Towards human capability estimation to enhance human-robot team performance

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Methods

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Towards human capability estimation to enhance human-robot team performance

Abschätzung der menschlichen Fähigkeiten zur Verbesserung der Performanz von Mensch-Roboter-Teams

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Abstract: Skilled labor shortage is a prominent challenge in the world of work. Meanwhile, age-related disabilities or injury lead to at least temporary performance limitations, which make people unfit to work. Consequently, even less workers are available. By employing human-robot teams, the performance of these people may be restored. This requires a good artificial understanding of the human's capabilities, as generic robot behavior is not feasible with the highly individualized manifestations of disability. We present an approach that allows the robot to autonomously assess human capabilities based on standards from occupational medicine. The method does not only indicate the presence/absence of capabilities, but gives them a discrete rating. This allows the robot to better define its own behavior as a mixture of supportive actions based on gaps in the detailed capabilities.

Keywords: human-robot teaming; cognitive robotics; capabilities; people with disabilities

Zusammenfassung: Der Fachkräftemangel ist eine große Herausforderung für die Arbeitswelt. Gleichzeitig führen altersbedingte Behinderungen oder Krankheiten zu zumindest vorübergehenden Leistungseinschränkungen, die Menschen arbeitsunfähig machen. Folglich sind noch weniger Arbeitskräfte verfügbar. Durch den Einsatz von Mensch-Roboter-Teams kann die Leistungsfähigkeit dieser Menschen wiederhergestellt werden. Dies erfordert ein gutes künstliches Verständnis der Fähigkeiten des Menschen, da ein generisches Roboterverhalten bei den hochgradig individuellen Erscheinungsformen von Behinderungen nicht möglich ist. Wir stellen einen Ansatz vor, der es dem Roboter ermöglicht, die menschlichen Fähigkeiten auf der Grundlage von Standards aus der Arbeitsmedizin autonom zu bewerten. Die Methode zeigt nicht nur das Vorhandensein oder Fehlen von Fähigkeiten an, sondern gibt ihnen eine diskrete Bewertung. Dadurch kann der Roboter sein eigenes Verhalten besser als eine Mischung aus unterstützenden Aktionen definieren, die auf Lücken in den detaillierten Fähigkeiten basieren.

Schlagwörter: Mensch-Roboter-Teaming; Kognitive Robotik; Fähigkeiten; Menschen mit Behinderung

1 Introduction

In the verge of work 4.0 or the inherently more human-centric paradigm Industry 5.0, human-machine systems become more important to industry. However, the change back from an automation-focused paradigm to a human-centric paradigm is majorly hindered by the lack of skilled work force. In Europe, there is a large projected gap between required and available work personnel in the oncoming years, but already stretching into today, where vacant labor positions may not be filled within a year in some sectors.[1] If we further take into consideration, that the three pillars of demographic development – fertility, life expectancy/mortality, and migration – are developing poorly and, that all European countries are predicted to experience a decline in population and an excessive dependence on the ageing population [2], there appears to be no solution.

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[1] Only four European countries are able to fill in the majority of vacant job positions within three months. In Germany, 55.3 % of vacant positions can only be filled within more than three months and up to over a year (14.8 %) [1].

A major challenge in aging work population is the decline of performance and proneness to more age-related disabilities. Latter are cognitive, motor and perception limitations, with foot problems, arthritis, cognitive impairment, heart problems and vision being the most common disabilities through aging [3]. In addition, people with congenital disabilities are not yet sufficiently included in the work market, also due to insufficient capabilities. Some research has already shown that the performance of people with impaired capabilities may be raised using collaborative robotics and AI [4]–[9], but none are adaptive to a larger variety of disabilities. We do not consider the interaction or hardware design as the major driver in adaptive teaming of people with impaired capabilities and autonomous robots, but the perception of human capabilities as a measure for human performance. The continuous monitoring of human capabilities states a necessary condition to derive optimal assistance in human-robot teams. In fact, by frequent monitoring, the loop may be closed to control the team's performance as an action of the autonomous agent. This will make work places more adaptive to the needs of an ever-changing workforce and mitigate some of the consequences of the demographic change.

In this work, we introduce a framework which allows to autonomously estimate and quantify human capabilities. The framework is based on occupational standards. We discuss how the methodology may be implemented by means of Bayesian networks with the example capability *Standing*. The estimated capabilities may then be matched with process requirements in order to analyze the performance gap in only human work. From the performance gap, a robot action may be synthesized, that supports the person while raising the team's performance. We show this relation and its implications in an outlook.

First, we discuss teaming in human-autonomy systems (Section 2), showing how humans and autonomous agents interact on a shared system. We also discuss some approaches, in which people with disabilities are already supported by artificial agents, indicating a need for more adaptive assistive technology. In Section 3, we discuss human capabilities from a philosophical and occupational perspective. This later states the base to the capability estimation, which we introduce in Section 4. The framework is based on the standards "International Classification of Functioning, Disability, and Health" (*ICF*) [10] and "Integration of people with disability into work"[2] (*IMBA*) [11] and implemented by means of Bayesian networks. We show an example of the modelling of the capability *Standing*, including required input modalities and auxiliary methods in Section 4.2. Finally, we validate parts of the proposed framework in a persona-based exploration, discuss the implications of the technology – particularly on the data that is required to train the models – and give an outlook on behavior synthesis (Section 5).

2 Human-robot and human-autonomy teaming

To model an interaction between multiple autonomous and/or human agents, it is imperative to assess which agent interacts in which individual way, and how the individual interaction is embedded in the team's interaction strategy. While the autonomous agent is designed by a human engineer, who synthesizes an idea of interaction into the artificial mind, the human agent reacts intuitively in a situation, applying learned behavior within a personal and societal framework.[3] According to *Dual Process Theory* (e.g., Gawronski and Creighton [12]), the human processes information within two type of processes: Automatic data processing, i.e. fast, automatic and intuitive, and controlled data processing, i.e. slow, deliberate and analytical. Particularly, the intuition of the human is what makes the major difference between the autonomous and the human agent's interaction behavior. In the following, we focus our work on teams of a single autonomous and a single human agent. We mainly use the paradigm human-robot teaming (HRT) or human-autonomy teaming (HAT) in contrast to the similar but different paradigms human-robot collaboration (HRC) and human-robot interaction (HRI). We use a discrimination similar to Bauer, Wollherr, and Buss [13]. HRI is the generic term that includes HRC. In HRI, both agents interact with each other, although they do not necessarily benefit equally or at all. In HRC, both agents collaborate on a common task. The term HRC is not sharply defined and ranges from spatially or temporally isolated to fully symbiotic collaboration on the task, depending on the definition and level of collaboration, e.g., by Bauer et al. [14] or Helms, Schraft, and Hagele [15]. Teams are composed of a small number of partners with complementary skills, that are committed to reach a common goal through collaboration. HRT extends the HRC paradigm by high-level concepts like common purpose and shared goals, which are not necessarily required for pure collaboration.

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[2] Translated from German "Integration von Menschen mit Behinderung in die Arbeitswelt".

[3] These are also influential factors in the *ICF* standard [10] (see Section 3.2).

2.1 Human-autonomy interaction

In teams of human and autonomous agents, we consider three entities: human agent, autonomous agent, and the application. The application is the entity that is subject to shared control or shared influences of both agents. In contrast to others, we do not only consider the application to be a technical system [16], but a broader entity, also covering non-physical applications (e.g., home assistant) or processes potentially featuring non-mechanical, lifeless objects (e.g., manufacturing a part). In many domains the application is equated with the autonomous agent, whereas we understand autonomy as a feature that has a physical embodiment (see, e.g., [17], [18]), e.g., a robot or a car, through which the autonomous agent acts. This leads to a mutual split in between the two agents and the shared control system defined by the application on which the agents act. The interaction in a shared control system may be described as between the autonomous and human agent with the application as a mediator. Hence, the interaction reduces formerly to a dyad between autonomous agent and human constrained by the application. The interaction and shared action or control decision in the shared application, is mediated by means of arbitration [16]. In the legislation domain, Snijders [19] discusses a potential change from human arbitrators to "robiters" (AI arbitrators) in legal practices. He comes to the conclusion, that it is against practical law and technically impossible to hand over legal arbitration to only AI ("it would be a mortal sin" [55, p.242]). In purely technical systems, arbitration is already used either as consensual decision of human and autonomous agent [16] or by employing an AI mediator [20]. In recent work, Mandischer et al. [21] argue that it is impossible for an autonomous agent to arbitrate a decision or at all interact to find a consensus if they are unaware of the human agents capabilities – and vice versa. Figure 1 depicts an arbitration process including the initial perception of capabilities.

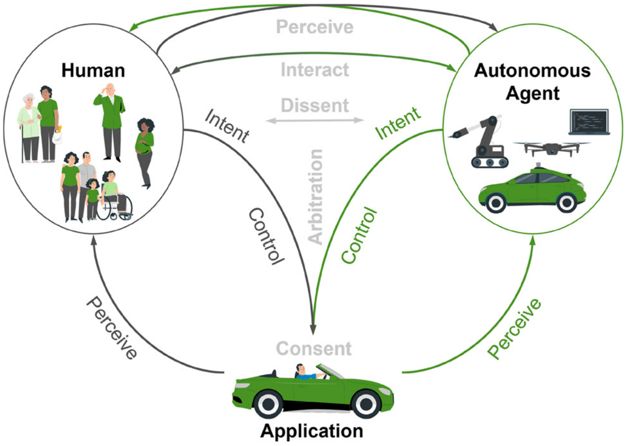

Figure 1: Arbitration between an autonomous agent and a human to control a shared application, analogous to [21]. Arbitration is solving an initial dissent of intents to a consensual control decision. To arbitrate, agents perceive the application and each other – particularly to get insights on the other's capabilities – and then interact to solve the dissent. The depicted partially autonomous car is an example for such applications subject to shared decision making. There are many other potential applications.

The interaction of the two agents is treated separately to the arbitration itself. Freire et al. [22] propose a cognitive architecture which enables adaptive HRC with the aim of seamless interaction, i.e. intuitive and organic. Seamless interaction is also strongly connected to the flow theory [23], in which the person is absorbed into the (work) task. Recently, Prajod et al. [24] and Chen et al. [25] proposed frameworks which shall allow a human-robot or human-autonomy team to reach the flow state. However, both are more on a conceptual level but indicate an improvement to modern human-autonomy teaming if implemented.

2.2 Assistants for people with disabilities

Already in 1999, Newell and Gregor [26] emphasized that it is important to consider "extraordinary" human-machine interaction (HMI) in the sense of HMI with people with disabilities[4] (PwD). In many applications, the performance of PwD may be raised by using PwD-centered systems design. They also highlighted, that PwD often develop special skills which may be exploited in customized HMI. In few applications, PwD are already assisted by autonomous agents in work processes. However, most methods address a specific type of disability or work, hence, are less or not adaptive at all. Thus, it requires expert knowledge to adopt such methods into work, which is currently lacking in the industry [27]. Mondellini et al. [8] analyze the behavior of people with autism spectrum disorder (ASD) in collaborative manufacturing processes. They observe deviant behavior patterns from neurotypical work persons, indicating a need for specialized interaction and assistance patterns. Kremer analyzes the participation of PwD in work processes through the use of robots [7] and the allocation of work [28] between them in virtual scenarios, while focusing on learning disabilities. Miralles et al. [29] describe an improvement in performance in PwD through the use of line production. The results can also be transferred to parts of the primary labor market, where processes are typically cycle time bound. Berreta et al. [4] investigate implications for the design process of human-AI workplaces, in particular needs, skills and job identity. Wilkens et al. [9] give recommendations for the

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[4] Disability as used in this work covers all kind of disabilities including congenital, acquired, and temporary disabilities.

implementation of human-AI workplaces in industry. The last two articles are part of the competence center *HumAIne*, which deals with human-centric AI in the world of work and also considers participation. Nevertheless, there is little applied research on HRC with PwD in work processes. Chutima and Khotsaenlee [30] propose a method for planning and balancing line work incorporating people with and without disabilities as well as robots. However, all agents are spatially isolated. There is no real HRC. Kildal et al. [6] use a robot in scenarios with people with cognitive disabilities to highlight components in work steps using a laser. Again, there is no direct collaboration, but the robot must be able to interpret the work context and progress. Weidemann et al. [31] assist PwD with collaborative robots in workshops for PwD. While their interaction design method is adaptive to person's individual capabilities, the implementation of the interaction is static, allowing no *in-situ* adaptation. Further, tasks are assigned to either robot or human, resulting in a non-cooperative process. To this end, the task of adaptive and seamless assistance of PwD by means of collaborative robots remains unsolved. In the following, we will showcase an improved way to design autonomous assistants: through the usage of capability estimation.

3 Human capabilities

To design a capability estimation framework it is imperative to understand the meaning and implications of capabilities. We define a capability as a modal semantic (compare Jaster [32]) that describes the ability of a person to interact with their static and dynamic environment. A capability has a quality or rating indicating the extent to which a person can exercise this capability. Each task is an agglomeration of capabilities. There are multiple perspectives that help to understand how capabilities influence the behavior of a person and how they relate to the environmental and teaming context.

3.1 A philosophical perspective

In philosophy, there exist two common perspectives on abilities: the conditional logic and the modal theory. All are more or less semantic expressions of relations between an objective (e.g., do a task) and a condition (e.g., has the ability). In teaming, philosophical analysis of abilities – or in our case capabilities – helps to understand the requirements for abilities to be present. This complements the otherwise technical approaches, we ought to implement in systems engineering. Particularly, the conditional logic helps to better understand and implement relations between capabilities and their reflectors in the actual world.

Table 1: De Finetti table according to Baratgin, Over, and Politzer [35]. The table depicts the conditional event $a \rightarrow b$.

a\b	**1**	***unknown***	**0**
1	1	*unknown*	0
unknown	*unknown*	*unknown*	*unknown*
0	*unknown*	*unknown*	*unknown*

The conditional logic centers about the logical relation “if a then b” (written $a \rightarrow b$) and its inferences used for reasoning on the terms. Conditionals enable Boolean operations and mathematical proofs [33]. However, in material conditionals, inverting the initial statement is not easily done, not only on a language and grammatical but also on a factual level. This leads to, e.g., the *paradox of material implications*: Some true statements that are intuitively false. In material conditional logic a statement is false only if within the conditional “a then b” a is true and b is false. Thus if a vacuous truth is used, i.e. a conditional of which the antecedent cannot be satisfied. Given the absence of a condition a, which is required for b to make intuitive sense, b is always true as both b and $\neg b$ exist. For example, “if someone else would have written this paper, it would be about autonomous driving”. This statement is trivially true as both possible consequents b and $\neg b$ are plausible – or true. Therefore, instead of binary conditionals, i.a. de Finetti [34] proposes trivalent conditionals, in which the state value of a and b may become unknown. In this case, “a then b” is true only if both a and b are true, and false only if a is true and b is false. All other combinations are undefined. The so-called de Finetti tables (see Table 1) are also used in Bayesian approaches to explain and explore human reasoning models [35].

Adams [36] and Lewis [37] propose two ways of dealing with probabilistic conditionals, mainly based on conditional probabilities. Adams defines the probabilistic conditional $P(a \rightarrow b)$ for the two Booleans a and b as

$$P(a \rightarrow b) = P(b|a), \qquad P(a) > 0. \tag{1}$$

In other words: the probability of the statement “a then b” is the same as the conditional probability of b given a. This means, that probabilistic conditionals are fully based in Bayesian probabilities, which will later enable them for further exploitation in our framework. Lewis further proposes a *triviality theorem*:

$$P(a \wedge b) > 0 \wedge P(a \wedge \neg b) > 0 \Rightarrow P(a \rightarrow b) = P(b), \tag{2}$$

i.e. given a compatibility of a with both consequents b and $\neg b$, the probability of $a \rightarrow b$ degrades to the unconditioned probability of b. Probabilistic conditionals are further extended to compound conditionals, which feature

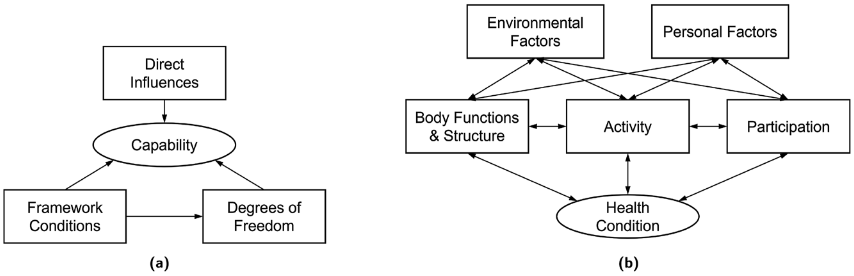

Figure 2: Influences on the human's performance according to *IMBA* and *ICF*. Arrows point in direction of influence, e.g., framework conditions influence DOFs. (a) Influences on a capability in *IMBA*. Usually a framework condition defines the opportunity for a DOF which may then be used by the work person. (b) Influences on the health condition in *ICF*. A core concept of *ICF* is that the majority of factors influence each other indicated by bidirectional influences. The model is based on the biopsychosocial model [41].

nested probabilities, e.g., $P(a \rightarrow (b \rightarrow d))$ [38]. These were also applied to de Finetti tables [33].

The modal theory is centered about the possibility of an agent to perform an action, i.e. "[…] for [an agent] x to have an ability a it is necessary, but not sufficient, that it be possible that x does b"[5] [39]. Hence, also in modal analysis, abilities are subject to possibility – or, more technical, probabilities. These are reflected by *Possible Worlds* (e.g., Stalnaker [40]). If the statement is true in any possible (i.e. thinkable) world, it is possible. The specific possible world then states an extra condition for the statement: "x has the ability to b only if x does b in some world satisfying d", where d are the conditions of the possible world that enables $P(b|a \wedge d) > 0$, and a is the ability that defines the "ability to b" [39]. The sentence states the *modal analysis of ability*. In fact, conditional logic may be coined a sub-class of the modal theory. Both may be combined into the statement: "x has the ability to b only if x does b in a world in which x tries b that is otherwise maximally similar to the actual world" [39]. The actual world is one of the possible worlds that equals the real world [40].

3.2 An occupational perspective

To give a less abstract perspective on actual work, our methodology mainly incorporates standards from occupational medicine and analysis. The *IMBA* documentation procedure [11] defines a set of 70 top-level capabilities sorted into nine categories. Some top-level capabilities have subordinate capabilities, e.g., *trunk movement* has the subordinates *rotation movements while sitting*, *rotation movements while standing*, and *bending/straightening*. Hence, capabilities are representatives of elemental abilities of the human. *IMBA* defines a scale $\{0, 1, 2, 3-, 3+, 4, 5\}$ on which the human's individual capabilities and the requirements in the work task are rated. Larger values indicate better fulfillment of the capability. If the person's capability equals or exceeds the defined requirement for each capability involved in a work task, the person is able to fill in the according job position. The distribution of values is based on the normal distribution, hence, 3− and 3+ characterize the average worker. The evaluation of a person's capabilities is depending on direct influencing factors (DIs), framework conditions (FCs), and degrees of freedom (DoF). DIs are derived from the work task and indicate mostly physical work characteristics, e.g., frequency and duration of a task. FCs indicate which opportunities for variation the work person has within the work process and DoF indicate which of these opportunities the person can utilize. These dependencies are depicted in Figure 2a. *IMBA* is used to indicate in which work tasks a person has insufficient capabilities. Therefore, it may be used to allocate tasks between the human and an autonomous agent, as demonstrated by Hüsing et al. [5]. "Capability profile for the integration of people with disabilities into work"[6] (*MELBA*) [42] is a variant of *IMBA*, which focuses on key qualifications. The documentation procedure employs a progressive scale $\{1, 2, 3, 4, 5\}$ to evaluate its 29 capabilities. Achterberg et al. [43] studied the inter-rater reliability of physicians applying *MELBA*. They observed good reliability for most capabilities. These results are also indicators for the related standard *IMBA*.

ICF is a standardized classification procedure issued by the *WHO* [10]. *ICF* is more generalist than *IMBA* and *MELBA*. It indicates how a person's performance is influenced by body functions, activities, and participation. These again, are influenced by personal factors and the environment (see Figure 2b). Therefore, *ICF* accounts for more influences

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[5] Nomenclature adjusted.

[6] From German "Merkmalprofile zur Eingliederung Leistungsgewandelter und Behinderter in Arbeit".

from indirect factors. *IMBA* is more focused on work-related influences loosing the broader scope on a person's social and societal environment, and living conditions. In contrast to *IMBA* and *MELBA*, *ICF* is open source and developing into a *de facto* standard on the classification of people with disabilities. Hennaert et al. [44], [45] proposed a matching of *IMBA* onto *ICF*, in which all physical capabilities were found to have a representation between standards. Note that *ICF* operates on a linear decreasing scale $\{0, 1, 2, 3, 4\}$, in which 0 is a regular capability and there is no indication of better then average performance. In fact, *ICF* does not declare the rating of a capability but the severity of an impairment, i.e. 0 indicates no impairment on a capability.

4 Human capability estimation

In the following, we define a framework for autonomous capability estimation and show how it may be used to model a capability. We discuss the proposed methodology along the example of the capability *Standing*. In the following, we first design the framework for the capability estimation (Section 4.1). The framework formalizes the semantic relation between aspects of both standards, *ICF* and *IMBA*, and the team performance in accordance with a robot. Second, we show an example of the modelling of the capability *Standing* (Section 4.2). The capability is modelled by means of its influences on the environment and vice-versa.

4.1 Capability framework

Both standards discussed in Section 3.2 have pros and cons regarding the estimation of capabilities. On the one hand, *ICF* defines broad influences also taking into account metadata that enriches the decision making of a potential AI method. The relation between influences and health is indicated but not described quantifiably. The more than 1,400 health indicators are too complex to properly be modelled, whereas only a subset is really relevant for capability estimation in the work context. In addition, *ICF*'s scale is incapable of modelling better than regular capabilities, which looses the nuancing in more demanding work processes. *IMBA*, on the other hand, has less, more work-focused capabilities, a more nuanced scale, and better description of the relation between influences and capabilities. However, still the majority of influences are not quantifiable and assessment is based on the experience of the occupational physician. In addition, *IMBA* is closed source, which prevents a widespread usage. Therefore, in a capability estimation model, both standards shall be combined. The lack in quantifiability, which is subject to both standards, is mitigated by the use of machine learning. We theorize, that the observed features of the target human and the rating by the occupational physician can be correlated if sufficient data is available. Hence, a machine learning method will learn to imitate the reasoning of the physician. However, we do not want to train such AI end-to-end, but use as much predetermined dependencies and influences as possible. Therefore, our aim is to combine the standards with machine learning. Figure 3 shows the semantic influences between aspects of the capability framework used for this cause. Within the semantic model, there are five main components:

Resources: The data that defines the baseline or rationale of the process and capacity. It is taken from *ICF* and indicates how the person's environment and opportunities for participation influence the framework of work. The activity indicates how motivated the person is in taking potential opportunities in the framework. Body functions is the functioning of human body parts,

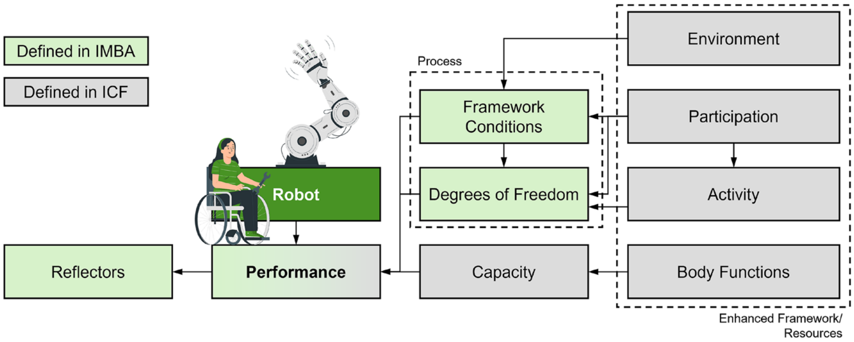

Figure 3: Capability Framework combining the *ICF* and *IMBA* standard and indicating, that the robot may influence the humans performance as part of the interaction context.

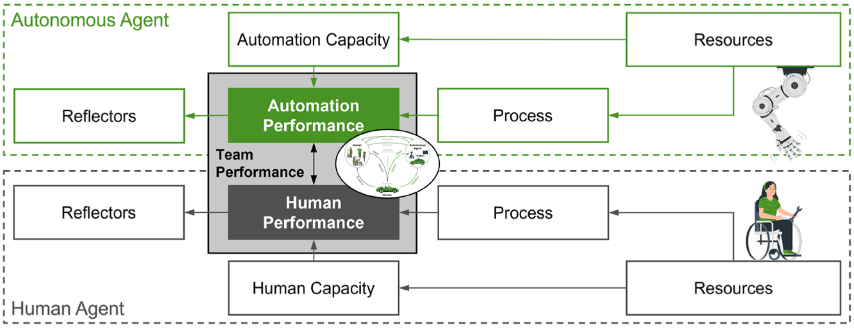

Figure 4: Influences on the agents in a teaming context. The interaction of the agents influences the reflectors. The agents interact as discussed in Section 2.1 and Figure 1.

including limbs and organs. Resources are less measurable by means of sensors, but meta-data defined prior to capability estimation.

Process: Analogous to *IMBA* as indicated in Figure 2a.

Capacity: The capability of the human isolated from any external restrictions or aids established by the interaction context.

Performance: The capability of the contextualized human under influence of external factors. The performance may be raised by using a robot as assistive device.

Reflectors: The reflectors of the human's performance within observable features by means of sensing, e.g., gait. It may be required to build chains to infer performed capabilities from observed features as not all are directly observable. For example: strength is not directly observable by means of just RGB cameras, but may be inferred from semantic object relations, human posture, or even facial expressions of stress. Note, that many reflectors are the inversion of the DIs in *IMBA*.[7]

This structure promotes an interesting observation: While the capacity is bound to the individual agent, the performance is an amalgamation of diverse contextual factors including other agents. We could now be tempted to account the performance directly to the team. However, the context defined in the process may be different for each agent. The same accounts for the resources. For example: an aid placed at a work station may not be accessible for a robot or not contribute to its capabilities. The autonomous agent will also not be subject to societal factors regarding the use of aids and, particularly, not peer-pressured into, e.g., refraining to use aids. On the contrary, once we define another agent as part of the context, the performance is not separable for the agents anymore. It is possible to assess the ratio of contribution put into the shared performance [16], [21], but the outcome is the performance of the team. Thus, if we apply the structure in Figure 3, we need to account for contextual influences (process and resources without influences on capacity) of both agents, but indicate a shared performance. This interaction symbiosis is depicted in Figure 4. The reflectors observed from the team performance are separable by agent, but influenced by the context. Hence, it will be hard to assess isolated human capabilities in case, that the robot is already part of the shared action, as it influences the observed data. In addition, in a team the individual agents may take back their individual performance and act less than possible based on their capacity [21].

4.2 Bayesian modelling of capabilities

In the following, we use the notation c_j for a capability, where j refers to a specific capability according to a standard, e.g., $c_{1.02}$ is the second capability in the first category of the *IMBA* standard, i.e. *Standing*. Capabilities are closely connected to capacity (person isolated from context) and performance (person in context) according to the *ICF* standard (see Section 3.2). We, define the quantification of a capability, i.e. the rating of the capability according to an agent, as capacity c^i_j or performance $\hat{c}^i_j$, accordingly. The specific agent is denoted by the superscript i. Based on the framework introduced in Section 4.1, we show the example modelling of the capability *Standing*. Table 2 lists all capabilities in the complex "body posture" according to the *IMBA* handbook [11], including their FCs, DoF, and DIs. The capability *Standing* is denoted $c_{1.02}$. Other capabilities are listed to give a better grip on the differences within a capability complex.

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[7] In *IMBA*, DIs are process requirements put on the human, e.g., a duration in which a part shall be manufactured. In the inversion, the reflector is the duration the human really takes to manufacture the part, which may be different from the process requirement, either faster or slower.

Table 2: Semantic relation of capabilities and influences in the complex body posture as defined by *IMBA*. Some influences are not equal for different capabilities even though they are agglomerated in the same row, e.g., the duration and frequency are capability-specific.

	Influence	1.01	1.02	1.03	1.04	1.05	1.06
01	Activity-related fixation of the posture	FC	FC	FC	FC	FC	
02	Activity-related posture changes	FC	FC	FC	FC	FC	FC
03	Activity-related posture variation	FC	FC	FC	FC		FC
04	Activity-related shift of the body’s center of gravity from the vertical body axis		FC				
05	Additional forced posture of the hands/fingers or head						FC
06	Partially without visual control of the activity						DoF
07	Condition of the floor space		FC	FC			
08	Condition of the lying surface				FC		
09	Condition of objects						FC
10	Condition of the seating	FC					
11	Duration	DI	DI	DI	DI	DI	DI
12	Energy effort						DI
13	Extra loads					DI	DI
14	Frequency	DI	DI	DI	DI	DI	DI
15	Inclination angle of torso					DI	
16	Initial position, joint position(s)					DI	DI
17	Leverage effect					DI	
18	Movement space or area	FC	FC	FC	FC		DoF
19	Option for flexible arrangement of work equipment	DoF	DoF				
20	Option of posture variation	DoF	DoF	DoF	DoF		DoF
21	Option to change posture	DoF	DoF	DoF	DoF	DoF	
22	Option to lean or support the body or parts of the body		DoF	DoF		DoF	FC
23	Option to stabilize the torso						DoF
24	Presence of aids		FC	FC			
25	Prone, side or supine position				DI		
26	Type of arm posture						DI
27	Type of footwear		FC				
28	Working Height						FC

$c_{1.01}$: Sitting, $c_{1.02}$: Standing, $c_{1.03}$: Kneeling/Crouching, $c_{1.04}$: Lying, $c_{1.05}$: Bent over/Stooped, $c_{1.06}$: Arms in Compulsory Posture.

In contrast to how Bayesian reasoning is usually used, we neither try to find a state on the start or end of a chain, but an intermediate state within the Bayesian network (see Figure 3). The graph is composed of nodes representing features, capabilities, and resources. Capability nodes carry seven states $0, 1, 2, 3-, 3+, 4, 5$ according to *IMBA*. The states of other nodes depend on the specific node type. Most are binary with annotated unknown state, i.e. $\{1, \mathit{unknown}, 0\}$. For such extended binary nodes, the probability tables from capability philosophy are applicable. These define the transition of inputs to outputs. Given the state X_{k-1} of the predecessor node n_{k-1}, node n_k may be assigned a value X_k based on the de Finetti table (see Table 1), where X_k is the value of node k. Assume the conditional $X_{k-1} \rightarrow X_k$ or $X_{k-1} \rightarrow \neg X_k$ as a defined precondition, then the probability according to de Finetti with unknown state is

$$P(X_{k-1} \rightarrow X_k) = \begin{bmatrix} 1 & 1/3 & 1/3 \\ 0 & 1/3 & 1/3 \\ 0 & 1/3 & 1/3 \end{bmatrix} \mathbf{X}_{k-1}, \tag{3}$$

$$P(X_{k-1} \rightarrow \neg X_k) = \begin{bmatrix} 0 & 1/3 & 1/3 \\ 0 & 1/3 & 1/3 \\ 1 & 1/3 & 1/3 \end{bmatrix} \mathbf{X}_{k-1}, \tag{4}$$

where $\boldsymbol{X}_k$ is the vectorized form of the most probable state, i.e.

$$\mathbf{X}_k = \begin{bmatrix} P(x_k = 1) > \max(P(x_k = \mathit{unkn.}), P(x_k = 0)) \\ P(x_k = \mathit{unkn.}) \geq \max(P(x_k = 1), P(x_k = 0)) \\ P(x_k = 0) > \max(P(x_k = 1), P(x_k = \mathit{unkn.})) \end{bmatrix}. \tag{5}$$

For example: to have an option to support the body weight, an aid needs to be present (compare influences 22 and 24 on $c_{1.02}$ in Table 2). Therefore, we can define the precondition $X_{i_{24}} \rightarrow X_{i_{22}}$, read “if aids are present, then there is an option to lean or support the body or parts of the body”. If no other influences on $X_{i_{24}}$ are present, the conditional probability $P(X_{i_{22}} | X_{i_{24}})$ of the precondition is according to Equation (3). Defining parts of the graph this way lowers the overall number of parameters to be trained, with the

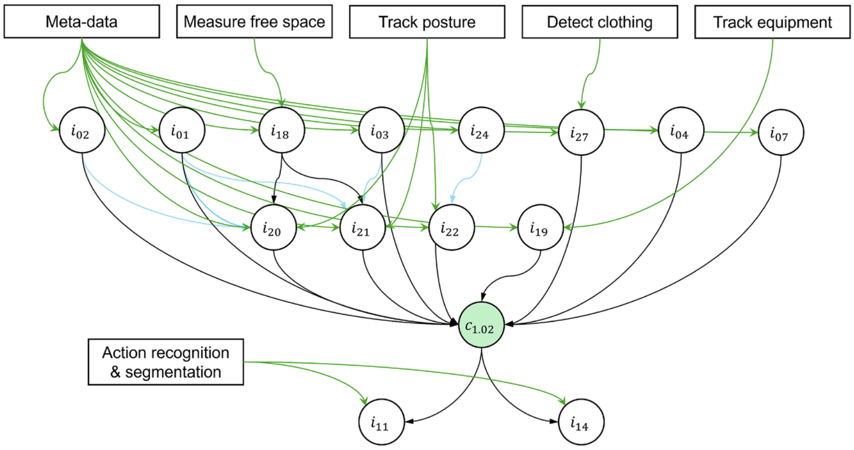

Figure 5: Bayesian network of capability $c_{1.02}$ (*Standing*) based on the semantics depicted in Table 2 including input modalities (meta-data and perceived/processed sensor data). Circles depict nodes, rectangles are input data. Flat-back arrows are influences pointing from source to effect. Blue flat-back arrows are de Finetti-style influences. Green acute-back arrows are data streams from sensors, input models, or process meta-data to nodes. Nodes ordered by FCs, DoF, capability, DIs as reflectors (top-down).

downside that these parts need to be defined beforehand and become static. In addition, this is only applicable on binary nodes. In case that the binary node does not carry an *unknown* state, the probability of the *unknown* state is divided among the 1 and 0 states. However, we advise against removing the *unknown* state as this would implicate a system without uncertainties despite being subject to uncertainty internally (e.g., within the parameters) and externally (e.g., sensors, learning data).

4.2.1 IMBA components

Purely based on the dependencies described in the *IMBA* handbook [11] (see Table 2), it is possible to construct a Bayesian network for a capability. As indicated in Figures 2a and 3, framework conditions influence the capability, a DoF, or both. Likewise, reflectors[8] influence the capability directly. Missing influences are supplemented through logical reasoning, e.g., we argue that the movement space (i_{18}) has significant influence on posture variations (i_{20}) and changes (i_{21}). If the movement space degrades, there are fewer options for different postures while standing. The strength of the influence is learnt in the form of the conditional probabilities within the Bayesian network. We also model the input modalities that are needed to measure or estimate the state values within the nodes. Note that a state value may be unknown and can be inferred within the Bayesian network if sufficient other states are known. The modelled input modalities indicate one option to set the state values. For some states there are multiple options. We choose the modalities in hindsight of using fewest sensors and with an optical camera as main sensor. Figure 5 depicts the model of the capability *Standing*. All FCs and DoF are subject to meta-data. Some nodes' state values may be measured as an additional modality or as an alternative data source, e.g., movement space may be taken from the work documentation or a CAD, or be measured *in-situ* by a (3D) camera. Feeding all DoF and FCs with only meta-data is not reasonable, as this would result in a rather static model, which may be completely unable to detect dynamic capability changes. Reflectors are typically not enriched by meta-data as they tend to change more rapidly than FCs and DoF. For example: a person refraining from using an aid is a slow process compared to fast changes in the duration of a (partial) work task. In prior work, Mandischer et al. [46] modelled this aspect as a Langevin system, in which the uncertainties of the slow system are superimposed by the fast system part. Similar behavior is expected here. As the chains to the fast part (i.e. reflectors) are shorter, less uncertainty is expected due to error evolution. Consequently, the fast system has less intra-model uncertainties. Combined with the Langevin system properties, this may help to reduce the overall uncertainty in the model, i.e. by modelling the fast part with uncertainties, while the slow part is subject to less or no uncertainties in the model.

In $c_{1.02}$, many influences are binary with annotated *unknown* state: i_{01}, i_{02}, i_{03}, i_{04}, i_{19}, i_{20}, i_{21}, i_{22}, i_{24}. The other nodes may be characterized by discrete sets or discrete

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[8] The direction of influence between capabilities and reflectors may be unintuitive. However, let us consider a person has a limited capability of *Standing*. This will effect the continuous duration the person can stand, hence, lowering the observable duration (i_{11}) in the reflector. Therefore, the capability influences the reflector and not vice versa.

Table 3: Types of nodes used for modelling capability $c_{1.02}$, annotated with the suggested number of state values and the configuration used later in the exploration (Section 5.2). Binary nodes are extended by an *unknown* state, range nodes carry ranges of continuous values split into ≤7 categories, and discrete nodes have a pre-defined set of discrete/qualitative values.

	Suggestion		Exploration			Suggestion		Exploration	
Node	**Type**	s_k	**Type**	s_k	**Node**	**Type**	s_k	**Type**	s_k
i_{01}	Binary	3	Binary	3	i_{18}	Discrete	3	Discrete	3
i_{02}	Binary	3	Binary	3	i_{19}	Binary	3	Binary	3
i_{03}	Binary	3	Binary	3	i_{20}	Binary	3	Binary	3
i_{04}	Binary	3	Binary	3	i_{21}	Binary	3	Binary	3
i_{07}	Discrete	≤7	Discrete	3	i_{22}	Binary	3	Binary	3
i_{11}	Range	≤7	Discrete	4	i_{24}	Binary	3	Binary	3
i_{14}	Range	≤7	Discrete	4	i_{27}	Discrete	5	Discrete	3
$c_{1.02}$	*IMBA* capability			7					

ranges (i_{07}, i_{11}, i_{14}, i_{18}, i_{27}). While i_{07} and i_{27} are categorized according to the subject, e.g., i_{27} according to the categories in ISO 20345:2021 [47], and i_{18} may be categorized in $\{none, limited, unlimited\}$, i_{11} and i_{14} need to be categorized into value ranges. These ranges are dependent on the capability and task as the time scales may vary harshly. Optionally, these ranges may be converted in qualitative ranges, e.g., $\{slower, on\,par, faster\}$. An overview of node types and number of state values is listed in Table 3. We also annotated the configuration used in the exploration in Section 5.2. The categories shall be selected as detailed as needed, but as few as possible. A reasonable count shall be lower than the categories of the capabilities (here: $s_{c_{1.02}} = 7$). This means, that in the suggested case, the node $c_{1.02}$ already requires a conditional probability matrix $P(X_{c_{1.02}} | X_{i_{01}}, X_{i_{02}}, X_{i_{03}}, X_{i_{04}}, X_{i_{07}}, X_{i_{19}}, X_{i_{20}}, X_{i_{21}}, X_{i_{22}}, X_{i_{27}})$ with the size $(7 \times 229,635)$ as there are

$$\prod_{k \in N^-(n_{c_{1.02}})} (s_k) \leq 229,635 \tag{6}$$

permutations for the predecessor nodes' (N^-) state values. However, these may be evaluated with only

$$\sum_{k \in N^-(n_{c_{1.02}})} (s_k) \cdot s_{c_{1.02}} \leq 252 \tag{7}$$

parameters, which is the agglomerated size of each individual conditional probability matrix $P(X_{c_{1.02}} | X_k)$, where $k \in N^-(n_{c_{1.02}})$. This shows that a Bayesian network analyzing only one capability[9] may be trained with reasonable training data, but a network analyzing multiple capabilities simultaneously may fastly become very complex and demanding to train. Note, that we are interested in an intermediate state (capability). This state's value has to be inferred.

4.2.2 ICF components

We have not yet included aspects of *ICF* into the Bayesian network. Features in *ICF* may help to overcome some of the limitations of the pure *IMBA*-based reasoning. If we would only base the estimation of the DoF states on the de Finetti influences, the network would assume that, e.g., if an aid is present, the human would always use it. This is a flaw in deterministic modelling as already pointed out in Section 3.1. The motivation of the human to use the opportunity of using an aid is part of the activity (i.e. motivation) in *ICF* and may be modelled accordingly. However, the standard does not indicate a quantifiable way to assess the activity of a person. This aspect needs to be learned as part of the conditional probability within the according influence. The need to model and compute motivation in a quantifiable manner has already been discussed in literature [48]–[50]. Vijayaraghavan and Roy [51] propose a transformer-based network to track mental states in a conversation which is trained with weakly annotated data. We consider the motivation in a work task to be detectable by means of another language than vocalization: the observable human behavior. If the motion of the human body is considered the semantic language of capabilities including mental states, it is reasonable to use transformer or GPT (generative pre-trained transformer) models to detect states such as the activity or motivation within a work task. The activity may then be considered as the resource that allows a human to take opportunities and manifest their capacity (see Figure 3). Figure 6 depicts the adaptation of one chain in Figure 5 towards *ICF*. We have omitted other chains for the sake of clarity. The participation is not directly measurable but input by means of meta-data, e.g., from the work

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[9] We have only shown the size of the largest matrix in the network. We also need to account for the influences between the nodes $n_{k \neq c_{1.02}}$ which are of significant smaller size.

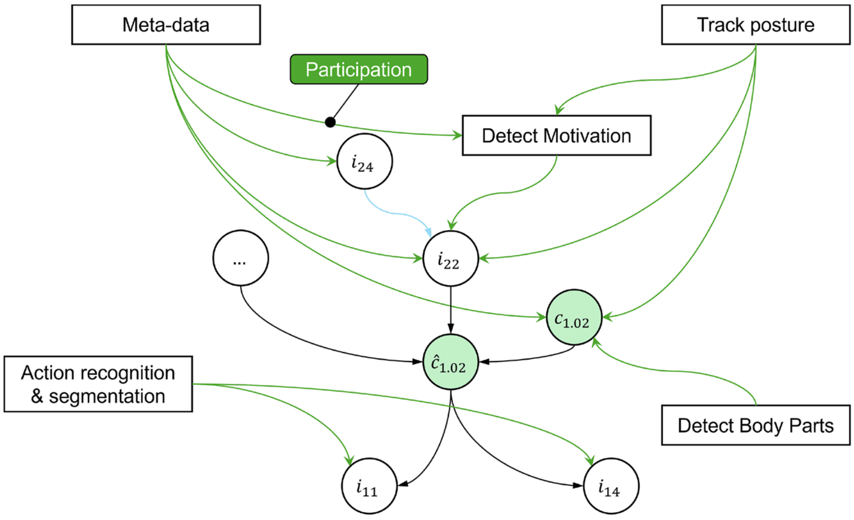

Figure 6: Adaptation of the Bayesian network for $c_{1.02}$. The depiction focuses on the influences on $c_{1.02}$ and nodes $n_{i_{22}}$ and $n_{i_{22}}$. The additions cover the *ICF* resources participation, activity, and body functions. $c_{1.02}$ is the capacity, while $\hat{c}_{1.02}$ is the performance.

documentation or legal documents. The motivation is detected based on the body movement as reflector. The participation hereby is a major influence, as it would otherwise be unclear if the person does not want to, or is not allowed or unable to partake in the work task. The capacity $c_{1.02}$ is based on the isolated individual. Therefore, only meta-data on the person (e.g., from initial medical examinations), the presence body parts (e.g., missing limbs), and the body movements (e.g., limping) is required to assess the capacity. The capacity again is the baseline to the performance $\hat{c}_{1.02}$ (individual in context), which influences the reflectors. It becomes obvious that *ICF* adds a new level of complexity on (a) the network itself and (b) the methods generating the input for the network. However, particularly the introduction of capacity leads to less variance in the network leading up to the performance. Further, the addition of motivation gives the DoF better clues on the nature of the person's behavior in taking opportunities. This may later be an effective tool to perform diagnostics on the Bayesian network. The Bayesian network's property to infer state values gives the method more transparency, which is a required feature if the networks shall be used in a medical product or together with a human.

5 Towards the validation of the capability estimation framework

We have presented the methodology on how capabilities may be estimated based on suitable sensor data and according machine learning algorithms. In order to train the methods, we need training data that is not readily available. At the moment this establishes a barrier that cannot be overcome without significant effort, potentially over multiple years. Therefore, we cannot present a full validation of the algorithms in this work. However, in the following we, first, show the challenges in collecting and working with *IMBA* data (Sections 5.1.1). Next, we partially validate the method in form of a qualitative analysis based on the persona method (Section 5.2). Lastly, we give an outlook on how the capability estimation may be integrated in human-robot teaming to facilitate assistive action (Section 5.3).

5.1 Challenges in data collection

There are two main data-related challenges when working with the *IMBA* standard: the availability of data and the quality of data. We discuss both aspects in the following and give an example for the basic population required in the Bayesian network.

5.1.1 Training data

As discussed in Section 4.2.2, to train a Bayesian network manifold data are required. These data are not readily available as there exist virtually no data sets that cover the behavior of people with varying capabilities. There exist specialized data sets on various expert motions, like dancing [52], which would qualify for higher than regular capabilities. Further, there exist data sets on medical diagnosis, including rated capabilities but using other standards than *IMBA* or *ICF*, e.g., of people with communication and intellectual disabilities [53]. There is a good overview of accessibility data sets in [54]. However, some usable data is available for specific disabilities featuring either image, motion, or video data. *IncluSet* [55] provides a good overview of these. For motor disabilities (or disabilities that influence the motor system), *IncluSet* lists reasonable[10] data of Parkinson's disease and ataxia [56]–[58], stroke-related disabilities [59], and dementia [60]. None of these are published together with capability profiles, but these could be added by occupational experts. Hence, the latter are the most promising to build a training data set, but additional data is necessarily required. It is reasonable to assume that the limited available data may already be feasible to train a reduced capability estimation algorithm for a single capability. There are capabilities with less influences than *Standing* in *IMBA*, e.g., "crawling" ($c_{2.03}$) has four DIs, three FCs and three DoF, but which are less relevant for common work processes. Consequently the medium-term availability of a proof of concept is realistic but challenging. To train a capability estimation method for all capabilities involved in a work task, however, is not feasible with the data at hand. There is major effort required to collect and curate the required amount of data.

To craft a good training data set a large variety of different limitations and their severity would need to be depicted. Most disabilities do not occur isolated in people but as part of a disability complex, in which each disability might be of varying severity. An interesting approach would be to target participants in rehabilitation as they usually do not have multiple disabilities. However, this target group is focused on specific disabilities, which would then require much more data to depict all required disabilities and severity. By using combinatorics, it might be possible to reduce the number of data required, given people with multiple disabilities. As combinations of disabilities may lead to completely different behavior, we expect manifold outliers, which are hard to tackle with fewest samples. Further, to find participants with fitting combinatorial disabilities or complementary capabilities to the required extend seems virtually impossible. Consequently, there is a distinct balance between amount of data and depicted variety of disabilities that needs to be considered during data collection and curating. We expect some ratings in specific capabilities to be reconstructable through the machine learning approach without a need to be present in the training data.

5.1.2 Bias in capability profiles

Bayesian networks, besides data on the dependencies within the network, require a statistical population within the state to be inferred (here: the capabilities). These are generated from *IMBA* capability profiles. These are, again, generated by occupational experts. However, as *IMBA* and similar standards are rather subjective, there is a certain variance between evaluators. Further, *IMBA* profiles are made in relation to a work process. When testing people according to *IMBA*, tests become increasingly time-consuming. Therefore, an occupational physician commonly starts with the easier tests and if the worker is successful, they employ more elaborate testing. If there exist no relevant work processes that require a higher capability rating, the evaluator may choose to not test for it. For example: if there are no processes requiring a 4 or higher in a specific capability, it is sufficient to test for 3+ and lower to cover all possible work positions for the worker. This results in distorted populations. Figure 7 depicts a basic population for $c_{1.02}$ computed from 290 samples.

The samples are taken from a rehabilitation clinic and feature individuals from diverse companies at the end of their stay. The data was generated as part of the rehabilitation process. The publication of the data is in accordance with the data owner. While the population approximates the normal distribution reasonably well, 3− is overpopulated compared to 3+. Further, there are no samples in the 0 and 5 categories. The former is expected, as the data covers mostly people who shall be reintegrated into work. However, this highlights an issue in data collection: Usually capability profiles are made in situations where an impairment is expected (e.g., rehabilitation) or when employing people with disabilities. Both groups lead to a left shift in the normal distribution and violate the *IMBA*

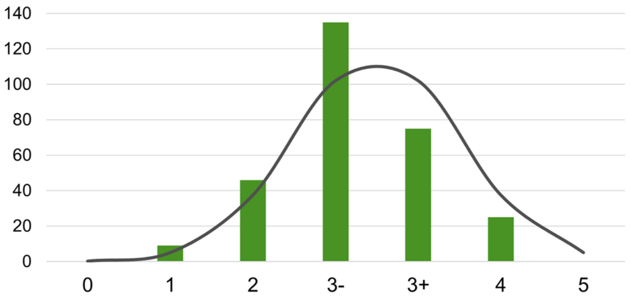

Figure 7: Population for capability $c_{1.02}$ compared to a normal distribution with $\mu = 3$ and $\sigma = 1$ scaled to the sum of samples $n = 290$ (lines interpolated). Samples taken from a rehabilitation clinic covering people from different companies, focused on manual labor. Data from multiple evaluators.

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[10] In the sense of our methodology, reasonable data require at least optical 2D or 3D data of human motion or behavior, or a digital representation thereof (pose data).

assumption of capability ratings being distributed according to the standard normal distribution (c.f. Section 3.2). In addition, the extended scale[11] in *IMBA* is comparably new, with 3 being the old mean. In the new scale, 3− is the "aesthetic" mean, i.e. the center value of a septet, which may promote the usage of 3− instead of 3+. In conclusion, we will (a) require more and more diverse data to build a good estimate on the statistical population – potentially also capability profiles generated explicitly on regular work personnel – and (b) cover a wide range of applications, particularly also featuring the ratings 0 and 5.

5.2 Persona-based exploration

Due to the reasons stated in Section 5.1, there is no sufficient real data available to train our methods, yet. Training the network on artificial and/or simulated scenarios would just validate the functioning of the Bayesian network, but not the applicability of the method in real scenarios. Therefore, we refrain from validating the end-to-end Bayesian network on artificial data, but we still want to validate some core aspects of the methodology: the input modalities, the applicability of de Finetti influences, and the interconnection of the influences towards the capability (here: for *Standing*). We see the exact Bayesian network in Section 4.2 as an example of how the general methodology and architecture is applied. The capability *Standing* is interchangeable by any other capability in *IMBA*. To give a qualitative validation of parts of the methodology, we use a persona-based exploration, which is discussed in the following.

5.2.1 Method, personas, and work process

Personas are stereotypical representations of people, typically used for systems and interaction design with a focus on marketable value (e.g., Pruitt and Grudin [61]). We design our personas to depict people with idealized limitations or improvements (relative to the average person) based on traceable health conditions or personal background, e.g., a person after stroke rehabilitation. All personas are evaluated using the *IMBA* standard and influences according to Section 4.2.1 are quantified based on the personas' backgrounds. As work process, we choose the operation of a lathe. The process is demanding on the capability *Standing*, as only few posture variations are possible and as it requires the worker to stand for longer periods. The exact personas and the work process are described in Table 5 in the appendix.

We use two variants of the work process. In variant 1 (V1), aids are available. This eases the work process, requiring only a capability of 3−, which could arguably be lowered to 2 given the type of aid. In variant 2 (V2), no aids are offered. This raises the *IMBA* requirement to 3+. To analyze certain aspects of the Bayesian network, we use synthesized data of the measurable and pre-determinable (meta-data) state values for all personas within the given variants of the work process. The according state values are listed in Table 4. We assume that all actions of the worker are fully observable. In case of persona 8, who is paraplegic, the process is not accessible. Hence, we define the DoF as *unknown* and the reflectors as 0.

5.2.2 Findings

Due to the structure of *IMBA*, most influences are derived from the FCs, which are determined by the process. Therefore, many influences are directly derived from the process parameters and there are only few influences which are allocated *in-situ*. As already indicated by the Bayesian network in Figure 5, only the reflectors i_{11} and i_{14} are not influenced by meta-data. Hence, they are the only fully dynamic measures. We can deduct, that the FCs will set a range in which the performance is located most likely. From the data in Table 4, some personas have equal state values compared to the process. This is also mirrored in the equilibrium of performance and requirement (compare V1 and P1, P2, P3, P4, P7). This suggests, that the range span by the FCs is centered about the process requirement. From the range set by the FCs, the agents may vary in form of the DoF and their acted behavior observed in the reflectors. The number of dynamic influences gets even lowered if FCs indicate absence, e.g., the absence of aids ($i_{24} = 0$) in Table 4b also voids the option to use aids ($i_{22} = 0$). We can conclude, that only few influences determine the exact performance and the majority indicate the rough range of potential performance ratings. This aspect highlights the Langevin property of the system (see Section 4.2.1).

As indicated by persona 8, people who cannot participate in the work process appear as anomaly. This indicates that their capability is too low to even solve the process with a significant impact on the reflectors, e.g., in a much longer duration. We assume, that such an anomaly is always equivalent to $c_j^i = 0$, as a $c_j^i = 1$ would usually allow a person to participate with significant limitations. Thus, anomalies should be easily identified by the Bayesian network or filtered out with a high-level anomaly detection.

In the exploration, there are two individuals (P5 and P6) which refrain from using aids despite their availability. When applying solely the de Finetti influences, this

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[11] $\{0, 1, 2, 3-, 3+, 4, 5\}$ (new) compared to $\{0, 1, 2, 3, 4, 5\}$ (old).

Table 4: State values for the Bayesian network in Figure 5 based on the eight personas and the process of lathe operation.

(a) Process with aids available

Node	Ratings	V1	P1	P2	P3	P4	P5	P6	P7	P8
i_{01}	Binary	1	1	1	1	1	1	1	1	1
i_{02}	Binary	1	1	1	1	1	1	1	1	1
i_{03}	Binary	1	1	1	1	1	1	1	1	1
i_{04}	Binary	1	1	1	1	1	1	1	1	1
i_{07}	{Major, minor, no} disturbances while moving	no	no	no	no	no	no	no	no	no
i_{18}	{No, limited, unlimited} movement space	lim.	lim.	lim.	lim.	lim.	lim.	lim.	lim.	lim.
i_{24}	Binary	1	1	1	1	1	1	1	1	1
i_{27}	{Insufficient, uncomfortable, comfortable}	comf.	comf.	comf.	comf.	comf.	comf.	comf.	comf.	comf.
i_{19}	Binary	0	0	0	0	0	0	0	0	unk.
i_{20}	Binary	1	1	0	1	1	1	1	1	unk.
i_{21}	Binary	1	1	0	1	1	1	1	1	unk.
i_{22}	Binary	1	1	1	1	1	0	0	1	unk.
i_{11}	{0, less, at par, longer}	at par	at par	less	less	less	at par	longer	at par	0
i_{14}	{0, more, at par, less} breaks	at par	at par	more	more	more	at par	less	at par	0
$c_{1.02}$	{0, 1, 2, 3−, 3+, 4, 5}	3−	3+	2	3−	3−	3+	4	3+	0

(b) Process without aids available

Node	Ratings	V2	P1	P2	P3	P4	P5	P6	P7	P8
i_{01}	Binary	1	1	1	1	1	1	1	1	1
i_{02}	Binary	1	1	1	1	1	1	1	1	1
i_{03}	Binary	1	1	1	1	1	1	1	1	1
i_{04}	Binary	1	1	1	1	1	1	1	1	1
i_{07}	{Major, minor, no} disturbances while moving	no	no	no	no	no	no	no	no	no
i_{18}	{No, limited, unlimited} movement space	lim.	lim.	lim.	lim.	lim.	lim.	lim.	lim.	lim.
i_{24}	Binary	0	0	0	0	0	0	0	0	0
i_{27}	{Insufficient, uncomfortable, comfortable}	comf.	comf.	comf.	comf.	comf.	comf.	comf.	comf.	comf.
i_{19}	Binary	0	0	0	0	0	0	0	0	unk.
i_{20}	Binary	1	1	0	1	1	1	1	1	unk.
i_{21}	Binary	1	1	0	1	1	1	1	1	unk.
i_{22}	Binary	0	0	0	0	0	0	0	0	unk.
i_{11}	{0, less, at par, longer}	at par	at par	less	less	less	at par	longer	at par	0
i_{14}	{0, more, at par, less} breaks	at par	at par	more	more	more	at par	less	at par	0
$c_{1.02}$	{0, 1, 2, 3−, 3+, 4, 5}	3+	3+	2	3−	3−	3+	4	3+	0

dependency would be impossible as the availability of aids would inevitably lead to their usage. In the Bayesian network, the node is also influenced by meta-data. However, with just the modelling of Figure 5, meta-data is not necessarily sufficient to solve this issue. In the model also featuring *ICF* components (see Figure 6), this challenge is mitigated by also evaluating motivation. Here, the detection of motivation degrades to a binary decision between the static influence modelled in the de Finetti influence and its inversion through a lack in motivation (or theoretically, vice versa). Thus, a well defined algorithm to detect motivation is imperative for the proposed method.

Table 4a emphasizes the importance to differentiate between capacity and performance. Note, that *IMBA* as performed by an occupational physician usually evaluates the capacity of the worker. Many personas (P1, P5, P6, P7 in V1) will act less in the work process than their potential capacity. It is questionable whether the deployment of these personas in the work process is reasonable, given they may feel under-challenged. In this case, it would also be suitable to model an influence from the difference of capacity and requirement onto the motivation. However, this is not easily modelled in a Bayesian network, as it would cause a loop within the graph.

An interesting observation is, that i_{11} and i_{14} are essentially an inversion while evaluating *standing*. If a person stands for a longer period, they will inevitably take fewer breaks. Hence, there are only three feasible combinations of $(i_{11}, i_{14}) \in \{(\mathit{less}, \mathit{more}), (\mathit{at\ par}, \mathit{at\ par}), (\mathit{longer}, \mathit{less})\}$. Given that there is also not much variance within the DoF

(i_{19}, i_{20}, i_{21}, i_{22}), we may come to two conclusions: (1) The evaluation problem is under-defined and the network will only produce similar capability estimates. This would indicate that nodes and influences are missing, potentially reflectors. (2) The model is too complex given the simple capability *Standing* and the variance of options degrades as a consequence of the over-determined system. As the state values for each agent compared to the process seem reasonable, we assume that the system degrades. However, we cannot easily reduce the dimension of the problem, as the FCs are needed for the range of potential performance ratings and the other influences seem just sufficient to depict the variance within the *IMBA* scale. In fact, there are just 243 state combinations in Table 4a and 81 in Table 4b. It is questionable whether less combinations are sufficient to approximate the population shown in Figure 7.

5.2.3 Limitations and discussion

The significance of the exploration is limited as we can only discuss qualitative characteristics of the Bayesian network. The influences and structure of the Bayesian network originate from our framework and the underlying standards *IMBA* and *ICF*. Therefore, qualitative characteristics analyze the feasibility of the framework and quantitative characteristics validate the conditional probabilities and estimation quality of the Bayesian network. Since we want to make a statement about our proposed framework and its usage in Bayesian networks, we consider the findings of the persona-based exploration to be of satisfactory informative value.

The findings of the exploration indicate, that the de Finetti influences are feasible in scenarios with purely static conditionals. In scenarios with a real decision value, e.g., the usage of aids, de Finetti influences may function as an indicator of the desired option, but cannot model the decision by the human. This is also not possible when only considering meta-data and no influences from other *IMBA* capabilities as modelled in Figure 5. Thus, in case of the motivation as additional factor in decision making, we either have to model the activity/motivation according to *ICF* as demonstrated in Figure 6, or model the capability together with other *IMBA* capabilities from the complex *Key Qualifications*, that allow to assess mental capabilities. Note, that there is no singular capability that can be equated with activity in the sense of *ICF*, but there are multiple candidates depending on the context, e.g., *Drive* ($c_{9.01}$), *Attention* ($c_{9.04}$), [mental] *Stamina* ($c_{9.05}$), or *Tolerance of Failure* ($c_{9.14}$). We observed diverse features of our modelling approach in the exploration: the division into performance and capacity, the importance of motivation, the structural influences of FCs, and the interdependence of capability and process. Therefore, we conclude, that based on the findings in the exploration, the structural approach proposed in this work is feasible.

In application, the methodology may be limited by two factors: The availability of training data and the adaptability of the Bayesian network. On the one hand, we assume that there is sufficient motivation in the industry and in rehabilitation centers to provide the data, but the recording of data will take significant time and effort. While no training data is available, the validation of our estimation methods will remain incomplete to some degree. This also indicates a need for methods to generate artificial training data (which would also need to be validated against real data of human behavior), which is part of ongoing research. However, once data is available, we foresee a significant impact not only on our research but also on the research community, as similar data is virtually not available to this day. On the other hand, the modelling of the capabilities in form of Bayesian networks with a rather strict influence graph is majorly dependent on the quality of the underlying standard in the application of capability estimation. Note, that all standards discussed in this work are used for generating a capability profile of the current capabilities of a person. The matching of the capability profile with a process profile is then performed by an occupational expert, who may decide to also test the person in processes that are unsuited on paper, but are subject to uncertainty. This uncertainty is not directly modelled within the Bayesian network, which gives a sharp estimate with annotated probability. The standards themselves were not made for our application. In addition, there may exist states and influences that are not (yet) considered by the standards and may, therefore, not be modelled within the Bayesian network. This may lower the estimation quality of the network. We conclude from this, that a system designer shall not only rely on the standards, but should be enabled to add auxiliary nodes in the Bayesian network, if they contribute to the estimation quality. To allow the assessment of estimation quality, data is missing.

5.3 Outlook on capability-based autonomous teaming

In recent work, Mandischer et al. [21] introduced the concept of capability deltas, that offer a quantifiable source to assess the gap between a human's individual performance and the fulfillment of task requirements r_j^k. This results in an n-dimensional vector $\mathbf{\Delta}^{i,k}$ of individual deltas $\delta_j^{i,k}$, where j is the capability, k the task identifier, and i is a specific person. The objective of teaming is now to minimize the vector norm

$$\|\boldsymbol{\Delta}^{T,k}\| \rightarrow 0 \tag{8}$$

by applying any norm. The team delta is subject to capability-individual agglomeration rules

$$\boldsymbol{\Delta}^{T,k} = \boldsymbol{r}^k - \hat{\boldsymbol{c}}^T, \tag{9}$$

$$\hat{\boldsymbol{c}}^T = (f(\hat{c}^i_j, \hat{c}^A_j))_{j \in \boldsymbol{B}^k}, \tag{10}$$

where $\boldsymbol{B}^k$ is the index set of relevant capabilities in a task and superscript A and T refer to the automation and team, accordingly. Note, that task fulfillment may be reached by different combinations of capabilities, e.g., in a task to reach forward, an impaired arm's reach may be compensated by bending the torso more. Therefore, the simple minimization of Equation (8) by means of $\left(\hat{c}^A_j\right)_{j \in \boldsymbol{B}^k}$ will just reach one feasible solution but not necessarily the best one. In fact, it is not necessary to compensate all capabilities with $\delta^{i,k}_j > 0$, but only the ones that are not yet compensated by the human agent themselves. The best possible policy for minimizing the team delta will need to be subject to exploration. We theorize that there is a tolerable leftover error that still allows to fulfill the requirements on the team (similar to how experts apply *IMBA*) while still promoting satisfaction of the human.

It is hard to foresee the best possible solution to the stated problem. Even though we consider a "best" solution to exist, there is a realistic possibility of equally suited ambiguous solutions. We assume that the human is motivated to work. Hence, the team shall promote the independence of the human within the work process. To this end, the automation has to support as less as possible:

$$\sum_{j \in \boldsymbol{B}^k} \left(\hat{c}^A_j\right) \rightarrow 0. \tag{11}$$

The consequential problem is that there is no clear definition of least support. As stated before, we can rearrange the problem such that some capabilities are less challenged while others are more [21]. It is unclear if supporting two human capability deltas $\delta^{i,k}_j = 1$, where $\delta^{i,k}_j = r^k_j - \hat{c}^i_j$, is to be considered fewer support than supporting a single $\delta^{i,k}_j = 2$, or vice versa. We can argue with an analogy from human behavior: an objective function used in human movement simulation is to minimize muscle activation and effort (e.g., Veerkamp et al. [62]). Hence, one possible "best" solution to the teaming problem – at least in physical tasks – is the one that simultaneously minimizes the total support by the automation and the human muscular effort.

6 Conclusions

In this work, we introduced a framework for autonomous capability estimation. Capabilities are a common subject in philosophy and work. We discussed the two perspectives and derived a framework model incorporating aspects of both. In multi-agent systems and particularly teaming, capabilities are less prominently used, or at least on a less elemental level. Consequently, we showed how an autonomous agent may estimate a human's capabilities at the example of the capability *Standing*. The method implements the occupational documentation procedure *IMBA* in a Bayesian network. However, for such a seemingly simple capability as *Standing*, the Bayesian network already becomes large by means of parameters. We showed how the number of parameters may be reduced by implementing de Finetti tables for quasi-static dependencies in the network. Next, we proposed to add aspects of the occupational classification standard *ICF* into the Bayesian network, which we account for as resources. These are mainly environmental, societal, and personal aspects, extending the network towards more *ex situ* and *a-priori* knowledge on the person, while allowing to better depict human decision making in context of motivation. We then discussed how training data needs to be designed in order to train the Bayesian networks and which challenges come with generating new data on the subject. There virtually are no data sets that properly qualify for training. Therefore, we only validated the framework and Bayesian network qualitatively by employing a persona-based exploration. The results of the exploration indicate a general feasibility of the proposed methods, subject to the fully trained and validated Bayesian networks. Finally, we gave an outlook on how the framework will be integrated in action planning of the team by means of minimizing the capability deltas between the team and a work task. As a next step, we are in the process of organizing multiple studies to record data on human behavior in unison with *IMBA* capability profiles. As the studies will require ethics votes and significant effort, we cannot project when the first data sets will be available. We are motivated to publish all future data open-access, such that the community can engage in joint and participatory research.

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Data availability: Not applicable.

Appendix

See Table 5.

Table 5: Personas and work process descriptions used in the exploration.

	Persona (name, age)		Description
1	Claude	45	Average person. No entries in the medical record. Works out regularly, but not excessively.
2	Dana	31	Multiple Sclerosis patient. Limited muscle strength and rapid fatigue in the back. Sudden onset of pain during movement. Avoids extra movements.
3	Chima	50	Reintegration after stroke rehabilitation. Only minor restrictions due to partial signs of paralysis. Posture bent sideways when standing straight. Average muscle strength.
4	Jie	63	Short before retirement. Age-related weakening of the muscles and joints. Ignores progressive signs of ageing.
5	Rajani	17	New trainee taking his first steps. Young and reckless. Prefers appearance over safety. Regularly over-strains themselves.
6	Allyn	28	Sporty person. Works out almost every day. Trains for an *Iron Man*. Highly resilient, feels little exhaustion from regular work.
7	Ivory	29	Single-leg amputee. Is mostly settled with the situation and wears leg prosthesis with pride. Strong minded but body-conscious. Works out regularly.
8	Rene	34	Paraplegic after work accident. Bound to wheelchair. Enjoys logic puzzles, like Sudoku. Is motivated to work despite the obvious limitations.

Work process:

Operation of a lathe in a large company with high capacity utilisation. The shift is 7 h with breaks according to German work standards (two short, one longer break). The person is required to stand for longer periods and perform repetitive tasks at the lathe. Due to the position of the control panel, the posture and position of the person are very limited. Safety equipment is prescribed and strictly enforced by the company. For the desired standing frequencies and duration, we assume 5 min of continuous work without repositioning. Sitting down is permitted if leftover time between work steps is sufficient but in general sitting outside of breaks is discouraged by the company.

References

[1] European Commission, "Average amount of time that it takes small- and medium-sized enterprises (SMEs) to hire appropriately skilled workers in Europe in 2023, by country," in *Statista*, 2024. Available: https://www.statista.com/statistics/1446300/average-hiring-time-skilled-employees-sme-europe/

[2] Eurostat, *Population Structure Indicators at National Level*, Luxembourg, Eurostat, 2024.

[3] L. Griffith, P. Raina, H. Wu, B. Zhu, and L. Stathokostas, "Population attributable risk for functional disability associated with chronic conditions in canadian older adults," *Age Aging*, vol. 39, pp. 738—745, 2010.

[4] S. Berretta, A. Tausch, C. Peifer, and A. Kluge, "The job perception inventory: considering human factors and needs in the design of human—ai work," *Front. Psychol.*, vol. 14, 2023, https://doi.org/10.3389/fpsyg.2023.1128945.

[5] E. Hüsing, C. Weidemann, M. Lorenz, B. Corves, and M. Hüsing, "Determining robotic assistance for inclusive workplaces for people with disabilities," *Robotics*, vol. 10, p. 44, 2021.

[6] J. Kildal, M. Martín, I. Ipiña, and I. Maurtua, "Empowering assembly workers with cognitive disabilities by working with collaborative robots: a study to capture design requirements," *Procedia CIRP*, vol. 81, pp. 797—802, 2019, 52nd CIRP Conference on Manufacturing Systems (CMS).

[7] D. Kremer, *Teilhabe durch robotik*, Munich, Germany, InnoVisions, 2019.

[8] M. Mondellini, *et al*., “Behavioral patterns in robotic collaborative assembly: comparing neurotypical and autism spectrum disorder participants,” *Front. Psychol.*, vol. 14, 2023, https://doi.org/10.3389/fpsyg.2023.1245857.

[9] U. Wilkens, V. Langholf, G. Ontrup, and A. Kluge, “Towards a maturity model of human-centered AI — a reference for AI implementation at the workplace,” in *Competence Development and Learning Assistance Systems for the Data-Driven Future*, W. Sihn and S. Schlund, Eds., Berlin, Germany, Lehmanns Media, 2021.

[10] World Health Organization, “How to use the ICF: a practical manual for using the international classification of functioning, disability and health (ICF),” *Exposure Draft Comment*, 2013. Available at: https://www.who.int/publications/m/item/how-to-use-the-icf---a-practical-manual-for-using-the-international-classification-of-functioning-disability-and-health.

[11] Entwicklungsgemeinschaft IMBA, *Imba — Handbuch*, 2019.

[12] B. Gawronski and L. A. Creighton, “Dual process theories,” in *The Oxford Handbook of Social Cognition*, D. E. Carlston, Ed., New York, NY, USA, Oxford University Press, 2013, pp. 282—312.

[13] A. Bauer, D. Wollherr, and M. Buss, “Human—robot collaboration: a survey,” *Int. J. Humanoid Rob.*, vol. 5, pp. 47—66, 2008.

[14] W. Bauer, M. Bender, M. Braun, P. Rally, and O. Scholtz, *Lightweight Robots in Manual Assembly — Best to Start Simply!*, Munich, Germany, Fraunhofer, 2016.

[15] E. Helms, R. D. Schraft, and M. Hagele, “Rob@work: robot assistant in industrial environments,” in *11th IEEE International Workshop on Robot and Human Interactive Communication*, 2002, pp. 399—404.

[16] F. Flemisch, M. Heesen, T. Hesse, J. Kelsch, A. Schieben, and J. Beller, “Towards a dynamic balance between humans and automation: authority, ability, responsibility and control in shared and cooperative control situations,” *Cognit. Technol. Work*, vol. 14, pp. 3—18, 2012.

[17] P. Beckerle, C. Castellini, and B. Lenggenhager, “Robotic interfaces for cognitive psychology and embodiment research: a research roadmap,” *Cognit. Sci.*, vol. 10, p. e1486, 2018.

[18] E. Deng, B. Mutlu, and M. J. Mataric, “Embodiment in socially interactive robots,” *Found. Trends Rob.*, vol. 7, pp. 251—356, 2019.

[19] H. Snijders, “Arbitration and AI, from arbitration to ‘robotration’ and from human arbitrator to robot,” *Arbitration: Int. J. Arbitration, Mediation Dispute Manage.*, vol. 87, pp. 223—242, 2021.

[20] M. C. A. Baltzer, A. Ripkens, D. López-Hernández, and F. Flemisch, “Interaction mediation for meaningful human control over highly automated vehicles,” in *IEEE International Conference on Systems, Man, and Cybernetics*, 2023.

[21] N. Mandischer, M. Usai, F. Flemisch, and L. Mikelsons, “Exploring capability-based control distributions of human-robot teams through capability deltas: formalization and implications,” in *IEEE International Conference on Systems, Man, and Cybernetics*, 2024.

[22] I. Freire, O. Guerrero-Rosado, A. F. Amil, and P. F. M. J. Verschure, “Socially adaptive cognitive architecture for human-robot collaboration in industrial settings,” *Front. Rob. AI*, vol. 11, 2024, https://doi.org/10.3389/frobt.2024.1248646.

[23] M. Csikszentmihalyi, *Flow: The Psychology of Happiness*, London, England, UK, Random House, 2007.

[24] P. Prajod, *et al*., “Flow in human-robot collaboration — multimodal analysis and perceived challenge detection in industrial scenarios,” *Front. Rob. AI*, vol. 11, 2024, https://doi.org/10.3389/frobt.2024.1393795.

[25] H. Chen, S. Alghowinem, C. Breazeal, and H. W. Park, “Integrating flow theory and adaptive robot roles: a conceptual model of dynamic robot role adaptation for the enhanced flow experience in long-term multi-person human-robot interactions,” in *Proceedings of the 2024 ACM/IEEE International Conference on Human-Robot Interaction*, 2024.

[26] A. F. Newell and P. Gregor, “Extra-ordinary human-machine interaction: what can be learned from people with disabilities?” *Cognit. Technol. Work*, vol. 1, pp. 78—85, 1999.

[27] M. Rojas, D. C. Balderas, J. Maldonado, P. Ponce, D. Lopez-Bernal, and A. Molina, “Advantages of assembly lines in sheltered work centres for disabled. a case study,” *Int. J. Sustainable Eng.*, vol. 17, no. 1, pp. 1—21, 2024.

[28] D. Kremer and S. Hermann, “Auf dem weg zu virtuellen szenarien für die arbeitsteilung in der barrierefreien mensch-roboter-kooperation,” in *Innteract Conference 2016 “3D SENSATION” — transdisziplinäre Perspektiven*, 2016.

[29] C. Miralles, J. P. García-Sabater, C. Andrés, and M. Cardos, “Advantages of assembly lines in sheltered work centres for disabled. a case study,” *Int. J. Prod. Econ.*, vol. 110, nos. 1—2, pp. 187—197, 2007.

[30] P. Chutima and A. Khotsaenlee, “Multi-objective parallel adjacent u-shaped assembly line balancing collaborated by robots and normal and disabled workers,” *Comput. Oper. Res.*, vol. 143, 2022, https://doi.org/10.1016/j.cor.2022.105775.

[31] C. Weidemann, E. Hüsing, Y. Freischlad, N. Mandischer, B. Corves, and M. H. Ramb, “Validation of a software tool for determining robotic assistance for people with disabilities in first labor market manufacturing applications,” in *IEEE International Conference on Systems, Man, and Cybernetics*, 2022.

[32] R. Jaster, “Agents’ abilities,” in *Philisophical Analysis*, Berlin, Boston, De Gruyter, 2020.

[33] P. Egré and H. Rott, “The logic of conditionals,” in *The Stanford Encyclopedia of Philosophy*, Winter 2021 edition E. N. Zalta, Ed., Stanford, CA, USA, Metaphysics Research Lab, Stanford University, 2021.

[34] B. de Finetti and B. Angell, “The logic of probability,” *Philos. Stud.: Int. J. Philos. Anal. Tradit.*, vol. 77, pp. 181—190, 1995.

[35] J. Baratgin, D. E. Over, and G. Politzer, “Uncertainty and the de finetti tables,” *Thinking Reasoning*, vol. 19, pp. 308—328, 2012.

[36] E. W. Adams, “The logic of conditionals — an application of probability to deductive logic,” *Synthese Library*, vol. 86, 1975.

[37] D. Lewis, “Probabilities of conditionals and conditional probabilities,” *Philos. Rev.*, vol. 85, pp. 297—315, 1976.

[38] B. C. van Fraassen, “Probabilities of conditionals,” *Found. Probab. Theor. Stat. Inference Stat. Theor. Sci.*, pp. 261—308, 1976, https://doi.org/10.1007/978-94-010-1853-1_10.

[39] J. Maier, “Abilities,” in *The Stanford Encyclopedia of Philosophy*, Fall 2022 edition E. N. Zalta and U. Nodelman, Eds., Stanford, CA, USA, Metaphysics Research Lab, Stanford University, 2022.

[40] C. Robert, “Stalnaker. Possible worlds,” in *Symposium Papers to be Read at the Meeting of the Western Division of the American Philosophical Association in New Orleans*, vol. 10, 1976, pp. 65—75.

[41] G. L. Engel, “The need for a new medical model: a challenge for biomedicine,” *Science*, vol. 196, pp. 129—136, 1977.

[42] F. Föhres, A. Kleffmann, A. Sturtz, and S. Weinmann, *Melba — Manual Zum Verfahren*, Miro, 2011.

[43] T. Achterberg, H. Wind, P. Prinzie, and M. Frings-Dresen, "Inter-rater reliability of the 'merkmalprofile zur eingliederung leistungsgewandelter und behinderter in arbeit' (melba) in young disabled adults with psychosocial limitations," *Work*, vol. 44, pp. 491—497, 2013.

[44] S. Hennaert, *et al*., "Linking of the 'integration von menschen mit behinderungen in die arbeitswelt' (imba) to the 'international classification of functioning, disability and health' (ICF)," *Work*, vol. 72, no. 4, pp. 1359—1380, 2022.

[45] S. Hennaert, S. Decuman, H. Désiron, L. Braeckman, S. De Baets, and D. Van de Velde, "Imba-ICF linking by integrating consensus methods: how group consensus of experts can contribute to in-depth linking of instruments to the ICF," *Work*, vol. 75, no. 2, pp. 479—493, 2023.

[46] N. Mandischer, *et al*., "Toward adaptive human—robot collaboration for the inclusion of people with disabilities in manual labor tasks," *Electronics*, vol. 12, no. 5, p. 1118, 2023.

[47] Personal protective equipment — Safety footwear. StandardInternational Organization for Standardization, Geneva, CH, 2021.

[48] T. T.-J. Chong, V. Bonnelle, and M. Husain, "Quantifying motivation with effort-based decision-making paradigms in health and disease," *Prog. Brain Res.*, vol. 229, pp. 71—100, 2016.

[49] A. de Vicente and H. Pain. "Motivation diagnosis in intelligent tutoring systems," in *Conference Paper: 4th International Conference, ITS '98*, San Antonio, Texas, USA, 1998, pp. 86—95.

[50] N. Otani and E. Hovy, "Toward comprehensive understanding of a sentiment based on human motives," in *57th Annual Meeting of the Association for Computational Linguistics*, 2019, pp. 4672—4677.

[51] P. Vijayaraghavan and D. Roy, "Modeling human motives and emotions from personal narratives using external knowledge and entity tracking," in *WWW '21: Proceedings of the Web Conference 2021*, 2021, pp. 529—540.

[52] D. Bisig, F. Li, and A. Koch, *E2-Create Motion Bank Dataset*, Geneva, Switzerland, Zenodo/CERN, 2022.

[53] N. Pavlidis and V. Perifanis, *Flamenco Learning Disabilities Dataset*, IEEE DataPort, 2024.

[54] R. Kamikubo, L. Wang, C. Marte, A. Mahmood, and H. Kacorri, "Data representativeness in accessibility datasets: a meta-analysis," *ASSETS*, vol. 8, 2022.

[55] H. Kacorri, U. Dwivedi, S. Amancherla, M. K. Jha, and R. C. Incluset, "A data surfacing repository for accessibility datasets," *ASSETS*, vol. 72, 2020, https://doi.org/10.1145/3373625.3418026.

[56] B. M. Bot, *et al*., "The mpower study, Parkinson disease mobile data collected using researchkit," *Scientific Data*, vol. 3, 2016, https://doi.org/10.1038/sdata.2016.11.

[57] R. Jaroensri, *et al*., "A video-based method for automatically rating ataxia," in *Proceedings of the 2nd Machine Learning for Healthcare Conference*, 2017, pp. 204—216.

[58] M. H. Li, T. A. Mestre, S. H. Fox, and B. Taati, "Vision-based assessment of parkinsonism and levodopa-induced dyskinesia with pose estimation," *J. NeuroEng. Rehabil.*, vol. 15, 2018, https://doi.org/10.1186/s12984-018-0446-z.

[59] E. Dolatabadi, *et al*., "The toronto rehab stroke pose dataset to detect compensation during stroke rehabilitation therapy," in *Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare*, 2017, pp. 375—381.

[60] K. Avgerinakis, A. Briassouli, and I. Kompatsiaris, "Activity detection and recognition of daily living events," in *Proceedings of the 1st ACM international Workshop on Multimedia Indexing and Information Retrieval for Healthcare*, 2013, pp. 3—10.

[61] J. Pruitt and J. Grudin, "Personas: practice and theory," in *Proceedings of the 2003 Conference on Designing for User Experiences*, 2003.

[62] K. Veerkamp, *et al*., "Evaluating cost function criteria in predicting healthy gait," *J. Biomech.*, vol. 123, 2021, https://doi.org/10.1016/j.jbiomech.2021.110530.

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