

Knowledge Sharing in the Age of Artificial Intelligence: Exploring Motivational Pathways

Abstract

In the age of transformative Artificial Intelligence (AI) investment, exemplified by the groundbreaking initiatives like the *Stargate Project* - a \$500 billion effort to revolutionize AI infrastructure - understanding how AI reshapes individual and organizational behavior has never been more critical. This study explores how the use of intelligent systems, such as ChatGPT, in knowledge sharing, influences individuals' motivation to share knowledge in the workplace. Drawing on insights from Social Exchange Theory and adopting Deci and Ryan's full spectrum of motivational types presented in the Self-Determination Theory, we uncover the impact of AI adoption on individuals' knowledge sharing behavior. Our findings, based on a survey of 700 AI users, indicate that AI adaptation significantly increases intrinsic motivation, fosters identified and integrated forms of extrinsic motivation regulators, and helps individuals overcome amotivation. Its effect on external and introjected regulation appears negligible, suggesting that AI use in the workplace primarily enhances autonomous motivation while having little to no impact on controlled motivation. These results pave the way for deeper, more comprehensive, and multifaceted insights into the integration of knowledge-based processes in the AI era.

Key words: AI, Amotivation, Extrinsic motivation, Intrinsic motivation, Knowledge sharing, Self-Determination Theory

1. Introduction

The question is not “*whether to adopt* AI but rather *how to use* AI” (Dell’Acqua et al., 2023). Artificial Intelligence (AI), is rapidly developing into an ‘intelligent agent’, imitating and replicating human understanding (Singh & O’Keeffe, 2023), and while there is a concern that AI may lead to job displacement, there is great potential in its adaptation at work. The 2023 McKinsey report on the state of AI does not show a rapid influx of AI usage beyond one business function between 2021 and 2023, however, the 2023 study by the National Bureau of Economic Research estimated that 36% of research and 41% of professional services can be automated using generative AI, allowing knowledge workers to bring their attention to more valuable practices (Eisfeldt et al. 2023). Consequently, the adoption of AI is not a matter of *if* but *how*.

Educational researchers have been looking at ways to drive student motivation to engage with AI (Baez et al., 2024; Lin et al., 2021), and first findings emerge on how working with AI is impacting workplace behavior. Dell’Acqua et al. (2023, p.17) report that AI significantly increases knowledge workers’ performance and work quality, “benefitting bottom-half performers the most.” In a similar vein, Olan et al. (2024) show that AI used alongside robust knowledge sharing mechanisms fosters more efficient knowledge flows, bridging the gap between existing and newly created knowledge, stimulating continuous innovation, and enhancing organizational performance. However, findings by DeStefano et al. (2022) show AI adoption reduces decision-making performance. To add to the empirical research on how AI shapes work performance we study the impact of AI on individuals’ motivation to share knowledge at work.

Research on knowledge management (KM) points to a positive correlation between knowledge sharing and overall firm innovation and performance (Ode & Ayavoo, 2020;

Palacios & José, 2006; Wang et al., 2016), and O’Leary (1998) discussed how AI can facilitate KM systems (see also Smith & Farquhar, 2000). In this study, the focus is not on the impact of AI on an organization’s ability to optimize its operation systems, but on the impact AI has on an individual’s motivation to share knowledge with their system. In this study we define knowledge sharing “as the behavior when an individual disseminates their acquired knowledge to other members within an organization” (Hsu and Ju, 2007, p. 154). The heavy investment in AI, of \$47.4 billion of private investment in the US in 2022 alone (Maslej et al., 2023) and transformative initiatives like the *Stargate Project* - aiming to invest \$500 billion over four years in AI infrastructure in the US to secure leadership in AI, create jobs, and bolster economic growth (OpenAI, 2025) - only underscores the importance of managing knowledge in the time of AI (Botega & da Silva, 2020).

We build on Deci and Ryan’s Self-Determination Theory (SDT; 1985; 2012) and draw on Ferger and Rechberg’s (2024, p.1170) review of SDT “as an applied predictor of knowledge sharing behavior”. To complement this psychological lens, we also draw on Social Exchange Theory (SET; Blau, 1964), which explains how perceived reciprocity and relational rewards shape individuals’ willingness to share knowledge - especially in technology - mediated environments. We asked 700 AI users on the impact of AI on their motivation to share knowledge at work and find that AI has a significant direct effect on individuals’ knowledge sharing behavior in the workplace. Specifically, AI usage in sharing knowledge significantly increases intrinsic motivation, fosters the identified and integrated extrinsic motivation regulators, and helps individuals overcome amotivation. Its effect on external and introjected regulation appears negligible, suggesting that AI use in the workplace primarily enhances autonomous motivation while having little to no impact on controlled motivation.

In what follows we develop hypotheses on how the application of AI in knowledge sharing may drive an individual’s motivation to engage in knowledge sharing behaviors at work. We report on our method and findings, followed by discussions and conclusions. Honing in on SDT, we differentiate between intrinsic, extrinsic, and amotivation, to inform

research and practice on ‘how to’ effectively integrate AI for individuals to share knowledge at work.

2. Theoretical background and research model

To assess AI’s impact on knowledge sharing and motivation, Deci and Ryan’s (2012) SDT provides a valuable framework. SDT differentiates between intrinsic motivation, various forms of extrinsic motivation (external, introjected, identified, and integrated), and amotivation. Understanding these motivational regulators helps organizations determine how AI can encourage knowledge sharing behavior. To enrich this psychological lens, we also incorporate SET (Blau, 1964), which highlights how perceived reciprocity, social rewards, and cost-benefit appraisals influence individuals’ willingness to share knowledge - particularly relevant in digitally mediated contexts. To align with the hypothesis’s development, Table 1 summarizes the six motivation regulators and categorizes extrinsic motivators as autonomous or controlled, in alignment with Ryan and Deci (2000). Each category includes an explanation and an example illustrating its role in knowledge sharing practices.

Table 1: The six motivation regulators, their function and impact on knowledge sharing

Motivation regulator	Category	Explanation	Example in Knowledge Sharing
Intrinsic Motivation	Intrinsic	Performing an activity for its inherent satisfaction, enjoyment, or personal fulfillment.	Employee shares insights about a project with their team, genuinely enjoying helping others to solve problems.
Integrated Motivation	Autonomous Extrinsic	Sharing knowledge because it aligns with deeply held values that are integrated into one’s sense of self.	Employee shares knowledge because they view collaboration as an integral part of their professional identity.
Identified Motivation	Autonomous Extrinsic	Sharing knowledge because the activity is personally meaningful and in alignment with one’s values and goals.	Employee shares knowledge because they see doing so as crucial for the team’s success and their professional development.
Introjected Regulation	Controlled Extrinsic	Sharing knowledge out of internal pressure, guilt, or the desire to	Employee contributes to the team’s knowledge base to prove their expertise;

		maintain self-worth or to avoid shame.	avoiding feeling inadequate compared to colleagues.
External Regulation	Controlled Extrinsic	Sharing knowledge purely to gain rewards, recognition, or avoid punishment.	Employee shares an innovative idea in a meeting because their manager promised a bonus for contributing solutions.
Amotivation	Lack of Motivation	The individual sees no value or reason to share knowledge.	Employee withholds information about a workflow because they don't see its importance or any benefit in sharing insights.

2.1. AI's impact on Knowledge Sharing Behavior

Knowledge sharing is essential for organizational success, and employers rely on employees' voluntary engagement (Cyr & Choo, 2010). Although knowledge is “innately a human quality, residing in the living mind of a person” (Myers, 1996, p. 2), AI can enhance knowledge acquisition by integrating insights from diverse fields, simplifying knowledge sharing processes, and reducing cognitive effort for contributors. AI can function as a digital nudge (Dennis et al., 2020) to streamline processes and improve accessibility, making knowledge sharing more efficient (Su, 2024).

Beyond improving knowledge acquisition, AI automates repetitive tasks, allowing individuals to allocate more time to sharing knowledge, fostering a culture of continuous learning. However, AI's impact on decision-making is debated. While AI-generated insights can support decision-making, DeStefano et al. (2022) found that AI adoption may sometimes reduce decision-making performance. Despite this, AI tools have been shown to improve accessibility, enhance information retrieval, and increase human participation on knowledge sharing platforms, leading to more and longer contributions (Su, 2024). We therefore predict that:

H1: AI use in knowledge sharing has a positive effect on knowledge sharing.

2.2. Knowledge Sharing, AI and Intrinsic Motivation

Although concerns about job displacement and AI anxiety exist (Li & Huang, 2020), SDT suggests that when AI is perceived as supportive of autonomy, competence, and relatedness, it can foster intrinsic motivation (Deci & Ryan, 2000). Motivation is a fundamental driver of behavior (Deci & Ryan, 2000) and a strong predictor for knowledge sharing (Ferber & Rechberg, 2024; Gagné et al., 2019). AI can enhance intrinsic motivation by providing real-time feedback boosting engagement, and by facilitating skill-building, confidence to share knowledge may increase. Intrinsic motivation, the most autonomous form of motivation, is rooted in the enjoyment of sharing knowledge per se (Law et al., 2017; Ryan & Deci, 2002). Intrinsic motivation can foster confidence, self-esteem, and fulfillment (Martin-Perez et al., 2012) and may influence an employee's willingness to share knowledge (van den Hooff et al., 2012). AI may support intrinsic motivation by reducing cognitive burden, enabling meaningful contributions (Welschen et al., 2012). The ability to build new skills through AI may also inspire knowledge sharing, reinforcing a cycle of continuous learning and engagement. Thus, we predict that:

H2a: AI use in knowledge sharing has a positive effect on intrinsic motivation.

H2b: Intrinsic motivation has a positive effect on knowledge sharing.

2.3. Knowledge Sharing, AI and Extrinsic Motivation

AI driven tools streamline processes, making contributions more efficient and measurable, while personalized incentives and gamification elements encourage sustained engagement (Su, 2024; Wu et al., 2021). From a SET perspective, individuals engage in knowledge sharing processes when the perceived rewards (e.g., recognition, support, reputation gains) outweigh the costs (e.g., time, effort, vulnerability) (Blau, 1964; Homans, 1958). AI systems facilitate

recognition or traceable contribution (e.g., automated logging, tagging, visibility features) can enhance perceived reciprocity and fairness – critical to reinforcing participation. Conversely, when AI tools bypass human feedback or reduce interpersonal interactions, the perceived “social return” may diminish, weakening motivation, especially among those relying on external or introjected motivation. Thus, we hypothesize that:

H3a: AI use in knowledge sharing has a positive effect on extrinsic motivation.

H3b: Extrinsic motivation has a positive effect on knowledge sharing.

To explore how AI supports extrinsic motivation, we examine each of the four regulatory types defined by SDT - integrated, identified, introjected, and external - ranging from the most autonomous to the most controlled. This breakdown allows us to understand how the adoption of AI may foster specific motivational regulators and drive knowledge sharing behavior in the workplace.

Knowledge sharing, AI and integrated regulation: Integrated regulation refers to the internalization of organizational values such that knowledge sharing aligns with one’s self-concept and long-term identity (Roche & Haar, 2011). An individual shares knowledge because doing so aligns with deeply held values that are integrated into one’s sense of self. An individual who is motivated in this way pursues to share knowledge as their goals align with that of the organization, and when relationships are reciprocal (Coleman & Lieberman, 2015; Stenius et al., 2016). An employee shares knowledge because they view collaboration as an integral part of their professional identity. Indeed, Bock et al. (2005) found that reciprocity can drive knowledge sharing. AI can facilitate motivation by satisfying core psychological needs outlined in SDT - particularly competence and autonomy. For instance, AI tools can automate low-value tasks, enabling employees to focus on strategic knowledge contributions, which reinforces their perceived autonomy over work processes (Gagné & Deci, 2005). At the same time, AI’s ability to generate, synthesize, or adapt content (e.g., through translation or

summarization) helps users produce more impactful contributions, enhancing perceived competence (Ryan & Deci, 2000).

Furthermore, from the perspective of SET (Blau, 1964), AI-mediated knowledge sharing supports long-term relational investment by signaling expertise and reliability, thereby reinforcing reciprocal value exchange and professional identity. This dual lens strengthens the case for AI as a facilitator of integrated regulation. In accordance we propose:

H3a.1 AI use in knowledge sharing has a positive effect on integrated regulation.

H3b.1 Integrated regulation has a positive effect on knowledge sharing

Knowledge sharing, AI and identified motivation: Identified regulation occurs when an individual consciously values a behavior because it serves a personally meaningful outcome (Gagné et al., 2019). Unlike controlled forms of motivation, such as introjected or external regulation, identified regulation is volitional and reflects a self-endorsed reason to act (Vallerand, 1997; Koestner et al., 1996). In this case, AI supports goal alignment: by reducing friction in the knowledge-sharing process (e.g. via document classification or idea clustering), employees are better able to contribute to knowledge they deem important for their team's goal. For instance, Chen and Hsieh (2015) find that individuals driven by the identified regulator may share knowledge about a new process because they see it as crucial for the team's success and their professional development. This satisfies autonomy, and competence needs central to the SDT (Deci & Ryan, 2000).

From a SET lens (Blau, 1964), this form of motivation reflects a calculative exchange where employees expect that their input will produce desirable results—whether increased team efficiency, innovation, or reputational gain. AI enables this by enhancing the signal-to-noise ratio in communication and helping knowledge reach the right audiences effectively, thus maximizing its impact. For this reason, we propose:

H3a.2 AI use in knowledge sharing has a positive effect on identified regulation.

H3b.2 Identified regulation has a positive effect on knowledge sharing.

Knowledge sharing, AI and introjected motivation: Knowledge shared when motivated by the introjected regulator, is done so to avoid a feeling of guilt, but also to promote one's reputation at work (Hsu & Lin, 2008). AI helping with data management allows the individual to redirect their work in a way that will allow them to focus on what matters most in order to look favorable among their team. From a SET perspective (Blau, 1964) such reputation-driven sharing reflects a perceived exchange of effort for social standing. AI may reinforce this mechanism by increasing visibility or enabling faster responses, helping employees contribute to the team's knowledge base, proving their expertise and avoiding feeling inadequate compared to colleagues. We thus propose:

H3a.3 AI use in knowledge sharing has a positive effect on introjected regulation.

H3b.3 Introjected regulation has a positive effect on knowledge sharing.

Knowledge sharing, AI and external motivation: External regulation is wholly external where individuals share their knowledge in exchange for compensation, a promotion or recognition. For instance, an employee may share an innovative idea in a meeting because their manager promised a bonus for contributing solutions. Previous research shows that external rewards can promote a feeling of significance, encouraging knowledge sharing behavior (Welschen et al., 2012). From the perspective of SET (Blau, 1964), individuals engage in such behavior when they perceive the exchange to be beneficial – i.e., when the expected social or material rewards outweigh the costs (Homans, 1958). AI tools may strengthen external motivation by increasing visibility and traceability of contributions, making recognition more immediate or measurable. At the same time, AI's automation and reduced human interaction may limit the quality of relational cues and social feedback that typically sustain reciprocal knowledge

sharing (Grefen et al., 2003). Nevertheless, to the extent that AI tools facilitate recognition or reward-based systems – such as tagging contributions, credit attribution, or gamified performance dashboards – they can support externally motivated knowledge sharing. For this reason, we propose:

H3a.4 AI use in knowledge sharing has a positive effect on external motivation.

H3b.4 External motivation has a positive effect on knowledge sharing.

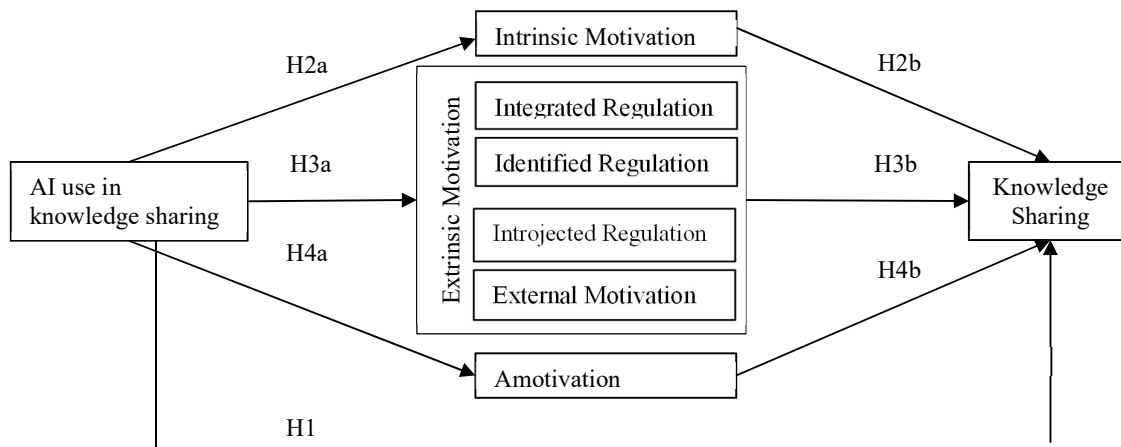
2.4. Knowledge Sharing, AI and Amotivation

When an individual is experiencing amotivation, Deci and Ryan (2000) predict that no motive or reason to invest any effort into a task is present. According to SDT, amotivation arises when individuals perceive a lack of competence, value, or contingency (Deci & Ryan, 2000). An amotivated individual does not partake in work activities beyond what they might absolutely have to, as they either do not care or do not believe to have a valuable contribution to make. AI may reduce amotivation by lowering task complexity, offering real-time feedback, and enabling individuals to feel more competent in their contributions. We cannot conclude from Dell’Acqua et al. (2023) report to what degree the bottom-half performers were motivated by AI, it is however positive that they benefited the most from the adoption of AI into their work practices. An amotivated individual may thus adopt AI not to enhance, but to replace their knowledge sharing, with AI making knowledge sharing ‘easy’ an amotivated individual may move from non-engagement, to engagement, allowing for some knowledge to be shared. We therefore propose:

H4a: AI use in knowledge sharing has a negative effect on amotivation.

H4b: Amotivation has a negative effect on knowledge sharing.

Figure 1 illustrates our Research Model.

Figure 1: Research Model

3. Method

We tested our hypotheses with a sample of 700 individuals who filled out an online survey.

This part describes the sample, research setting, and measurement instruments.

3.1. Sample and Procedure

Data for this study was gathered from a professional online platform that compensates participants for their involvement in surveys. The decision to remunerate participants was instrumental in ensuring high-quality data acquisition, as it incentivized thoughtful and comprehensive responses. Before initiating the survey, respondents were briefed about the study's objectives and the estimated duration it would take to complete the survey. It was emphasized that all information provided by the participants would be treated with the utmost confidentiality, ensuring no personal identifiers would be linked to the responses. To ensure the validity and relevance of the data, participants were required to confirm two essential criteria before proceeding: (1) they had to be over 18 years of age, and (2) they had to be regular users of AI tools, including but not limited to ChatGPT, Midjourney, CoPilot, and similar platforms. This exclusion of non-users was deliberate: because the study aimed to assess how the use of AI affects motivational states and knowledge sharing behaviors, only

individuals with regular, firsthand AI experience could meaningfully respond to the survey items. Including non-users would have introduced noise and speculation-based responses, reducing the interpretability of findings related to actual AI use.

We collected a total of 700 responses. The data screening procedure included testing for missing data and outliers (e.g., unengaged responses). In this step, we suppressed five respondents, leading to a total of 695 respondents. The response rate is this high as compensation was only generated following the completion of the survey. Testing for normality, we can report that overall kurtosis scores were below 2.200 (Sposito et al., 1983). The average age was 36.22 years ($SD = 9.89$). 260 (37.4%) of the sample were female, and 431 (62%) were male; three people identified as non-binary, and one person did not want to disclose their gender. The majority had bachelor's (312) or master's degree (147) and were full-time employed (657). The majority was from the UK (243) and South Africa (120) (see Appendix 1. for more information on the sample).

3.2. Measurement Scales

This study utilized various scales from established research to assess different constructs related to knowledge sharing and the impact of AI on job roles. In alignment with our theoretical development, we introduce the measuring scale from the most self-determined to the least here.

Intrinsic motivation scale was adapted from Gagné et al. (2015). This scale had 4 items ($\alpha = .85$). An example item is “Because it is interesting and satisfying to share my professional knowledge.”

Integrated regulation scale was adapted from Gagné et al. (2015). This scale had 4 items with three retained ($\alpha = .87$). An example item is “Because sharing knowledge aligns with my personal values.”

Identified regulation scale was adapted from Wu et al. (2021). This scale had 4 items ($\alpha = .90$).

An example item is “Because I think that it is an important personal attribute to share what I know with others.”

Introjected regulation scale was adapted from Wu et al. (2021). This scale had 4 items with two retained ($\alpha = .65$). An example item is “Because I want my supervisor to think I am a good employee.”

External regulation scale was adapted from Wu et al. (2021). This scale had 4 items with two retained ($\alpha = .70$). An example item is “Because I know that I will get a reward for doing so.”

Amotivation was measured with Levin et al.’s (1992) scale. It had 5 items ($\alpha = .88$). An example item is “I see no reason to share my knowledge.”

Knowledge sharing behavior was measured using Hsu and Ju’s (2007) scale. It had 5 items with 4 items retained ($\alpha = .85$). An example item is “I usually actively share my knowledge with my colleagues.”

AI use in Knowledge Sharing was an original scale developed specifically for this study with the help of ChatGPT. The prompt was “Please generate 12 concise survey statements for scientific research purposes that measure how AI tools impact knowledge sharing in the workplace, with each statement suitable for a 5-point Likert scale (from 1 = Strongly Disagree to 5 = Strongly Agree).” This scale consisted of 12 items, nine were retained ($\alpha = .93$). The nine of the 12 AI-generated items were vetted by two human researchers and loaded on a single factor, explaining 64.23% of the variance (loadings: 0.77–0.83). The scale showed strong internal consistency (Cronbach’s Alpha: 0.92–0.93), while descriptive statistics revealed acceptable means (3.12–3.59), moderate standard deviations (0.98–1.12), and skewness (–0.678 to –0.175) and kurtosis (–0.943 to –0.074) values within normal ranges. We further conducted a CFA with JASP 0.19.3 version. The CFA results confirm a strong one-factor model for AI-driven knowledge sharing, $\chi^2(27) = 240.523$, $p < .001$. All factor loadings

(0.903–1.128) were significant ($p < .001$), with low residual variances (0.360–0.467), indicating the items effectively capture the construct. The factor variance (0.653, $SE = 0.055$, $p < .001$) supports model stability, affirming a well-fitting and reliable measurement model. Appendix 2 shows the factor loadings of retained items and the model fit. Table 2 illustrates the generated and retained items, items that were excluded are those crossed out.

Table 2: AI generated survey questions on AI use in Knowledge Sharing

AI1	AI tools significantly improve my ability to access necessary knowledge for my job.
AI2	AI tools have made it easier for me to access information that was previously difficult to find.
AI3	AI tools have changed the way I collaborate with colleagues in my job role.
AI4	AI tools contribute to a culture of continuous learning in my job role.
AI5	Because of AI tools I communicate less with my colleagues.
AI6	Using AI tools in my job has increased the frequency of my knowledge sharing with colleagues.
AI7	AI tools make it easier to distribute relevant information to my colleagues.
AI8	The use of AI tools has positively affected the quality of the knowledge I share at work.
AI9	With the assistance of AI tools, I feel more confident in the accuracy of the knowledge I share.
AI10	The use of AI has improved my work processes, enabling more time for knowledge sharing.
AI11	AI tools have encouraged more knowledge sharing in our team.
AI12	I believe that AI tools have fostered a culture of open knowledge sharing in our workplace.

4. Results

The present study employed Hayes's PROCESS Procedure for SPSS Version 3.4 to investigate the relationships between AI use in knowledge sharing and individual's knowledge sharing behavior, mediated by intrinsic, extrinsic, and amotivation. The covariates included age, gender, seniority, and education.

4.1. Direct Effects of AI use on Knowledge Sharing

The findings indicate that AI use in knowledge sharing has a significant direct effect on knowledge sharing behaviors. The positive effect of AI use on knowledge sharing is statistically significant ($\beta = 0.167$, $p < .001$), supporting H1.

4.2. Direct Effects of AI on Motivation

Our findings demonstrate that AI has a strong positive effect on intrinsic motivation ($\beta = 0.312$, $p < .001$), supporting H2a. Regarding extrinsic motivation, AI significantly impacts integrated regulation ($\beta = 0.293$, $p < .001$) and identified regulation ($\beta = 0.189$, $p < .001$), supporting H3a.1 and H3a.2, respectively. However, AI does not significantly affect introjected regulation ($\beta = 0.026$, $p = .568$) or external motivation ($\beta = 0.012$, $p = .748$), meaning H3a.3 and H3a.4 are not supported. Furthermore, AI has a negative effect on amotivation ($\beta = -0.157$, $p < .001$), supporting H4a.

Overall, these results indicate that AI use to share knowledge primarily enhances autonomous forms of motivation (intrinsic, integrated, and identified), while having no effect on controlled extrinsic motivators (introjected and external). Additionally, AI use in knowledge sharing reduces amotivation.

4.3. Direct Effects of Motivation on Knowledge Sharing

When examining the direct effects of motivation on knowledge sharing, the results show that intrinsic motivation has a positive effect on knowledge sharing ($\beta = 0.214$, $p < .001$), supporting H2b. For extrinsic motivation, integrated regulation has a positive effect on knowledge sharing ($\beta = 0.121$, $p = .003$), supporting H3b.1, and identified regulation has a positive effect on knowledge sharing ($\beta = 0.303$, $p < .001$), supporting H3b.2. Introjected regulation ($\beta = 0.005$, $p = .802$) and external motivation ($\beta = 0.015$, $p = .574$) do not have a significant effect on knowledge sharing, meaning H3b.3 and H3b.4 are not supported. Moreover, amotivation has a negative effect on knowledge sharing ($\beta = -0.080$, $p = .010$), supporting H4b.

Among the covariates, only education appears to significantly affect knowledge sharing with a coefficient of 0.0241 and a p -value of .0703. Age, gender, and seniority do not show significant effects on an individual's knowledge sharing behavior.

4.4. Indirect Effects of AI use through Motivation on Knowledge Sharing

AI use has a statistically significant indirect effect on knowledge sharing through intrinsic motivation (0.067, $p < .001$), identified regulation (0.057, $p < .001$), integrated regulation (0.036, $p = .005$), and amotivation (0.013, $p = .021$), as indicated by their confidence intervals not including zero. The indirect effects through external motivation (1.698×10^{-4} , $p = .780$) and introjected regulation (1.326×10^{-4} , $p = .819$) are not statistically significant, as their confidence intervals include zero. Table 3 and Figure 2 showcase the results of our study.

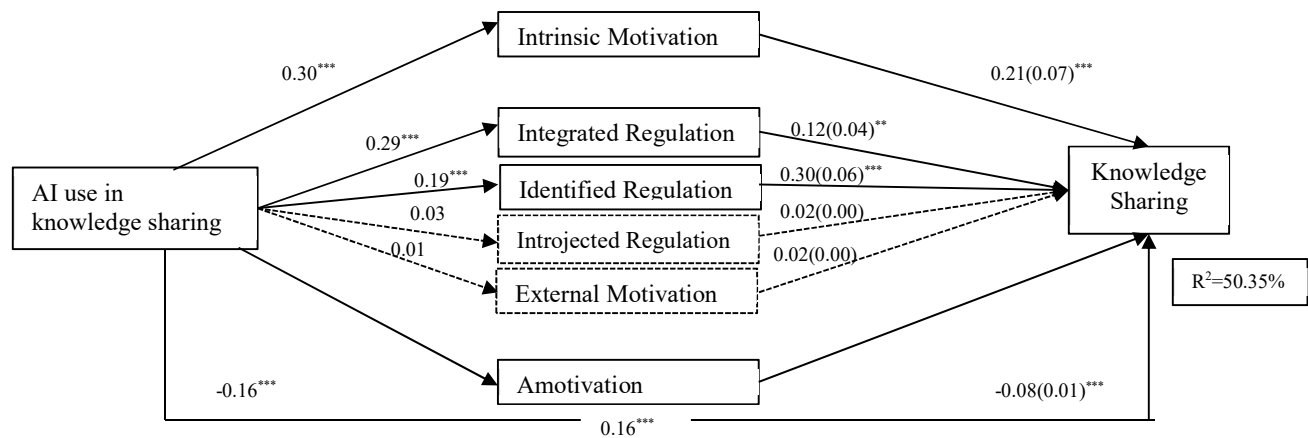
Table 3: Mediation analysis

Effect Path	Coefficient	SE	t-value	p-value	95% Confidence Interval (LLCI, ULCI)
Direct Effects of AIKS:					
AIKS → INT	0.312	0.030	153.62	< .001	(0.253, 0.371)
AIKS → INTEGREG	0.293	0.033	137.92	< .001	(0.227, 0.358)
AIKS → IDREG	0.189	0.026	123.54	< .001	(0.139, 0.240)
AIKS → INTRO	0.026	0.045	55.72	0.568	(-0.063, 0.114)
AIKS → ENTREG	0.012	0.036	53.22	0.748	(-0.059, 0.083)
AIKS → AMOT	-0.157	0.031	-0.74	< .001	(-0.218, -0.096)
Direct Effects on KS:					
AIKS → KS	0.167	0.023	121.27	< .001	(0.121, 0.213)
INT → KS	0.214	0.040	103.26	<.001	(-0.036, 0.066)
INTEGREG → KS	0.121	0.041	79.73	0.003	(-0.140, -0.019)
IDREG → KS	0.303	0.049	111.33	< .001	(0.041, 0.201)
INTROREG → KS	0.005	0.021	52.50	0.802	(0.206, 0.399)
EXTREG → KS	0.015	0.026	55.62	0.574	(-0.035, 0.045)
AMOT → KS	-0.080	0.031	24.12	0.010	(-0.036, 0.066)
Age	-0.0002	0.0021	-0.0881	.9298	(-0.004, 0.004)
Gender	-0.0255	0.0371	-0.6877	.4919	(-0.098, 0.047)
Education	0.0241	0.0133	1.8127	.0703	(-0.002, 0.050)
Seniority	-0.0027	0.0089	-0.3078	.7583	(-0.020, 0.014)
Indirect Effects:					

AIKS Via INT	0.067	0.014	97.37	< .001	(0.039, 0.094)
AIKS Via INTEGREG	0.036	0.013	78.16	0.005	(0.011, 0.060)
AIKS Via IDREG	0.057	0.012	97.10	< .001	(0.033, 0.081)
AIKS Via INTROREG	1.326×10^{-4}	5.788×10^{-4}	52.29	0.819	(-0.001, 0.001)
AIKS Via EXTREG	1.698×10^{-4}	6.086×10^{-4}	52.79	0.780	(-0.001, 0.001)
AIKS Via AMOT	0.013	0.005	73.05	0.021	(0.002, 0.023)
Artificial Intelligence in Knowledge Sharing (AIKS) and Knowledge Sharing (KS), mediated by Intrinsic Motivation (INT), Integrated Regulation (INTEGREG), Identified Regulation (IDREG), Introjected Regulation (INTROREG), External Regulation (EXTREG), and Amotivation (AMOT),					

The confidence level for all confidence intervals was 95%, and 5000 bootstrap samples were used for the percentile bootstrap confidence intervals.

Figure 2: Statistical Model



The model for knowledge sharing behavior explained 50.35% of the variance ($R^2 = .5035$, $F(10, 684) = 69.3552$, $p < .001$).

5. Discussion

Our study highlights the significant impact the integration of AI can have on an individual's motivation to share knowledge at work. Drawing from SDT and surveying 695 AI users, the results reveal that AI adoption directly fosters knowledge sharing behaviors, primarily by enhancing intrinsic motivation and supporting knowledge sharing tendencies in amotivated individuals. Furthermore, AI positively influences extrinsic motivation in cases of integrated

and identified regulation, whereas external and introjected regulators remain unaffected. These findings provide crucial insights into how AI transforms motivational dynamics in knowledge sharing processes. Our findings are consistent with SDT distinguishing between autonomous and controlled forms of motivation, and with SET, which emphasizes perceived reciprocity and value in relational exchanges (Deci & Ryan, 2000; Blau, 1964).

5.1. AI's Influence on Intrinsic and Amotivated Individuals

One of the most compelling findings is AI's ability to enhance intrinsic motivation. Individuals who derive satisfaction from knowledge sharing for its own sake are supported by AI's efficiency, accessibility, and automation. This aligns with previous research (Ryan & Deci, 2002) indicating that autonomous motivation fosters engagement and satisfaction in tasks. AI's role in reducing cognitive load and enabling knowledge workers to focus on creative problem-solving may further stimulate intrinsic motivation.

Additionally, AI plays a notable role in addressing amotivation. By simplifying information retrieval and lowering the barriers to contribution, AI can engage individuals who might otherwise lack the drive or confidence to participate in knowledge sharing activities. This aligns with Dell'Acqua et al. (2023), who found that AI particularly benefits lower-performing workers, enabling them to contribute more effectively.

5.2. The Selective Impact of AI on Extrinsic Motivation

Our findings reveal a nuanced impact of AI on extrinsic motivation. AI significantly supports KS behaviors when driven by identified and integrated regulation, meaning individuals who align their personal values with knowledge sharing objectives or those who see AI as a tool to enhance work efficiency are more likely to engage. This corroborates prior studies emphasizing the importance of self-endorsed motivation in workplace knowledge sharing (Gagné et al., 2019; Wu et al., 2021). On the other hand, AI does not appear to impact external or introjected regulators. Employees motivated by controlled regulation - whether external

rewards (e.g., financial incentives, promotions) or internal pressures (e.g., guilt or reputation maintenance) - do not show a significant change in knowledge sharing behavior due to AI. This aligns with prior work on political and social internalization showing that introjected motivation depends heavily on interpersonal dynamics, not instrumental affordances (Koestner et al., 1996). Our findings suggest that while AI can enhance knowledge sharing for those with a self-determined drive, it does not inherently generate motivation in individuals who depend on external validation.

6. Theoretical Contributions and Implications for Organizations

Our findings contribute to the ongoing discourse on AI's role in workplace motivation by demonstrating that AI serves as an enabler rather than a primary motivator. SDT, which structurally aligns motivation types along a continuum from amotivation to intrinsic motivation, with extrinsic forms ranging from controlled (external, introjected) to autonomous (identified, integrated) regulation (Ryan & Deci, 2000), provides a valuable framework for understanding AI's effects on knowledge sharing behaviors, highlighting the importance of internalized motivation in successful AI integration.

Complementing SDT, SET enriches our understanding of why AI selectively enhances autonomous forms of motivation. By highlighting the role of perceived reciprocity, social reward, and relational cost-benefit analysis (Blau, 1964; Homans, 1958), SET offers a plausible lens for why introjected and external regulation were unaffected. AI tools may lack the social cues, emotional recognition, or interactive rituals that typically sustain controlled motivation types such as external and introjected regulation, thus limiting their impact. This layered theoretical lens provides a more complete account of how AI systems shape motivation across different regulatory spectrums.

For organizations, our findings underscore the need to tailor AI implementation strategies along motivation profiles. The lack of impact on externally regulated individuals

suggests that AI alone is insufficient to foster knowledge sharing behavior in those primarily driven by rewards or peer-pressure. To address this, companies may complement AI tools with recognition systems tied to knowledge sharing platforms (e.g. leaderboards, peer-nominations, or credit attribution on dashboards) to fulfill extrinsically motivated employees' need for validation.

For autonomously motivated employees, Management by Objectives (MBO) strategy can be reframed: rather than focusing on quantifiable output targets alone, MBO schemes can include qualitative goals such as mentorship, best-practice sharing, or AI-enhanced collaboration tasks, aligning performance evaluation with intrinsic goals. Managers can conduct regular alignment conversations to ensure that individual development plans reflect both organizational needs and employees personally endorsed goals.

To address amotivation, onboarding and training programs may include guided hands-on AI use cases to demonstrate how AI can reduce workload, enhance contribution visibility, and support competence development. For example, structured workflows can be designed where AI-generated summaries and suggestions are incorporated into team documents with authorship visibility acknowledged.

7. Limitations and Future Research Directions

Despite its contributions, this study has limitations. While the survey captures self-reported behaviors, future research may incorporate longitudinal or experimental designs to assess causal relationships. In addition, AI's effects on knowledge sharing may vary across industries, job roles, and organizational cultures, warranting further exploration. Moreover, since the sample was restricted to regular AI users, there is a risk of selection bias, as these individuals may already hold favorable attitudes toward AI or differ in motivational profiles compared to non-users. This may limit the generalizability of the findings to less AI-integrated contexts. Future studies could include comparison groups of non-users or apply statistical

corrections such as Heckman's two-stage selection model (Heckman, 1979) to address this issue. As AI continues to evolve, future studies may examine whether newer AI capabilities - e.g., more advanced decision-support systems, or personalized AI assistants will enhance or diminish its role in motivation. Furthermore, more studies on the positive implications of AI on amotivation can lead to fruitful insights into how to revamp employee engagement, beyond knowledge sharing.

8. Conclusion

Our study recognizes the need to address motivational profiles in the success of AI adoption across different workplace contexts. Our findings reinforce AI's transformative role in workplace knowledge sharing by fostering intrinsic motivation and reducing amotivation. AI is particularly effective in supporting individuals driven by more autonomous forms of extrinsic motivation, namely identified and integrated regulation, but its impact is limited for those relying on external rewards or social pressures. These insights emphasize the need for a nuanced understanding of AI's integration into knowledge-centric processes, ensuring that organizations leverage AI not just as a technological tool but as a strategic enabler of meaningful knowledge sharing.

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Appendix 1.

Years of Experience in Companies (code)	Frequency	Percent	Valid Percent	Cumulative Percent
Less than 6 months (1)	37	5.3	5.3	5.3
6 months to 1 year (2)	76	10.9	10.9	16.3
More than 1 year, up to 2 years (3)	144	20.7	20.7	37.0
More than 2 years, up to 3 years (4)	103	14.8	14.8	51.8
More than 3 years, up to 4 years (5)	76	10.9	10.9	62.7
More than 4 years, up to 5 years (6)	38	5.5	5.5	68.2
More than 5 years, up to 10 years (7)	140	20.1	20.1	88.3
More than 10 years (8)	47	6.8	6.8	95.1
More than 15 years (9)	21	3.0	3.0	98.1
More than 20 years (10)	12	1.7	1.7	99.9
Prefer not to answer (11)	1	0.1	0.1	100.0
Total	695	100.0	100.0	

Years in the Job (code)	Frequency	Percent	Valid Percent	Cumulative Percent
Less than 6 months (1)	17	2.4	2.4	2.4
6 months to 1 year (2)	33	4.7	4.7	7.2
More than 1 year, up to 2 years (3)	73	10.5	10.5	17.7
More than 2 years, up to 3 years (4)	48	6.9	6.9	24.6
More than 3 years, up to 4 years (5)	56	8.1	8.1	32.7
More than 4 years, up to 5 years (6)	51	7.3	7.3	40.0
More than 5 years, up to 10 years (7)	186	26.8	26.8	66.8
More than 10 years (8)	104	15.0	15.0	81.7
More than 15 years (9)	64	9.2	9.2	90.9
More than 20 years (10)	62	8.9	8.9	99.9
Prefer not to answer (11)	1	0.1	0.1	100.0
Total	695	100.0	100.0	-

Employment Status (code)	Frequency	Percent	Valid Percent	Cumulative Percent
Full Time (1)	657	94.5	94.5	94.5
Part Time (2)	12	1.7	1.7	96.3
Self-Employed (3)	23	3.3	3.3	99.6
Unemployed (4)	2	0.3	0.3	99.9
Student (5)	1	0.1	0.1	100.0
Total	695	100.0	100.0	-

Education Level (code)	Frequency	Percent	Valid Percent	Cumulative Percent
High School (1)	82	11.8	11.8	11.8
College or No Degree (2)	92	13.2	13.2	25.0
Associate Degree (3)	37	5.3	5.3	30.4

Bachelor's Degree (4)	312	44.9	44.9	75.3
Master's Degree (5)	147	21.2	21.2	96.4
Doctorate or Professional Degree (6)	25	3.6	3.6	100.0
Total	695	100.0	100.0	-

Income Range (Code)	Frequency	Percent	Valid Percent	Cumulative Percent
Under \$20,000 (1.00)	105	15.1%	15.1%	15.1%
\$20,000 to \$39,999 (2.00)	209	30.1%	30.1%	45.2%
\$40,000 to \$59,999 (3.00)	176	25.3%	25.3%	70.5%
\$60,000 to \$79,999 (4.00)	84	12.1%	12.1%	82.6%
\$80,000 to \$99,999 (5.00)	45	6.5%	6.5%	89.1%
\$100,000 to \$149,999 (6.00)	50	7.2%	7.2%	96.3%
\$150,000 or more (7.00)	12	1.7%	1.7%	98.0%
Prefer not to say (8.00)	14	2.0%	2.0%	100.0%
Total	695	100.0%	100.0%	

Country Name (Code)	Frequency
Australia (1)	30
Belgium (2)	2
Bosnia and Herzegovina (3)	1
Canada (4)	24
Chile (5)	6
Czech Republic (6)	5
Estonia (7)	4
Finland (8)	1
France (9)	5
Germany (10)	18
Greece (11)	15
Hong Kong (12)	1
Hungary (13)	11
India (14)	4
Indonesia (15)	1
Israel (16)	7
Italy (17)	24
Latvia (18)	4
Lithuania (19)	1
Mexico (20)	30
Netherlands (21)	10
New Zealand (22)	7
Nigeria (23)	8
Norway (24)	1
Philippines (25)	2
Poland (26)	44

Portugal (27)	10
Romania (28)	3
Slovenia (29)	3
South Africa (30)	120
Spain (31)	11
Sweden (32)	1
Switzerland (33)	1
Turkey (34)	2
UK (35)	243
USA (36)	29
Zambia (37)	1
Zimbabwe (38)	5

Appendix 2

Confirmatory Factor Analysis Scale AI use in Knowledge Sharing

Model fit

Chi-square test

Model	X ²	df	p
Baseline model	4336.863	36	
Factor model	240.523	27	< .001

Note. The estimator is ML. The test statistic is standard. The standard error method is standard.

Parameter estimates

Factor loadings

Factor	Indicator	Estimate	Std. Error	z-value	p	95% Confidence Interval	
						Lower	Upper
Factor 1	AI1	1.000	0.000			1.000	1.000
	AI4	0.997	0.046	21.451	< .001	0.906	1.089
	AI6	1.128	0.049	23.137	< .001	1.032	1.223
	AI7	1.012	0.044	22.964	< .001	0.926	1.099
	AI8	1.050	0.045	23.181	< .001	0.962	1.139
	AI9	0.960	0.045	21.474	< .001	0.872	1.048
	AI10	0.903	0.044	20.662	< .001	0.817	0.988
	AI11	1.034	0.046	22.661	< .001	0.945	1.124
	AI12	1.042	0.046	22.447	< .001	0.951	1.133