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Impact of Artificial Intelligence on Knowledge Sharing in the Workplace

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Artificial Intelligence and Knowledge Sharing

Full research paper

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Abstract

The increasing use of digital communication tools in the workplace coupled with the ability of AI gives rise to new ways to capture knowledge from everyday communications such as work email and online meetings, and share this knowledge with others. While this has benefits for organisations, little is known of how employees may respond. The aim of this study is to examine factors that influence employees' willingness to share their knowledge knowing that their communications may be analysed, and the knowledge shared with others. Drawing on the Theory of Reasoned Action (TRA), this study examines the impact of motivating and inhibiting factors on knowledge sharing. The findings point to the importance of self-efficacy, reciprocity, and reputation for enhancing knowledge sharing in this context. However, concerns about being monitored may hinder knowledge sharing.

Keywords Artificial intelligence, knowledge sharing, Theory of Reasoned Action.

1 Introduction

Knowledge sharing is a two-way process of exchanging knowledge between individuals, teams and systems. (Liyanage et al., 2009). This process is considered critical to knowledge transfer that supports organisations in generating ideas, encouraging collaboration, building business opportunities (Deloitte, 2020), and enabling remote work. Organisational knowledge sharing also contributes to innovation, improved performance and overall organisational effectiveness (Nadason et al., 2017). Yet organisations continue to struggle to capture and share the knowledge generated within them (Alavi & Leidner, 1999; Donnelly 2019).

One avenue that is emerging as a promising way of improving knowledge management (KM) in organisations lies with the use of KM systems that are powered by Artificial Intelligence (AI) technologies and support processes such as knowledge creation and storage, and knowledge sharing (Jarrahi et al., 2022). Such systems have the potential to address some of the traditional individual and technological barriers of knowledge sharing, such as those related to the effort and time required to capture and codify knowledge, by eliminating some of the steps needed to record and store knowledge when it is generated. For example, through speech recognition technology, collaboration platforms such as Zoom and Microsoft Team are now capable of transcribing conversations in meetings and providing a transcript, the content of which can then be organised and tagged and the insights shared across organisations using advanced AI systems (Deloitte, 2020; Jarrahi et al., 2022). At the same time the use of AI for knowledge capture when focused on the analysis of employees' communications may create new types of anxieties and concerns that impact their views about such systems (Kolbjørnsrud, et al., 2017) and, in turn their willingness to share their knowledge via these channels (Arias-Pérez & Vélez-Jaramillo, 2021).

Traditionally, research on knowledge acquisition and sharing has focused on motivating people to share their knowledge, and on developing systems that can preserve and utilise such knowledge through extraction, codification, and enhanced storage and retrieval systems (Arias-Pérez & Vélez-Jaramillo, 2021; Jarrahi et al., 2022). However, research on AI and KM, and people's beliefs and concerns about such systems is nascent, with few considering employee responses regarding AI and knowledge sharing (Arias-Pérez & Vélez-Jaramillo, 2021). Yet, this is important given the unique issues that may arise with such systems such as concerns about privacy and online monitoring.

To address this gap, this study draws on the Theory of Reasoned Action as a starting framework to examine the relative importance of various factors that influence knowledge sharing when employees are aware their communications may be analysed and codified, and using various algorithms, knowledge extracted from them for storage and use in KM systems. In this study, we focus on peoples' motivations and concerns, and the impact on knowledge sharing. For organisations, the findings aim to shed light on ways to address employee concerns and encourage knowledge sharing. The findings may also help inform workplace policies and strategies to provide better integration of AI for knowledge sharing.

2 Prior Research

Alavi and Leidner (1999) refer to knowledge as information that is possessed in the mind of an individual: it is personalized or subjective information related to facts, procedures, concepts, interpretations, ideas, observations and judgments (which may or may not be unique, useful, accurate, or structurable). The management of such knowledge therefore refers to the systemic processes implemented by organisations for acquiring, organizing and communicating the knowledge of employees (both tacit and explicit) in ways that others can use it to be more effective in their work (Alavi & Leidner, 1999). Effective knowledge management can therefore only be achieved when knowledge from individuals and groups are successfully shared, captured and transformed into organisational knowledge assets.

Traditionally, the focus for knowledge acquisition and sharing has been on motivating people to share their knowledge, and on developing systems that can preserve and utilise such knowledge through extraction, codification, and enhanced storage and retrieval (Arias-Pérez & Vélez-Jaramillo, 2021; Bock et al., 2005; Jarrahi et al., 2022; Todorova & Mills, 2018). The importance of knowledge retention in the organisation and need for knowledge sharing has also led to studies into factors that can mitigate knowledge loss. DeLong (2004) argued for a holistic approach in knowledge management strategy, whereas Khoza et al. (2017) considered that since knowledge resides in individuals' brains, such strategies should start with people. The consensus towards encouraging knowledge sharing behaviour therefore begins with integrating knowledge strategy into different areas of the organisation while understanding the factors that encourage knowledge sharing.

Given the potential for AI to help improve knowledge sharing and its use, it is important to understand how an AI-strategy can be successfully integrated with knowledge strategy, and to address issues that may arise, such as concerns about privacy and online monitoring. To address, in this study we examine people's views about sharing their knowledge, knowing that their communications may be analysed, codified, integrated with other knowledge, and shared with others.

3 Research Model

Numerous studies have investigated knowledge sharing. One approach has been to draw on widely used theories such as the Theory of Reasoned Action (TRA) to explain knowledge sharing through behavioural intention. Formulated as a motivational model, the TRA seeks to explain behaviours and actions that people have control over by focusing on intentions (Ajzen & Fishbein, 1980). More specifically the TRA argues that individuals' actions and behaviour are driven by an intention to perform that behaviour. The TRA posits that intention is determined by their attitude towards the behaviour (i.e. the degree to which a behaviour is considered favourable or unfavourable) and subjective norm (i.e. a person' belief that people who are important to them think they should perform the behaviour).

For behaviours shaped by volitional control where people can freely choose whether to perform the behaviour, it is expected that if individuals have a positive attitude towards a behaviour (like knowledge sharing) and believe others expect them to perform that behaviour (subjective norm), they are likely to intend (or be willing) to do so (Ajzen & Fishbein, 1980). Attitude, in turn, is influenced by beliefs about the consequences of a behaviour. Prior research has therefore extended the TRA by including beliefs such as self-efficacy, reciprocity, and rewards (as consequences of knowledge sharing behaviour), as antecedents of attitude alongside subjective norms to explain why individuals share their knowledge (Bock et al., 2005; Hsu & Lin, 2008; Todorova & Mills, 2018).

In this paper, we examine and present findings of a model of knowledge sharing where employee communications (through email, document sharing, audio / video-conferencing, etc) may be processed and the knowledge therein extracted and shared with others using AI-enabled knowledge capture and management systems. Utilising the TRA, we examine the impacts of beliefs about self-efficacy, reputation and reciprocity and inhibitors (i.e. monitoring), on attitude towards knowledge sharing, and of attitude and subjective norms on willingness to share knowledge in this context (See Figure 1).

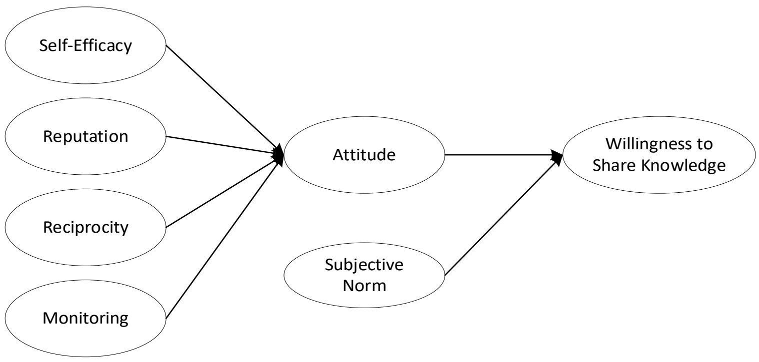

Figure 1. The Research Model

3.1 Hypothesis Development

Attitude in this study refers to the evaluation of AI-enabled KM systems as a tool for capturing knowledge from employee communications for sharing it with others. Research on individuals' attitudes towards knowledge sharing suggests that a positive attitude directly influences willingness to share knowledge (Bock et al., 2005; Jalili & Ghaleh, 2021; Lin, 2007). Hence, it is expected that:

H1: Attitude is positively related to willingness share knowledge.

Motivating factors reflect individuals' beliefs that the use of AI systems for knowledge sharing will result in individuals receiving benefits. This includes intrinsic motivation which refers to individuals' inherent enjoyment that results in engagement in activities (Lin, 2007), and extrinsic motivation being driven through external rewards and recognition. Intrinsic motivation is seen as a stable and significant indicator with sustained effect (Pee & Lee, 2015). Extrinsic motivation, on the other hand, has had mixed results. Some studies show, for instance, that anticipated extrinsic rewards have negative effects on attitude and intention (Khankanhalli et al., 2005), while others argue that extrinsic motivators such as rewards may result in temporary short term compliance (Lin, 2007; Pee & Lee, 2015). In this study, we examine both intrinsic and extrinsic motivators focusing on self-efficacy, reputation and reciprocity.

People's perception of their competency and capability is referred to as *self-efficacy* (Ergun & Avci, 2018). Self-efficacy is considered a key motivation affecting knowledge sharing attitude and behaviour. For example, in online knowledge sharing, employees with higher self-efficacy are expected to be more self-motivated, resulting in more active knowledge sharing (Nguyen, 2020). Confidence in ones' ability to contribute to organisational objectives may also result in a more positive attitude towards knowledge sharing (Lin, 2007; Todorova & Mills, 2018). Therefore:

H2. Self-efficacy is positively related to attitude towards knowledge sharing.

The perceived *reputation* gained from sharing knowledge may also provide motivation for employees to share knowledge. For example, Todorova and Mills (2018) found that the benefit of enhanced reputation has a positive effect on knowledge sharing attitude. Hsu and Lin (2008) considered knowledge sharing as a transaction, and extrinsic factors such as reputation as necessary incentives for knowledge sharing. Their study indicated individuals might be motivated to share knowledge if there is opportunity for enhanced social relationships and reputations. Hence:

H3. Reputation is positively related to attitude towards knowledge sharing.

R*eciprocity*, as a key extrinsic motivator, refers to an expectation of rewarding actions (Nguyen et al., 2019). To an extent, reciprocity can be viewed as long term mutual benefits obtained through knowledge sharing (Hsu & Lin, 2008). As knowledge is considered a valuable resource that can be exchanged, the reciprocal obligation that comes with these exchanges can increase employees' contributions through cooperation and development of social norm within an organisation (Reychav & Weisberg, 2010). Employees who share knowledge therefore expect reciprocal actions for their time and efforts. Studies have viewed reciprocity as an important social factor; where employees' relationships are strong, knowledge sharing is significantly enhanced (Chow & Chan, 2008). Individuals also view knowledge sharing as more favourable if they believe they can obtain reciprocal benefits in the future through their sharing (Lin, 2007). Hence:

H4. Reciprocity is positively related to attitude towards knowledge sharing.

Inhibitors of knowledge sharing often focus on three areas: individuals, organisational factors and technological factors (Nadason, et al., 2017). The majority of the barriers to knowledge sharing are concerned with people. While there are many factors that inhibit knowledge sharing such as codification effort (Khankanhalli et al., 2005) in this study we will examine perceived monitoring.

Perceived monitoring refers to concerns associated with AI monitoring employees' behaviour, in this case their communications through digital media. Although workplace policies largely regard communications using a work-provided medium (e.g. work email, work-issued mobile device, and collaboration tools such as Microsoft teams) as belonging to the organisation, typically one's day-to-day communications will include non-work-related communications. As AI systems do not distinguish between private and work-related communication, its use can be seen as an intrusion into employees' activities. Notably, it can be seen as violating workers' privacy leading to anxiety and concerns (Li & Huang, 2020) so have a negative effect on knowledge sharing. Hence, it is expected:

H5. Perceived monitoring is negatively related to attitude towards knowledge sharing.

Subjective norm refers to the social pressure exerted within the organisation to share knowledge (Bock et al., 2005). Where an organisation and relevant others, such as colleagues and management exert significant influence on knowledge sharing behaviour, this can directly affect individuals' willingness to share knowledge (Bock et al., 2005). As such, persons who are influenced by others (e.g. peers) may incline to comply with those expectations (Nguyen, 2020). Employees who perceive greater social pressure to share their knowledge are therefore more likely to share. Hence:

H6. Subjective norm is positively related to willingness to share knowledge.

Methodology

To assess the research model, survey data was collected from knowledge workers that is, persons who think for a living and use communication tools as part of their job on a daily basis. The online survey was created using Qualtrics and the link distributed via Facebook, LinkedIn, and through Qualtrics data collection services.

All constructs were assessed using items adapted from existing studies to the study context. Attitude (5 items), subjective norm (3 items) and willingness to share knowledge (3 items) were based on Lin (2007) and Bock et al. (2005). Measures for motivators and inhibitors were adapted from Kankanhalli et al. (2005), Bock et al. (2005) and Spreitzer (1995): self-efficacy (3 items), reciprocity (5 items), reputation (4 items), and perceived monitoring (4 items). All responses were captured using seven-point Likert scales, anchored as “strongly disagree” and “strongly agree”.

The sample comprised of 259 respondents of which 49.2% were male and 49.8% female (0.8% responded “other”; 1 missing). The mean age group was 36-40 years; 30.1% had some postgraduate study or had completed a postgraduate degree, 42.8% had completed some undergraduate study or an undergraduate degree and 15.1% had a secondary qualification (e.g. high school) as their highest level of education. Respondents came from a range of industries, including information technology and communications (15.8%), the financial sector (12.0%), and retail (10.0%). All respondents used email; chat and file-sharing were frequently used followed by video and web conferencing tools, Google Workspace/Microsoft 365 and collaboration tools like Microsoft Teams.

The study followed recommended guidelines for minimising common method bias (Podsakoff *et al.*, 2003) including selecting measures of the dependent and independent variables from different studies, and assuring respondents of anonymity and confidentiality of their responses. After data collection, common method bias was assessed using Harman’s one-factor test. No single factor accounted for more than 44% of the variance observed, suggesting common method bias was an unlikely issue.

The partial least squares approach to structural equation modelling (PLS-SEM) was used to analyse the research model. PLS-SEM was considered suitable given the focus on prediction and the aim to explain the variance observed in the dependent variable, that is, attitude and willingness to share knowledge (Hair, et al, 2018). Smart PLS 3.3.7 (with 1000 resamples) was used to evaluate the research model.

All constructs were modelled as reflective. For the measurement model, construct reliability, convergent validity and discriminant validity were assessed (Hair et al., 2018). Internal reliability of the constructs was assessed using composite reliability (CR) scores; CR ranged from 0.927 to 0.957 (Table 1) exceeding the recommended cut-off of 0.70 (Hair et al., 2018). Convergent validity indicates the extent to which constructs share a high proportion of variance in common; ideally items should load more on their own construct than on others (Hair et al., 2018). To assess, average variance extracted (AVE) was evaluated; these ranged from 0.761 to 0.848 (Table 1), exceeding recommended cut-off of 0.50. Item loadings also ranged from 0.816 to 0.939 exceeding 0.70. For discriminant validity, the hetereotrait-monotrait ratio (HTMT) was evaluated; all values were below 0.85 (Table 1), satisfying this criterion.

			Hetereotrait-monotrait ratio (HTMT)					
Constructs	CR	AVE	SE	RC	RP	MO	AT	SN
Self-efficacy (SE)	0.943	0.847	-					
Reciprocity (RC)	0.951	0.794	0.538					
Reputation (RP)	0.948	0.820	0.431	0.788				
Monitoring (MO)	0.957	0.848	0.067	0.146	0.097			
Attitude (AT)	0.957	0.816	0.402	0.580	0.551	0.212		
Subjective Norm (SN)	0.943	0.846	0.409	0.670	0.736	0.040	0.589	
Willingness to Share (WIL)	0.927	0.761	0.368	0.573	0.535	0.271	0.803	0.602

Table 1. Construct reliability, Average Variance Extracted (AVE) and Hetereotrait-monotrait ratio (HTMT)

The results showed the antecedents explained 0.356 and 0.582 of the variance observed for attitude and willingness to share respectively. Self-efficacy (H2, 0.126, $p \leq 0.10$), reciprocity (H3, 0.288, $p \leq 0.001$) and reputation (H4, 0.242, $p \leq 0.001$) were significant and positively related to attitude. The results also supported hypothesis H5, with perceived monitoring (H5, -0.132, $p \leq 0.05$) being inversely related to attitude. For willingness to share, attitude (H1, 0.633, $p \leq 0.001$) and subjective norms (H6, 0.202, $p \leq 0.05$) were significant, supporting hypotheses H1 and H6 respectively.

4 Discussion

This research aims to identify motivating and inhibiting factors influencing employee willingness to share knowledge using AI-based knowledge systems. Drawing on the TRA, the study identified self-efficacy, reciprocity, reputation and monitoring as significant factors influencing employees' attitude.

As expected, all three motivators were significant. This is consistent with previous studies (Lin, 2007; Nguyen, 2020; Todorova & Mills, 2018) indicating a more positive attitude for those who believe that use of AI knowledge systems to share knowledge would enhance their reputation in the organisation. The results also suggested, in general that persons were confident in their ability to share valuable knowledge with others and were willing to do so. Reciprocity was also positively related to attitude indicating persons who believe their knowledge sharing would enhance relationships through reciprocal knowledge sharing had a positive attitude towards sharing their knowledge (Bock et al., 2005; Lin 2007). Given knowledge sharing often relies on a culture of trust, enhanced reputation together with reciprocal benefits help foster the relationships necessary for a knowledge sharing culture in an organisation.

By contrast, the study showed online monitoring had a significant yet negative influence on attitude towards sharing knowledge. This result suggests employees were concerned about how information captured from their digital communications might be used by the organisation, so were less positive about its use in knowledge sharing. This may be compounded by the non-voluntary nature of such systems given the increasingly pervasive nature and embeddedness of AI in organisational systems and that most workplace communications today are computer-mediated.

Finally, consistent with prior research and the TRA (Ajzen & Fishbein, 1980), the results confirmed attitude and subjective norms as having positive impacts on willingness to share knowledge (Bock et al., 2005), suggesting that a positive evaluation of AI systems to support knowledge sharing, alongside expectations of others would encourage employees to share their knowledge through such systems.

Altogether, the results of this study has implications for sharing of knowledge through AI systems. The findings suggest organisations first focus on addressing concerns people have regarding knowledge capture and sharing through AI systems. On the positive side, evidence of safeguards or transparent policies that indicate what information is captured and retained and how this is used could provide reassurance that lowers the negative effect of perceived online monitoring on knowledge sharing. To encourage knowledge sharing via such platforms, it is important that contributors are recognised as signalled by the importance of reputation.

5 Conclusion

As technology advances, there is increasing opportunity to use AI-based systems to capture, extract, codify and share knowledge derived from workplace communications through tools such as emails, file sharing, and video and conference communications. The aim of this paper was to present findings on what would motivate or inhibit persons from sharing their knowledge through everyday organisational communication tools, when they know that their communications would be analysed using AI, and the knowledge extracted and shared with others. The findings showed self-efficacy, reputation and reciprocity had positive impacts on willingness to share knowledge via AI-enabled systems through attitude. On the other hand, concerns about being monitored by AI systems led to a less favourable attitude towards sharing knowledge through AI systems. As expected, both attitude and subjective norms were positively related to knowledge sharing (Bock et al., 2005)

Given the limited research to date at the intersection of AI and knowledge sharing, this study aims to contribute new insights by integrating people-related factors in to a model that examines how knowledge sharing is impacted by the technology that is used, in this case AI-enabled systems to capture knowledge from people's communications in the workplace. Although there have been many studies examining use of technology for knowledge management, an emerging technology such as AI is expected to automate much of the work required in the knowledge capture and sharing process, and in so doing to raise new opportunities as well as challenges. This research provides insights into the impact of human-related factors where it is likely to become increasingly difficult to avoid using technologies that enable knowledge capture as they become more embedded in the workplace.

Finally, there are some limitations and opportunities for future work. First, this study focused on a technology which is emergent and not yet available in most organisations. As such, people were evaluating a technology that they may not understand fully. At the same time, the increasing use of digital platforms to communicate coupled with advances in technologies such as Microsoft Teams, is making the possibility of automated knowledge capture imminent. Second, in this study the focus was on self- efficacy, reputation, reciprocity and online monitoring. There is opportunity to examine other that may impact knowledge sharing in an AI-enabled context such as rewards and concerns about job loss. Finally, it is expected that findings may vary over time, hence it is suggested that future research reassess the model as the technologies evolve and are embedded in more processes in the workplace.

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