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The Role of Emotions in Human-AI Collaboration

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Short Paper

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Abstract

Because AI has distinct abilities that enable the automation of tasks that usually require human intelligence, it can affect various emotions ranging from excitement about efficiency gains to the fear of being replaced. At the same time, emotions constitute key drivers of employee behavior and thus may determine whether and how AI users collaborate with AI. We raise the question of what AI users consider important in the light of human-AI collaboration and how these aspects relate to their emotional attitudes towards this technology. We address this research question by collecting longitudinal data regarding the AI implementation in three companies. We use qualitative coding to identify important aspects of human-AI collaboration from semi-structured interviews conducted at different stages of the AI implementation. Moreover, we use voice analysis to measure the interviewees' emotional state while speaking about different aspects of human-AI collaboration.

Keywords: human-AI collaboration, emotions, voice analysis

Introduction

Artificial intelligence (AI) increasingly enables the automation of tasks that usually require human intelligence. By contrast to traditional information technology (IT), AI can act autonomously and improve with experience while, at the same time, being inscrutable to many users (Berente et al., 2021). Due to these unique facets, AI is particularly likely to evoke emotions in employees, ranging from high expectations (Glikson and Woolley 2020) to the fear of being replaced (Mirbabaie et al. 2022). However, only little is known about what AI users consider important when collaborating with AI and which of these specific aspects drive their emotional attitudes towards this technology. In this study, we aim to advance this literature by examining the role of emotions in human-AI collaboration.

Better understanding AI users' emotions towards AI is important, because emotions constitute key drivers of attitudes, behavior, and cognition (Elfenbein 2007, 2023). Previous research suggests that humans experience emotions about 90% of the time in their everyday lives (Trampe et al. 2015) and that emotions affect social judgments (Forgas 1995), consumer preferences (Lee et al. 2009), and personal financial risk attitudes (Bassi et al. 2013). Given this evidence, emotions may also determine whether employees accept or resist collaborating with AI. Considering that companies are expected to make substantial investments into this novel technology (McKinsey Global Institute 2018), gaining a deeper understanding of how AI implementations affect emotions may ultimately help better understanding the impact of AI implementations on organizations. We thus ask the questions: *What do employees consider important when collaborating with AI and which of these specific aspects affect their emotions towards AI?*

We address this research question by drawing upon the Affective Events Theory (AET), an important concept in organizational psychology. The AET suggests that so-called "affective events", i.e., changes or events in the workplace, can elicit emotional responses (Brief and Weiss 2002; Weiss and Cropanzano 1996). Building on this theory, we consider the introduction of AI as an affective event and trace back AI users' thoughts, opinions, and emotional responses towards AI along several steps of an AI implementation.

We collect longitudinal data regarding an AI implementation in three companies and conduct semi-structured interviews with AI users pre, during, and after the implementation of the AI. We use a data-driven qualitative coding approach (Miles et al. 2020; Myers 2009) to aggregate the information from the interviews and to identify the key aspects that AI users consider important when collaborating with AI. Because previous research suggests that a speaker's *vocal cues* broadcast a large array of emotions (Cowen, Elfenbein, et al. 2019) that are incrementally informative to the content of spoken words (Gorodnichenko et al. 2023; Mayew and Venkatachalam 2012), we enrich our analysis by using speech emotion recognition models to track the interviewees' emotional states while discussing their thoughts and opinions on human-AI collaboration. We use regression analyses to quantify which specific aspects of human-AI collaboration are most likely to affect the interviewees' emotions. Because previous research suggests that emotions are dynamic and may change over time (Kuppens and Verduyn 2017), the longitudinal data collection allows us to test whether the AI users' opinions and emotions towards AI change during different stages of the AI implementation. Finally, we aim to use our insights to develop a framework on the role of emotions in human-AI collaborations.

The contribution of this study is both theoretical and practical in nature. Specifically, we contribute to the literature on human-AI collaboration by providing new evidence on what AI users consider important for human-AI collaboration and which of these aspects drive their emotional attitude towards AI over the course of the implementation. These findings also have practical implications. By shedding new light on the process of AI implementations and how they shape emotional responses in employees, our findings can help practitioners to better manage AI implementations.

Theoretical Background

Emotions in the Workplace

Research in organizational psychology has clearly established the importance of emotions in the workplace (for a recent review see Elfenbein 2023). Emotions can be broadly defined as adaptive responses to environmental stimuli that drive our attention and prepare us to act (Scherer and Moors 2019). Central to this definition of emotions is the cognitive appraisal theory. According to the theory, cognitive appraisal is our personal evaluation of an emotional response eliciting event, including the interpretation of our bodily responses (Scherer 1997; Scherer and Moors 2019). Whether emotions lead to thoughts (Zajonc 1998) or thinking about a situation leads to emotion (Lazarus 1991) remains an open debate (Todd et al. 2020). Clear is, however, that emotions are a central component in human experience and thus are key drivers of how individual experience their workplace (Elfenbein 2007, 2023).

The study of emotion at work dates back to Hersey (1932). In his pioneering work, he observed the fluctuations in workers' emotions throughout the day over a period of several weeks to assess the correlation between emotions and performance. Apart from this study, the emotional component of work experience has not been a focal point of subsequent research (Judge et al. 2017), with some exceptions (Cranny et al. 1992; Williams and Alliger 1994). However, the seminal work of Weiss and Cropanzano (1996) marks a turning point to the study of emotions in an organizational context (Elfenbein 2023; Judge et al. 2017), as they proposed the AET. According to AET, changes or events in the workplace can serve as exogenous shocks to existing behavioral and attitudinal patterns, thereby directly influencing attitudes (e.g. job satisfaction), performance, and well-being (Brief and Weiss 2002; Weiss and Cropanzano 1996). A key concept in AET is the idea of "affective events," which are incidents or occurrences in the workplace that lead to affective responses. Affect is generally a broad term that describes feelings, moods, or emotions in varying intensity or duration (Elfenbein 2023). In the sense of AET, affect refers to state affect, elicited by an event that leads to an emotional response (Weiss and Cropanzano 1996). These events can be positive, such as receiving praise or recognition, or negative, such as experiencing conflict with a coworker, receiving criticism, or organizational change (Ashkanasy et al. 2017; George and Jones 2001). Besides studying the nature of these events and the emotions they relate to, previous research mainly focuses on their impact on attitudes, cognition and behavior (Elfenbein 2023).

In information systems research, studies on the emotional components of work experience focus on emotions evoked by IT-related phenomena. For example, Beaudry and Pinsonneault (2010) emphasize the importance of incorporating emotions in studying the use of IT. They argue that cognitive-based models like TAM or UTAUT exclude this experience and complement these models by showing the emotions offer insights in various IT-related behavior, including use. Additionally, Zhang (2013) offers an in-depth evaluation of the concepts of affect and incorporates them in an information communication technology context, emphasizing the importance of affect in the human experience. Stein et al. (2015) explore the IT use patterns that emerge from different emotions elicited by IT, and explore the role of emotions in IT use. Other studies focus on the emotional reaction to IT security threats (D'Arcy and Lowry 2019) or the role of emotions in compliance with information security policies (Liang et al. 2019).

However, findings from a "pre-AI" world may not translate to modern workplaces that increasingly invest into AI tools. Berente et al. (2021) define AI as "the frontier of computational advancements that reference human intelligence in addressing ever more complex decision-making problem" (p.1435). In this context, they emphasize that managing AI is different from dealing with traditional IT, especially due to its defining characteristics, namely. autonomy, learning, and inscrutability. AI's ability to autonomously make decisions (Baird and Maruping 2021; Möhlmann et al. 2021; Murray et al. 2021), learn from data and experience (Chen et al. 2012), while, at the same time, having an opaque decision making process clearly separates AI from traditional IT. We argue that these defining characteristics can challenge employees' self-perception and lead to emotional ramifications as employees have to reconsider their own value proposition in the light of fast evolving tools that permeate into work processes that have previously been exclusive to humans.

Human AI-Collaboration

The development of AI is leading to an increasing presence of AI in our everyday lives and workplaces. As AI's ability to learn, mimic human ability, and emulate human thinking advances, the tasks that can be performed by AI increase massively (Berente et al. 2021; Brynjolfsson and Mitchell 2017). At the same time, however, not all tasks, especially in the realm of decision making, can be fully automated by AI (Brynjolfsson et al. 2018; Fügener et al. 2022). Hence, previous literature argues that the best outcomes emerge from the collaboration between humans and AI (Bansal et al. 2019; Fügener et al. 2022). Therefore, it is important to understand how humans and AI can collaborate successfully (Rai et al. 2019).

A few studies have already addressed this topic. Research on human collaboration with algorithms has shown mixed results. On the one hand, some studies document that humans tend to trust human forecasts over the algorithmic forecasts, even though the algorithms continuously outperforms the human – a behaviour coined *algorithmic aversion* (Berger et al. 2021; Dietvorst et al. 2015, 2018). On the contrary, Logg et al. (2019) established the term *algorithmic appreciation*, as they show that humans tend to adhere more to advice coming from an algorithm than to advice from another human. Moreover, Dietvorst et al. (2018) showed that a way to overcome algorithmic aversion is to enable humans modifying the algorithm, which led to humans trusting imperfect algorithms.

In the context of human-AI collaboration, Fügener et al. (2022) have shown that humans are notoriously bad at delegating tasks to AI as they overvalue their own abilities, although productive delegation is a key factor for successful collaboration. On another end, Glikson and Wooley (2020) argue that humans have unrealistically high expectations about AI, while successful collaboration between humans and AI largely relies on a realistic assessment of AIs abilities to asses when and when not to trust AI (Bansal et al. 2019; Taudien et al. 2022). Generally, in collaboration with AI, humans need to be aware of how AI can best complement their own abilities (Bansal et al. 2019; Fügener et al. 2021; Vössing et al. 2022). Apart from the direct collaboration and division of tasks, another challenging factor to successful human-AI collaboration might be the anxiety and the fear of being replaced that can be evoked by AI and the black box nature of it (Mirbabaie et al. 2022), or challenge self-efficacy at work (Jussupow et al. 2022).

Research Setting and Method

To observe whether the introduction of AI elicits emotions in employees and to monitor which topics are particularly relevant in this context, we are in the process of conducting longitudinal case studies at three companies. In each of the three companies, we have the opportunity to closely accompany the introduction of an AI with unrestricted access. In our study, we employ a mixed-methods approach, following the guidelines by Venkatesh et al. (2016).

Case Studies

All three companies are in the process of implementing the same AI tool to their sales functions. The AI tool is designed to help sales personnel identify cross-selling and upselling potential in their own customer base and identify new customers and sales potential. For this purpose, the sales personnel collaborate directly with the AI. The AI identifies new or existing customers that fit the company's profile and suggests suitable products, sales potential, and contacts in and information about the target companies. The sales personnel can filter these suggestions and provide feedback to the AI. The use of the AI is expected to increase employee efficiency and sales, as the AI can take over tedious research tasks, and is able to evaluate data faster than the employees.

The three companies in our study are German medium-sized enterprises from the manufacturing industry (automotive, automation, and drive technology). None of the companies already uses AI, and the companies generally have in common that their sales are business to business (B2B). B2B sales are characterized by longer sales cycles, high-volume transactions that require detailed explanation, and long customer relationships (Dotzel and Shankar 2019; Gupta et al. 2019; Hartmann et al. 2018). Due to the technical and consulting-intensive nature of B2B sales, salespeople play an important role in companies and B2B sales have long been considered difficult to automate (Bongers et al. 2021). This setting is particularly well-suited for examining the emotional reactions of employees, as the introduction of the AI shifts a currently important task from the sales personnel to the AI. Many salespeople are proud of their ability to identify new customers and are used to working independently on their own terms. With the introduction of the AI, for example, they will be handed potential leads from the AI, their collaborator, which are purely based on data and not on intuition or feeling, which the salespeople should then simply work through. In theory, this should enhance the productivity of the salespeople, with the AI taking over the time-consuming, data driven research tasks and the people taking over the human interaction driven tasks. In practice, however, this change in the role of the salesperson serves as a prime example of the tension that may arise from the collaboration with AI for a wide range of employees. On the one hand, there is the potential for salespeople to benefit from the support of AI and willingly work with it. On the other hand, they may reject it because they trust their own abilities more. It will also be interesting to see how these emotions change over the course of the implementation and what other emotions and behaviors they will lead to, for example, increased satisfaction because working with AI efficiently decreases diligence or maybe frustration because the collaboration is not working, or even anxiety because the AI is working too well, and the person feels threatened. We aim to shed light on these questions, to provide insights into emotion driven behaviors of employees when collaborating with AI to be able to manage AI implementation in organizations effectively and successfully from the employees’ perspective.

Data Collection

Because previous research suggests that emotions are dynamic (Kuppens and Verduyn 2017), we collect data pre, during and after the implementation of the AI in the three companies by conducting semi-structured interviews. This longitudinal data collection enables examining whether and how emotional attitudes change over different stages of the AI implementation. We interview the employees that directly collaborate with the AI. The interviewees' positions range from CEO to sales assistant and thus cover a whole spectrum of positions in the company. In total, we identified 22 interviewees across the three companies that are going to work directly with the AI and are therefore going to be interviewed three times. This will lead to a total of 66 interviews. Every interview will start with a short introduction of the interviewees and the interviewer as a baseline. Then, the interviews will first address the interviewees perceptions about working with AI, their wishes, requirements and, if applicable, also fears, and in the further course, reflect on their experiences in working with AI.

Data Analysis

We aim to provide comprehensive insights into the role of human-AI collaboration by examining AI users’ views and opinions on human-AI collaboration and link their statements to their emotional states. The data analysis follows a four step multi-method process that is shown in Figure 1.

Based on the obtained interview data, we qualitatively code and aggregate the data to identify aspects that AI users consider important when collaborating with AI. This part of the analysis mainly focuses on the content (i.e., the transcribed text) of the interviews. To gain insight into the interviewees' emotional states that go beyond the content of the interviews, we run voice analysis on the interview recordings to derive emotion measures from vocal cues. Because the voice analysis will result in a large array of emotions, we simplify the data by conducting factor analysis. Factor analysis enables transforming a large number of observable emotional responses into factors that capture broader concepts of emotional responses, thereby simplifying the data while retaining as much information as possible. Next, we run OLS regressions of the emotional factors on the aggregated topics to identify which aspects of human-AI collaboration affect the emotional state of the interviewees. Thereon, we use these results and the insights derived from the qualitative analysis to develop a framework that describes the relationship how different aspects of human-AI collaboration relate to emotional responses.

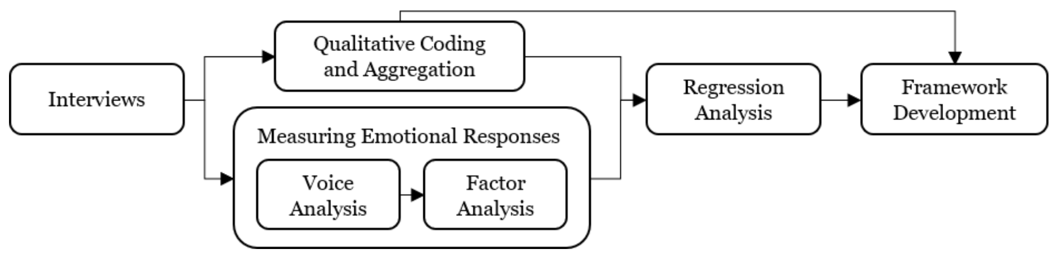

Figure 1: Data Analysis

Coding and Aggregating the Interviews

We employ a data-driven qualitative coding approach (Miles et al. 2020; Myers 2009) to aggregate information from the interviews. The goal of this step of the analysis is (i) to prepare the data for the subsequent regression analysis, and therefore assign a code to each sentence, and (ii) aggregate the information from the interviews to obtain information on the collaboration of AI. Therefore, we begin by descriptively coding (Myers 2009) each sentence of the interviews. As we need to assign a code to each sentence for the subsequent regression analysis, we assign the same code to paragraphs that refer to similar topics. The goal is to identify similarities and differences in the topics the interviewees mention regarding the implementation and collaboration with the AI, the experiences they describe and the consequences they undertake and grouping them together. Thereon, we use interpretative coding (Myers 2009) to further group the descriptive codes, going back and forth with the current findings on human-AI collaboration to identify key topics that shape the collaboration and track the patterns that arise from those.

Voice Analysis

To examine whether the interviewees show emotional responses to certain topics brought up in the interviews, we conduct voice analysis. Whenever we speak, we do not only communicate with words, but also convey emotion through our voice. Recent research suggests that humans can express a large array of emotions with short vocal bursts (Cowen, Elfenbein, et al. 2019; Cowen, Laukka, et al. 2019). At the same time, speech production is something of an anatomical wonder as the human voice is made of utterly complex interactions of muscles, vibrations in the vocal fold, and nuanced positions of the jaw and tongue (Titze and Martin 1998). Due to this complexity, vocal cues are revealed in a relatively uncontrolled manner. While we can control the words we use, we cannot fully prevent how we really feel from subtly permeating *how* we say things (Ekman et al. 1991). Because archival research confirms that vocal cues convey information beyond the content of spoken words (Gorodnichenko et al. 2023; Mayew and Venkatachalam 2012), vocal cues may give away genuine information about our emotional state that is not otherwise stated.

To measure emotional responses during the interviews, we use the audio recordings of the interviews and segment the audio files into audio snippets, each of which represents a sentence. To examine emotional responses from vocal cues, we rely on Hume AI, a research lab and technology company that provides comprehensive machine learning models that are built to identify emotional expressions from non-verbal cues such as the human voice based on large and carefully evaluated databases (Baird, Tzirakis, Brooks, Kim, et al. 2022; Cowen, Elfenbein, et al. 2019; Cowen, Laukka, et al. 2019; Monroy et al. 2022). We use the Speech Prosody API to identify 48 distinct tune, rhythm, and timbre patterns that refer to emotional responses in speech (Baird, Tzirakis, Gidel, et al. 2022; Baird, Tzirakis, Brooks, et al. 2022). This approach allows us to assign each sentence from our sample of interviews a vector of 48 emotions such as anxiety, distress, excitement, and relief.

Because we are initially interested in interviewee's general emotional responses rather than specific emotion categories, we perform a principal component factor analysis to extract the most important emotional components from a (48 x 48) variance-covariance matrix of the *Hume AI* categories. This approach assumes the existence of underlying emotion factors – i.e., linear combinations of *Hume AI* categories that are not directly observable but pertain to emotional responses in interviewees.

This research design addresses several key challenges of measuring affect. Previous research suggests that it is difficult for individuals to reflect on their own emotional responses which raises questions of whether survey evidence can generate objective data on emotional responses (Elfenbein 2023). In contrast to self-reported measures or to inferring emotions from words, vocal cues are revealed in a relatively uncontrolled manner, and thus provide information that is *incremental* to the content of spoken words. Moreover, interviews are ideal to examine emotional responses because psychology research suggests that most emotions arise during interpersonal interactions (Andersen and Guerrero 1996). In this sense, we consider voice analysis as a *complementary tool* to grasp emotional aspects of the interviews that cannot be captured by the qualitative coding approach described above.

Second, both emotional states and vocal cues can change over during dialogues (Mayew and Venkatachalam 2012; Mayew et al., 2020). Hence, it is desirable to construct a measure of emotional responses that allows us to pinpoint which aspects of human-AI collaboration drive the interviewees' emotions. Hence, applying voice analysis to interviews may further improve empirical identification strategies by relating emotional responses to certain topics brought up during interviews.

Regression Design

To measure whether, and if so, which topics of AI introduction and human-AI collaboration elicit affective response, we employ an OLS regression design. Formally, the regression can be expressed as follows:

$$EMOTION\_FACTOR_{i,s} = CODES_{i,s}^{k} + FE,$$

where $EMOTION\_FACTOR_{i,s}$ is an emotional response from interview i and in sentence s. $CODES_{i,s}^{k}$ are k different codes identified from manual coding and assigned to sentence s in interview i. All regressions include interview-fixed-effects (FE) to only examine *within-interview* variation of emotional responses. This way, the regression tightly controls for omitted variables that do not directly arise during the interview such as individual's daily mood fluctuations, or time-invariant interview-characteristics such as the interviewee's gender, age, or any personal characteristics. To further alleviate concerns about omitted variable bias, further controls such as lagged values of the emotion factor or the interviewer's vocal emotions can be added. This regression design allows to quantify whether certain aspects of human-AI collaboration discussed during the interviews relate to AI users' emotions.

Framework Development

To integrate the findings from the regression analysis and the qualitative analysis we aim to generalize them into a comprehensive framework. The goal of the framework is to broaden our understanding of the relevance of emotions in the process of AI implementation and subsequent human-AI collaboration. Moreover, the framework will aid in understanding which specific aspects of human-AI collaboration (e.g., efficiency gains, attitude towards autonomy, or even personal attributes) are driving AI users' emotional attitudes towards AI.

Contribution and Conclusion

In conclusion, this study makes both theoretical and practical contributions. With respect to theoretical contributions, we add to the literature examining human-AI collaborations. While previous studies have mainly focused on the nature of collaboration with AI, like task delegation and assessment of respective strengths (e.g., Bansal et al. 2019; Fügener et al. 2022). This study is first to analyze the role of emotions in human-AI collaboration. Emotions play a significant role in employee well-being, and it is essential to understand the mechanisms by which AI can elicit emotions. Our research sheds light on this question by following and analyzing the process of AI implementation and human-AI collaboration. Our multi-method approach allows us to objectively quantify emotional responses and map them to relevant topics of human-AI collaboration capitalizing on the qualitative analysis of our interviews. This allows us to identify which aspects of AI implementation and human-AI collaboration elicit emotions and what consequences emerge from them comprehensively.

Therefore, our findings also have practical implications. According to a report by McKinsey (2018), AI has the potential to deliver additional global economic activity of around $13 trillion by 2030 with 70% of companies implementing at least on AI solution, making AI a core component of organizational decision-making processes in the future. Hence, better understanding the emotional component of AI implementation is more critical than ever and can help organizations to better predict and manage the consequences of implementing AI tools.

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