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Types of Human-AI Role Development - Benefits, Harms and Risks of AI-Based Assistance from the Perspective of Professionals in Radiology

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Abstract: *In this paper we analyse the role development of professionals in healthcare in face of AI applications to their workplaces. The conceptual background is role development theory aligned to human-AI work settings. The empirical fundament is a case study analysis conducted at Charité including a profile analysis of survey data from radiology (N=128) and a structured content analysis of ten semi-structured interviews with professionals. The outcome is the distinction of two most typical human-AI role concepts, (1) the AI-embracing human-AI role concept, and (2) the AI-ambivalent human AI-role concept. These types are based on the same set of antecedents in terms of AI literacy, former digital experience, individual perspective on the technology and the impact of AI on the overall change of individual tasks. This allows to understand why the first type experiences benefits from the human-AI role development while the second type cannot exclude personal harms. The AI-embracing role concept enhances role making with AI and incorporates AI implementation, the latent risk of AI in the AI-ambivalent concept leads to role taking against the technology.*

Keywords: artificial intelligence, role theory, role development, healthcare, technology acceptance

1. Introduction

The means and ends of artificial intelligence (AI) applications at work are subject of certain discourses and disciplines. This includes the potential benefits and merits for better solutions for work and society (Markoff, 2016; Fischer, 2018) but also the harms due to the opacity and shortcomings of a technology built on biased data (Smith, 2021; Asan et al., 2020; Nusir & Rekik, 2022) up to risks such as negative consequences for the employment in some job families (Zuboff, 1988; Boyd & Holton, 2018; for a more distinctive view Fleming, 2019). Current research shows that a profound evaluation needs contextualization (Widder & Nafus, 2023) with respect to the concrete field of application (Wilkens et al., 2021) and is influenced by the meta-perspective on the human-AI interaction, i.e. whether AI is considered as a tool for, a medium between or a counterpart of human beings at work (Anthony et al., 2023). Against this background, scholars call for context-specific empirical substantiation with ethnographic elements (Widder & Nafus, 2023; Anthony et al., 2023, Raisch & Krakowski, 2021).

Healthcare is a most relevant field of AI applications as a breakthrough can be observed due to the potential for high precision medicine and better care in this industry (Castaneda et al., 2015; Hashimoto et al., 2018; Monteiro et al., 2017). There is a wide range of possible applications in diagnosis, treatment, surgeries, nursing or even co-creation with the patient (Ciasullo et al., 2022; Lee & Yoon, 2021; Mabillard et al., 2021; Caic et al., 2019; Dewey & Wilkens, 2019; Lee, 2018). Especially radiology is a use case where employees made real experience with AI and where one can assume an overall adaptation to AI-supported solutions during the next years (Dewey & Wilkens, 2019; Thrall et al., 2018). This implies that the human interaction with AI and individual role development is an issue for certain professions including radiologists or physicians in general, X-ray or nursing staff and indirectly also includes patients and their relatives (Scheek et al., 2021; Lee & Yoon, 2021; Asan et al., 2020). One the one hand there are visions and conceptual outlines for healthcare in general and radiology in particular that AI applications lead to better care for patients and human-centered approaches in medicine as well as augmentation of clinical experts in terms of their self-concept as professional (Galsgaard et al., 2022; Asan et al., 2020; Scheek et al., 2021; Davenport & Kalakota, 2019; Dewey & Wilkens, 2019). On the other hand, there is empirical evidence that the professionals fear risks and that there are considerable obstacles of AI implementation at least if one not just asks AI experts but the broader group of potential users of AI applications (Ardon & Schmidt, 2020; Scott et al., 2021). There is a need to understand the adaption of AI from the perspective of those employees who are confronted with the technology in the work context.

Research approaches most likely describe the potential of AI from the perspective of the technological advancements considered as a sufficiently convincing argument for its use (Ahmed et al., 2020; Xu et al., 2021). Technology acceptance models go beyond and understand user acceptance as an issue of usability while individuals interact with a technology. These scholars emphasize user-centered technological characteristics (Davis, 1993; Venkatesh & Davis, 2000) with a current focus on the explainability of AI (XAI) which is of particular interest in healthcare (Amann et al., 2020; Srinivasu et al., 2022). However, this is a rather narrow view of human-AI interaction; a contextualization of AI applications needs to go beyond technological features and individual reactions to these characteristics. It requires a sociotechnical system perspective on human-AI role concepts integrating the dynamics in the work context, how AI is experienced and enacted by organizational citizens. Structuration theory emphasizes the institutional properties and individual evaluations of the means and ends of technology adaption within a work system (Orlikowski, 1992). Individuals' attributions of technology in general as of AI in particular depend on the assumed consequences for the occupational identity of the users (Nelson & Irwin, 2014). This pivotal issue is rather independent from the features of the technology but rooted in the individual role concept in the organization.

The individual professional status resulting from an occupation is of high relevance in healthcare systems (Hafferty & Light, 1995) and can thus be assumed as the basis of employees' identity. AI acceptance and implementation in healthcare has recently been proposed to depend on the perceived human-AI expertise (Galsgaard et al., 2022; Asan et al., 2020) but has not been systematically investigated on empirical basis against this background in a concrete work context. There is already knowledge about technology innovation and implementation in organizations (Orlikowski et al., 1995; Orlikowski, 1996; Leonardi, 2011; 2013; Nelson & Irwin, 2014) but whether this knowledge can be fully transferred to AI applications in their pervasive nature (van Krogh, 2018) and high interrelatedness with the human agent (Anthony at al., 2023) or whether there are additional impact factors that need to be taken into consideration is an open question calling for empirical foundation. Our aim of analysis is to specify the antecedents of individual role development of professionals in healthcare who are confronted with AI applications. There is a need to specify human-AI role concepts, how differences can be explained and what the practical implications are for AI integration in the workplace.

In the next section, we outline the conceptual pillars for understanding AI and individual role development in face of AI application to a professional work context. In the third section we explain the methodological approach of a case study analysis conducted in radiology at Charité. The analysis includes some ethnographic elements and is based on a profile analysis of survey data from radiology (N=128) and a content analysis applying the Gioia methodology (Gioia et al., 2013) of ten semi-structured interviews with two groups of professionals, radiologists and radiographers. The core research finding of an AI-embracing human-AI role concept and an AI-ambivalent human AI-role concept will be described in section four. The identified antecedents of human-AI role concepts and implications in terms of role making with or role taking against AI contribute to a comprehensive conceptual outline. This elaborates on findings from former technology innovation research by new empirical insights deduced from the case study analysis. The limitations of the study and perspectives for future research will be summarized in the final section.

2. Conceptual pillars

2.1. AI and single-purpose AI applications in healthcare

AI is an umbrella term for those software applications that are based on neural networks and various machine learning (ML) algorithms in order to detect patterns. The concrete definition depends on the generation of technology development, which is most often described in three waves (Launchbury, 2017; Xu, 2019) and meanwhile leads to a distinction between single-purpose AI and general purpose or generative AI (Fischer, 2022). While the first wave did not lead to practical applications, the second wave of AI development is based on statistical learning and single-purpose software giving machines "the ability to reason and perform cognitive functions such as problem solving, object and word recognition, and decision-making" (Hashimoto et al. 2018, p. 70). These applications, primarily from supervised ML which are pre-trained and fine-tuned for detecting patterns on the basis of a mass of data, e.g. for classifying X-ray images, are the most typical applications of AI in healthcare. This is the fields of technology considered in our case analysis. Professionals do not just talk about AI but have first user experiences. The rising research interest in the third wave of AI development in general-purpose AI (Fischer, 2022) is currently not an issue of AI applications in healthcare.

In healthcare technological artifacts appear in different forms of materiality for the users (Leonardi; 2011). It is sometimes more the physical artifact such as robots in surgery but also nano-robots for precise drug delivery, exoskeletons for stabilizing muscles or carebots for carrying patients which is considered as relevant (Hamet & Tremblay, 2017; Grudin, 2009) and sometimes more the virtual artifact in terms of software, e.g. imaging, which matters. Physical AI influences the job design as it is related to questions of what tasks are performed or assisted by robots (Davenport & Kalakota, 2019; Kyrarini et al, 2021). Virtual AI is much more related to ML-based decision making (Hamet & Tremblay, 2017) but does not change the overall job profile as long as individual decision making is just supported but not substituted by the technology (Wilkens et al., 2021).

2.2. AI in the eyes of the user - Ensemble view and role development

The application of AI in healthcare requires a sociotechnical system perspective including technological characteristics, organizational settings and individual behavior (Salwei & Carayon, 2022). Scholars with a more technical background in sociotechnical system design refer to the physical proximity between the human agent and the robot and distinguish different levels of separation, integration and collaboration between machines/robots and human beings while performing tasks (Bengler et al., 2012). Currently the focus relies on human-robot-teaming (Demir, McNeese & Cooke, 2020; Groom & Nass, 2007) or human-AI-teaming (Hagemann et al., 2023) with a high level of human-computer-collaboration while prior concepts emphasized the division of tasks between robots and employees (Ajoudani et al., 2018).

Following structuration theory as another direction in sociotechnical system research (for an overview see Herzog et al., 2022), technology at work is not a pre-planned object and isolated entity of job design but interrelated and entangled by institutional properties, individual perceptions, attributions and adaptions including unexpected ways of use or missing acceptance of the technological artifact (Orlikowski, 1992; Orlikowski et al., 1995; Orlikowski, 1996). Orlikowski & Scott (2008, p. 434) argue that “there is an inherent inseparability between the technical and the social“, respectively an “inseparability of meaning and matter” (Scott & Orlikowski, 2014, p. 28). It is the social which interprets and frames the technical. This is why technological innovation can be reflected under the lens of an ensemble view (Orlikowski & Iacono, 2001; Akhlaghpour et al., 2013) emphasizing the collective action and entanglement of technology in institutional fields. It is the way of using and enacting a technology which defines its purpose and becomes an issue of meaning. Current research contributions underline that AI in its pervasive nature and facets of non-human agency are more than a new technology but generate also a new social (van Krogh, 2018; Agarwal & Jayant, 2019; Anthony et al., 2023). Empirical contributions emphasize that context matters when applying AI in organizations and that contextualized research approaches are necessary (Widder & Nafus, 2023). Obviously, a job design with a specific outline for human-AI-interaction or human-AI-teaming does not necessarily correspond with the individual role concept of the professionals addressed in the outline.

Former research in technology innovation can help to structure human-AI role concepts with insights gained from other human-technology entanglements. Leonardi (2011, 2013) underlines that individuals’ past experiences play an important role as they either foster a positive technology perception (affordance) and consequently adjustment of human routines or a negative technology perception (constraint) and related adjustment of technology. Affordances and constraints already matter if there is only a future outline for a new technology in a job profile and not necessarily already a real confrontation with it. The individual action and adaption depends on the interpretation of a technology, its means and ends while transferring experiences from the past to future work. Technology integration implies sociotechnical system dynamics resulting from expectations, new experiences and interpretations (Langholf & Wilkens, 2024).

Current research adds a meta-perspective to the attribution of AI in human-AI interaction. Anthony et al. (2023) explored from a literature review that scholars understand AI either as a tool or as a medium or as a counterpart and that research findings are permeated by these often-implicit perspectives on technology. This distinction can also be assumed as a perspective of a user whether the individual attributes AI as a tool, a medium or a counterpart. Former generations of new technologies were considered as tools. But understanding technology as a medium or counterpart increasingly comes to the foreground.

Asan at al. (2020) and Galsgaard et al. (2022) conceptualize the role development of physicians respectively radiologists in face of AI applications while following a counterpart perspective. Galsgaard et al. (2022) explain technology acceptance in dependence of the perceived expertise in psychological self-concepts of interacting with AI and argue that a separated expertise between radiologists and AI tends to be conflictual and causes implementation barriers while a collective human-AI expertise supports the development of new role concepts. In more detail, they describe four types of expertise (see Figure 1) depending on the level of task integration and on perceived individual agency of who is in control when interacting with AI (for agency see Berberian et al., 2012; Legaspi et al., 2019; Wagner, 2019). Following the propositions provided by Galsgaard et al. (2022) a separated expertise between human beings and AI generates barriers for technology integration while the experience of augmentation or even an inseparable collective human-AI expertise fosters AI implementation.

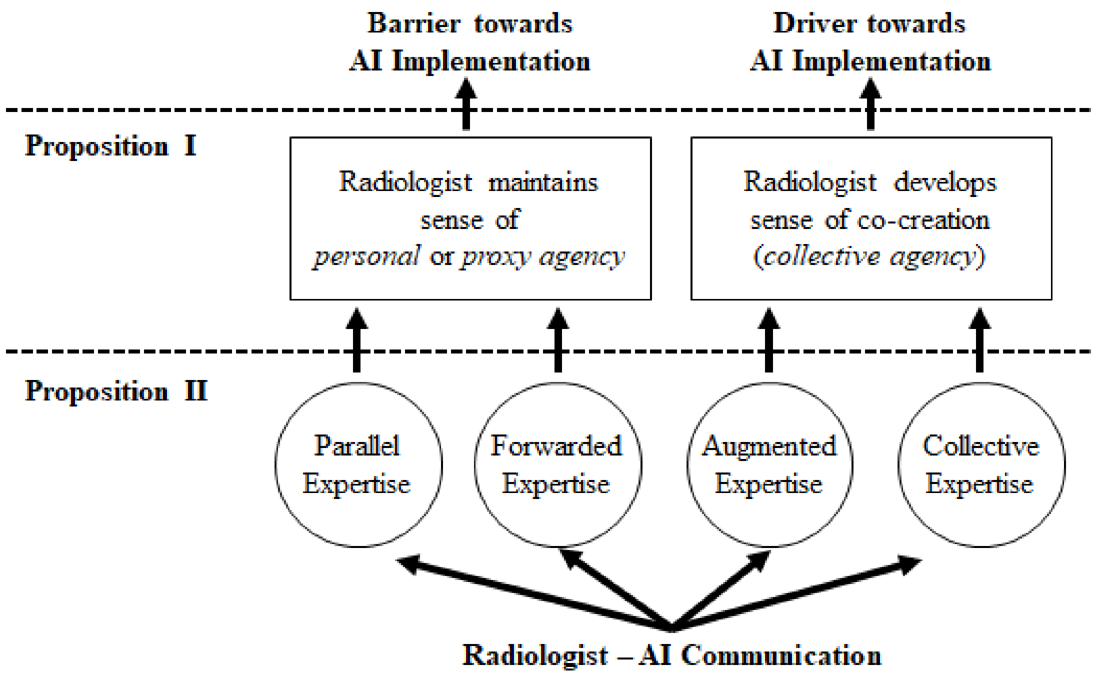


Figure 1. AI and professional role development - the example of radiology
Note. According to Galsgaard et al. (2022, p. 7).

2.3. Role development as an issue of role making vs. role taking

Even though there are outlines for role concepts in the current discourse on human-AI interaction including job design descriptions and individual interpretations of the professional identity while working with AI (Galsgaard et al., 2022; Scheek et al., 2021; Lee & Yoon, 2021), concrete descriptions of the role development process are still rare (Scheek et al., 2021; Langholf & Wilkens, 2024). Nelson & Irwin (2014) show for the professional group of librarians and their adaption or non-adaption to internet search as at that time of their analysis new technological option the “paradox of expertise” (Nelson & Irwin, 2014, p. 892). Their qualitative longitudinal study explores that occupational identities condition the perception and evaluation of new technologies and that especially librarians with high expertise in non-internet search strategies resist new options. However, the study also shows that attitudes change with rising interaction with the technologies while new occupational identities can unfold. Field research among medical experts confirms that a further individual development is time-consuming and that individuals outweigh the opportunities and disadvantages of AI in dependence of the specific situation (Lebovitz, 2019). Time is a matter of change and role development.

The understanding of the process of role development can also be further substantiated by scholars' work in role theory. A role is defined as the bundle of expectations related to agentic action (Gross et al., 1958; Kahn et al., 1964). This also includes ambiguities and contradicting expectations as an issue of role conflicts. "Most versions of role theory presume that expectations are the major generators of roles, that expectations are learned through experience, and that persons are aware of the expectations they hold. This means that role theory presumes a thoughtful, socially aware human actor" (Biddle, 1986, p. 69). Obviously, roles are interdependent and conceptualized in the social context they are embedded in and cannot be separated from it (Biddle, 1986; Mintzberg, 1989). Transferred to healthcare it can be assumed that human-AI role concepts are constituted from individual self-concepts to behave as a professional (see also Galsgaard et al., 2022) as well as from supervisors', colleagues' and patients' expectations of how to use and interact with technology as a professional.

Role theory provides a useful lens to understanding how technology is changing organizations (Cascio & Montealegre, 2016) and thus serves as a framework for empirical findings. For example, Man Tang et al. (2022) could show in three studies that intelligent machines were able to contribute to work outcomes but also challenged professional roles especially of high performing conscientious employees. They benefited less from the use of intelligent machines than less conscientious employees because of role overlaps and role conflicts with the tasks performed by the machine. In a study of the car sales workflow, Barley (2015) shows how the role of salesperson changes from a negotiating salesman to a data-driven price-giver when there is a digital medium between the salesperson and the customer. The concrete process description of role development as a matter of expectations, observations, experiences and adjustments can be taken from leader-member-exchange (LMX) theory, which is about how leaders interact with their followers (Graen, 1976). Role making takes place in constellations with high mutual trust where expectations of self and expectations of followers are harmonized while role taking indicates inconsistencies, latent conflicts and rising mistrust between the human agents (Graen & Cashman, 1975). The description of role making and role taking has not been adapted to human-AI-interaction but can at least serve as a metaphor. While mistrust in AI and a latent conflict to the own role as professional might lead to role taking against AI, a harmonized role development concept while using AI can foster role making as a natural pathway of the own professional identity and at the same time incorporated technology implementation.

2.4. Summary: antecedents of human-AI role concepts

Considering the ensemble view and role theory as outlined in this section, it becomes obvious that human-AI role development is not a primary issue of a planned job design but of sociotechnical system dynamics including the self-concepts of professionals and their attribution of and experience with technology. Technology integration and its adaption in a work context depends on how professionals proposed to work with AI perceive, interpret and enact the artifact in face of their self-concept and expectations. These expectations include the assumptions concerning the development of the own expert status and the outcomes of technology integration.

In this section we could underline that there is already a body of research in technology innovation and role theory that can serve as a conceptual framework for analyzing human-AI role development: The overall individual attribution of AI as a tool, as a medium or as a counterpart (Anthony et al., 2023) can influence the development of a self-concept. Following Galsgaard et al. (2022) it is especially the counterpart perspective that is considered as advantageous for developing a role concept of collective human-AI expertise and from the authors' lens open a pathway to AI acceptance as an issue of role making. Understanding AI as physical AI is more likely related to a counterpart perspective than the perception of AI as virtual software. In combination with LMX theory role making as a human-AI expert is based in a high level of human-AI interaction and can be assumed if there are no role conflicts while role taking is caused by individual role conflicts in the fulfillment of expectations from relevant stakeholders (Graen & Cashman, 1975). In reference to Nelson & Irwin (2014) or Man Tang et al. (2022) it is the level of expertise in the profession – in our case in the professions in radiology – that impacts the openness for AI applications or resistance against it. Professionals with high individual expertise in the use field, e.g. in classifying X-ray images, tend to experience a higher conflict in their occupational identity compared to individuals with lower proficiency. But if it is the expertise in the field of the new technology – in our case AI literacy – it is individuals with high technological proficiency who are more likely to develop a human-AI expert identity. With respect to the impact of time, it can be assumed for all employees that a longer period of experiencing AI in the workplace is advantageous for adapting to it as an experienced-based process of further developing the professional identity (Nelson & Irwin, 2014). Moreover, there is high plausibility that it is not just the experience with a specific new technology such as AI that defines affordances or constraints (Leonardi, 2011; 2013) but also other artifacts of technology innovation of former periods. Consequently, the overall process of digitalization can also define affordances or constraints.

With respect to the real change of the overall job profile it can be assumed that it makes a difference whether there is a new job design and division of tasks or if it is just individual decision making which is supported but not substituted in selected fields while the task remains the same (Wilkens et al., 2021). The higher the real change of the job profile the higher the possibility that there are role conflicts. This summary serves as a comprehensive view on human-AI role development deduced from technology innovation research and role theory. The findings from the empirical exploration can be mirrored against this background.

3. Empirical exploration: Questionnaire and interview study at Charité

3.1. Case study analysis in radiology

In order to better understand the process of human-AI role development in radiology we conducted case study research at Charité, Germany's most research intensive and well-known hospital. The integration of AI in certain professional tasks especially that of radiologists and radiographers is ongoing in the selected field of AI application and conceptual outlines on role development explicitly address this field (Dewey & Wilkens, 2019; Galsgaard et al., 2022).

Our case analysis took place in between 2019 and 2021. During this period Charité initiated certain research project for AI-based diagnosis in radiology in which some of the interview partners (see below) were involved. Moreover, the technological infrastructure for taking X-ray pictures was recently renewed but also in a further process of continuous renewal.

Data collection included a quantitative employee survey and a qualitative interview study. Both components of field analysis had an explorative character and were related to each other (Yin, 2014). The design of analysis does not fully exploit all characteristics of an ethnographic study (see Marda & Narayan, 2021) but gears into this direction. The employee survey aimed at exploring expectations, attributions and experiences related to AI respectively digitalization in the workplace while the interview studies tried to gain deeper understanding for the explored different attributions and expectations that can be condensed to human-AI role concepts. The interviews allowed to explore how individuals consider AI in the light of their professional identity.

The employee survey was conducted at the end of 2019 and included all staff members at the Department of Radiology of Charité. The data evaluation was a profile analysis (see Figure 2) which led to a distinction of attributions and the identification of two different groups of actors. The first group were primarily radiologists in an early stage of their career and the second group were primarily radiographers. Thus, the second step of analysis were interviews among radiologists and radiographers representing these two groups. This second part of the analysis was conducted at the beginning of 2021 as the process had to be interrupted in 2020 due to the COVID-19 situation.

3.2. Quantitative employee survey for exploring AI attributions

The analysis of actors' perceptions and attributions of technological artifacts is considered as suitable methodological approach to understand role concepts based on the assemble view emphasizing individual perceptions and interpretations as well as affordances and constraints from former experiences (Leonardi, 2013; Scott & Orlikowski, 2014). This is why we conducted an employee survey as a first screening searching for typical attributions. The goal of the survey was to identify patterns and to outline which attribution pattern is typical for whom. In this sense, the survey outcomes define the starting point for the subsequent qualitative study (see section 3.3).

The questionnaire asked for agreement or non-agreement with closed statements related to digital transformation and the use of AI. It was assumed that respondence do not always make a clear distinction between digitalization and AI and that affordances and constraints can rather be traced back to experiences with digitalization. The survey was submitted online to 528 staff members. 142 complete surveys were sent back. 14 data sets were excluded because less than three items were answered. Therefore, 128 data sets were used in statistical analyses. As Charité is a hospital closely related to medical research it can be assumed that the staff is in principle more open minded to technological change. This may result in a somewhat biased cohort with which however it will be possible to understand individual attributions and interpretations and how they differ between groups of respondents. The research focus is on the observable patterns of attitudes as a qualitative research outcome. The overall distribution of these patterns at Charité is not representative but this is negligible as quantifications are not of interest in this research approach.

The exploration of attributions related to digital transformation and AI was integrated in an overall employee survey on workplace conditions, especially work-life-balance and a family friendly organization. This gave the opportunity to integrate a few technology-related items in the survey without leading full attention to the evaluation of AI. It can be assumed that this provided more unbiased responses to this issue and to focus on the meaning of technology within a work context. However, a slight overemphasis of the relatedness to work-life-balance cannot be excluded. Due to the integration in a broader survey the number of items in use was limited. As the analysis provided a starting point for entering the field of interest on an empirical basis the mentioned circumstances were considered as acceptable.

We explored employees' attributions to the six statements summarized in Table 1. Two items directly addressed the assumption and beliefs with respect to AI while the other four items referred to the overall experience with and meaning of digitalization (job characteristics and expected effects of digitalization) as well as its effects for the employees' themselves (techno-stress) respectively patients' care. The item formulation takes into account that attribution is based on previous experiences with technologies. The respondents could agree or disagree with the six statements on a five point-scale (1 = strongly disagree, partly disagree, neither agree nor disagree, partly agree, 5 = strongly agree). In addition, the survey asked for biographical data and context factors in terms of age, sex, vocational field, parenthood and employment type.

Table 1. Items for the meaning of digitalization and AI

Items
Digitalization enhances the decentralization of tasks. (asks for meaning related to the overall experience of the respondent with respect to job characteristics)
The decentralization of tasks leads to better and more family-friendly working conditions. (asks for meaning related to current experiences and future related expectations of own working conditions)
Artificial intelligence allows to enhance the quality of diagnosis in radiology and related treatment suggestions considerably. (asks for the meaning of AI in terms of attributions towards AI)
Better diagnosis and treatment suggestions have positive effects on the working conditions of the medical staff. (asks for the meaning with respect to expected future working conditions directly related to AI)
Digitalization enhances techno-stress. (asks for the meaning related to the overall experience and expectations with digitalization)
Further digitalization reduces personal care for the patients. (asks for the meaning with respect to experiences and expectations of the outcome of digitalization)

Data evaluation aiming at the identification of first patterns was based on a latent profile analysis (e.g. Stanley, Kellermanns, & Zellweger, 2017; Gabriel et al., 2015). This allowed to detect relatively homogenous groups of participants based on their responses on the six items on the meaning of digitalization and AI. This approach is used to identify distinct types of attribution that coexist within the Department of Radiology. At a first step, the number of distinct profiles is estimated using the maximum-likelihood estimator for mixture models EM (Muthén & Shedden, 1999). The correct number is determined using normative and theoretical criteria as suggested by Nylund et al. (2007). In a second step, the most likely profile for each participant is calculated and used for further analysis. This allows to gain a deeper understanding of the different attributions and their composition also with respect to biographical data and context factors.

For the estimation of different profiles, we calculated six separate mixture models that differ only in the number of latent classes by using Mplus (Muthén & Muthén, 1998-2017). Models with more than six classes were discarded because the resulting class memberships of three and lower did not contribute to a better understanding of distinct attributions. AIC and BIC were used as badness of fit indicators as normative criteria for the number of classes with smaller numbers indicating a better fit. The AIC is lowest, and therefore best, in the model with six classes. The BIC is best in the model with four classes. Since the BIC is considered to be more reliable than the AIC (Nylund et al., 2007) and the six classes solution consists of two classes with only three members, we chose the four classes solution for further analysis. This four class solution consists of two dominant profiles and two sub-profiles. Fit indicators for all six models are presented in Table 2.

Table 2. Normative criteria for the six different mixture models; best fit is bold

	1 class	**2 classes**	**3 classes**	**4 classes**	**5 classes**	**6 classes**
Loglikelihood	-1126	-1073	-1056	-1037	-1028	-1015
Free parameters	12	19	26	33	40	47
AIC	2277	2183	2164	2140	2137	**2124**
BIC	2312	2239	2241	**2238**	2255	2263

3.3 Qualitative interview study for understanding the attribution of AI and antecedents of human-AI role concepts

The interview study was conducted in March 2021 and included five interviews with radiologists in an early stage of their career and five interviews with radiographers as these were the typical representatives of the two dominant groups explored in the profile analysis (see Table 3). The interviews took place in German language and followed a semi-structured interview guideline including structured questions, a few closed questions and additional space for free statements (see English translation of the guideline in the appendix). The interviews took in-between 25 and 40 minutes each, were conducted in a tandem and transcribed afterwards. The interviewers asked for the individual definition of AI in order to better understand what the interviewees have in mind while talking about AI, related challenges and expectations. Where definitions and understandings come from gives access to the perspective on AI and also provides information of interviewees' AI literacy. Moreover, the interviews allowed to explore how employees of radiology relate AI to their task and their professional identity and to talk about their former experiences. The interview guideline included a few closed statements in order to motivate the interviewees to explain their position behind a rating.

With a number of 10 qualitative interviews no further information about AI in the work context and the individual role concept could be gathered. This is why the total number of interviews was sufficient and led to a high maturity of information (Hennink & Kaiser, 2022).

The interview tandem (first and second author of the paper) was responsible for data evaluation and cross-validation. The goal was to further substantiate the meanings of the identified profiles and to explore the underlying processes of human-AI role development. As the meaning cannot be sufficiently deduced from a specific wording we decided for an open coding process with cross validation among the two raters. For an explorative but structured content analysis we built on Gioia's methodology and adopted its orientation towards first- and second-order concepts (Clark et al., 2010; Corley & Gioia, 2004; Gioia et al., 2013). First order concepts include all distinct insights derived from interview statements that shed light on perceptions of AI, AI introduction at the workplace and implications for the own professional role. First-level concepts revealed largely differing views on technology and differing stances towards working with AI. We therefore organized first-order concepts into two groups with largely coherent views within the group. Second-order concepts include a structured summary of first-order concepts that turned out in two distinct human-AI role concepts for which the first-order concepts (the overall AI perception, AI literacy, former experiences with technology and perceived technological impact on the change of the overall job design) build antecedents. The aggregated constructs are the behavioral patterns of role development in face of AI.

The qualitative data evaluation showed that each of the two dominant profiles identified in the quantitative analysis can be combined with the thematically related sub-profile but that the characterization of these profiles has to be adapted. While the quantitative data showed a more optimistic and a more pessimistic attitude the qualitative data allowed to understand that there is no overall pessimistic but rather an ambivalent attitude and that there is no naive optimism but that a high level of AI literacy allows to remain in control about AI and therefore fosters an embracing attitude. It can be assumed that these two most characteristic types do not represent the ends of a bipolar scale, but that there are other, possibly more extreme types that did not occur in this work setting or were not part of the interview study.

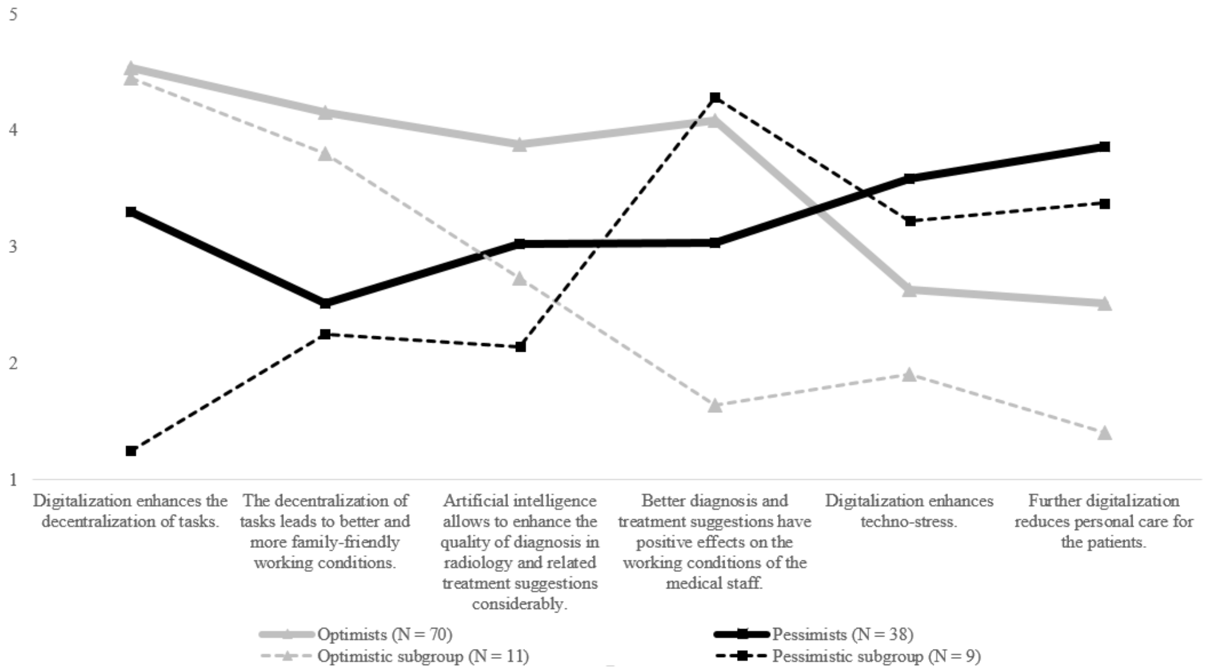
Table 3: Sample of interview study

	Radiologists		Radiographers
1	27 years old; Male	6	24 years old; Male
2	28 years old; Male	7	39 years old; Female
3	28 years old; Female	8	39 years old; Female
4	30 years old; Female	9	40 years old; Male
5	31 years old; Male	10	48 years old; Female

4. Findings

4.1. Profile analysis – more optimistic and more pessimistic attributions of AI

As a result of the latent profile analysis, four distinct attribution patterns with two core patterns and two sub-patterns as variations of the core attribution patterns could be identified. The first one is characterized by a strong belief in the expertise of AI and related overall opportunities of digitalization with respect to own working conditions and outcome factors (e.g. family-friendly work environment, quality of diagnosis). There is no negative attribution and no serious concerns about potential problems like techno-stress and reduced personal care for patients. We therefore refer to the first pattern as optimistic (N=70). This pattern gives AI the meaning of making things better for the own quality of work and for patients’ care. A more pessimistic pattern (N=38) gives digital technologies the meaning of making things worse, the own quality of work and patients’ care. The attribution primarily results from negative experiences with former processes of digitalization, which leads to pessimistic expectations especially related to family-friendly working conditions and techno-stress. Comparing the two patterns, it is interesting to note that there is a rather small difference with respect to the attributed expertise of AI as there is an overall believe in its potential in both groups. The items related to AI do not differ as much as the other statements. The core distinction between both patterns results from a negative or positive attribution of what digital transformation means for the individual working conditions and the care for patients. Both patterns have a subgroup, which slightly differs from the dominant attribution. The subgroup of the optimistic pattern (N = 11) trusts in the optimization of working conditions through digitalization but tends to be more skeptical towards the expertise of AI. The subgroup of the pessimistic pattern (N = 9) believes stronger in the merits of better diagnosis and treatment suggestions but does not expect better working conditions as a consequence. This adds a more ambivalent stance to the overall pessimistic pattern. The results are depicted in Figure 2.



1 = strongly disagree, 2 = partly disagree, 3 = neither agree nor disagree, 4 = partly agree, 5 = strongly agree

Figure 2. Two dominant attribution patterns for meaning of digitalization and AI in the workplace

The descriptive analysis of demographic data shows that the optimistic and the pessimistic patterns have different distributions in terms of occupational field, age and sex. Young professionals between 18 and 34 years old are mostly optimists (76 % optimists; 12 % subgroup of optimists). Optimists are frequent among early career radiologists (81 %; 15 % subgroup) and research associates (88 %; 0 % subgroup). The pessimistic pattern is frequent among radiographers (41 %; 24 % subgroup) and medical specialists (40 %; 0 % subgroup). Since 77% of the pessimistic subgroup are radiographers, there seems to be a specific but rather unusual perception of digitalization and AI among radiographers. Elder professionals between 55 and 75 years old are also more likely to show a pessimistic pattern (56 %; 17 % subgroup). All descriptive data are listed in Table 4.

Following the survey data, a preliminary outcome is that the meaning of digitalization and AI is attributed differently among different occupations. Early career radiologists are almost exclusively optimists. Radiographers tend towards a pessimistic pattern, even though there are also radiographers with optimistic attributions. Almost the entire subgroup of the pessimistic pattern consists of radiographers. Core findings of the survey are in line with former technology innovation research that experiences of the past matter (Leonardi, 2011; 2013) and long experience in an occupation foster reservation against a new technology (Nelson & Irwin, 2014). This seems to be the case even though the technology is new; it is rather the experience from overall digitalization which raises reservation. A deeper qualitative approach is necessary to better understand the meanings and assumptions of the respondents. This is why early career radiologists and radiographers were interviewed in the second step of analysis. Since optimistic and pessimistic patterns are equally frequent among other medical specialists (46 % and 40 % respectively), this group is not represented in the interview study.

Table 4. Composition of patterns in absolute numbers and percent in relation to sex, age and profession

	Optimists	Pessimists	Optimistic subgroup	Pessimistic subgroup
Male	31 (62 %)	11(22 %)	6 (12 %)	2 (4 %)
Female	37 (49 %)	26 (35 %)	5 (7 %)	7 (9 %)
Diverse	0 (0 %)	1 (100 %)	0 (0 %)	0 (0 %)
No Answer	2 (100 %)	0 (0 %)	0 (0 %)	0 (0 %)
18 - 34 years	32 (76 %)	4 (10 %)	5 (12 %)	1 (2 %)
35 - 54 years	31 (47 %)	24 (36 %)	6 (9 %)	5 (8 %)
55 - 75 years	5 (28 %)	10 (56 %)	0 (0 %)	3 (17 %)
No Answer	2 (100 %)	0 (0 %)	0 (0 %)	0 (0 %)
Early career doctor	21 (81 %)	1 (4 %)	4 (15 %)	0 (0 %)
Radiographer	10 (34 %)	12 (41 %)	0 (0 %)	7 (24 %)
Medical specialist	16 (46 %)	14 (40 %)	5 (14 %)	0 (0 %)
Leadership position	6 (67 %)	2 (22 %)	1 (11 %)	0 (0 %)
Research associate	7 (88 %)	1 (13 %)	0 (0 %)	0 (0 %)
Other/No answer	10 (48 %)	8 (38 %)	1 (5 %)	2 (10 %)

4.2 Content analysis: antecedents of human-AI role concepts

The structured content analysis of the interviews with radiologists and radiographers allowed to better understand differences behind the optimistic and pessimistic profiles and to specify human-AI role concepts including explanations for the differences. The result is the adaption of the prior characterization while distinguishing two types of role concepts, an *AI-embracing human-AI role concept* and an *AI-ambivalent human AI-role concept.* Representatives of the first type who embrace AI have experience in using AI applications and understands the technology as a useful but context-specific and imperfect single-purpose software tool which can however assist considerably in isolated tasks. The embracing role concept goes along with active role making in an integrative fashion and natural pathway of implementing AI by interacting with the technology. The use of the technology is incorporated in the role concept as a professional but not experienced as challenging this expert role. Representatives of the second type are ambivalent and understand AI as something powerful and as a largely competent counterpart for patients' care without specifying the concrete purpose of its use. They emphasize improvements in accuracy for patients but with potentially harmful effects for the own role as professional. A new or further developed AI-related role concept as a professional could not be identified and was not a topic of an organizational or personnel development process provided to the interviewees. The ambivalence goes along with a more skeptical role taking behavior against AI.

The two distinct human-AI role concepts, their antecedents and caused effects in terms of role making and role taking are summarized as first-order concepts, second-order concepts and aggregate dimensions in Figure 3. Table 5 illustrates the coding process how the concepts are based on interview statements.

Table 5: Understanding human-AI role concepts from a structured content analysis

First-Order Concepts	Second-Order concepts	Aggregate Dimensions
• AI described as virtual technology • AI is considered to have restricted but useful capabilities • Critical reflection on biases and trust-worthiness	• Overall attribution of AI as a tool	*AI-embracing human-AI role concept*
• High professional expertise related to AI, individual knowledge • Participation in development projects • Scientific research as source of information	• High AI literacy	
• Merits of technology already experienced	• Focus on affordances of AI & digitalization because of positive experiences	
• Use of AI considered for specific tasks instead the whole job profile	• Perception of low technological impact on the change of the overall job design	
• Substitution of monotonous tasks appreciated • Compensation of own deficits appreciated	• Task-specific openness for AI implementation	*Role making with AI*
• AI described as physical technology • AI is considered to have comprehensive capabilities	• Overall attribution of AI as a counterpart	*AI-ambivalent human-AI role concept*
• Vague knowledge related to AI • No participation in projects and discourses • *Popular media, family & friends as source of information*	• Low AI literacy	
• Problematic consequences of technology usage already experienced	• Focus on constraints of digitalization because of negative former experiences	
• Use of AI affects the entire job profile • Technology described as powerful (efficient and precise) for patients care	• Perceived high technological impact on the change of the overall job design	
• Substitution of any tasks rejected • Loss of own role feared	• Overarching reservations against AI implementation.	*Role taking against AI*

The *overall attribution of AI* is different among professionals representing AI-embracing and AI-ambivalent role concepts. Professionals with an embracing role concept describe AI as very effective single-purpose ***virtual software tool*** under the right circumstances and with competent application. They think of virtual AI applications that have to be administered and interpreted: „AI is sometimes a fuzzy term. But in reality, we are mostly talking about these […] algorithms that are based on machine learning or deep learning and are trained for a specific task, e.g., image analysis for a specific criterion“ (Embracer, Radiologist 2). However, they regard the technology not as an intelligent agent and point to dangerous consequences when AI is treated that way: “Once there was this well-known example where one trained AI to identify on oversized heart in radiography of the thorax. And one fed the AI accordingly and thought the AI is true. The AI could say there is an oversized heart and this was true. It definitely took a while until one recognized that the AI is not able to measure the heart but detects a staple in the thorax of patients who got the staple after a heart surgery. And this is the wrong indicator. This was not the right reasoning" (Embracer, Radiologist 2). This overall attribution of AI as a potentially useful but highly restricted tool is not shared among professionals representing an AI ambivalent role concept. They think of AI as efficient machines and thus envision physical AI: "From the radiographer's point of view, I'm thinking less about the diagnostic aspects and more about all the assistance systems, some of which we are already working with or have already worked with. And how they are integrated into the daily work routine" (Ambivalent, Radiographer 2). They emphasize the high quality of machine outputs: "When I see what [a specific assistance system] gives me there: that's always right. I have never seen it do anything wrong" (Ambivalent, Radiographer 3). This attribution does not fit to a tool perspective but rather to a counterpart perspective based on physical AI. The ***material counterpart*** is even regarded as potentially superior to humans: "Some days I look a little curved and I might see it differently today than tomorrow in terms of the angulation or something like that. I believe that the computers are actually much superior" (Ambivalent, Radiographer 3). The overall attribution of AI as software tool or material counterpart is one aspect of understanding embracing and ambivalent role concepts.

Major differences between professionals with AI-embracing and AI-ambivalent role concept exist in AI-related expertise, namely ***AI literacy*** due to prior experience, available sources of information, and concrete project involvement. Representatives of the embracing type have a very precise understanding of AI: "I associate artificial intelligence mainly with machine-learning approaches and neural networks, there are different competing technological methods to establish such algorithms. I have more experience with machine-learning approaches and in principle these are big data sets which are used to train an algorithm in the best possible way to get more or less optimal results" (Embracer, Radiologist 3). These professionals draw on their academic educational background and specific project involvement: "So here at the Charité, I haven't actually had any contact [with AI] in my daily work routine. In Heidelberg, at the German Cancer Research Center, there was [...] an automatic detection of pulmonary nodules" (Embracer, Radiologist 5). In contrast, representatives of the AI-ambivalent type have a less precise and rather vague understanding of AI: "We didn't think about it that much. It was presented and it was done. It was only afterwards that it became clear: okay, this is actually going in that direction [of AI]. The Siemens device, which has been around for a while, is actually more anatomical. I'm always unsure whether that counts or not. But the techniques have also improved. Since 2011, if not earlier. You haven't noticed that for yourself. It's more of a slow process that you don't even realize" (Ambivalent, Radiographer 2). Information on AI is acquired in a non-systematic and rather anecdotal way, even though interest is there: "[I think] definitely, [that direct contact with AI developers would be helpful]. Like I said, from my friend's husband, he's doing that, and I think if I ever sit down and have a conversation with him, I'm going to find that conversation totally interesting and awesome, what's going on. But I've actually never done that before" (Ambivalent, Radiographer 3). Missing information is occasionally replaced by representations from the media: "You see that already in movies, of course, and I don't think they're lying, that you can really get a lot out of there in the later future or even in the near future. Let's see. I think technology will just be far superior to us at some point" (Ambivalent, Radiographer 3). Lower AI literacy is thus associated with an AI-ambivalent role concept and high AI literacy with an AI-embracing role concept. The high AI literacy gives the professionals the feeling of being in control instead of being overrun by a technology movement.

Assessments of ***former experiences*** reveal a further difference in focus when evaluating AI use. Representatives of the AI-embracing type report positive experiences with regard to the performance and quality of AI applications: "And there are also already applications in AI where you can tell what kind of mass it is based on hundreds or thousands of data sets of different masses. So a kind of additional information that the human eye would not pick up at all" (Embracer, Radiologist 2). This potential is also assessed as high by representatives of the AI-ambivalent type (see above) but their individual experience is more related to the harm for their own role: "I see a devaluation in the sense that radiographers are not properly seen and recognized as a profession. So when you see how it works in the practice, they're taking care of their next patient every 15-20 minutes, and they have to take appointments and do patient care on the side" (Ambivalent, Radiographer 2). Previous experiences that digitalization was in use for process optimization and higher workload also impacts the interpretation of AI integration in the workflow. "And maybe employers even exploit that because they think they have the software, the new fast device that is doing all the work" (Ambivalent, Radiographer 2). Former experiences from technology innovation can thus be characterized as an antecedent of the role concept, AI is experienced either as affordance or, with regard to one's own professional role, as a constraint or threat.

Another aspect in which the two types of human-AI role concepts differ concerns the perceived technological impact on the ***change of the overall job design***. Representatives of the AI-embracing type do not see their own professional role much affected since AI is only regarded to get introduced for selective tasks: "It makes our daily work easier and we may be able to examine and diagnose more patients. Simply because it takes a step away from us, because we only have to look over the results that it shows us to see if we can see anything else. But it always needs a human examination afterwards" (Embracer, Radiologist 1). Representatives of the AI-ambivalent type, however, expect AI to completely change their job profile: "The computer takes everything off our hands, it already places everything and I actually only have to say okay. [...] I see [...] that I am becoming more dispensable" (Ambivalent, Radiographer 3).

It can be summarized that the overall attribution of AI as tool or counterpart, high or low AI literacy, former experiences with digitalization or AI as affordance or constraint and perceived low or high technological impact on the change of the overall job design jointly determine whether an AI-embracing or AI-ambivalent human-AI role concept is formed.

The analysis also reveals how the role concepts lead to different interacting behavior in terms of role making with AI or role taking against AI. Representatives of the AI-embracing type engage in proactive behavior directed at identifying suitable applications for AI usage and determining areas where AI should not engage. AI is imagined to be of great use in areas where human capacities are limited or tasks are monotonous: "I believe at some point the attention threshold is simply no longer the same after five hours as it was after the first hour. And I think that's what it's good for. If a machine learning program runs in the background like a safety net and really displays 'So, I find this striking, don't you want to look at it again?' Or perhaps during the shifts in the hospital, the radiologists are not on site 24 hours a day, that the clinicians in the emergency department justify their images themselves and make decisions, and if they are young colleagues, then they simply haven't seen so many images yet, and I believe that machine learning can be a good support as a safety measure" (Embracer, Radiologist 3). There is also reflection on specific strengths of the technology that constitute advantages over humans: "So it's very important especially in the MRI area, because we [...] can save an insane amount especially in image creation. The fact is, when we look at images as humans, we have a certain form of quality that we can perceive with our eyes. A machine can handle a fraction of information. You can, so to speak, already read something where the human being only sees noise. That's why it [AI] is so important, especially in accelerating examinations and creating images. There is always skepticism when humans derive a diagnosis from the images" (Embracer, Radiographer 4). The assistance by specific AI applications is regarded as a way to foster human strengths: "So, in a manner of speaking, this can also represent a gain in that medicine is once again turned a bit more towards people and this very time-consuming routine, I would say, e.g., searching for pulmonary nodules, moves a bit into the background. I believe that this could make everyday work easier and at the same time increase the number of possible diagnoses that can be made. In other words, it would relieve us" (Embracer, Radiologist 2). These deliberations go along with perceptions of further rising expertise and fulfillment of expectations especially for the generation of pioneers in using AI in the workplace: "I would personally say that by not being able to use these technologies now in this generation, but having to rely on recognizing everything ourselves, [AI] would rather enhance our work" (Embracer, Radiologist 1). Overall, representatives of the AI-embracing type actively engage with the role of AI and the role of humans and start to enact AI in a manner that is beneficial for themselves and performance outcomes. The enacting behavior can be characterized as **role making with AI** where AI implementation is incorporated in the role concept.

Representatives of the AI-ambivalent type see their own professional role in danger. They have an exaggerated idea of the capabilities of AI and derive a problematic development of being replaced in a creeping process of substituting the human expertise. "And [the radiographers] can now walk about and do more administrative work and they can save a secretary or something. Um, okay. This makes me wonder if some divisions won't be benefitting all that much from that" (Ambivalent, Radiographer 2). Although the likelihood of this scenario is strongly doubted by other professionals - “You can't replace the radiographers who have to position the patients and so on, the computer can't do that. […] So, I don't think that AI will eliminate jobs” (Embracer, Radiologist 1) - AI ambivalent professionals remain skeptical about what happens to them in future. Their behavior can be characterized as **role taking against AI**.

4.3 Integrated data interpretation

In a synopsis of the quantitative and qualitative results, two different human-AI role concepts could be identified. They are not the ends of a bipolar concept but aggregated constructs constituted by a set of four antecedents (see Figure 3). There is an AI-embracing type who has a comprehensive understanding of AI with its strengths and weaknesses. Benefits from the use of AI are expected if it is well managed and used in conjunction with human strengths. This type has positive former experience with digitalization as well as first experience with AI and understands AI as a software tool that can provide valuable assistance in selected areas of decision-making, with certain implications for efficiency and accuracy. These outcomes are appreciated as selective support in fields where the human senses have their limitations, e.g. in classifying blurred pictures. AI applications do not change the overall job design but make some time-consuming or failure-intensive parts of the job better in the light of experienced professional status. Radiologists and radiographers behind this type experience AI applications as augmentation, as further development of their own status as a professional but do not see any role conflicts. Under these conditions, role making with AI can take place. Representatives of this type have both, high professional expertise as either radiologist or radiographer and high technological expertise in AI. Their evaluations are not based on mere attributions or assumptions but result from concrete experiences.

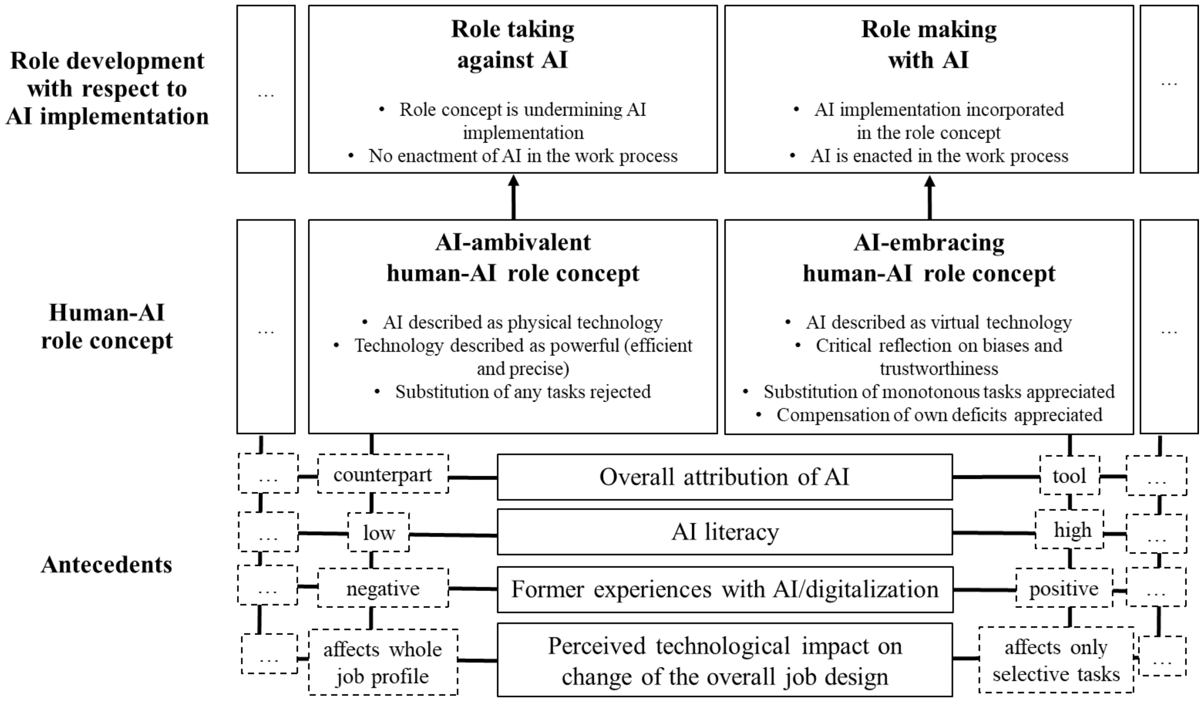


Figure 3. Human-AI role concepts, their antecedents and behavioral effects

The second type is an AI-ambivalent role concept. The overall AI literacy of this type is lower than that of the first type as definitions of representatives remain unspecific. Their knowledge is fed by sources of information such as media reports on robots killing jobs. There is experience with digitalization but less conscious experience with concrete AI applications. Representatives use the former and almost rather negative experience with digitalization - the interviewees describe digitalization as a way to higher workload in terms of more cases per time - on behalf of the missing AI experience while interpreting the system dynamics. They are neither involved in AI-projects but are rather confronted indirectly and experience a creeping process. As a consequence, this type overestimates the strengths of AI while weaknesses tend to be underestimated. A rather negative influence on one's own professional role is expected, which makes AI appear as a diffuse danger. However, AI applications themselves are regarded as superior for diagnoses as the machines are experienced as extremely powerful. Representatives of this type appreciate AI applications from the eyes of a patient as long as it is pure diagnosis and not care in all its facets but resist from the perspective of an employee. This explains their ambivalence. The use of technology is considered as overall change of the own job design and there are uncertainties due to missing information and participation with respect to further development of job profiles. As a consequence, this type experiences role conflicts in face of the solid expertise as radiographer or radiologist and is afraid that the own professional expertise might suffer. This is why this type practices role taking against AI.

The decisive factor for the emergence of an embracing or ambivalent role concept is not age or profession as such but the overall attribution of AI as tool or counterpart, AI literacy, former experiences with digitalization or AI and perceived technological impact on the change of the overall job design. Age is just an indicator how long the professionals already have an expert profile in more conventional non-AI-supported ways of performing a task. A high solidity in the profession as radiologist or radiographer is not fully independent from age and is therefore indirectly relevant for being an embracer or more ambivalent type, since the profile analysis revealed that elder radiologists were less positive than younger radiologists with respect to AI applications.

Considered together, these findings can be transformed into a comprehensive model that contains the four antecedents with those characteristics that support an embracing or ambivalent human-AI role concept (see Figure 3). Embracing and ambivalent role concepts lead to different outcomes for role development with respect to AI implementation. An embracing role concept provides the basis for a constructive engagement with AI; AI is enacted in the work process as an issue of role making incorporating its implementation. Support factors, involvement in development processes and organizational development processes including the professional role development are missing when it comes to an AI-ambivalent role concept. The overall setting of change and sociotechnical system dynamic hinders technology enactment. It is professionals themselves as well as the work context of radiology who suffer the resulting negative consequences.

5. Discussion

Our data led to a comprehensive model of human-AI role concepts. In reference to the assumptions summarized in section 2.4 the case study analysis is in line with key findings from the state of the art in technology innovation but also adds important new insights for the human-AI role development, its antecedents and consequences for AI implementation:

In line with Nelson & Irwin (2014) we could observe for the field of AI applications that with rising expertise in the field of a new technology including knowledge and concrete work experience – in our case AI literacy – a further development of role concepts as professionals interacting with the technology can take place. AI literacy is proposed to be an antecedent of human-AI professional role development.

The further key finding from Nelson & Irwin (2014; see also Man Tang et al., 2022) that employees with a high proficiency in performing a task without the technology tend to resist most because they assume a loss of their expert status could not directly deduced from the interview data. It was rather that the representatives of the AI-embracing type had high expertise in both, performing the task in a more conventional manner and in AI literacy. However, the circumstance that younger radiologists are overrepresented in this type can serve as an indicator that this type does not have a solidified expertise in conventional ways of classifying X-ray images without AI applications. In this regard, the age of the surveyed employees is a proxy. Future studies can further clarify whether conventional expertise and AI expertise rather overlap or can be classified into two distinct parameters.

In line with Leonardi (2011; 2013) it became obvious through our case study analysis that former experience with a technology plays an important role in terms of affordances and constraints, influences overall attributions, openness or resistances. Following our empirical findings, it is not necessarily the former experience with a very specific technology in terms of a concrete AI application. It is rather the former experience in a broader field of digitalization which matters. Overall experiences with digitalization impact the attribution of AI and are thus proposed as an antecedent of human-AI role development.

In reference to and further development of Anthony et al. (2023) we could explore that there are different overall perspectives on AI, not just from a scientific point of view but also as an individual attribution related to the technology. Two of the perspectives characterized by Anthony et al. (2023), the tool perspective and the counterpart perspective, were observable in our case study. The observations in our field analysis are not in full harmony with the implicit propositions provided by Anthony and co-authors respectively with the explicit research proposition from Galsgaard et al. (2022) that an AI counterpart would most likely lead to an augmented or collective expertise providing the pathway to AI implementation. Our findings show that understanding AI as a sophisticated single-purpose tool and nothing more than that is most likely attributed to augmentation of individual expertise and enhances perceived human-AI expertise as supporting factor for human-AI role making. If AI is perceived as a counterpart it is much more evaluated as a competing entity enhancing role taking against the technology. Future research on human-AI teaming (Hagemann et al., 2023) should treat this finding seriously in order to avoid metaphors that rather raise fear instead of trust in AI. However, in correspondence with both groups of scholars, especially Galsgaard et al. (2022), we could observe that AI acceptance and implementation is an incorporated function of human-AI role concepts. This is an important empirical foundation for better understanding pathways to AI implementation. AI acceptance is not an isolated dependent variable as considered in technology acceptance research (Venkatesh & Davis, 2000) but incorporated in the human-AI role concept. This finding is in line with sociotechnical system perspective of the ensemble view (Orlikowski & Iacono, 2001; Akhlaghpour et al., 2013) which could be substantiated with empirical findings for AI-based work settings. In this regard, we could relate established concepts in sociotechnical system research and current conceptual outlines for human-AI role development to each other and underpin the new conceptual outline with empirical findings.

Another outcome is that the descriptions of role making and role taking from LMX models in leadership studies (Graen & Cashman, 1975) can be transferred to questions related to human-AI role development. We could observe that role making as a human-AI expert takes place when there are no role conflicts and the overall self-concept as expert can further rise while interacting with AI. Role taking against AI is caused by individual role conflicts in the fulfillment of expectations from relevant stakeholders and in fear of losing expert status as a professional. This supports a complementary perspective to established technology acceptance research with its emphasize on technological characteristics (Davis, 1993; Venkatesh & Davis, 2000; Gade et al., 2019).

Based on our case study we could specify the antecedents of individual role development of professionals in healthcare who are confronted with AI applications leading to a comprehensive model of human-AI role concepts (see Figure 3). With this model we can add an explanation to AI acceptance as incorporated in role constellations situated in a concrete work context and field of implementation. These issues are not in the foreground in laboratory research aiming at technology development but need to be taken into consideration when facing work place environments as an issue of sociotechnical system analysis (Herzog et al., 2022). The findings are of high relevance to understand technology implementation in work settings.

We were searching for different types of human-AI role concepts reflecting the technology from the individual lenses and attribution of the user. Both identified types, the AI-embracing and the AI-ambivalent type are based on the same set of antecedents in terms of AI literacy, former digital experience, individual perspective on the technology and the technological impact on the change of the overall job design. This is of high practical relevance as two of the four identified antecedents can be supported in organizational development processes and are subject to organizational responsibility. This is AI literacy with its components in research-based knowledge and concrete involvement in projects. This is also the change level whether employees experience an overall new job design or a support in selected fields where individual weaknesses are compensated by technology (see also Wilkens et al., 2021). Former individual experience with digitalization including affective elements cannot fully be influenced in organizational development approaches but at least be compensated by literacy, substantial information and project participation in order to provide the space for new and better experiences. Also, the fourth impact factor, the perspective on AI is supposed to be influenced by AI literacy. The higher the knowledge the broader the scope to estimate where AI can support and where it has its own limitations. AI literacy helps to keep the topic in a proper size instead of oversized. This is an important contribution to support human-AI role development as an issue of individual well-being and also contribution to benefit from the AI potential in workplace settings (Langholf & Wilkens, 2024).

6. Limitations and Outlook

The case-study design with some ethnographic elements allowed to identify patterns in terms of human-AI role concepts, provides an empirical fundament where currently conceptual outlines dominate and can contribute to a more comprehensive model integrating findings from technology innovation research and sociotechnical systems perspective on human-AI role concepts. The case study at the Charité offers a promising starting point for contextualizing the discourse on AI at work, its means and ends. It was especially helpful to better understand ambivalence and to not confuse it with overall resistance against AI. However, generalizations beyond the proposed typologies and their antecedents are not possible and are not aimed at with the study. It can be assumed that the explored two types also exist in other fields of AI implementation but the considerable high percentage of employees with an optimistic view at Charité cannot be generalized, neither for other hospitals nor for other branches. There is high plausibility that at most other sites there is a higher percentage of employees representing a pessimistic view or ambivalent role concept as Charité is a research-intensive hospital providing high AI literacy and involvement in projects leading to concrete individual experience. All questions related to the distribution of the identified types within healthcare and in other industries should be seen as an important task for future research. Future research needs also to be directed to the validation of the proposed model of antecedents of human-AI role concepts, role development processes in terms of role making and role taking incorporating technology acceptance as an issue of enactment. With the help of a broader sample it can be tested whether other combinations of antecedents would generate further human-AI role concepts or whether extreme points on an overall scale exist in practice. E.g. a group with high AI literacy but without any professional background in the use field radiology was not included in the study but could generate another type. Future research could also explore additional antecedents.

Another limitation results from the comparatively short item list used in the employee survey. As the focus of the overall survey was not on AI, the depth and number of questions was limited due to the core subject of the analysis. However, the collected data allowed to detect profiles of attribution and more detailed information could be gathered with and added by the qualitative interviews. The part of the analysis is based on ten interviews but as the selection was well prepared by the survey and there was a maturity of information there is no real limitation. There are no indicators that more interviews would have led to more role concepts or another set of antecedents characterizing these types with respect to case of radiology at Charité. But other types could result from neighbored medical fields.

An interesting research question that came up from the interviews but could not be fully outlined in this data evaluation is related to human-AI role concepts of future generations. Current research analyzes users who are also familiar with more conventional ways of performing a professional task. It can be assumed that next generations without these experiences differ in their role concepts. This needs to be explored in anotherset of research comparing different levels of user experience.

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Appendix: Interview guideline ©of submitting authors

Interview guide: Acceptance of AI in radiology

We want to find out how AI in radiology can be used in the future so that those involved in the work process feel appropriately supported and see an improvement in their work experience and/or results.

For this reason, we would like to find out what experiences have already been made and what risks and opportunities are perceived through interviews with those who are involved with AI in their work process today or in the future. Only with this knowledge work design can be oriented towards people.

Please answer as spontaneously as possible, there is no right or wrong. Your personal assessment is crucial.

May I record the interview? It will be anonymized and will not be shared with others at any time. In the event of a review of my work, the recording should make it possible to document that all the statements made exist and were not made up.

Question 1: There has been a lot of talk about **AI in radiology** in recent years. It is often not clearly defined what this actually means. What do you think of when we talk about AI? Are we talking about very specific technologies?

Question 2: Please tell us a bit more about your **career here at the Charité**. How many years have you been working in this field?

a) How long have you been confronted with AI or have you had experience with it? Has AI brought about any specific changes in your tasks and your workflow?
b) If there is no concrete experience yet, in which areas do you assume that AI will be used in the next few years?

Question 3: Do you think that the topic of AI in radiology is currently overrated or underrated? Or is it receiving just the right amount of **attention**? How do you determine this?

Question 4: When you think about the use of AI in radiology, what **opportunities and risks** do you see?

Opportunities:

Risks:

Question 5: Have you noticed any particular **obstacles** to the use of AI?

e.g. legal nature or organizational hurdles or too little knowledge and expertise, too little reliability?

Question 6: Do you **personally feel up** to the subject or are there areas in which you would like to learn more before getting involved?

Question 7: Do you see AI as **enhancing or devaluing** your own work or does it have no influence?

Question 8: I will now read out 8 statements one after the other and would like to ask you to rate each statement on a scale of 1-5 as to whether you fully agree or disagree. I will give you the statements and the scale and, if possible, ask you to give a brief explanation for each statement:

1. People sometimes make mistakes at work and their attention wavers. AI is good at compensating for these human weaknesses.

   1 strongly disagree - 2 somewhat disagree - 3 partly/partly - 4 somewhat agree - 5 fully agree

   Explanation:

2. AI is still quite unreliable because there are problems with the data it is based on and the comprehensibility of the AI-generated diagnosis or treatment recommendation.

1 strongly disagree - 2 somewhat disagree - 3 partly/partly - 4 somewhat agree - 5 fully agree

Explanation:

3. The main function of AI is to protect people in the work process by protecting them from heavy physical labor or excessive strain.

   1 strongly disagree - 2 somewhat disagree - 3 partly/partly - 4 somewhat agree - 5 fully agree

   Explanation:

4. The use of AI can further strengthen what humans can achieve with their intelligence and experience. Humans and AI together - this makes many things even better.

   1 strongly disagree - 2 somewhat disagree - 3 partly/partly - 4 somewhat agree - 5 fully agree

   Explanation:

5. You have to be very careful that AI does not gain the upper hand over humans and that the machine's decision ultimately counts more than the human decision.

   1 strongly disagree - 2 somewhat disagree - 3 partly/partly - 4 somewhat agree - 5 fully agree

   Explanation:

6. You don't have to fool yourself. In the end, AI will lead to certain tasks in radiology being rationalized, i.e. no longer performed by humans but by machines.

   1 strongly disagree - 2 somewhat disagree - 3 partly/partly - 4 somewhat agree - 5 fully agree

   Explanation:

7. When AI plays a role in the work process, it also changes the way teams work together and the way they interact with each other.

   1 strongly disagree - 2 somewhat disagree - 3 partly/partly - 4 somewhat agree - 5 fully agree

   Explanation:

8. AI is inferior to human intelligence and therefore ultimately remains an unfulfillable promise.

   1 strongly disagree - 2 somewhat disagree - 3 partly/partly - 4 somewhat agree - 5 fully agree

   Explanation:

Question 9: If you had three **wishes for AI developers**, what would they be?

Question 10: Have you been in **contact with AI developers** and have they been interested in your work experience?

Question 11: Which question did I **not ask** that you would like to answer?

Question 12: Finally, can you tell me your age and how many years you have been working?

Thank you very much for your willingness to talk to us. It is a great help to our research.