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Why Do or Don't You Provide Your Knowledge to an AI?

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ABSTRACT

This study examines the factors that influence individuals' readiness to share knowledge with artificial intelligence (AI) in organizational settings. With the increasing integration of AI into business processes, there are benefits such as increased operational efficiency and decision support. AI systems require the expertise of skilled employees to adequately support decisions and improve performance. However, providing knowledge and experience can also pose a risk to employees as it could jeopardize job security. Using an explorative approach, including literature review and qualitative interviews, this study identifies key motivators and barriers for providing knowledge to an AI. At the individual level, benefits such as learning opportunities encourage contribution. At the team-level, motivators include individual reliance on collective knowledge. Cultural norms such as reciprocity in sharing also play a role. However, there are barriers, including fear of job loss due to automation, interpersonal issues such as criticism, and distrust of both management and AI. Strategies to positively influence these factors include strengthening employability, transparent management communication and communities of practice to mutually share experiences with AI.

Keywords: Knowledge contribution, Knowledge sharing, Knowledge management system, Artificial intelligence, Motivators, Barriers

INTRODUCTION

Artificial Intelligence (AI) has become an indispensable part of today's organizational infrastructure (Jarrahi, Askay, Eshraghi & Smith, 2023). Defined as a system capable of human-like intelligence and learning, AI offers numerous benefits, such as improving operational efficiency and enabling faster and more informed decision making. Despite these benefits, AI is also perceived as a potential disruptive factor that could threaten jobs (Zirar, Ali & Islam, 2023).

Human knowledge is a key component for fine-tuning AI results to ensure that those results are both relevant and of interest to users in the given situation. Human knowledge also enables AI to learn and continuously improve its performance (Van den Bosch, Schoonderwoerd, Blankendaal & Neerincx, 2019). Moreover, AI is also increasingly used in the field of knowledge management, serving as a means to make human knowledge accessible to others (Jarrahi, Askay, Eshraghi & Smith, 2023). The active participation of people and their willingness to make their knowledge available to AI systems is of great importance for the progress and development of AI. Therefore, it is crucial to design an environment that not only enables people to contribute their knowledge, but also motivates them to do so.

This study addresses the research gap regarding the motivators and barriers for knowledge contribution. The goal is to identify technical and organizational factors that promote or inhibit knowledge contribution to AI. The insights gained should help to design AI systems and organizations that promote knowledge transfer.

The following chapters provide an overview of the theoretical foundations, describe the methodology of the study, and present the results. The conclusion summarizes and discusses the results and derives recommendations for the further development of AI systems that support effective knowledge management.

RELEVANT FACTORS FOR PROVIDING KNOWLEDGE TO AN AI

By the literature review, seven key factors influencing people's readiness to provide knowledge to an AI were identified. These form the basis for this study.

Subjective perceived benefit is a critical factor in determining the readiness to contribute knowledge. This benefit must be proportionate to the effort and time required for the contribution to be considered meaningful (Al-Busaidi, 2013; Wang & Noe, 2010). Often, this benefit is perceived through experienced reciprocity or published success stories (Waefler, Fischer, Kunz & Saric, 2018). Benefits can be diverse, ranging from increased status in the group to better career opportunities or opportunities for personal learning (Ardichvili, 2008; Bock, Zmud, Kim & Lee, 2005).

Trust in AI is crucial to successful human-AI interaction. Low trust can lead to non-use or loss of efficiency (Hoff & Bashir, 2015; Lee & See, 2004). Trust is more likely to develop when it is assumed that knowledge will be used in a trustworthy manner (Mayer, Davis & Schoorman, 1995). Therefore, transparency and interpretable output from the AI are important to gain user trust, further it is important to minimize risks such as data security (Lee & See, 2004).

Positive job prospects influence the readiness to contribute knowledge. However, the introduction of AI may increase uncertainty about job security (Glikson & Woolley, 2020; Nam, 2019). This reduces employees' readiness to contribute knowledge and undermines their trust in the organization (Ipe, 2003; Moser, 2002). A competitive environment where jobs are often linked to performance encourages knowledge hoarding as a self-protective measure (Anand, Centobelli & Cerchione, 2020).

Trust in management is critical to the readiness to contribute knowledge (Lo, Tian & Ng, 2021; Renzl, 2008). When trust in management is lacking, the acceptance of technical solutions and the readiness to contribute knowledge decrease (Al-Busaidi, 2013). Top management support, such as clear statements and actions (i.e., provision of resources) regarding the importance of knowledge contribution plays a key role and can promote knowledge contribution both directly and indirectly by strengthening trust (Huemer, von Krogh & Roos, 1998; Waefler et al., 2018).

Trust in a team promotes knowledge contribution and is essential for effective collaboration. It involves a readiness to make oneself vulnerable to the actions of others (e.g., risk of misuse of knowledge) (Al-Busaidi, 2013; Mayer et al., 1995; Waefler et al., 2018). The experience of trust influences future interactions.

Psychological safety promotes knowledge contribution by facilitating interpersonal risk-taking, especially among individuals with low self-efficacy expectations (Siemsen, Roth, Balasubramanian & Anand, 2009). With psychological safety, employees are more likely to experiment and communicate openly, which promotes learning and knowledge contribution (Newman, Donohue & Eva, 2017). Factors such as supportive leadership, trusting relationships, and organizational norms influence the level of psychological safety in a team and create a culture in which knowledge contribution is viewed less as a risk and more as a collective gain (Kahn, 1990).

Reciprocity promotes knowledge contribution because people are more likely to contribute their knowledge if they expect others to do the same (Moser & Schaffner, 2003). This expectation is based on a social balance of give and take (Kramer, 1999). If this balance is disturbed, for example by perceived inequalities or potential exploitation, trust dwindles. Strong social norms can further promote the readiness to mutually contribute knowledge (Ardichvili, 2008; Gagné, 2009).

METHODS

An exploratory research design was selected for this study due to the limited research on the topic. This design was considered most appropriate for addressing the research question and context.

A literature review was conducted to identify influencing factors. Based on this, an interview guide was developed to explore these factors in depth. A hypothetical scenario was developed to introduce interviewees to AI and was briefly presented. Seven people from various professional backgrounds and age groups, within the context of high-precision grinding, were interviewed. The content analysis was performed using the method of Kuckartz (2016). Higher level categories were deductively derived from existing literature, while subcategories were inductively derived from transcribed interview texts. Recommendations for potential actions were developed through a brainstorming process based on the identified motivators and barriers. These recommendations were subsequently elaborated on a theoretical basis.

MOTIVATORS AND BARRIERS FOR KNOWLEDGE CONTRIBUTION

This section presents the identified motivators (see Table 1) and barriers (see Table 2). Motivators as well as the barriers are numbered consecutively and are abbreviated M for motivators and B for barriers.

Table 1. Motivators for knowledge contribution to an AI.

Individual motivators (M1)	
Learning & development (M11)	Interviewees are more likely to contribute knowledge when they see an opportunity to improve their working methods and to acquire new skills by learning from or alongside AI. This readiness is enhanced by the access to a broader knowledge base that AI provides.
Emotional Motivator (M12)	Interviewees feel inspired to contribute knowledge when they derive satisfaction and enjoyment from helping their peers. However, this motivation seems to be related to human-to-human interactions and is not necessarily recognizable when contributing knowledge to an AI.
Material incentives (M13)	Material incentives such as bonuses are not necessarily the primary motivator for most skilled workers to contribute knowledge. There are also concerns that material incentives increase competitive orientation.
Team-related motivators (M2)	
Reliance on others (M21)	Due to their high level of specialization, interviewees depend on collaboration with others, requiring knowledge contribution for challenging or complex tasks.
Support for less involved peers (M22)	The use of AI enables better networking with colleagues from different countries, which is particularly advantageous for less well-integrated or linguistically limited skilled workers.
Collective benefit (M23)	Interviewees see knowledge contribution to an AI as collectively beneficial (i.e., to increase the group's competitiveness). The more knowledge is contributed, the more useful the AI becomes.
Normative motivators (M3)	
Reciprocity (M31)	The culture of knowledge contribution in the team is closely linked to reciprocity; low participation reduces overall motivation.
Conformity (M32)	Interviewees view knowledge contribution as an integral part of their employment contract and fear that violators may face consequences.
Shared values and visions (M33)	Interviewees see knowledge contribution as a normative duty and important for the good of the company.

Table 2. Barriers for knowledge contribution to an AI.

Individual barrier (B1)	
Fear job loss (B11)	Fears that the introduction of AI could lead to job losses due to automation combined with concerns that more intensive use of technology will reduce skills and tacit knowledge.
Interpersonal barriers (B2)	
Fear of criticism (B21)	Fear of criticism and lack of appreciation inhibit knowledge contribution. A constructive feedback environment is therefore crucial.

(Continued)

Table 2. Continued.

Fear of giving inaccurate information (B22)	Context understanding is critical for effective knowledge contribution; misunderstandings could lead to serious harm. The use of AI could increase these uncertainties.
Team conflicts (B23)	Team conflicts can significantly impede direct knowledge contribution among humans, whereas contributing knowledge indirectly through an AI was deemed less problematic.
Procedural barriers (B3)	
Lack of time (B31)	Time constraints and concerns about delayed benefits make it necessary for the AI to provide efficient benefits in a timely manner and for this to be supported by training.
Uncertainty knowledge sharing (B32)	Uncertainty about the level of confidentiality is a barrier to the contribution of knowledge. Internal contribution is more accepted, but external contribution is perceived as risky and could damage customer relationships. Readiness to contribute also varies depending on trust in colleagues and their geographic location.
Cultural barriers (B4)	
Competition think (B41)	For the most part, there is a harmonious atmosphere in the team without competition. Nevertheless, withholding knowledge can be seen as a supposed competitive advantage. While people are open to contribute knowledge internally, they tend to be cautious towards other departments. In general, knowledge contribution is seen as beneficial if there is no competitive dynamic.
Distrust in management (B42)	Distrust of the management and unclear communication, especially regarding the use of AI, inhibit knowledge contribution. Clear intentions and transparency on the part of management could allay these fears and promote trust.
Technological barriers (B5)	
Lack of reliability (B51)	Skilled workers expect the AI to work reliably and accurately to avoid reduced benefits. Errors and misunderstandings affect trust in AI. Moreover, ineffectiveness in the AI's initial stages gives rise to concerns of wasted resources.
Distrust in AI (B52)	Interviewees expressed that they need to trust that the AI will not misuse confidential information or pass it on without their knowledge. Furthermore, interviewees are concerned about data privacy and control when using AI. They wish for clear mechanisms to verify data security and understand exactly how AI processes their data. Fear of hacking and data misuse are also present, with security standards at least equivalent to those for email.

DISCUSSION OF THE RESULTS

The findings highlight the critical role of both individual and team-oriented motivators in encouraging knowledge contribution to AI. Individual motivators include learning opportunities and emotional benefits from interacting with colleagues. However, these incentives are most effective when there is a reciprocal exchange of knowledge with AI among co-workers. A lack of reciprocity creates an imbalance in the give-and-take dynamic that can discourage future knowledge contribution. To maximize the benefits of AI, efficient and reliable use is essential, especially for skilled workers who are often faced with time-pressure and performance-driven tasks. Furthermore, a thorough understanding of AI capabilities is important for adjusting work strategies and determining the level of trust to place in the technology. Excessive expectations of the benefits AI can provide, can quickly lead to disappointment and a subsequent loss of confidence in the technology (Glikson & Woolley, 2020). Trust is especially important when it comes to sensitive information. Fears of potential disclosure of sensitive data can inhibit the readiness to engage in knowledge contribution. Therefore, creating a safe environment that fosters trust among stakeholders is paramount. Concerns about job security, fuelled by fears that automation will replace humans, are significant barriers to open knowledge contribution. Improving employability serves as a countermeasure to feared job insecurity. In addition, cultural elements play an important role, such as psychological safety, which is a key factor. An atmosphere of safety encourages even those with lower expectations of self-efficacy to contribute their knowledge without fear of external criticism. Effective leadership is critical in this equation, serving to build trust and allay any lingering fears. Management buy-in is essential to emphasize the value of knowledge contribution and to lend credibility to the initiative. Factors mentioned for management credibility include transparency, clear and comprehensible communication, and management behavior that confirms the communicated intentions.

RECOMMENDATIONS

This study so far has addressed motivators and barriers to knowledge contribution to AI. The following chapter proposes concrete recommendations based on these findings. The numbers indicated refer to motivators and barriers (as in Tables 1 and 2) to which the recommendations relate. The recommended measures aim to improve the subjectively perceived influencing factors. However, an evaluation of their technical or practical feasibility is not part of this study.

To promote motivation to contribute knowledge, it is vital to make the contribution visible and to enhance **feedback.** Three key feedback strategies can be combined: Transparency of contributed knowledge (M31), emotional feedback options such as "thank you" for appreciation (M12), and feedback on the practical usefulness of contributed knowledge for the benefit of the original knowledge provider (M11). **Knowledge quality** is relevant for a reliable benefit and therefore crucial for the acceptance and the generation of confidence in content (B51). A quality assurance process increases the system's reliability. Complementary measures such as checking the adequate description of the relevant context and peer evaluations can further improve the quality of contributed knowledge. There are great **expectations** for the benefits of the system, but also concerns that it may not meet such expectations (B51, B52). To avoid disappointment, transparent communication about the capabilities of AI is crucial. Additionally, incorporating explainable AI (XAI) may facilitate users' understanding of AI generated output and foster effective collaboration between the skilled worker and AI.

Lack of trust in AI is a potential barrier to knowledge contribution. To promote **building of trust**, a dual approach is advisable. First, explicit transparency about the purpose and the utilization of contributed knowledge, encapsulated in a comprehensible data policy, can mitigate underlying concerns (B42, B52). Second, to ensure transparency, it is important to clearly indicate who has access to the provided knowledge. This will enable the distribution of knowledge to be traced transparently. The combination of rules and transparency ensures that knowledge is not misused and strengthens trust in the management (B42, B52). The introduction of AI may trigger concerns about job loss, which reduces contribution of knowledge. To mitigate such fears, fostering **professional growth** is crucial, thereby enhancing user employability and reducing job insecurity. Changing job requirements make it necessary to identify development needs and to create personalized skill-enhancement programs. It is essential for AI-design to facilitate reciprocal learning, allowing both the skilled worker and the AI to learn from each other (see Renggli et al. 2022); (M11, B11). This study's findings reveal a high level of motivation for learning, as well as for working efficiently with AI. Therefore, it is crucial for the user to understand how to work and learn effectively with this technology. Establishing **Communities of Practice** (CoP) to share experiences and learning strategies between users offers a promising approach. This can help mitigate uncertainties in the use of the technology and increase experience of self-efficacy. In addition, CoPs offer the opportunity to reflect on a culture of collaborative working and appropriate rules of conduct (netiquette) for working with AI (M11, B21, B32).

LIMTIATIONS & CONCLUSION

The study scenario was based on a hypothetical AI, resulting in differing interpretations by participants that are difficult to compare. The results are limited in their generalizability due to the specific and small sample size.

This study shows that skilled workers are intrinsically motivated to contribute their expertise, thereby unlocking collective benefits in effectiveness and efficiency at work. To effectively encourage knowledge contribution to an AI, both technical and organizational measures are essential. AI platforms should be tailored to provide a learning environment, while organizations need to allocate sufficient time to create learning opportunities. The benefits of knowledge contribution increase with participation. Therefore, it is important that as many skilled workers as possible contribute their knowledge, which requires creating a trusting, psychologically safe environment. In addition, a culture that values recognition and respect for shared insights is essential. In establishing such an environment, a credible leadership is imperative. When it comes to contribution of sensitive information, trust in AI systems is critical and requires maximum transparency and control over data handling. Implementing AI should not be viewed as a one-time event, but rather as a dynamic, collaborative learning journey. A thoughtful mix of technical and organizational measures can amplify motivators and mitigate potential barriers.

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