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Automation as an equal team player for humans? – A view into the field and implications for research and practice

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A R T I C L E I N F O

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A B S T R A C T

The practical reality and feasibility of Human-Autonomy Teaming (HAT) are analyzed from an experts' point of view, considering current possibilities of various fields. We aim to find out whether the topics discussed scientifically are also practically relevant, to identify requirements for successful HAT, and to derive further research needs. Intensive guideline-based interviews with 28 experts from different industries are conducted and compared to the results of our literature review. The topics discussed scientifically are also practically relevant. Today's technology is far from being able to meet the practical requirements for successful HAT, as postulated in the literature. Contrary to the Human-Automation Interaction, the concept of HAT is hardly applied in the field. Identified key aspects for successful HAT are converted into a model. Future research needs with practical impact exist especially in the area of heterarchy, system knowledge, anticipation of mental states, and consideration of human needs and emotions.

1. Introduction

Humans increasingly have to interact with automation in a wide variety of contexts. The so-called human-automation interaction (HAI) exists whenever humans program goals and constraints to the automation; start, stop, or change the automation's performance; or obtain information or objects from the automation (Sheridan and Parasuraman, 2005). Automation, thereby, represents a technological entity that is designed to fulfill a narrow and pre-defined set of specific tasks (Hancock, 2017). Today, technological advances in machine learning and artificial intelligence (AI) enable the further development of automation to autonomous agents that are able to deal with uncertainties, adapt their capacities to dynamic situations, and make intelligent decisions autonomously (Demir et al., 2019; Hancock, 2017). As a result, technology is no longer considered as a tool, but increasingly as a team member for humans (Demir et al., 2019; Fiore and Wiltshire, 2016; McNeese et al., 2018). Accordingly, the team and automation research are increasingly dedicated to the topic of human-autonomy teaming (HAT).

A human-autonomy team consists of at least one person and one autonomous agent that work together interdependently to successfully complete a common task (O'Neill et al., 2020). Agents are recognized as computer-based "entities which continuously monitor their environment and perform activities consistent with pursuing one or more goals within that environment" (Miller et al., 2020, S. 521). To be considered as *autonomous*, agents must be able to act with little or no human intervention (Endsley, 2017; Wooldridge, 2013). They can control "their own internal state and [...] their behaviour" (Wooldridge, 2013, S. 5). Autonomy represents an increased level of automation (Hancock, 2017). Since full autonomy is technologically difficult to achieve, most systems have a level of partial autonomy (Endsley, 2017; Wooldridge, 2013), which by definition can be further referred to as an autonomous agent (O'Neill et al., 2020). Autonomous agents in the sense of team members could be used in a variety of contexts, e.g. as wingmen for military pilots or as a remotely piloted aircraft in a mission flight, to help in the search and rescue of victims in a chaotic disaster, or to respond to cyber-attacks (Cooke et al., 2020; Endsley, 2017).

While the HAI literature is extensive, the HAT literature is still in its infancy (Lyons et al., 2021; O'Neill et al., 2020). Therefore, we focus especially on the latter. Many papers deal with work design requirements for successful HAT (e.g., Battiste et al., 2018; Chen et al., 2018; Langan-Fox et al., 2009) and its challenges from a theoretical point of view (e.g., Christoffersen and Woods, 2002; Klein et al., 2004). Most of the studies test the effectiveness of HAT experimentally (cf.

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O'Neill et al., 2020). O'Neill et al. (2020) call for more qualitative research to better understand the concept of HAT. Especially, a more in-depth analysis from an experts' point of view on HAT, considering different industries, has been missing so far. However, this perspective is crucial, *first*, to find out whether the scientifically discussed topics are also practically relevant, *second*, to identify practical challenges in order to address them with relevant research, and *third*, to derive further research needs that are relevant to link science and practice.

This paper contributes to this gap by an expert study on the practical reality and feasibility of HAT, considering current possibilities of various fields. We complement this study by an ongoing literature review. The leading research questions are: What is the current state of HAT in the field? Can, from the experts' point of view, autonomous agents function as team members for humans? What are the requirements for HAT so that automation can be used as effectively as possible in the sense of a team player for humans and are those in line with the scientific debate? We thereby help to better understand HAT from a practical perspective and are thus contributing to bring science and practice closer together to *jointly* pave the way for successful HAT.

2. Method

2.1. Literature research

An ongoing comprehensive literature analysis on HAI and HAT was conducted. It was done in multiple periods between April 2019 and December 2020. The used databases were Psyndex, PsycINFO, Web of Science, EBSCOhost, and Google Scholar. Before conducting the expert study, we started with broad keywords such as human-automation interaction, human-autonomy teaming, human-machine interaction, or autonomous agent. We then specified the research in the course of our expert study by searching for the topics mentioned in the interviews, such as transparency and flexible function allocation. The identified literature was used for comparisons with interview results and deriving further research needs.

2.2. Expert study

We conducted 28 semi-structured interviews with the help of an interview guideline with experts from different industries and in various functions as well as from science between January and May 2020. The respondents were chosen based on their expertise in the fields of automation and the interaction between humans and technology. Only those experts were included who had at least five years of experience on those topics ($M = 13.61$, $SD = 9.51$). To find appropriate experts, we carried out extensive web-based research and asked for recommendations within our network. In addition, we received recommendations from interviewees. To ensure the intended expert level, a preliminary conversation with all experts took place in advance.

The interviews were conducted via (video)telephony and lasted an average of 50 min ($SD = 13.08$). All interviews were conducted by the same person, who is one of the authors. Participation was voluntary and data analysis anonymous. Informed consent was obtained from each participant.

During preliminary conversations, we noticed that the interviewees, similar to the literature, used the term automation in a teaming context synonymously with autonomous agent. Therefore, we also used the terms interchangeable to adapt to their language and to be able to refer to the original statements without modifying.

To ensure an easy interview entry, we started with demographic and job-related questions. We continued with questions regarding the interaction of humans and automation in the experts' fields. To introduce the topic of HAT, respondents were asked to verbalize any thoughts and associations they had about the following statement: "Automation can be considered an equal team player for humans". We thereby defined the concept of equality as follows: Equality does not refer to an equal responsibility or liability of the human and technological teammate but is used in the sense of an equal fulfillment of tasks through own initiative. Equality thereby means that both can contribute equally to achieving the overarching goal through interaction. If available, we asked for industry examples of HAT and for the requirements for successful HAT. We also raised the question of new competence requirements. Finally, we asked for further research needs and a summary statement.

With the participants' consent, all interviews were recorded and anonymously transcribed. We analyzed them according to the structuring qualitative content analysis by Mayring (2014) using the software MAXQDA 18. First, categories, to which the text material is assigned, were deductively developed. Then, in the course of the evaluation, these were supplemented by inductively new categories based on the interview material. For each category, a definition, a typical sample text passage, and coding rules to differentiate between the categories were established. Direct foreign-language quotes used in this paper are translated into English.

Table 1 provides an overview of the characteristics of the interviewees and their industry affiliation. Seven women and 21 men participated with indicated age ranging from 31 to 61 years ($M = 44.14$, $SD = 9.90$).

3. Results

3.1. Feasibility of HAT

In accordance to the automation model of Parasuraman et al. (2000), we analyzed the state of automation within the different industries. As the included industries use different and sometimes very unique taxonomies, an overall comparison of the specific level of automation turned out to be impractical. Instead, we asked for the actual stage of automation (information acquisition, information analysis, decision and action selection, action implementation; cf. Parasuraman et al., 2000). Except for three (E17, E25, E28), all experts from practice stated they have automation in use at the decision support level or higher, or at least developing and testing it. This indicates that the involved fields are very advanced within the area of HAI. We also asked for the main advantages and disadvantages of the interaction between humans and automation and the awareness of those within the fields. The common ones discussed in the literature, such as increased safety and performance (e.g., Onnasch, 2015) and complacency (e.g., Parasuraman and Manzey, 2010) or deskilling (e.g., Sheridan and Parasuraman, 2005), are known within the industries and are mostly considered (for more details see Supplementary Material).

In contrast, the concept of HAT is hardly applied in those fields as it comes, from a practical perspective, with many challenges. This is why our paper is focused on the results of HAT in order to investigate the potential need for action. The experts were asked to comment on the statement "Automation can be considered an equal team player for humans". As three experts could not answer the question, responses were received from 25 experts. All experts share the opinion that responsibility, liability, control, and the final decision should always rest with humans. However, the experts disagree on the feasibility of automation as an equal team player in the field. The answers could be classified according to whether this was considered possible or impossible and whether this was seen as desirable or not. Table 2 shows the distribution of answers and presents details and example quotes.

Ten experts assessed automation as an equal team player for humans as possible, while ten experts thought it was impossible. One reason against the possibility of automation as an equal team player trace back to the demand that liability and control should always lie with the human. The experts explained that this makes it impossible to achieve an equal fulfillment of tasks and to equally contribute to the overarching goal through interaction (e.g., E4, E5, E9, E26). Another reason why automation cannot be considered an equal team player for humans was

Table 1
Characteristics of participants.

ID	Industry	Gender	Age [years]	Experience [years]	Location	Interview Duration [min]
E1	Air Traffic Control, Aviation	Male	52	6	Germany	52
E2	Science	Male	54	7	Switzerland	44
E3	Science, Nursing	Male	37	5	Germany	65
E4	Air Traffic Control	Male	59	30	Austria	50
E5	Air Traffic Control, Rail Industry, Maritime Industry	Female	52	13	Austria	55
E6	Manufacturing	Male	56	9	Germany	41
E7	Military Aviation	Male	56	39	Germany	71
E8	Science	Female	42	15	Germany	25
E9	Medical Diagnostics, Maritime Industry, Manufacturing	Male	34	8	Germany	31
E10	Science, Intensive-care Medicine	Female	41	8	Germany	27
E11	Air Traffic Control	Male	50	25	France	60
E12	Rail Industry	Male	36	7	Switzerland	52
E13	Automotive Industry	Male	35	9	Germany	40
E14	Manufacturing, Logistics	Male	30	6	Germany	47
E15	Science, Military Aviation	Male	53	30	Germany	44
E16	Surgery	Male	45	11	Germany	36
E17	Manufacturing	Male	31	6	Germany	37
E18	Automotive Industry, Manufacturing	Male	41	6	Germany	54
E19	Automotive Industry	Male	33	8	Germany	50
E20	Manufacturing	Male	57	21	Germany	85
E21	Surgery	Male	34	10	Germany	53
E22	Automotive Industry, Rail Industry, Aviation	Female	41	10	Germany	55
E23	Rail Industry	Male	52	11	Germany	38
E24	Nuclear Sector	Male	54	24	Norway	66
E25	Nuclear Sector	Male	61	31	Germany	53
E26	Rail Industry	Female	33	11	Germany	60
E27	Science	Female	36	10	Germany	50
E28	Maritime Industry	Female	31	5	England	58

Note. Some participants had expertise in multiple industries. Including those, the following frequencies result for the different fields: Science (6); Manufacturing (6); Rail Industry (5); Air Traffic Control (4); Maritime Industry (3); Civil (2) and Military Aviation (2); Nuclear Sector (2); Medicine, including Surgery (2), Medical Diagnostics (1), and Intensive-care Medicine (1); Nursing (1); and Logistics (1).

technologically justified. The experts claimed that the technology - even in the long term - would not be sophisticated enough to act as a teammate (e.g., E6, E25, E28). E8 and E22 emphasized the difficulty of building an interpersonal relationship with automation, which is necessary for teamwork.

Those experts who considered equal teamwork between humans and automation as possible argued that, despite human-sided liability and control, an equal task fulfillment could be realized. They compared it to a human-human team in which teammates also can have different responsibilities but all can equally contribute to the overarching aim. However, they also were of the opinion that the technology needs to be developed further to function as an equal team member (e.g., E16, E17, E19, E23, E27).

Nine of the experts stated that automation as an equal team player should always be aimed for in the sense of an "ideal" (E1) and "design template" (E24). Two respondents strictly rejected this for ethical reasons. There was no industry-specific pattern.

3.2. Requirements for successful HAT

One interview focus was to identify the key aspects that are necessary for a successful realization of automation as an equal team player for humans and to compare them to the literature. The derived key aspects can be divided into one superordinate paradigm demand and three subordinate categories (Table 3): automation-sided (aspects the automation must accomplish), human-sided (aspects the human must accomplish), and both-sided requirements (aspects that lie on both sides), indicating no industry-specific pattern. In the following, they are each addressed individually and compared with the results of the literature review.

3.2.1. The paradigm of heterarchy

Interviewees demand a paradigm shift from hierarchy to heterarchy. It describes the relationship between the human and technological teammate (Schulte and Donath, 2018). Instead of a supervisory control, whereby the user delegates tasks to the automation, monitors and corrects it (Sheridan and Parasuraman, 2005), heterarchy refers to a non-hierarchical relationship. The human and technological agent are partners in a team (Lange and Gutzwiller, 2016). In a hierarchical relationship, only the human operator is responsible for achieving the overarching work target while the automation solely undertakes a subtask. In comparison, in a heterarchical relationship, both, the human and technological actor, are able to contribute to the overall work target through their own initiative and, as a result, can increase performance (Brand and Schulte, 2021). Nevertheless, the ultimate decision and responsibility should always rest with the human. Heterarchy can function as a suitable new paradigm for HAT but literature on it is relatively rare.

3.2.2. Safety and reliability

According to the experts, automation has to increase safety and work reliably which represent fundamental requirements for successful HAT. Those topics are well-discussed within the scientific debate (e.g., Ferraro and Mouloua, 2021; Metzger and Parasuraman, 2005; Onnasch, 2015; Parasuraman and Manzey, 2010). Reliability refers to the automation's performance and can be defined as its failure rate (Dekker and Woods, 2010). A high level of reliability can lead to overreliance and consequently to a misuse of automation (Parasuraman and Riley, 1997) and increases the likelihood of complacency (Parasuraman and Manzey, 2010). A low level of reliability can impede the user's trust in automation (Endsley, 2017; Lee and See, 2004), increase workload (Chen et al., 2011), and impair performance due to missed critical events (Wickens and Dixon, 2007). Similar to the experts' opinion, reliability in the literature is also seen as a fundamental characteristic for successful performance in human-autonomy teams (O'Neill et al., 2020). O'Neill et al. (2020) summarized that in human-autonomy teams high reliability consistently leads to positive outcomes and therefore, high reliable autonomous agents should always be aimed for. O'Neill et al. (2020) also showed that transparency can reduce the negative effects of a low level of reliability.

Table 2
Experts' responses (n = 25) for the statement "Automation can be considered an equal team player for humans."

Response Categories	Response Frequencies	Interviewee IDs	Details and Example Quotes
Not possible	10	E4, E5, E6, E8, E9, E21, E22, E25, E26, E28	**Not possible because of:** • **Human-sided liability and control** "If a person makes a mistake, he or she has to be liable for it. The system doesn't. Therefore, one cannot consider that [the contribution to the overarching goal] as equal. Because the final decision and therefore the responsibility is always with the human." (E4, translated) • **Technology is not sophisticated enough** "Teamwork is based on a dynamic relationship and I don't see that being possible for automated technology." (E28) • **Difficulty of building an interpersonal relationship** "I don't think that humans can build an interpersonal relationship with automation, but that plays an essential role in teamwork." (E8, translated) "[I believe] that we, as living beings with years of experience in the social world, can interpret a lot of non-verbal signals and we also need and use this knowledge for our teamwork. No matter how good the classifier is we teach the technological system, it will never be able to do it as well as a human. […] This is a vision that, in my opinion, cannot be implemented in reality, not even with artificial intelligence." (E22, translated)
Possible	10	E2, E3, E7, E14, E15, E16, E17 E19, E23, E27	• **Possible but technology needs to be developed further** "I think [equal teamwork] can happen, but it cannot happen now. Looking at the level of technological development today, I think we are still a long way off." (E23, translated)
Should be aimed	9	E1, E2, E7, E12, E13, E15, E18, E19, E24	• **Considered as ideal** "That describes the ideal." (E1, translated) • **Should be used as a design template** "It is like a design template, something that can help you to come up with system design, that will be efficient when it comes to developing the [human and machine] roles and functions." (E24)
Should not be aimed	2	E8, E26	• **Ethical concerns** "It is irresponsible […]. It stirs up uncertainty and fear." (E8, translated)

3.2.3. Transparency and explainability

To achieve HAT, the experts demand an explainable and transparent automation. This is in line with the current literature, in which these topics are receiving increasing attention (cf. Bhaskara et al., 2021; Chen et al., 2018; Janssen et al., 2019; Lyons et al., 2017; O'Neill et al., 2020; Schelble et al., 2020; Skraaning and Jamieson, 2021; Wright et al., 2021). Transparency means that the automation continuously communicates its actions, decisions, behavior, and intentions to the human operator "through an appropriate interface" (Bhaskara et al., 2020, p. 216). It is one of the three postulated elements according to Battiste et al. (2018) that are required for successful HAT as it helps to understand the automation functioning easily. They compare human-autonomy teams with human teams and explain that the automation's intentions are often less apparent. In order to make them more apparent, they postulate the need for better transparency for successful teaming. Transparency enables the system's predictability and understandability to operators (Endsley, 2017) and can increase performance (Bhaskara et al., 2020; Wright et al., 2021), the operator's trust, situation awareness, and perceived usability (cf. Bhaskara et al., 2020). However, studies show that transparency is not always beneficial, depending on the type of automation, the type of transparency, and the extent of transparency information presented (cf. Bhaskara et al., 2020; Bhaskara et al., 2021). The underlying processes are still unclear and more research is needed to fully understand transparency as a design principle (cf. O'Neill et al., 2020).

Explainability refers to the automation's decision process. The experts required that decisions made by an automation are comprehensible for humans. The reasons leading to a decision should be made transparent so that the human operator can understand the basis on which an automation's decision is based (Janssen et al., 2019). This is important for user acceptance, trust, mutual mental models, and performance (Endsley, 2017). Arrieta et al. (2020) showed that especially since 2018 the topic of explainable AI has received increasing attention in the scientific discourse. Since it is a relatively young field, a lot of questions still remain open: E.g., many systems make a lot of parallel decisions over time. Should these all be made transparent to the user? Or should only strategically relevant decisions be made explainable? When does it lead to information overload and when does it influence the user's attention negatively? (cf. Janssen et al., 2019).

3.2.4. Considering human needs

The experts demand that the automation should always consider the needs of humans and act accordingly. If the human operator is tired or cognitive workload is high, automation should notice and support more, e.g. by taking on more subtasks. If the operator is bored or out-of-the-loop, the tasks must be reallocated in such a way that the operator

Table 3
Identified key aspects for a successful realization of automation as a team player for humans representing interview categories, definitions, representative quotes, and the number of codings (n = 17).

Categories	Definitions	Representative Quotes	No. of Codings
Paradigm			
Heterarchy	A non-hierarchical relationship suggesting that the human and technological agent are partners in a team and both are able to contribute to the overall work target through own initiative	"We actually assume that people […] enter into a heterarchical working relationship with automation. […] that doesn't say anything about [responsibility]. So, you can work in a team and still someone is responsible for what happens there. […] The acting person should always be responsible for what happens. And for this, of course, a paradigm shift has to take place because I no longer have an automation that I control, that I switch on and off, where I know exactly what is happening. Rather, I have to deal with automation that is similar to a human team member with its own initiative […]." (E15, translated)	2
On the Automation Side			
Safety & Reliability	A safe and reliable automation with a low failure rate	"Safety is the most important thing, otherwise there is no acceptance." (E20, translated)	4
Transparency & Explainability	Transparency means to create an operator's awareness of the automation's behavior, mode, and intentions, while explainability refers to providing the reasons leading to a decision so that it becomes comprehensible for the human	"Transparency, i.e. a comprehensibility of the [automation's] action, is very important in order to be able to consider automation as a team player." (E27, translated) "The [automation] should not simply say 'that has to be done that way', it has to provide arguments for it. This way, humans and [automation] are increasingly becoming peers who have to interact with each other like humans and then we speak of human machine teaming." (E2, translated)	7
Considering human needs	Considering the needs of the human team member and acting accordingly	"The system knows what a person actually needs, so we can make that available to the human now. Not too much so that the human might be confused but just to the extent that he or she needs it and can process it." (E1, translated)	4
Considering human emotions	Considering the emotions of the human team member and acting accordingly	"The machine knows […] in extreme cases possibly even the emotional and affective components." (E15, translated)	3
On the Human Side			
System knowledge	The human's understanding of the general system logic, it processes, capabilities, and limitations	"It is necessary that the person has a certain understanding of how the system works, otherwise he or she will not perceive it as a team player." (E18, translated)	3
Data disclosure	The willingness to share personal data so that the automation can consider human needs correctly	"It will be crucial […] that we […] disclose our personal data. […] then [the automation] will be much better and we will be much happier if we get the right information at the right time." (E1, translated)	2
On Both Sides			
Understanding the work target	The fundamental requirement to understand the overall work target in order to be able to fulfil a task on one's own initiative	"People should know the work target and pursue it on their own initiative, and this machine part, this agent, should do that too. This is the absolute, most elementary basic requirement for such a cooperation." (E15, translated)	2
Anticipation of mental state	Being able to estimate current *and future* mental states and adapting teamwork behavior accordingly	"You have to think about how you want to organize such a team and the anticipation of mental states often plays a role. […] I have to be able to assess their [the team members'] mental state in some way, so that I notice when someone is overworked or unchallenged or that I notice when someone can do something better than me. That is what you also expect from a machine." (E15, translated)	7
Human-centered strength-based function allocation	The allocation of tasks and functions according to the human team member's strengths instead of a left-over principle	"[…] that the allocation of tasks is designed in such a way that humans take on the tasks they are good at. […] And of course, it is a problem if you relieve the driver of all tasks that he is good at and leave him with doing nothing or monitoring tasks. Often the development is also driven by technology, i. e. you implement what is technologically possible and the driver should do the rest and in my opinion that doesn't work well. You have to consider what the driver	8

(*continued on next page*)

Table 3 (*continued*)

Categories	Definitions	Representative Quotes	No. of Codings
		is good at and let him do that and take away from him what he is not good at." (E13, translated)	
Flexible function allocation	A flexible, dynamic allocation process that allows an ad hoc reallocation if needed instead of a pre-planned, static one	"I believe that you need a flexible function allocation […] when for instance the workload of the operator is too high, you lowered it then and automation will work more. It's quite more flexible than a predefined function allocation." (E24)	2

gets more involved and engagement increases. Similar demands are postulated by O'Neill et al. (2020) who ask for a dynamic adjustment to human characteristics and needs by autonomous agents. This remembers of the decades old concept of human-centered automation design (Billings, 1991; 1996). It focuses on "organizing technology around the user's goals, tasks, and abilities" (Endsley and Jones, 2012, p. 9) and leads to higher overall performance, lower error rates, higher user acceptance, and satisfaction (Endsley and Jones, 2012). Incorporating human needs is considered as an important aspect for successful HAT performance (Demir et al., 2019). However, according to the experts, it is technologically difficult to achieve as today's technology is often not that advanced.

3.2.5. *Considering human emotions*

According to the interviewees, there is a need for affective HAT, meaning the technological teammate is able to incorporate human emotions and adapt its behavior accordingly. This was first raised by Picard in 1995 and then was increasingly discussed in the literature under terms such as emotional AI (McStay, 2020), affective computing (Richardson, 2020), or affective human-computer interaction (Calix et al., 2012). As emotions interact e.g. with attention, working memory, information and decision processing, and thus also with safety and performance (c.f. Lottridge et al., 2011), it is important to consider them for effective HAT. Moreover, it can foster the perception of a *social* interaction, similar to purely human teams (Brave et al., 2005). Nevertheless, research on emotions in human-autonomy teams is rare. From a purely technological perspective, the implementation of affective computing would be feasible in practice by methods like analyzing facial expressions, body posture, gestures (Dzedzickis et al., 2020), and language (Calix et al., 2012). However, privacy and ethical considerations often contradict this approach since emotions represent personal data that requires one's explicit approval and comes with a risk for abuse (McStay, 2020; Richardson, 2020). More interdisciplinary research is needed to better understand affective computing and its consequences for HAT.

3.2.6. *System knowledge*

On the human side, interview participants demand a basic level of system knowledge. According to Rieth and Hagemann (2021), system knowledge refers to the human's understanding of the general logic and processes of the automation. Operators need to consider them correctly and be aware of the system's capabilities and limitations. This is in accordance to Battiste et al. (2018) who also requires system knowledge to develop precise mental models of the system's operating principle. The requirement for system knowledge is closely related to some of the other requirements mentioned by the experts, such as understanding the overall work target (as part of system knowledge) and mutual anticipation of the mental state (as a result of system knowledge). In the literature, the topic of system knowledge itself has rarely been addressed so far. Similar topics such as mode awareness (e.g., Sarter and Woods, 1995) or automation understanding (e.g., Endsley and Jones, 2012) are occasionally discussed, but a holistic understanding of system knowledge has been lacking so far. Questions like how much knowledge is needed, how can system knowledge best be trained, and how strong is its effect on human-autonomy team performance still remain unanswered.

3.2.7. *Data disclosure*

On the human side, experts demand the willingness to share personal data, such as cognitive, affective, and behavioral data as well as their health status so that autonomous agents can consider human needs and emotions correctly. This is discussed under electronic performance monitoring (Ravid et al., 2020) or tracking technologies (Abraham et al., 2019). The use of personal data, especially in the workplace, is still a very sensitive issue (Moore and Piwek, 2017). Data protection issues need to be further discussed to successfully implement HAT.

3.2.8. *Understanding the work target*

One fundamental requirement on both sides is to understand the overall work target. This is in accordance to the literature, in which the definition of HAT includes that both team members collectively strive to achieve a common aim (O'Neill et al., 2020). This implies both team members must be able to understand the work target and to divide it into its subtasks, underlying a degree of autonomy. Moreover, this requirement is part of the heterarchy paradigm (Brand and Schulte, 2021) and is inevitable for successful HAT.

3.2.9. *Anticipation of the mental state*

The requirement of the anticipation of the mental state lies on both, the human and automation side, and can be seen, according to the interviewees, as a bidirectional process. Compared to the common design principle of revealing mental states, the expert's demand goes one step further: They explain that it is not enough just to know the current mental state but that humans have to be able to anticipate them, i.e. forecasting future mental states. According to the experts, this implies mutual recognition of intentions and accurate mental models, which is also required by other researchers (e.g., Endsley, 2017; Klein et al., 2004; Onken and Schulte, 2010; Schneider et al., 2021). The issueof mental models is one of the most common studied variables within HAT (O'Neill et al., 2020). However, there is less research regarding understanding the mental state of humans *by the automation* and how to design HAT effectively so that a mutual anticipation of mental states is possible. Thereby, the technological feasibility is often one of the main challenges in the field. In this regard, Schneider et al. (2021) deal with ways of communication to foster coordination in human-autonomy teams, which offers a good reference point for further research.

3.2.10. *Strength-based and flexible function allocation*

Function allocation, also known as task allocation, "refers to strategies for distributing system functions and tasks across people and technology" (Roth et al., 2019, p. 199). Interviewees demand a *human-centered strength-based* and a *flexible* function allocation in human-autonomy teams. A human-centered strength-based function allocation implies an allocation based on the strengths and weaknesses of the *human* in the context of the *specific* goal – not in a generalizing manner like the Fitts' (1951) MABA-MABA list propose. The experts emphasize that this process should not be based on the capacities of the technology resulting in a left-over principle for humans as this can lead to inhumane work. This is in line with the widespread criticism of the MABA–MABA approach, which is a classic strength-based approach, encouraging a technology-centered perspective ending with performance problems due to left-over tasks for humans (Dekker and Woods, 2002; Roth et al., 2019).

In addition, experts demand a flexible, dynamic allocation process instead of a pre-planned one, which is also discussed as ad hoc allocation

(Tausch et al., 2020). Those requirements are in line with the literature, in which both, strength-based and flexible function allocation are discussed intensively (e.g., Feigh and Pritchett, 2014; Roth et al., 2019; Tausch et al., 2020). Two experts (E19, E24) added the human should have as much authority and control over the function allocation process as possible, which reminds of one of the three postulated requirements for successful HAT according to Battiste et al. (2018), the so-called human-directed execution. This is known as adaptable automation (e.g., Chavaillaz et al., 2016) and often comes with the questions of who should be responsible for the outcomes (cf. Feigh and Pritchett, 2014).

Contrary to traditional function allocation, recent research proposes designing for interdependent joint participation on shared tasks (coactivity) in human-autonomy teams (cf. Johnson and Vera, 2019; Johnson et al., 2012, 2018). This was not discussed in the interviews but seems to be a promising design principle for HAT.

The identified key aspects for successful HAT are converted into a model (Fig. 1).

3.3. Derived future research needs

As indicated for each identified key aspect before, the comparison of the interview results and the literature revealed some further research needs which are presented collectively in the following:

- Since, in contrast to HAI, the concept of HAT seems to be difficult to apply in practice, we see a great need for research in this field. We call for more field research to better incorporate the challenges of the practical reality. Reference should be made to the review papers by O'Neill et al. (2020) and Lyons et al. (2021) in which further HAT research needs are identified from a solely scientific perspective.
- The integration of the practical perspective showed that from the experts' point of view the current state of technology is not sophisticated enough to enable HAT in the field. We therefore need to investigate how to develop technology that enables equal teaming with humans. The identified key aspects for successful HAT can thereby serve as a guidance.
- The feasibility of the required paradigm shift to a heterarchy has great potential in the context of HAT and should also be further researched as the literature on this topic is rare.
- The underlying processes of system transparency and explainability are still unclear and more research is needed to fully understand these aspects as a design principle: E.g., at which level of transparency does information overload nullify the benefits? What type of transparency information is needed in what contexts? Does it vary by application?
- A holistic understanding of system knowledge is lacking so far, although related topics such as mode awareness (e.g., Sarter and Woods, 1995) or automation understanding (e.g., Endsley and Jones, 2012) are occasionally discussed. Questions like how much knowledge is needed, how can system knowledge best be trained, and how strong is its effect on HAT performance still remain unanswered.
- Within the human-technology collaboration, data security and protection need to be discussed further. E.g., which data do we need to track for successful HAT, how can we do that, how do people and organizations feel about it, and how can data protection in the context of HAT be complied with in the best possible way?
- We need more research regarding the mutual understanding and anticipation of mental states between humans and automation, especially in terms of integrating the automation's ability to understand human intent. Particularly, the technological realization of this demand seems to be a major challenge. We need to collaborate with practical partners to cooperatively achieve further technological advances to implement HAT.
- As both humans and autonomous agents can act on their own initiative, a broad ethical discussion is required regarding responsibility and liability. E.g., can a human operator be held accountable for the autonomous agent's behavior? If not, who is responsible instead? These questions have to be clarified on an interdisciplinary basis so that HAT has a realistic chance to become reality in practice.
- Our question regarding new (competence) requirements for employees due to increasing automation could not be fully answered. All respondents except for one agreed *that* new requirements arise. System knowledge ($n = 15$) and an affinity for technology ($n = 7$) were occasionally mentioned. Most of them had difficulties to put these into words and were not sure *which* specific competencies are needed. The subject does not seem to be sufficiently addressed yet

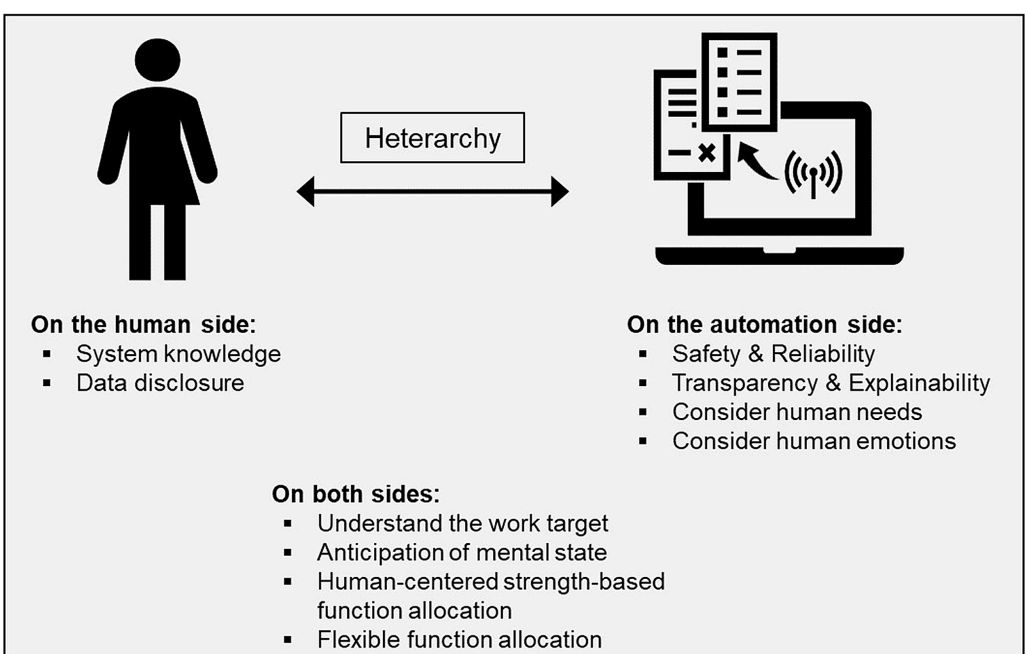

Fig. 1. Derived model of identified key aspects for a successful realization of automation as a team player for humans.

and more research, especially in terms of competence analysis with regard to increasing automation, are required.

4. Discussion

The purpose of the present study was to analyze the practical reality and feasibility of HAT from an experts' point of view, considering current possibilities of various fields. We aimed to find out whether the topics discussed scientifically are also practically relevant, to identify key aspects that are necessary for a successful realization of automation as an equal team player for humans, and to derive further research needs. We therefore conducted a literature review and expert interviews. This paper complies with the request to enrich HAT research with qualitative studies (O'Neill et al., 2020).

First, we were able to show that the participated industries are very advanced within the area of HAI. For an interaction with humans, most industries use or at least develop automation on decision selection or even action implementation (stage 3 & 4 according to Parasuraman et al., 2000). Contrary, the concept of HAT is hardly applied in those fields as it comes with many (technological) challenges. *Second*, we showed that the human-centered perspective seems to have entered the field as the common advantages and disadvantages of automation for humans discussed in the literature are also mainly considered within the industries. *Third*, we reveal an experts' disagreement on the feasibility of HAT in the field. While some consider HAT realizable and desirable, others deem it impossible or even reject it. However, they share the opinion that responsibility, liability, control, and the final decision should always rest with the human. *Fourth*, we identified key aspects for successful HAT from a practical perspective and converted them into a model (Fig. 1). It can serve as a guide for future research and practitioners to jointly contribute to the successful implementation of HAT in the field. *Fifth*, we compared each key aspect to the scientific debate and analyzed similarities and differences. *Sixth*, we identified future research needs from a practical perspective, which arise especially in the area of heterarchy, system knowledge, anticipation of mental states, and consideration of human needs and emotions. *Seventh*, it appears clear that today's technology is far from being able to meet the practical requirements for successful HAT, as postulated in the literature. More sophisticated technology is needed.

4.1. Implications

Results indicate that the topics discussed scientifically are also practically relevant. We, as a scientific community, seem to raise questions that are consistent with the concerns raised by practitioners. However, HAT research is still in its infancy. We need further research, as outlined in section 3.3, whereby our model of the key aspects for successful HAT can serve as orientation. As we believe the challenges of HAT cannot be overcome by one discipline alone, we call for an interdisciplinary collaboration between e.g. psychologists, computer scientists, and jurists to jointly find acceptable solutions. Moreover, we recommend more field research to better incorporate the challenges of the practical reality.

The integration of the practical perspective showed the current state of technology is not sophisticated enough to build a human-autonomy team in the field. E.g., there is still no technology that can anticipate and holistically consider human needs. We therefore request all practitioners such as system engineers, developers, managers, and other responsible persons to use the concept of HAT as a design template for further technological developments which are needed to pave the way for successful HAT in the field. The identified key aspects for successful HAT can thereby serve as a guidance. Furthermore, the question of changed requirements for employees due to increasing automation should be further analyzed as it is extremely important for personnel selection and training.

4.2. Limitations

The findings represent the subjective perception of the interviewees and could be limited by their ability to reflect. We had an uneven distribution within the various fields which could be a limiting factor. Referring to the interviewees' disagreement on the feasibility of automation as an equal team player, one might question the respondents' expertise. However, we tried to ensure this through a preliminary conversation. If the respondents indicated they did not have the necessary expertise for a question, we exclude them in the analysis to maintain an adequate expertise level in our results. Only 17 experts were able to name requirements for successful HAT as it is often not yet implemented in the field. Moreover, they mentioned many different requirements so that in some cases the number of codings is relatively small. However, this is negligible as the frequency distribution is not in the focus of qualitative research. Instead, the qualitative approach allows a deeper understanding (Leavy, 2014). We therefore aimed to provide a holistic overview of the mentioned aspects that are of concern to the respondents. Furthermore, we did not ask for the academic background of the interviewees. This could have explained the different perspectives on HAT as the topic receives different levels of attention depending on the field. However, we evaluated our results with regard to the interviewees' field of profession and could not find any dependencies. In addition, no prioritization of the requirements was made and it remains to be clarified whether *all* key aspects can be met at the same time and whether this would be expedient. Moreover, as the participated industries use diverse automation taxonomies, an overall comparison of the specific state of automation within the industries was only possible to a limited extent.

5. Conclusion

Overall, this study extends the emerging literature on HAT from a practical perspective by integrating an experts' point of view from different fields. We help to better understand HAT from a practical perspective, identify key aspects for successful HAT, compare them with the literature, and present further research needs. We are thus contributing to bring science and practice closer together which is, especially in the area of HAT, a key factor for success. It is now up to researchers and practitioners to *jointly* pave the way for successful HAT whereby the presented model and research needs might serve as a guidance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apergo.2021.103552.

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