ontologies developed typically use others as a foundation to build upon and add classes and relationships to evolve into a more focused ontology that is application and requirements specific.
The ontology discussed within this section is to represent human-robot collaboration within the manufacturing domain, with particular focus on assembly and disassembly tasks with aim to expand to represent many other collaborative tasks. As found in literature, it can be common for human factors, or the influence of these on the rest of the system, to be ignored when planning for HRC (Gualtieri et al., 2022). The second subsection (3.2) will discuss how different human factors and metrics have been considered and the relationships between these and other concepts in the ontology.
For the construction of the human-robot collaboration ontology, the Protégé editor was selected, which uses the Web Ontology Language (OWL) (W3C OWL Working Group, 2012). The overall structure is based on DOLCE and SUMO, and HRC specific classes are based on SOHO by Umbrico et al. (2022). The goal is to use elements from these pre-existing ontologies and then focus and expand on the development of the human factors and the specific use cases it will be applied to. This approach of ontology reuse is supported by the well-known ontology building methodology METHONTOLOGY (Fernandez *et al.*, 2007), where after defining the purpose and scope of the ontology it is recommended to integrate as much as possible from pre-existing ontologies.
The taxonomy of an ontology lends itself well to the structure of assembled components. To represent objects involved in the assembly/disassembly process, subclasses of *'PhysicalObject'* are used, which is defined by SUMO. Individual subclasses under *'ProductionObject'*, defined by SOHO, are classified for *'Tool'*, *'Sensor'*, *'Fixture'*, *'Part'*, *'Machine'*. *'Part'* is then divided further to represent *'Component'*, *'CompoundPart'*, and *'Fastener'*, where relationships are created to link these objects together in an assembly, e.g., *'CompoundPart hasComponent min 2 Part'* and *'hasFastener some Fastener'*. The *'Tool'* class is split into *'ManualTool'* for those equipped by a human worker, and *'RobotAttachment'* for tools that the robot arm can use.
For the representation of goals, tasks, and actions within the ontology, the set-up follows its own hierarchy. To achieve a goal, a certain number of tasks need to be completed. These tasks would then be composed of the actions needed to complete them. The ontology represents these as classes and stores each specific type of action that may be done by the human or robot (or any other objects that can have a function). For example, for a pick-place task for a human, the actions involved would be *'MoveTo'* (object), *'LiftObject'*, *'MoveObject'*, *'PlaceObject'*. Often, outside of the ontology there is some form of a task planning system, which can determine specific tasks and the order of which they will need to be done. Some of the actions will be directly related to certain tasks within the ontology as classes that must be associated. Additionally, to be specific for HRC, the tasks are further classified based on the

level of collaboration between the human and robot; where they can be either *'Independent'*, *'Sequential'*, *'Simultaneous'*, or *'Supportive'*. The different types of HRC tasks are explicitly defined by the combination of human or robot actions required.

For a task to be performed in the process, a set of preconditions must be met. These can be as obvious as checking that the correct objects are within the environment that are needed for the task. Other preconditions are more complex to define, such as human behaviour and physical properties that can influence whether they can complete a task, and how well they will be able to do this.

In many ontologies, capabilities are defined as a subclass of *'Quality'*. These are competencies the agents have according to structure and skills. E.g., for a human worker, certain work operations can only be performed if they have the relevant training for that task, are in a specific location, have the correct tools etc. Thus, these can change with time. Separation is made between human and robot capabilities, so that human capabilities can be linked directly to classes related to aspects such as emotions, perception, and trust. Robot capabilities are more specifically related to hardware or software availability. For a robot arm, the capabilities can change depending on robot attachments, such as if there is a gripper attachment the robot can have the capability to pick up objects (Dussard *et al.*, 2023).

The human's capabilities can be more complex to define in comparison to the robot. For some purposes they can just be defined as the types of skills humans have been trained on. So, the actions the human should be able to complete are indicated directly in the ontology related to a specific individual, depending on whether they have performed it before or if it is a simple action. There is the assumption that the human can perform that action if the required objects exist in the correct locations to perform the action. However, some capabilities can be affected by physical and emotional states of the human, past behaviour, and environmental aspects (Perugini and Conner, 2000). Which can be difficult to precisely define or calculate, especially within an ontology structure which benefits from concrete values and measurements. Complex thought processes, beliefs and desires can influence how a human works (Lemaignan *et al.*, 2014). It is one thing for the human to have completed a task, such as lifting an object, but another for the human to feel like they may be capable to repeat this task on another given day under a different set of circumstances. Capabilities can be entirely linked to the human's mental state, which is complex to understand and map.

3.2. Representation of human attributes

A core predicate of I5.0 implementation is the addition and integration of human, environmental and social factors. It is highlighted in literature that human responses to situations can vary greatly, so personalised interactions are key to ensure fluid interactions (Gervasi et al., 2023). This, therefore, carries over into the modelling of the required knowledge. An ontology must include all potential relationships between classes that are relevant to the human's state and behaviour. Figure 2. shows a segment of the ontology, showing how the *'Human'* class, real data and human focused attributes can be linked to other aspects of this system. The figure shows some of the direct class-subclass relationships. Other relationships between classes are labelled as they are in the ontology.

As mentioned in 3.1, performing an action requires the correct capability to perform it. The *'HumanCapability'* class, which is required to perform a specific *'Action'*, is related to *'HumanProperty'* through their subclasses (e.g., *'PsychologicalCapability'* is linked to *'CognitiveLoad'*). Cognitive and physical load are chosen to be two of the main classes related to the human's performance, alongside other behavioural aspects. To determine these properties within the ontology, the type of sensor or measuring technique must also be defined. In the ontology these classes are defined generally to be applicable to different types of sensors with different properties.

Certain tasks or actions may require the cognitive or physical load to be classified at a certain level, using a numerical scale or categorical values (high/medium/low) before they can be performed. Thus, there will be relationships between measured physiological data, the classification subclass of the cognitive or physical load, and specific actions. Cognitive load measures can be subjective or objective and are generally obtained either through self-reporting measures or related to physiological sensor signals. During a task it would be impractical to ask the human to provide constant feedback or answer questionnaires to provide an estimate of what the load could be, therefore certain wearable sensors may be the best option, e.g., EEG sensor, ECG sensor, heart-rate sensors, etc. (Al-Yacoub *et al.*, 2020).

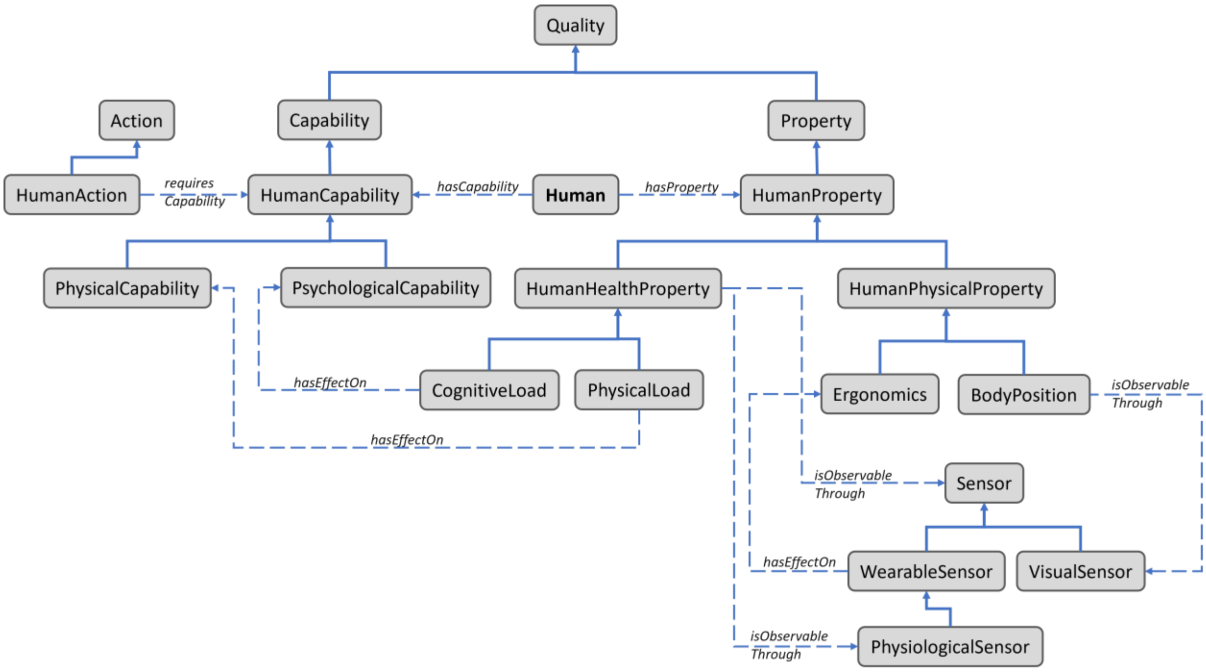

Figure 2. Simplified subsection of ontology focused on human attributes; Bold connections indicate class-subclass relationships and dashed connections show other relationships

Heart rate data is relatively easy to obtain and can be measured from an optical measurement device, such as that commonly found in smartwatches and fitness trackers, or with a chest strap. The wearers heart rate can be used to determine the heart rate variability (HRV), which is an indicator for cognitive load. The threshold for this is not really established but healthy values are above 100 ms, which could be used to indicate a low cognitive load. Unhealthy values are below 50 ms which may represent a high cognitive load. These values could be refined for individuals through training on tasks that may require a high/low cognitive load to determine baseline HRV. The values can act as a trigger to prevent certain actions from happening by changing the current capabilities, which if linked to a planning module would help indicate whether a robot would need to take over or assist with a task.

Electroencephalogram (EEG) data can also be used as some indicator of cognitive load. This data can be obtained from a headset or a cap capable of measuring EEG signals. Power spectrum values can be used by looking at the ratio of theta (4-7 Hz) and alpha (8-13 Hz) waves. A higher power in theta over alpha could indicate a higher cognitive load. However, the ratio may not be the same for different types of tasks and for different human workers. Wearing this type of sensor during standard work tasks is likely to be impractical, but if it could be used for an initial phase of working and relate to other more comfortable ways to obtain data, it could be useful. Ergonomics should be considered with measurement devices and the relationship between this and the human's performance should be established in the ontology, as shown in Figure 2.

Physical load can also be determined using heart rate. Resting heart rate can be compared to the heart rate reported during certain tasks, and if it exceeds an unhealthy threshold for an individual, adaptions can be made in the task, e.g., the robot can provide additional assistance in some tasks. Task planning component can be modified depending on the changes in the ontology, i.e., if the human isn't physically capable of performing a certain task, then planning needs to adapt accordingly and change the HRC task type. These attributes will be personal for each worker, so the ontology must be able to represent the potential influences classes will have on each other, then it can be used as a map to build the worker's personalised knowledge base when there is more information on their individual behaviour.

In literature, it is discussed that human emotional, physical and physiological attributes can affect performance during manufacturing tasks, especially when collaborative robots are introduced into the loop, bringing uncertainty and other safety concerns. Thus, the representation of human aspects is essential within an ontology for HRC to establish the connections between concepts within the system, such as physiological signals from sensors and physical or mental tasks.

4. Discussion

Current state-of-the-art literature on I5.0 is often centred on the industrial benefits of robots working closely with humans. Collaborative robots can bring higher efficiency and productivity to the workplace. However, it also brings in a new level of risk and uncertainty. It is impossible to program a robot to avoid all unpredictable movements of humans, accidents, malfunctions etc., which will reduce productivity. This relates to the issue of trust in the human-robot partnership. When working with other humans, workers can easily identify intent and communicate in a multitude of ways, whereas a robot is incapable of this higher level of reasoning and cognition. They can adjust movements, speed etc. to work fluidly with their co-workers, however, fast/sudden robot movements could increase human stress/anxiety negatively impacting productivity (Gervasi *et al.*, 2023). This also, consequently, increases the cognitive load during the task as the human is anticipating the robot's movements, even if there are adequate safety measures to prevent contact between human and robot. For robots to be commonplace in any manufacturing environments, they must be capable of identifying these human properties and adjust working patterns based on human behaviour. Some research has aimed to solve this issue by giving the robot system a model of the human (Buerkle *et al.*, 2022).

Within a manufacturing environment, human psychological and physical behaviour can influence performance of tasks. There is generally a lack of detailed human-robot collaboration aspects within current ontologies - what is often included contains assumptions on human behaviour or is shallow in terms of detail and description. Human-centricity is essential here. The ontology presented and described in this paper begins to classify some of the relationships between measured physiological data, cognitive and physical aspects of the human, and other classes (e.g. tasks). Metrics related to human measures such as, stress, perception, etc. are difficult to measure accurately in a concrete way that does not require self-reporting. Within the Fluently project, a Robo-training facility is envisioned which will allow human workers to become comfortable with tasks and working with robot in a safe and structured environment (Fluently, 2022). Using this approach, a database for each person trained on how they may react to certain situations can be captured to map the baselines for individual physiological sensor readings. Ongoing training before undertaking collaborative scenarios in industry can be used to determine capabilities of individual humans and gain some insight into their behaviour in certain situations. This data can be captured, clustered, and mapped within the ontology described in this paper. But it is recognised that these values will fluctuate due to human behaviour and task confidence and the ontology must be fluid to reflect this. The approach described in this paper is built on using existing ontologies but with a view to integrate human specific data to enable physiological (human) and machine data (robot) streams to co-exist and be mutually beneficial. Our structured, yet flexible approach will also ensure that we can map and add evolving human data sets (stress, health thresholds etc) as the Fluently ontology develops.

5. Conclusion and future work

In this paper, we investigated how an ontology for human-robot collaboration can be expanded to consider more in-depth human behaviour and metrics, which is key to achieving fluid working between humans and robots. The ontology design uses DOLCE and SUMO as a foundation, as these ontologies are well established and can be reused or extended further. The framework of how human attributes are represented in the proposed ontology is discussed, alongside how these affect other concepts in the system. The proposed Fluently Ontology is built based on data from specific use cases, where the idea is that it can be reused for any new situations. However, relationships may not be valid when different robots are used, or at other stages of assembly/disassembly processes, new tools are introduced etc. Therefore, the ontology will need to be continuously adapted.

Future work will comprise of developing the concepts and relationships that have been highlighted to be included to fully consider both sides of the human-robot interaction. The main aspects that will need to be developed are:

1. Potential thresholds for physiological sensors and how these can indicate cognitive and physical loads more effectively.

2. How emotions can influence the performance of different tasks and be influenced by aspects such as the robot properties and working environment.
3. Detailed safety considerations and risks for different types of tasks. Physical safety is important, but also with the integration of many sensory devices, security protocols are also required.
4. How trust and intention can play a role in collaborative tasks.

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