The Need to Collaborate: Opportunities for Human and AI Co-workers

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Abstract: Researchers studying the development of modern economies and their workforce agree that the work of professionals may change profoundly in the future. Technology is seen as the main driver of this change, especially machine learning and artificial intelligence (AI). The biggest benefits can be most likely achieved by complementary use of human and AI capabilities and intelligence. This qualitative study investigates what potential collaboration concepts can look like and how collaboration is evaluated by the human. The aim is to identify potential, beneficial collaboration concepts with AI and to gain a better understanding of the influencing factors on user acceptance. The results show that the evaluation of potential collaboration appears to be a process including two phases. In general, many different aspects influence the evaluation of the collaboration concept in this process, but not all aspects seem to have an effect at the same time. 10 qualitative interviews are conducted and to narrow the scope of this research the focus lies on academic professionals, namely knowledge workers such as consultants.

1 INTRODUCTION

The future of work is assumed to change profoundly for many academic professionals and knowledge workers, e.g. consultants, especially in the way of how they will provide services to their customers in the future. Technology is seen as the main driver of this development and looking into the future these professionals need to work differently. One of the challenges consultants are facing is the economic problem, that many cannot afford their services. The services delivered to their customers are perceived as inefficient, too costly and the appreciation of their expertise has declined. Questions which arise in this context are for example if there might be new and very different ways to organize professional work to make services more affordable, accessible, and even increase the quality of the results. A new division of labour seems necessary and technology, with AI being one example, can be the key to rethink task allocation. (Susskind & Susskind, 2017)

The impact which this revolutionary technology will have on the professions and the way people work is uncertain and widely discussed. Skilton and Hovsepian (2018) state that fusion is key and that human and machine intelligence are becoming increasingly entangled indicating that complementary use of human and AI capabilities most likely contains the biggest benefits. Still human professionals will not be replaced entirely by technology. (Fügener et al., 2019; Lichtenthaler, 2018; Poortmans et al., 2019) Regarding these promising prospects, it seems not surprising that many executives and leaders are viewing AI as a great opportunity which needs to be exploited. When trying to implement AI initiatives, companies struggle rather with human resistance than with technical difficulties (Schlögl et al., 2019). In addition, the selection of suitable AI technologies and specific use cases for the application are challenging as many AI applications are available, but complimentary use seems difficult (Bauer & Vocke, 2019).

In this research on collaboration concepts with AI the focus lies on knowledge workers (e.g. consultants) and how their work may change due to technology. If this highly professionalized group of experts can collaborate successfully with AI and is willing to do so it could imply that most other professionals could do

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so as well. Looking at consultants' tasks it can be agreed that they consist mostly of gathering, processing, and interpreting data which could also be done by AI with the potential to achieve even better results. Therefore, the question is if or when CEOs will turn to intelligent systems to ask for advice rather than consultants. (Libert & Beck, 2017)

Futurists predict a third of jobs may be eliminated through technology, but little research has been conducted on how employees perceive technological change (Brougham & Haar, 2018). Academic research on human-AI collaboration focuses rather on technical aspects or theoretical frameworks. This research studying potential collaboration concepts using AI in white collar jobs is relevant to close the research gap and contribute to future business success of professionals.

2 CONTEXT

The state of current research in the field of human-AI collaboration shows different opportunities of collaboration between human and AI co-workers. In decision-making for example, Colson (2019) proposes to evolve from data-driven to AI-driven decision processes. To fully leverage the value of data it can be suitable for routine decisions based on structured data to rely on AI only to eliminate human's cognitive bias. Often business decisions do not solely rely on structured data but also qualitative insights and additional information. Better decisions can be made by finding ways to leverage both humans and AI and create case-specific workflows. For example, AI can be used to generate different possibilities based on data and the human can pick the best alternative using the additional information it has access to. (Colson, 2019) This approach could be described as hybrid intelligence (Dellermann et al., 2019) or augmented intelligence (Rao, 2017). In terms of collaboration, an international group of researchers were the first to develop a set of algorithmic mechanisms which can learn and collaborate with humans as well as with other algorithms. (Breazeal, 2003; Crandall et al., 2018; Dautenhahn, 2007; Kamar et al., 2013) This research has proven that collaboration with an algorithm is possible on a level comparable to that with another human and gives insights on the potential of intelligent, autonomous systems as teammates.

How potential collaboration could be implemented in terms of applications was researched by Bittner et al. (2019). Instead of trying to copy the human brain, to overcome limitations of AI, the authors argue that the most valuable approach would be to combine the capabilities of human and AI agents to minimize each other's weaknesses. This view is supported by Fügener et al. (2019). Their study showed that collaboration and delegation between humans and AI can produce results that outperform humans or AI alone. Huang and Rust (2018) studied the potential impact of AI on the service industry and developed a theory of how AI may replace jobs. This theory supports the conclusions of Fügener et al. (2019) and Bittner et al. (2019) that the distribution of tasks is essential for job sharing of humans and AI.

In subsequent research, Huang and Rust (2019) focused on investigating and proving the emergence of the *Feeling Economy* assuming that the importance of feeling tasks, compared to mechanical and thinking tasks, will increase. This development will mean that human workers and AI need to work as a team with a task allocation matching the task requirements and respective strengths. AI will take over most thinking tasks while the human worker focuses on feeling tasks and interaction with others. Other studies focused on certain job profiles. Sowa and Przegalinska explored possible synergies between (2020) human workers in managerial positions and AI-powered computer systems while the research conducted by Wang et al. (2019) aimed at understanding future impacts automated AI applications may have on data scientists. In this research the general opinion was quite optimistic as a collaborative approach of data science work in the future using human and AI expertise was seen as most promising. (Wang et al., 2019) The authors mentioned above outline how collaboration can be brought to live in certain industries and jobs, but it remains unclear how human-AI collaboration concepts can be applied regarding the tasks of a knowledge worker.

As the attitude of employees toward technology and their acceptance of technological systems play an important role in the adoption of AI systems this related research stream needs to be included. The Technology Acceptance Model (TAM) developed by Davis (1989) is based on prior research by Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA) and focused on the topic of acceptance and use of information technologies. Davis based the model on the assumption that the attitude of a potential user toward using a certain system is the major determinant of the actual system use (Davis, 1993). This attitude is influenced by the *perceived usefulness* of the system and its *perceived ease of use.* The TAM was used as a foundation for the further development of TAM2, in which theoretical constructs regarding social influences and cognitive aspects were included preceding perceived usefulness (Venkatesh & Davis, 2000). With the TAM3, Venkatesh and Bala (2008) focused on the question how managers can support better acceptance and utilization of new IT systems (Venkatesh & Bala, 2008). To provide a unified view on user acceptance Venkatesh et al. (2003) reviewed and compared eight existing theories which resulted in the formulation of the Unified Theory of Acceptance and Use of Technology (UTAUT). (Venkatesh et al., 2003) The UTAUT (see figure 1) included the constructs *performance expectancy*, *effort expectancy, social influence*, and *facilitating conditions* as these were seen as major determinants of user acceptance and usage behavior (Venkatesh et al., 2003).

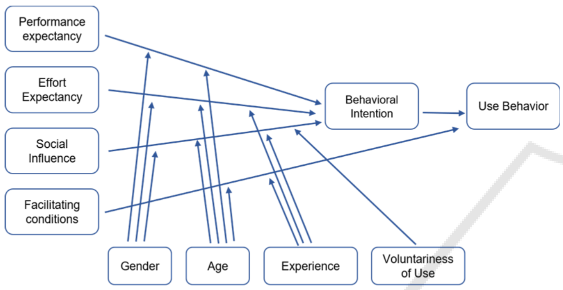

Figure 1: Illustration of UTAUT (own figure based on Venkatesh et al., 2003).

The UTAUT was also further developed, resulting in the UTAUT2 which focused on the consumer perspective of technology acceptance and use (Venkatesh et al., 2012). This rather specific context and point of view of UTAUT2 is not as relevant for this research as the focus lies on the organizational perspective, specifically on employees as users of systems. Therefore, a research gap is identified, as it has not been described yet how a technology acceptance model for the human co-working with AI can look like and which aspects are most important from the human-centric perspective. Furthermore, the question remains why or why not would the human like to co-work with AI? (RQ2)

Hence, the authors propose the following research questions:

- How is the (potential) collaboration with AI evaluated by the knowledge worker? (RQ1)
- Why or why not would the knowledge worker like to co-(work) with artificially intelligent systems? (RQ2)

In summary, best practices resulting from the literature review are evaluated regarding their applicability for tasks of a knowledge worker and different collaboration concepts are developed. These are described in six specific scenarios. Scenarios make it possible to include the context surrounding a specific research question and, with that, broadening the scope of the study (Ramirez et al., 2015). The six collaboration concepts are the following:

- AI as intelligent trend and market research assistant supports the knowledge worker in gathering and summarizing information on any given topic.
- The AI virtual tutor joins workshops with clients to detect and analyze emotions of participants signaling when further explanation or a break is needed.
- AI takes over process analysis and provides suggestions of how to improve them.
- Smart Sales and Marketing Forecasts can be provided by AI and the human + AI approach focusses on including quantitative data and qualitative input from the human co-worker.
- AI functions as agile and autonomous project manager handling planning, monitoring, and observing team performance.
- AI takes over team management and staffing by selecting suitable knowledge workers for each project.

3 METHODOLOGY

Focusing on the exploration and understanding of how individuals perceive new forms of collaboration with AI a qualitative research approach is chosen. As little research has been conducted on human-AI collaboration the Grounded Theory methodology is chosen to guide the research process. In addition, the aim of this research approach is not the verification of theory but rather the generation of a theory. (Glaser & Strauss, 1967)

3.1 Research Strategy

To apply the research method described above the following research approach is chosen. To set the frame and context of the qualitative research and to differentiate the collaboration concepts clearly, the six scenarios are classified and structured resulting in a working model (see figure 2). The x-axis offers a classification of the degree of collaboration between humans and AI following the suggestion of Rao (2017) and inspired by the conceptual models of human-machine collaboration developed by (Dellermann et al., 2019; Simmler & Frischknecht, 2020; Traumer et al., 2017).

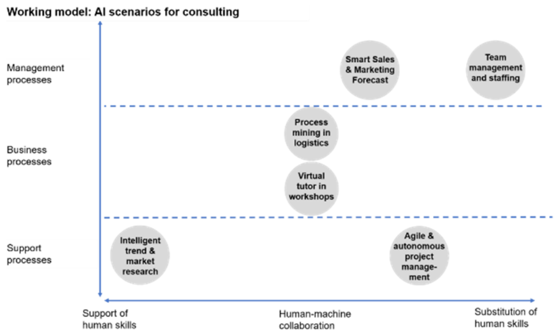

Figure 2: Working model for AI scenarios in consulting (own figure).

In this working model, an orientation shall be offered on how collaboration can gradually evolve. This shall be achieved by starting with applications that support human skills on the far left, then moving toward different modes of collaboration where human and AI workers have specific deliverable tasks to achieve a common goal and ending on the right with the potential substitution of human skills where AI takes over the tasks formerly performed by a human worker. The focus of the scenarios is set on the different forms of potential collaboration and task allocation. This is described as the most promising way of applying AI in business regarding synergy effects and performance increases through complementary capabilities.

The y-axis pictures the organizational structure and perspective concerning the business processes in which AI scenarios may be useful and value-adding. The three superordinate process categories of organizational value creation are classified according to the St. Gallen management model into management, business and support processes (Rüegg-Stürm & Grand, 2020). This working model and the scenarios serve as common ground and tool for the qualitative interviews, representing a comparable foundation and starting point for the data collection.

3.2 Data Collection

In preparation for the data collection with 10 qualitative interviews a semi-structured interview guideline was developed. Answers in these interviews often provide much deeper and more concrete insights from the perspective of the person affected than a standardized survey could.

For every scenario, questions are asked about the aspects of collaboration, usefulness, trust, control, and general attitude toward the scenario described. Questions like *would you like to collaborate with AI in this way?* or *how will this collaboration with AI impact performance?* are included. In the final part of the interview, knowledge workers are asked to reflect on the scenarios presented and to indicate which type of collaboration concept they would prefer with regard to the degrees of collaboration (as pictured on the x-axis of the working model). The interviews are scheduled for a duration of approximately 60 minutes, are conducted via video call, recorded, and transcribed.

3.3 Data Analysis

The analysis of the collected data follows Strauss and Corbin (1990) to generate theory in any form which explains behavioral patterns and to identify influencing aspects as well as the relations between them. Coding as systematic strategy of interpretative analysis is conducted in different styles of coding which are open, axial, and selective coding. Open coding is usually the first approach to data analysis and is used to intensively analyze the interview transcription, for example line by line or even word for word with the aim of exploration and concept identification which are then labelled with a suitable code of one or two words. Codes can be based on the data itself or the scientific knowledge in the research field. (Strauss & Corbin, 1990)

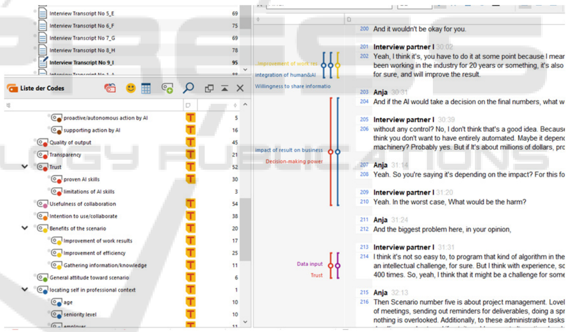

Figure 3: Coding example (MAXQDA).

To gain more insights into the relationships between concepts and categories in order to understand the phenomenon as a whole, a coding paradigm can serve as analytical tool to support axial coding around a category. The coding paradigm according to Strauss and Corbin suggests the following features: conditions, actions-interactions and consequences or outcomes.

In order to address the research questions the authors investigate the relations between categories and aim to integrate them into one overarching theory. It is a systematic and concentrated coding process focusing only on the central category. MAXQDA is used to operationalise this research.

4 ANALYSIS

Keeping in mind the research question RQ1 *how (potential) collaboration with AI is evaluated by the knowledge worker* it seems that the answer cannot be as simple as collaboration is evaluated positively or negatively, but rather it depends. The research question RQ2 *why or why not would the knowledge worker like to work with intelligent systems* focuses on the aspects on which the evaluation finally depends.

The result of the open coding process is a total of over 50 different codes labelling roughly 800 text passages in the interview transcriptions. As these 50 codes are located on different levels of abstraction, they are reviewed to eliminate redundancies and to regroup similar codes into higher-level concepts or categories. The review of the 50 initial codes leads to a consolidation of 12 categories (see figure 4) and their respective subcategories. The most important categories with the highest frequency are *usefulness of collaboration, confidence and trust in AI skills* and *expected outcome of collaboration.*

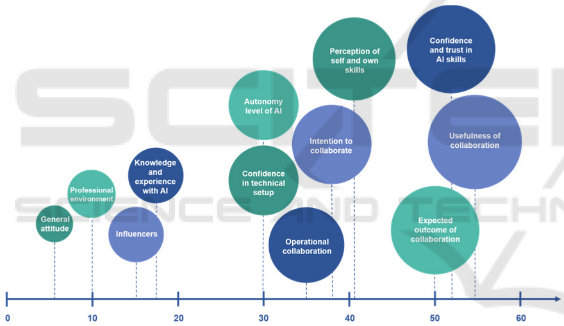

Figure 4: Consolidation of codes into 12 categories (own figure).

Following the open coding, the next step is the axial coding. The aim of this coding process is to understand the more holistic picture. Derived from the interview responses and the building of categories in the open coding the usefulness of collaboration seems to be the central phenomenon. The answers of the knowledge workers interviewed imply that they try to evaluate the usefulness of a potential collaboration in the first place. Therefore, the central phenomenon will be described as the evaluation of usefulness of collaboration.

The last step of coding in Grounded Theory is the selective coding. The aim of this coding process is the integration of the developed categories into one overarching theory. To visualize the results and the developed theory, a model is created showing how the evaluation of human-AI collaboration from the perspective of the human co-worker is performed. The model is presented in figure 5.

Through in-depth data analysis of the interviews the answers imply that there seem to be several stages of evaluating potential collaboration. This would mean that the overarching theory developed can be rather seen as process which is why the model presented is visualized as such. This model developed in axial and selective coding is based on the assumption that the whole process starts with the question how potential collaboration with AI is evaluated by the human collaborator. And it answers the RQ1 *how (potential) collaboration with AI is evaluated by the knowledge worker:* evaluation can be seen as a process incorporating two phases.

Phase 1: Personal evaluation. This input is being processed in the first phase of personal evaluation focusing on the core concept of evaluating the usefulness of collaboration. This evaluation of usefulness may be influenced by multiple aspects as mentioned before. The core aspects are the central categories that seem to be more important in this phase of personal evaluation as the context related aspects. The core aspects include four concepts which are part of the answer to RQ2 *why or why not would the knowledge worker like to work with intelligent systems.*

1. The expected outcome of collaboration centers around the question what is the value added that can be expected through collaboration? What are benefits and also consequences to be expected? As the interview partners expect a certain effort needed to realize collaboration with AI, they would like to know if it is worth this effort and if there is a return to be expected in some way. Either in increasing efficiency, saving resources or benefits and value adding aspects contributing to improved work results. The expectancy of a certain outcome could contribute positively or negatively to the perceived usefulness of collaboration.
2. The confidence and trust in AI skills is another core aspect which incorporates the overall opinion of the interview partners on the capabilities of AI in a certain scenario. The question to be answered here could be if the human collaborator is convinced that AI can take over a specific task and perform well. The confidence in AI skills may play an important role when delegating or outsourcing tasks to the intelligent system just like in a human team, one likes to be certain that team members are capable of handling the tasks they are responsible for. Being positive about the usefulness of

collaboration seems to be only given if one is convinced of the skills AI has. Otherwise, the human collaborator might worry that collaboration would not be beneficial but rather complicate things in daily work. This relates to the expected outcome as well.

3. Operational collaboration is evaluated regarding the aspect of usefulness in the sense of how easy it is perceived to implement into daily work, how interaction with AI is realized and if the task allocation is perceived as useful and beneficial. Again, this latter aspect links operational collaboration to the concepts of expected outcome and the confidence in AI skills.
4. The fourth core aspect is the perception of self and own skills the knowledge worker has. Regarding the evaluation of usefulness of collaboration, it seems to play a role for the interview partners if AI is taking over tasks that are associated with human-only skills or if they accept and recognize own limitations. Human-only skills or tasks that the knowledge worker expect themselves to perform well are unlikely to be outsourced to AI as this is not perceived as a useful action. While if the limitations of own skills are recognized or the tasks are considered as unsatisfying, the interview partners seem more willing or even pleased to allocate these tasks to AI. This quite subjective perception and judgement appears to influence the evaluation of usefulness.

As context related aspects, the concepts of professional environment, general attitude and knowledge and prior experience with AI can have an influence on evaluating usefulness as well and contribute as well to the answer of RQ2 *why or why not would the knowledge worker like to work with intelligent systems.*

For the aspect of professional environment especially, the area of work, project settings and prerequisites regarding the organizational structure seem to have an influence on the perceived usefulness of collaboration. The suggested collaboration scenario needs to be relevant and familiar to the interview partner and solve a known problem. Otherwise, the perceived usefulness may be lower as the knowledge worker does not understand how this collaboration should have a beneficial impact. The general attitude including the affinity and openness toward technology may have an influence in the sense that interview partners confirming to be open toward new technologies may have a more positive opinion on the usefulness of collaboration. Former experiences with AI or subject matter knowledge regarding AI could have a positive and negative influence on the perceived usefulness. Relating also to the expected outcome and confidence in AI skills as interviewees may know if the suggested collaboration could actually work well and if the expected results are realistic. This evaluation of usefulness results in an opinion on the usefulness of collaboration based on the discussed influencing aspects.

Phase 2: Consideration of external parameters. In the second phase of evaluating potential collaboration, external parameters are considered. These external parameters complete the answer of RQ2 *why or why not would the knowledge worker like to work with intelligent systems.* The formed opinion in the first phase could be influenced by certain gateway conditions which are the concepts of influencers, confidence in technical setup and the autonomy level of AI. Interpreting the answers of the interview partners it seems that although an opinion on the usefulness of collaboration has been established these gateway conditions could still impact this opinion and even act as showstoppers or no go's for the knowledge workers. Influencers like clients or managers could prevent knowledge workers from pursuing collaboration if they voice concerns or dislike. The confidence in the technical setup of the collaboration especially regarding transparency and data security, seems to be a prerequisite. Otherwise, a formerly positive opinion on the usefulness could not be sufficient to maintain the intention to collaborate. Autonomy levels of AI are often defined by the developing company and programmers creating the technological setting of the collaboration. In case these autonomy levels are non-negotiable or not adaptable to a potential collaborators' wishes, it might lead to a rejection of the collaboration concept as a whole.

The two phases of this evaluation process start with the core concept of usefulness as the answers imply that if usefulness is not seen as positive, interview partners seem not to think about the external parameters very deeply. If the usefulness is confirmed, the gateway conditions appear to come into play contributing to the decision if collaboration will be pursued. Therefore, the outcome of this procedural concept of evaluating collaboration with AI conducted by the human collaborator leads to the intention to collaborate or to not collaborate. And it is important to emphasize that not all influencing concepts and aspects seem to have an effect at the same time but rather sequentially.

Connecting the results of this research with the related work and specifically the UTAUT (see figure 1), the procedural manner of evaluating collaboration with technology (in this case AI) has not been

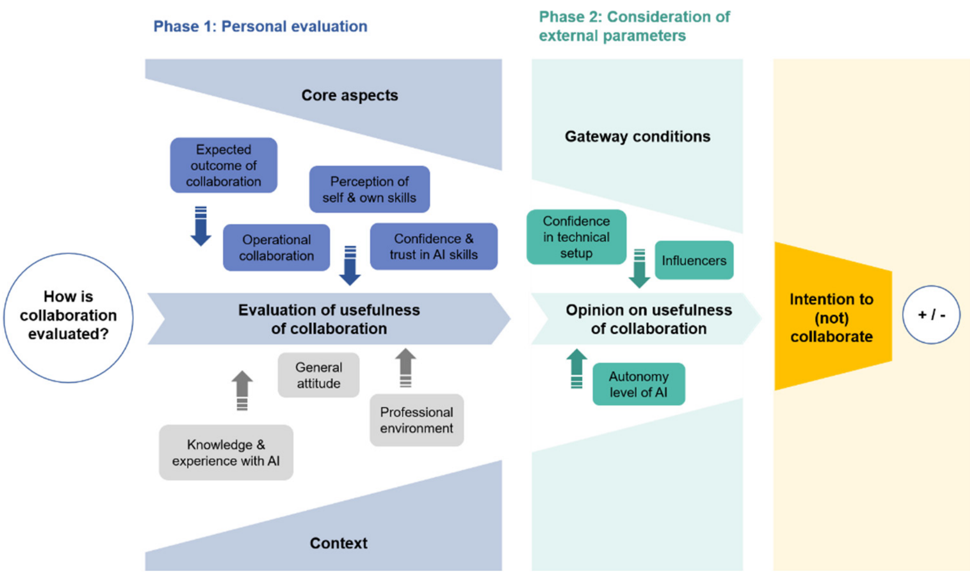

Figure 5: Funnel model of evaluating Human-AI collaboration (own figure).

emphasized. The concepts of the UTAUT model performance expectancy, effort expectancy, social influence and facilitating conditions could be similar in meaning to the mentioned concepts of expected outcome of collaboration, operational collaboration, professional environment/influencers, and confidence in technical setup. Although the congruence of these concepts would need to be analysed in more detail to draw a final conclusion. The newly discovered core concepts of confidence and trust in AI skills and perception of self and own skills have not been mentioned in the related work yet and add to the existing body of knowledge. In addition, the gateway condition autonomy level of AI is a new concept as well.

Hence, the following funnel model is proposed as presented in figure 5 and answers the research questions RQ1 *how (potential) collaboration with AI is evaluated by the knowledge worker* and RQ2 *why or why not would the knowledge worker like to work with intelligent systems.*

5 FURTHER RESEARCH

Based on the data analysis conducted in this research, four propositions for further research are suggested. Firstly, the data indicates that the evaluation of potential collaboration seems to be conducted in a procedural manner starting with the evaluation of usefulness and considering external parameters only in the second phase. Therefore, it is suggested to validate the following propositions P1 and P2 for verification by qualitative and quantitative means:

- Potential collaborators evaluate the usefulness of collaboration first before considering other aspects. (P1)
- Consideration of external parameters (e.g., data security) occurs later in the evaluation process. (P2)

Secondly, the responses show that several aspects influence the perceived usefulness of collaboration. Considered as especially interesting is the concept of self-perception. It would be interesting to know if this concept has such a high influence on usefulness that it could be a showstopper. Proposition P3 relates to this idea:

- Perceived usefulness depends mostly on the individual self-perception of own skills of the potential collaborator. (P3)

Thirdly, the gateway conditions seem to play such an important role that they could minimize the intention to collaborate although collaboration is perceived as useful. Therefore, the researcher suggests proposition P4 for verification:

- The intention to collaborate depends on the evaluation of the gateway conditions. (P4)

As a first step following this research it would be interesting to interview leading experts and researchers on the matter of human-AI collaboration to hear their opinion on the findings and results discovered. In general, it might be interesting to investigate human-AI collaboration in other white-collar jobs looking at different groups of academic professionals. To extend the research to other countries could offer interesting insights how the cultural background may influence the perception and evaluation of usefulness. To study the strength of influencing factors and their cause-and-effect relations more deeply and to verify these relations quantitatively could be another interesting future research subject. A longitudinal study that includes information on human-AI collaboration from the current period when collaboration concepts are not yet widely used and to investigate differences over time would offer be an interesting research approach as well.

6 REFLECTION

The research results show that further complementary aspects influencing human-AI collaboration were discovered which have not been discussed by former research.

Looking at the working model and the collaboration scenarios developed, it should be considered that these may constrain the view of the interview partners and the research itself. They served as common ground to make responses comparable as most interview partners did not have experience in collaborating with AI in a professional context. The selection of interview partners was done according to certain criteria and the researchers focused on selecting a heterogenous group of interview partners from diverse backgrounds, sectors, and areas of expertise. Ideally for the Grounded Theory approach, theoretical sampling would be desirable where the choice of interview partners depends on the obtained results from prior interviews.

A theoretical saturation could be noticed by the researchers during the coding process as with an increasing number of interviews conducted less new codes emerged from the responses. The sample of ten interviewees is quite small and focused on the professional group of consultants, all living in Germany. Therefore, the findings are not representative, and generalizability is limited. The different levels of experience and knowledge about AI of the interviewees could be seen as limitation as this may have influenced the responses

7 CONCLUSIONS

The aim of this research was to identify potential human-AI collaboration concepts focusing on the job profile of a knowledge worker, e.g. a consultant. Additionally, insights and findings should be generated how these collaboration concepts are evaluated and perceived by knowledge workers as well as what influences their willingness to collaborate with AI. The review and analysis of current research regarding collaboration of human and AI co-workers showed that the collaboration with AI is possible in multiple ways across sectors and that combining human and AI capabilities can be valuable.

Nevertheless, the size of the benefit depends on the specific collaboration concept. The division of work and task allocation would change but knowledge workers evaluate this, depending on the scenario, as desirable and reasonable. The intention to collaborate with AI and, with that, the acceptance of intelligent systems seems to be influenced by a diverse range of factors. Surprisingly was the finding that the evaluation of collaboration concepts appears to be a process for the interview partners including two phases of evaluation. This process is visualized as framework (see section 4) showing that not all of the influencing aspects have an effect at the same time.

If usefulness of the suggested collaboration scenario is not recognized or not seen as big enough, collaboration will not be pursued, and the second phase of evaluation is not entered. In case the evaluation of usefulness is assessed positively the consideration of external parameters comes into play. These gateway conditions should not be underestimated as they might be contradictory to the positive opinion on usefulness. Additionally, if they are weighed heavily by the individual, these conditions can be an obstacle and even showstopper for the decision and intention to collaborate with AI.

The diversity of influences that affect the evaluation of human-AI collaboration concepts, leading to the intention to collaborate and lastly to the actual collaboration itself shows how complex a successful implementation of AI initiatives may be. The human collaborator plays a crucial part in this implementation and should be onboarded and integrated in the AI initiative early in the process.

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