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The Inscrutable New Actor: An Employee Perspective on the Flipside of AI

Short Paper

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Abstract

An in-depth understanding of employees' threat perceptions towards AI or other ITrelated transformations could inform and elevate existing innovation processes, leading to higher adoption rates. Existing IS and management research mostly refers to organizational performance measures and customer perceptions, neglecting the critical role of employees. This paper argues that effective transformation and integration of this new actor AI predominantly depends on employees–acting as intermediaries between the technology and customers. Noting the largely neglected flipside of AI transformation from an employee perspective, the current article conducts a qualitative investigation among 103 healthcare professionals to derive important AI-adoption barriers. Drawing on self-determination and social impact theory, data among five AI-application categories were analyzed, leading to three important job-related threat dimensions: Professional Development & Leadership, Workforce Empowerment & Collaboration, Workforce Resilience & Risk Management. The resulting conceptual framework offers valuable cross-industrial insights, contributing to the broader understanding of adoption resistance.

Keywords: AI adoption, employee perspective, AI transformation, flipside of AI

Introduction

The use of artificial intelligence (AI) to optimize workflows and processes is by far not exceptional to a particular industry or specific supply chain activities anymore. AI applications are leveraged at different points of interaction, yielding new challenges and opportunities for all actors in the ecosystems (Acemoglu and Pestrepo 2019). For example, along the supply chain, AI is used for demand forecasting, or supplier selection (Feizabadi 2022). In production processes, AI assists in assembly lines (Kucukkoc and Zhang 2015) or is used for system integration and workflow automation (Toorajipour et al. 2021). AI increasingly crosses the line of visibility and moves from back-office to frontline interactions. Chatbots and other AI-based applications that assist or even replace frontline employees are nothing new (Robinson et al. 2020).

While research on the role of AI from a multi-actor perspective is still in its infancy, especially the role of employees in this new constellation of actors is underexplored (e.g., Cannavale et al. 2022). This seems surprising, given that employees still play a fundamental role in the service delivery process, interacting with (AI-based) technology and customers (Autor 2015), and, therefore, can have a profound impact on organizational performance in general. Yet, most AI studies in IS or management research take an organizational performance perspective with a focus on economic growth potential and customer perceptions. In addition, it seems that there is a publication bias towards positive antecedents of AI, missing important knowledge on the barriers that lead to adoption resistance (Selenko et al. 2022). To excel at human-centered AI design, which refers to human input and collaboration between systems and other actors, IS research must shift the focus toward employees (Shneiderman 2021). Studies considering the

flipside of the implementation of AI in transformation processes from an employee perspective are scarce (Mirbabaie et al. 2022). Strich and colleagues (2021) recently highlighted the importance of developing mechanisms through which organizations and employees can protect the professional role identity of employees and emphasize criteria and prerequisites for implementing AI systems.

This paper argues that digital transformation in the form of a successful and beneficial implementation of AI applications is largely determined by the employees who function as connectors between technology and service delivery to the end customers. Especially in the early stages of the transformation process, it is important to involve, familiarize, and train employees to facilitate a controlled shift in their behavior (Yu et al. 2023). Recently, Mirbabaie et al. (2022) have shown how AI-identity threat, which is referred to as the anticipated fear of AI harming self-beliefs, is driven by important work-related factors such as changes in work processes or a loss in status. While this study is an important first step to uncovering drivers of AI-identity threat, more work is needed that investigates what effect these work-related factors might have on how employees handle and perceive AI in their work context. For example, in a fertile and complex industry such as healthcare, threats and risks associated with AI developments constitute major adoption barriers that slow down the transformation of work processes (Selenko et al. 2022).

It is against this backdrop, that the present study takes an employee perspective to answer the following research question: What are important job-related threats associated with employee resistance towards AI adoption? To shed light on this question, this study analyzes qualitative data from open questions included in a questionnaire among 103 healthcare professionals facing direct or indirect AI transformation in their field of expertise (method stage 1). The dataset comprises five novel capabilities of the new actor AI, which were classified as follows: (1) speech-based, through Natural Language Understanding (NLU); (2) text-based, through Text Processing (TP), (3) image-based, through Computer Vision (CV), (4) roboticsbased, and (5) generative, through a mix of NLU and TP. Drawing on self-determination and social impact theory, the coding of the qualitative data reveals three important dimensions of threat that influence the employees' perception of AI: (1) Professional Development & Leadership, (2) Workforce Empowerment & Collaboration, (3) Workforce Resilience & Risk Management. For each of these dimensions, key constructs are derived and a conceptual model for robust and replicable testing is developed (method stage 2). The study contributes to the IS literature by providing important insights for human-centered AI development revealing critical barriers from an employee perspective. The rich qualitative insights show the importance of involving employees already in early development stages to shape performance expectations, increase trust, and improve the overall attitude to interact with the new actor AI.

Theoretical Background

According to Rai et al. (2019), AI can be defined as "the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem-solving, decision-making, and even demonstrating creativity" (p. 3). AI continuously evolves and can take multifaceted roles to support humans in their activities and tasks. Some of the most prominent examples include NLU, which enables computers and software to listen to human language, written or spoken, and extract meaning similar to how humans understand language. (Gil et al. 2019). TP, which is based on machine learning and deep learning algorithms, enables learning from data and improving over time, (Autor 2015). In addition, CV is based on a branch of AI that focuses on enabling computers to interpret and understand visual information from a large dataset. Finally, robotics is a form of AI that involves the use of machines that can to an extent sense, analyze, and act autonomously (e.g., Seeber et al. 2020). In its most advanced form, cognitive computing in AI is used to stimulate human thought processes, including reasoning, learning, and problem-solving (Yu et al. 2023). Figure 1 provides an overview of these forms with a corresponding example from the healthcare sector. The commonality among these healthcare examples is that the AI becomes a new actor in the ecosystem, where employees serve as connectors between the AI and the patient. Therefore, the performance of the AI-transformed care processes is to a large extent dependent on the employee's interaction with this new actor AI (Chowdhury et al. 2023). The more sensitive and complex employees consider their tasks, the more important their professional identity role, actions, and resulting responsibility to any socially embedded interaction become (Yu et al. 2023). In this context, where AI becomes a new actor in employee interactions, social impact theory (Latané 1981) and self-determination theory (Deci and Ryan 1980) are used as the theoretical backbone to uncover this process change.

Case 1: Speech-based (NLU)		Case 2: Text-based (TP)			
The interaction between computers and humans via		Reading from documents and databases			
natural language spoken or written		and writing of text output			
Healthcare example: virtual	Case 5: Generative (NLU, TP)		Healthcare example: AI-based		
assistant chatbot for patient	A mixed form AI that involves NLU & TP		digital patient documentation and		
appointments	algorithms in a neural form		discharge letter		
Case 3: Image-based (CV)	Healthcare example: documentation, synthesize and decision-making support in the shock room		Case 4: Robotics-based		
The application enables computers		The application involves machines			
to interpret and understand visual information		that can to an extent sense, act, and think autonomously			
Healthcare example: high-resolution dermatoscopic image recognition for skin cancer detection and diagnostics		Healthcare example: AI-based social-companion robot in elderly care			
Figure 1. Case Overview of AI Applications					

Social impact theory explores how the presence, behaviors, and opinions of others can influence an individual's decision-making and actions within a social context. (Latané 1981). Social impact theory is based on three important factors: (1) Strength describes how important the influence of surrounding actors is for the focal employee. It refers to the perceived authority, status, and expertise assigned to the actors present. (2) Immediacy describes how close the social surroundings in terms of physical and emotional closeness are, and (3) number refers to the number of actors present. It is expected that the presence of the social environment, their anticipated attitude towards AI, and the relative weight the focal employee assigns to this social environment significantly influence the overall perception of the focal employee towards AI transformation processes. The theory can therefore help to explain two important notions of AI deployment: first, it can provide a useful framework to uncover the role of the social environment in shaping the employees' perceptions and attitudes toward AI. Second, given that AI constitutes a new actor in the healthcare process, the role of the three factors of strength, immediacy, and number should be assessed in this new light, especially considering factors such as accountability, biases, mistakes, and data privacy.

Self-determination theory provides a complementary perspective on the AI-employee interplay, suggesting that employees perform best when the three psychological needs of autonomy, competence, and relatedness are fulfilled (Deci and Ryan 1980). Considering, that AI takes over specific tasks previously owned by the employee, this might have significant consequences on the three psychological needs. Focusing on the flipside of AI advancements, Candiran and Scherer (2020) find that employees can perceive a loss of control over their work, which can lead to the perception of reduced autonomy. In addition, if tasks are automated by AI, employees might feel stagnation or even reduced ability to leverage and extend their skill set (Jaiswal et al. 2021). Moreover, interaction with AI might reduce interactions among coworkers, leading to the perception of loneliness and reduced relatedness (Selenko et al. 2022).

The rapid development of AI and the resulting transformation of work processes have far-reaching implications for the ecosystem and interaction among actors. While this transformation certainly brings many benefits, it is important to prepare not only the infrastructure but also the employees for this process. Designing successful human-centered AI applications requires involving developers and executors to mitigate perceived risks and overcome obstacles (Strich et al. 2021). Failing to sufficiently prepare and involve critical actors in the process can be harmful to employees and costly for the organization at large. Building on the theoretical knowledge derived from social impact theory, and self-determination theory, stage one of this research conducts a systematic investigation of five AI applications in healthcare to derive barriers of resistance and translate these into an actionable conceptual framework for a deeper analysis in stage two.

Method

The study is conducted in healthcare, known as one of the most critical and resource-constraint sectors, where changes across patient treatment processes can have a profound impact. Given the sensible nature

of the topic and the time-critical job situation in healthcare, where professionals have limited time, in stage one an anonymous self-administered questionnaire was used to gain initial insights into the research question. The questionnaire contained open questions, allowing medical professionals to anonymously share their thoughts and feelings concerning the ongoing AI-driven transformation of their work processes. These qualitative insights served as an important basis for developing the conceptual framework that will be tested in a large-scale investigation in stage two. The context of this study comprises data collection within the five currently most common AI application areas outlined in Figure 1. For each case application area, at least two different healthcare organizations across Germany were selected to ensure a heterogeneous case setting in the healthcare sector. In some of the organizations, the AI application was already rolled out, in others not (yet). More information on the demographics is provided in the result section and Table 1. Data collection took place between October 2022 and February 2023. On average, participants spent 30 minutes completing the self-administered questionnaire.

In case 1, applications using speech-based AI supported by NLU technology were selected. The cases focus on a chatbot in the form of a virtual assistant that mimics human dialogue through text or audio. In this case, professionals working in patient care in hospitals and dentistry were selected. In both healthcare fields, chatbots replacing initial employee-patient interactions, e.g., to collect patient information and schedule appointments, are already introduced. Case 2 constitutes AI applications that are *text-based* and supported by text-processing technology. The selected cases constitute digital patient documentation and discharge letters generated with help of the AI. Here professionals, including nurses and physicians, dealing with patient documentation within hospitals were selected. In case 3, the study zooms into image-based AI, generated by CV, which constitutes a high-resolution image recognition system, based on convolutional neural networks that compare across a worldwide database of dermatoscopic images of patients with associated diagnoses to detect skin cancer. In this case setting, dermatologists from diverse organizations were selected. Case 4 considers *robotic-based AI* applications, which can to an extent sense, act, and think autonomously. The case focuses on a social companion robot used in elderly care institutions. In this case, nurses from elderly care institutions were contacted. Given the adaptability of different AI technologies, case 5 zooms into a mixed form, where the AI capability constitutes generating content based on NLU and TP algorithms. In this context, the AI serves as documentation, synthesis, and decision-making support through active advice generation in a shock room treatment process. Here, shock room physicians practicing in the emergency care sector of hospitals were contacted.

At the beginning of the questionnaire, the AI application was explained for each case setting (Case 1-5, Figure 1). This ensured that all participants understood the role and task taken over by the AI and their corresponding task after the process change, regardless of whether they already had experiences with the AI or not. In the remaining section of the questionnaire, participants were asked what their general experience with AI in their field of job expertise was, where they see potential risks using AI regarding their role as employees, and under which circumstances, they would not use the AI or stop using the AI. Participants were also asked to what extent their organization provided training and guidance for the interaction with AI in their work processes. Finally, participants were asked how the introduction of AI within an organization and the resulting transformation of processes could be optimized. The questions were kept open so that respondents could share their thoughts, experiences, and associations. The answers to these qualitative questions were then coded in an iterative process. This was done through two independent researchers. The emerging codes and themes are listed in the first column of Table 2. For example, the statement "I value the autonomy in my job, this is something that needs to be considered in designing AI applications [...]" was assigned to the code 'job autonomy'. For codes, where no conformity in labeling was achieved, a third coder was involved. After this coding process was completed, all three coders had an open discussion to assign the remaining text passages to an overarching dimension. The overarching dimensions constitute themes compiling a set related of constructs.

Preliminary Results

In total 103 healthcare professionals shared their views on work- and process-related factors that might hinder the adoption and successful implementation of AI applications. These professionals work in healthcare institutions that either already use the selected AI applications or are competing with those players using the AI applications. Table 1 provides an overview of the demographics. The sample consists

Participant age (years)	Case 1	Case 2	Case 3	Case 4	Case 5	Total
18-24	8	1	3	2	0	14
25-34	6	6	5	13	9	39
35-44	1	4	3	5	15	28
45-54	2	4	2	4	0	12
55 +	2	0	4	3	1	10
Job experience (years)						
1-3	8	4	7	4	8	31
4-6	6	4	2	6	7	25
7-9	1	2	1	2	5	11
10 +	4	5	7	15	5	36
AI-Job experience (years)						
0	10	4	8	21	0	43
1-2	4	5	3	2	16	30
3-5	4	4	6	2	9	25
5 +	1	2	0	2	0	5
Table 1. Demographics						

of 62 (60%) female and 41 (40%) male healthcare professionals. The different age groups are well represented, with 14% of respondents between 18-24 years, 38% 25-34 years, 27% 35-44 years, 12% 45-54 years, and 10% 55 or older. One-third of the participants (30%) are relatively recent in their job position, with one to three years of job experience. 24% of the participants have four to six years of working experience in their profession and almost half of the participants are working 7 or more years in their profession (47%).

After answering some demographic questions, participants were asked about their experience with AI in their profession. 41% of the respondents answered that they do not have job-related experiences with AI so far. 30% reported one to two years of experience, 24% three to five years, and five respondents (5%) indicated already more than five years of experience using AI in their profession. This is not surprising given the recent developments of AI in healthcare. In the open part of the questionnaire, respondents shared their thoughts on questions related to their personal experiences and perceptions of specific AI applications used in their work contexts. Starting with an open question concerning their general experiences and thoughts on AI in the work context, they are also asked whether they anticipate any risks in using AI and under which circumstances they would refuse to use AI applications. Table 2 provides an overview of the results. The first column lists the dimensions and identified constructs that correspond to them. Column two provides a definition of the dimension and column three shows some exemplary quotes from the different AI cases that were coded (for the case details, see Figure 1). Given the structure of this short working paper, only two quotes serve to illustrate each dimension.

In summary, the coding resulted in three overarching dimensions. The first dimension, *Professional* Development and Leadership, refers to the degree to which an employee perceives that their skills and expertise as well as their level of responsibility for their work-related tasks change after the introduction of AI. Across all five cases, employees raised the concern that interaction and reliance on AI increases the risk that skills and expertise are unlearned, and employees might rely too heavily on AI. The second dimension, Workforce Empowerment and Collaboration, refers degree to which employees feel encouraged to take ownership of their work, make decisions, and contribute collaboratively to the success of their organization after the introduction of AI. In this dimension, especially the identity and competence of employees to their co-workers emerged as a prominent construct. The discrepancy here seemed to prevail between the benefit of relatively automated tasks, that did not require a significant amount of cognitive involvement and where employees saw the greatest benefits for the AI taking over, as opposed to the value of their own competence and autonomy for final decision-making in the team. Dimension three, Workforce Resilience & Risk Management, refers to the degree to which the employee fears that the introduction of AI can lead to a loss of control or lead to job replacements. While the qualitative insights from the study suggest that in general participants do not seem to fear that their jobs will be completely replaced by the AI, they still raised the concern that the AI should not intervene in critical tasks such as providing diagnoses for patients.

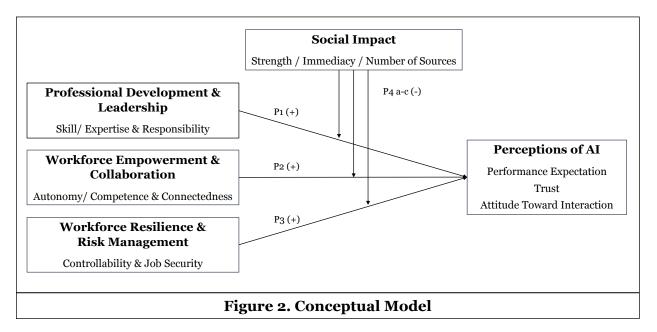
Dimension	Definition	Exemplary Quotes		
Professional Development & Leadership Coded constructs: Level of skills Level of expertise Level of responsibility	The degree to which an employee perceives that their skills and expertise as well as their level of responsibility for their work-related tasks change after the introduction of AI.	I have noticed that co-workers very much rely on the system and check their work to a lesser extent. This is dangerous given that the technical requirements are not yet at an optimal and warranted level. (Case 2) My knowledge is neither extended nor trained, which is unimportant in my age group, young colleagues will not acquire a lot of " human " knowledge from the beginning but rely on the AI. Anyone who has ever experienced a system collapse knows how valuable and important it is to have knowledge that is independent of the system. (Case 3)		
Workforce Empowerment & Collaboration Coded constructs: Level of competence Level of autonomy Level of connectedness	The degree to which employees feel encouraged to take ownership of their work, make decisions, and contribute in a collaborative manner to the success of their organization after the introduction of AI.	If AI were to take over the task of the doctor and give diagnoses, I would not continue to use it, as I believe that this task cannot be taken over by an AI. Personal contact with the patient is essential when making a diagnosis. The AI would make too many mistakes here, which could also have fatal consequences. (Case 1) I see potential of using it (here the AI in the shock room) in everyday clinical practice just to summarize what has been done so far, to prevent losing the overview given the many people involved in the process. (Case 5)		
Workforce Resilience & Risk Management Coded constructs: Level of controllability Threat of job security	The degree to which the employee fears that the introduction of AI can lead to loss of control or lead to job replacements.	For me as an employee, I think it's a risk to incorporate AI if it would completely replace a job. I believe that AI can be an important and useful help at work, but there are so many tasks that only humans should do. (Case 4) AI should not make diagnoses. It cannot replace the human eye. This could lead to fatal consequences and even endanger human life. (Case 1)		
Table 2. Summary of Preliminary Results				

Discussion

Building on the insights gained from this qualitative study and interpreting these insights considering theory and literature, a conceptual framework is derived. The introduction of AI into existing processes involves changes for employees in their work routines (Selenko et al. 2022). While the intention of AI transformation is to optimize service and delivery processes (Mao et al. 2021) and to enhance efficiency and effectiveness from an organizational point of view, it is yet to be determined to what extent this ongoing transformation benefits or harms employees and how organizations can optimize the transformation process (Chowdhury 2023). Recent work by Mirbabaie et al. (2022) show the importance of considering AI identity threats, defined as "the anticipation of harm to an individual's self-beliefs, caused by the use of an IT, and the entity it applies to is the individual user of an IT" (p. 75). The insights of this study show the importance of shedding light on the flipside of AI transformation and fundamental threats perceived by employees. In this qualitative study among 103 healthcare professionals, important barriers that lead to resistance or discontinued usage of AI applications were highlighted. The coding process generated a list of key constructs for further investigation. It is expected that these constructs are closely connected to employees' perceptions and intentions toward the interaction with AI. Extant literature highlights AI performance expectations, trust in AI, and the employees' attitude toward AI interaction as insightful dependent variables for organizations (e.g., Ardon and Schmidt 2020).

Embedding the findings of this study with existing research in this research area, Figure 2 depicts a conceptual model for further investigation (stage two). In total, four main propositions are formulated. The results of the qualitative investigation highlight the need to consider changing perceptions in the professional development and leadership functions of employees. Especially, skills, expertise, and the level of responsibility were raised as important constructs under this dimension. Recently, in the IS literature, single factors of resistance toward IT transformation have been identified. For example, Schemmer et al. (2022) find support for the deskilling of knowledge workers due to automated decision-making. In addition,

Craig et al. (2019) show how individuals resist change in their working routines, due to a shift of responsibility to the organizational level, where IT takes over a substantial number of tasks, traditionally performed by the individual. Therefore, the following proposition is derived:



P1: The lower employee's professional development and leadership role perceptions, the more negative will be their perceptions of AI transformation.

The second dominant dimension that emerged from the 103 surveyed respondents constitutes the role of workforce empowerment and collaboration. Drawing on self-determination theory, it is expected that the interaction with AI-based processes reduces employees' level of control and autonomy in decision-making (Nguyen and Sidorova 2018). In line with the qualitative insights, Calvo et al. (2020) find that the introduction of AI can influence the level of competence and autonomy in decision-making. Furthermore, Seeber et al. (2020) call for research to rethink the role of team constellations and collaboration roles to understand employee engagement with AI. Therefore, the following proposition is formulated:

P2: The lower employees' workforce empowerment and collaboration perceptions, the more negative their perception of AI transformation.

With AI technology advancing at an accelerating pace, the fear that the new actor AI may replace jobs was shared by participants. Since Raisch and Krakowski (2021) fuelled the discussion on the automation-augmentation paradox, it became evident that organizational long-term strategies and the role of the new actor AI when interacting with employees need rethinking. In this context, research that assesses to what extent the employees perceive the AI as job-threatening or fear that they lose control over their tasks is needed (Khogali and Mekid 2023). Therefore, the following proposition is derived:

P3: The lower the employees' workforce resilience and risk management perception, the more negative will be their perceptions of AI transformation.

In a highly insecure environment, where work processes change due to innovation, the social environment plays an important role in the adoption phase. Considering the healthcare context in which life and death are at stake, medical staff needs to comply with their social environment. Social impact theory suggests that the strength generated by the group of co-workers, the immediacy, caused by the environment and time element, as well as the number of people present, can have a profound impact on the employee (Latané 1981). It is therefore assumed that social impact significantly influences the handling and interaction with AI. Accordingly, H4a-c is proposed:

P4a): A strong social impact is expected to mitigate the negative effect of professional development and leadership loss on perceived AI transformation.

P4b): A strong social impact is expected to mitigate the negative effect of workforce empowerment and collaboration on perceived AI transformation.

P4c): A strong social impact is expected to mitigate the negative effect of workforce resilience and risk management on perceived AI transformation.

Conclusion and next steps

AI transformation has substantial positive implications for individuals and organizations at large. Yet, the role of employees in the transformation phase remains underrepresented in literature and practice. Often AI transformation stagnates, or its technological possibilities are not used to full capacity, where costly investments of organizations do not pay off (Lee et al. 2022). A major hurdle in the transformation phase constitutes employees' resistance to the technology (Mirbabaie et al. 2022). However, knowing the anticipated risks and fears of employees towards this new actor AI enables proactive prevention through co-creative implementation and training manuals that involve the employees at early stages. This can avoid costly setbacks and stagnating transformation processes for organizations. This qualitative study among 103 healthcare professionals from diverse healthcare organizations, unearths important barriers toward AI interaction in daily work processes. Drawing on self-determination and social impact theory, these insights inform a conceptual model for future testing and extensions.

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