Employees' Knowledge of ChatGPT and Motivational Factors

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ABSTRACT

This study investigates the relationship between employees' knowledge of ChatGPT and their motivational factors, such as achievement, recognition, and growth potential. In the context of rapid AI adoption, particularly in South Korea, a survey was conducted to measure employees' technological and empirical knowledge of ChatGPT alongside their motivational factors. Using descriptive statistical analysis, the findings reveal that technological knowledge is more closely related to higher motivational factors than empirical knowledge. Employees more familiar with ChatGPT's function and operation perceive higher achievement, recognition, and growth potential. The study also found that frequent use of ChatGPT positively influences employees' motivation. Ultimately, the study suggests that fostering employees' understanding of Technological Knowledge of AI can enhance their job motivation, contributing to improved job performance and organizational productivity.

Introduction

In the rapidly evolving corporate management environment driven by artificial intelligence, there is increasing interest in issues related to productivity enhancement. In the past, employees spent significant amounts of time in the workplace to achieve job performance, but now similar results can be achieved in relatively less time through Generative AI like ChatGPT. Likewise, there is a study indicating that the introduction of AI positively impacts corporate productivity (Wijayati et al., 2022 & Noy & Zhang, 2023). Therefore, companies strive to enhance overall productivity by actively adopting AI technologies and by improving employees' understanding of AI. However, as the introduction of AI transforms work processes and raises expectations, it may lead to a decrease in employee job satisfaction. Previous studies have shown a positive correlation between job satisfaction and job performance (Hoboui et al., 2017; Katebi et al., 2021), suggesting that, in the long term, such changes might reduce organizational productivity. Therefore, rather than solely focusing on the impact of AI adoption on corporate performance, it is crucial to study how AI affects employee job satisfaction. This approach can pave the way for an era of AI coexistence where both companies and their employees can achieve mutual satisfaction. Therefore, this study aims to investigate and analyze employees' knowledge of ChatGPT, the most commonly used generative AI model in the current work environment, and their motivational factors. Ultimately, the insights from this study will provide a research case for the effective interaction between artificial intelligence and human resource management by examining the relationship between the independent variable, employees' knowledge of ChatGPT, and the dependent variables, motivation factors.

Job satisfaction can vary depending on various factors such as the characteristics of the organization and individuals. Therefore, there are numerous studies and theories on the elements affecting job satisfaction. Among the various factors influencing job satisfaction, motivational factors are considered needs that increase an individual's satisfaction with their job. This study aims to measure these motivational factors by investigating elements such as achievement, recognition, and growth potential. The research builds the fundamental foundation of these factors by examining the knowledge of ChatGPT and motivational factors.

The primary research question guiding this study is:

How does knowledge of AI affect employees' motivation factors?

This research aims to contribute to future research on the correlation between the use of ChatGPT and job satisfaction by investigating and answering the above questions.

Literature Review

Various studies have shown that the adoption of technologies such as IT and ICT improve business outcomes such as productivity or job performance (Draka et al., 2006; Bloom et al., 2012). According to Castellacci & Viñas-Bardolet (2019), workers who actively use the Internet as a primary tool for their tasks tend to have higher average wage levels and better job prospects compared to their peers (Castellacci & Viñas-Bardolet, 2019). Similarly, considering the utility of generative AI, the introduction of GAI in companies is expected to significantly contribute to improving work efficiency. For example, using ChatGPT allows users to easily create Excel files by entering desired variable values or generating software code, thus reducing the time required for tasks. The usefulness of GAI increases the efficiency of labor relative to time, ultimately enhancing corporate productivity. Consequently, this suggests that employees capable of utilizing technology may have an increased likelihood of receiving more appropriate rewards for their contributions and performance on the job. The level of knowledge of GAI is expected to have an influence on workers' motivation to perform on the job. Workers that have higher levels of knowledge of the new technology may feel less threatened and more capable of handling the changes that occur when the technology is introduced.

Knowledge

The advancement of artificial intelligence brings unprecedented changes to companies. These changes significantly impact on corporate culture, work processes, and employee capabilities. As the use of technology based on knowledge increases, knowledge is increasingly recognized as an essential element in organizations. The dictionary definition of knowledge refers to understanding and information about a subject gained through experience or study. However, various studies on knowledge have been conducted for a long time, and there are various classifications of knowledge (Gilbert, 1949; Boshoff, 2014; Edmondson et al., 2003). To utilize technology more efficiently, it is necessary to acquire or develop this knowledge (Lapré et al., 2000; Maliphol, 2019). This study classifies knowledge into Technological Knowledge and Empirical Knowledge.

Technological Knowledge

According to Yu & Golden (2019), technological knowledge refers to understanding and adapting to the functions and operating principles of existing technologies (Yu & Golden, 2019). The functions and operating principles of technology can also be classified as factual, propositional, and declarative knowledge, suggesting that technological knowledge encompasses the characteristics of "Know-That" (Boshoff, 2014; Gilbert,1949). This type of knowledge, like the knowledge found in manuals, can be easily conveyed and shared through mediums like the Internet, which implies that Technological Knowledge can also be classified as Codified Knowledge (Edmondson et al., 2003). Based on this definition, this study interprets technological knowledge as "the ability to utilize technology by understanding the facts and concepts of the technology." To use AI like ChatGPT more effectively in a corporate environment, companies should ensure a clear understanding of AI's functions and limitations before implementation (Raj et al., 2023). When workers clearly understand these functions and limitations and utilize AI, they can enhance their capabilities and skills, accelerating work processes by avoiding unproductive and repetitive tasks (Xu et al., 2023). This convenience can also positively impact the quality of jobs and employee well-being (Broecke, 2023). Thus, if employees have a good understanding of how to use and operate generative AI like ChatGPT, they can apply AI tools more effectively and strategically to their work.

Empirical Knowledge

Borkman (1976) defined empirical knowledge as knowledge acquired through personal experience rather than from others or through observation (Borkman, 1976). Workers can acquire empirical knowledge, such as how to effectively use AI in their tasks and how to quickly access the information they need through AI, by using and experiencing ChatGPT over time. The nature of this knowledge is not a concept that can be documented and transmitted but rather knowledge acquired through long-term experience and observation, bearing characteristics similar to Tacit Knowledge and Know-How (Edmondson et al, 2003; Gilbert, 1949). Empirical knowledge can influence human-AI interaction. In studies on the complementarity between AI's main technology, Machine Learning (ML), and human interaction, it has been argued that the knowledge accumulated by individuals through prior learning can mitigate biases caused by the imperfections of ML, thus complementing AI and impacting productivity (Choudhury et al., 2020). Furthermore, if such empirical knowledge is shared within the organization, it can form bonds among employees, facilitate social communication, and ultimately improve collaboration, coordination, and organizational performance (Obrenovic et al., 2020). These results can naturally be connected to motivational factors for employees. Specifically, the conceptual framework used to measure employees' knowledge of ChatGPT is summarized in table 1.

Table 1. Definition of Knowledge

Factors	Definition	Sources	Examples
Technological Knowledge (TK)	Technological knowledge refers to an individual's acquaintance with how to use and operate existing technologies and applications by understanding the facts and concepts of the technology	(Gilbert, 1949) (Yu & Golden, 2019) (Boshoff, 2014) (Edmondson et al., 2003)	Knowing the operating mechanisms of ChatGPT and what features it provides.
Empirical Knowledge (EK)	Empirical knowledge is the understanding gained through direct personal experience with a phenomenon, as opposed to knowledge obtained through logical reasoning, observation, or reflection on information from others.	(Borkman, 1976) (Gilbert, 1949) (Boshoff, 2014) (Edmondson et al., 2003)	Understanding various applications gained through the use and experience of ChatGPT.

Motivation Factors

Organizations, such as companies, must maximize the use of their resources to achieve their visions. Therefore, organizations must motivate their human resources to enhance their capabilities to the fullest. To motivate members, it is necessary to provide a satisfactory environment, which is closely related to job satisfaction. Various studies have evaluated the factors that motivate job satisfaction, but there is no clear consensus since these factors can vary depending on multiple variables, such as job content and job conditions (Aziri, 2011). Rather than being an intangible concept, a job involves a complex interplay of various elements like achievement, responsibility, rewards, and relationships among colleagues. Therefore, to evaluate the factors that motivate job satisfaction, it is essential to first clearly understand and analyze each component that affects the job. Table 2 summarizes the factors that positively influence job satisfaction, as researched by various scholars.

Table 2: Factors Related to Job Satisfaction

Source	**Factors**
Herzberg (1964)	Advancement, work itself, responsibility, possibility for growth, recognition, achievement
Myers (1964)	Recognition, pleasure, promotion, growth, achievement, responsibility
Locke (1990)	Company policy, colleagues, supervision, working conditions, welfare, recognition, promotion, wages

Factors focused on personal characteristics and the nature of the job itself, such as achievement, recognition, and growth, have been commonly referenced by multiple scholars (Herzberg, 1964; Locke, 1990; Myers, 1964). Whether ChatGPT is perceived as a tool that makes one's job easier and more convenient depends on the nature of the job itself and personal characteristics. Accordingly, this study analyzed motivational factors by focusing on intrinsic elements such as achievement, recognition, and growth, rather than external factors of the job like compensation, relationships with colleagues, and safe working conditions.

Achievement

Achievement refers to the feeling experienced when one challenges a specific goal and accomplishes it. For example, achievement includes successes such as completing a difficult task on time, solving job-related problems, or seeing positive results from one's work. One of the key findings from studies on information technology and corporate performance is that IT reduces coordination and information access costs within companies while enhancing employee autonomy, enabling them to solve problems and complete tasks without relying on others (Viete & Erdsiek, 2020; Castellacci & Viñas-Bardolet, 2019). Given that job autonomy is a crucial factor in determining self-motivation and work morale, it can positively influence employee performance in the workplace (Deci & Ryan, 2023). Jyung et al. (2020) analyzed factors affecting problem-solving skills in technologically advanced countries like South Korea and Japan, and they argued that the use of ICT technology at home helps enhance problem-solving abilities. Considering these results, given that generative AI like ChatGPT is widely used in the information technology field, it can increase faster and easier access to information. This could ultimately enhance problem-solving abilities in the workplace and potentially increase employees' achievement.

Recognition

According to Vera & Boateng (2015), recognition is the timely, informal, or formal acknowledgment of an individual or team's behavior, effort, or business results that support the organization's goals and values. This includes elements such as monetary rewards, praise, and feedback (Vera & Boateng, 2015). Recognition in the form of monetary rewards, praise, and feedback is meant to reward employee performance with the implication that management is encouraging behavior that has improved business outcomes.

Possibility of Growth

The possibility of growth refers to the possibility of personal development and opportunities for promotion within the workplace. This includes professional growth, increased opportunities to learn new skills, training in new technologies, and acquiring new professional knowledge. For example, when new technologies are introduced, companies often conduct various training sessions and educational programs to effectively implement these technologies. According to Xu et al. (2023), opportunities for employees to acquire knowledge and skills related to artificial intelligence can enhance their Informal Learning in the Workplace (ILW), which can impact their Workplace Well-Being (WWB) and ultimately influence job performance (Xu et al., 2023). As various generative AI technologies like ChatGPT, Gemini, and Bing are rapidly integrated into corporate environments, many companies are providing training and seminars on AI technology to their employees. This offers employees the opportunity to gain knowledge of new technologies and apply them to their work, thereby increasing their potential for growth in their careers.

Table 3. Description of Motivation Factors

Motivation Factors	
Factors	**Description**
Possibility for growth	Possibilities for growth are the actual opportunities for a person to experience personal growth and be promoted in the workplace. This allows for professional growth, increased chances to learn new skills, undergo training in new techniques, and gain new professional knowledge.
Recognition	Positive recognition happens when employees receive praise or rewards for reaching specific goals at their job, or when they produce high-quality work.
Achievement	Positive achievement includes achieving a specific success, such as completing a difficult task on time, solving a job-related problem, or seeing positive results of one's work. Negative achievement involves failure to make progress at work or poor decision-making on the job.

Source: (Alshmemri, 2017)

Table 3 illustrates the components of the motivational factors selected as variables: achievement, recognition, and growth opportunities. These elements may all be triggered by the adoption of technology and have the potential to positively impact job performance by stimulating employee motivation. Therefore, this study compares and analyzes employees' knowledge of ChatGPT and motivational factors.

The hypotheses regarding these two variables are as follows:

H1. Employees with higher TK (Technological knowledge) of ChatGPT will have higher motivational factors.

- H 1.1. Employees with higher TK of ChatGPT will have higher achievement.
- H 1.2. Employees with higher TK of ChatGPT will have higher recognition.
- H 1.3. Employees with higher TK of ChatGPT will have higher possibility of growth.

H2. Employees with higher EK (Empirical Knowledge) of ChatGPT will have higher motivational factors.

- H 2.1. Employees with higher EK of ChatGPT will have higher achievement.
- H 2.2. Employees with higher EK of ChatGPT will have higher recognition.
- H 2.2. Employees with higher EK of ChatGPT will have higher possibility of growth.

Conceptual Framework

To summarize all the concepts discussed, a conceptual framework as shown in Figure 1 is formed. This study aims to measure employees' knowledge of ChatGPT through TK (Technological Knowledge) and EK (Empirical Knowledge) and compare them with motivational factors such as Achievement, Recognition, and Possibility of Growth. The objective is to understand how knowledge of generative AI impacts employees' job motivation. To compare the factors, the study evaluates the hypothesis by calculating the ratios between Knowledge and Motivational factors using a comparison chart as shown in Figure 5.

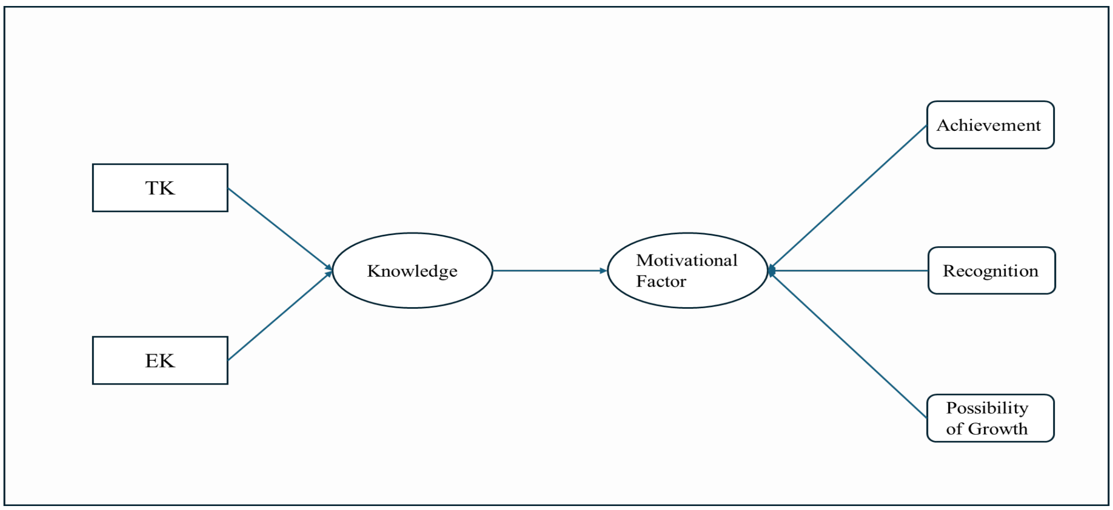

Figure 1. Conceptual framework of this study

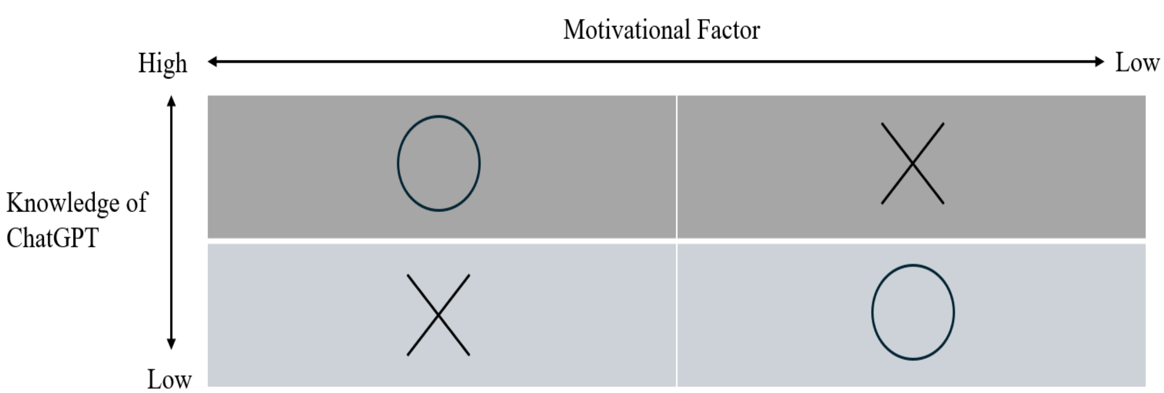

Figure 2. Comparison table of employees' knowledge of ChatGPT and motivation factors

As shown in Figure 2, observations with high Knowledge of ChatGPT and high Motivational factors would suggest that these elements have a positive relationship. Similarly, observations with low Knowledge of ChatGPT and low Motivational factors would also indicate a positive relationship. These relationships would support H1 and H2, as they demonstrate that elements related to Knowledge of ChatGPT, such as TK and EK, have a proportional relationship with motivational factors like Achievement, Recognition, and Possibility of Growth.

On the other hand, the relationship between low Knowledge of ChatGPT and high Motivational factors, as well as the relationship between high Knowledge of ChatGPT and low Motivational factors, suggest an inverse relationship between these elements. This would imply a negative relationship, indicating that H1 and H2 should be rejected.

Methodology

This study aims to measure and analyze employees' knowledge of ChatGPT and motivational factors, with the goal of enabling efficient coexistence between AI and human resources in the future. To achieve this goal, an online survey was conducted via Google Forms from April 15 to April 22, 2024, targeting South Korean office workers in the IT, manufacturing, environmental services, and construction industries. The survey format on Google Forms included an explanation of the study's purpose and content, and it was designed to allow only one response per email account.

Based on Descombe's survey methodology, this survey included three types of questions: Degree of Agreement, Rank Order, and Choose from a List of Options (Descombe, 2017). The questionnaire comprised 13 questions in total, with nine questions related to motivational factors and four questions related to employees' knowledge of ChatGPT. Specifically, among the nine questions, three each focused on achievement, recognition, and growth potential. All nine questions on job satisfaction were based on a 5-point scale (1=disagree to 5=agree). Of the remaining four questions, two each assessed technological knowledge and empirical knowledge. Questions on technological knowledge were similarly based on a 5-point scale, while questions on empirical knowledge were composed using Rank Order and Choose from list options (see Appendix A).

During the survey period, a total of 27 responses were collected. However, 2 respondents provided incomplete answers and were excluded from the analysis, leaving a final sample of 25 responses for analysis. Descriptive statistical analysis was conducted to organize, summarize, and interpret the data collected from the survey. For the 5-point scale items, mean, variance and standard deviation were calculated. For the empirical knowledge (EK) items, EK2 was a multiple-choice question, and to facilitate calculation on a 5-point scale, scores were assigned based on the 10 available options as follows: 0-1 choices: 1 point, 2-3 choices: 2 points, 4-5 choices: 3 points, 6-7 choices: 4 points, 8-10 choices: 5 points.

Additionally, to analyze the relationship between knowledge and motivational factors, the average scores for each variable were calculated. To calculate the average of each factor, this paper summed the averages of the corresponding questions for each factor and then divided them by the number of questions. An example of the calculation for respondents with an average score of 4 or higher for each factor were classified as having high knowledge or high motivational factors. Conversely, respondents with an average score of less than 4 were classified as having low knowledge or low motivational factors related to ChatGPT. Finally, the relationships between EK and TK and motivational factors were analyzed by comparing the averages and the proportions of these groups.

Results & Analysis

Below, Table 4 presents the descriptive statistics data based on the survey, showing the mean, variance, and standard deviation of the survey results. Overall, the responses regarding motivational factors and knowledge of ChatGPT were positive. The descriptive statistics indicated that all motivational factors, such as Achievement (AC), Recognition (RC), and Possibility of Growth (PG), had values close to 4 on each question. Among the motivational factors, the question with the highest average was PG1 (Avg = 4.44), with most participants indicating that their skills or performance had improved compared to the previous year. Conversely, the question regarding problem-solving ability within the job, AC3, had the lowest average (Avg = 3.84). In the Knowledge section, TK1 had the highest average (Avg = 3.92), while EK2 had the lowest average (Avg = 2.28).

Table 3. Descriptive statistics

Factors	Questions	Mean	Variance	Standard deviation	N of Responses
Achievement (AC)	AC 1	4.13	0.29	0.54	24
	AC 2	4.08	0.33	0.57	25
	AC 3	3.84	0.56	0.75	25
Recognition (RC)	RC 1	4.16	0.72	0.85	25
	RC 2	4.29	0.56	0.75	24
	RC 3	3.96	0.62	0.79	25
Possibility of growth (PG)	PG 1	4.44	0.42	0.65	25
	PG 2	4.28	0.63	0.79	25
	PG 3	3.96	0.71	0.84	25
Technological Knowledge (TK)	TK 1	3.92	0.86	0.91	25
	TK 2	3.80	1.42	1.19	25

Empirical Knowledge (EK)	EK 1	3.76	0.86	0.93	25
	EK 2	2.28	0.6	0.78	25

Furthermore, this study analyzed the relationships between various factors by calculating the mean values of each variable based on the survey data and then comparing these means with those of other variables. To avoid statistical uncertainty, respondents who did not answer AC1 and RC2 were excluded from the calculations, resulting in a total of 24 respondents' data being used. To determine the overall mean of each factor, the total average of the responses to the questions related to each factor was added and then divided by the number of questions. Table 5 illustrates the overall mean for each variable, showing that all variables, except EK, formed an average close to 4.00. This indicates that the survey participants provided positive responses to each factor.

Table 5. Total mean of each variable

Factors	Questions	The mean of each question	The mean of each factor
Achievement	AC 1	4.13	4.00
	AC 2	4.08	
	AC 3	3.79	
Recognition	RC 1	4.17	4.13
	RC 2	4.29	
	RC 3	3.92	
Possibility of growth	PG 1	4.42	4.22
	PG 2	4.29	
	PG 3	3.96	
TK	TK 1	3.92	3.88

	TK 2	3.83	
EK	EK 1	3.79	3.04
	EK 2	2.29	

In addition to calculating the mean values of each variable, this study compared the average values of each variable among respondents to examine the specific relationships between these variables. Respondents with values of 4 or above in EK and TK were classified as having high empirical and technological knowledge of ChatGPT, respectively, while those with values below 4 were classified as having relatively low technological and empirical knowledge of ChatGPT. For the motivation factor, respondents with an average of 4 or above were classified as a group with relatively high motivation factors, whereas those with an average below 4 were classified as a group with relatively low motivation factors. Based on these classifications, the ratios between knowledge of ChatGPT and motivation factors were measured, and the resulting ratios are shown in tables 6-14.

As shown in Table 6, this paper examined the relationship between technological knowledge and achievement. 15 respondents (62.5%) with high technological knowledge also exhibited high achievement. Similarly, 5 respondents (20.83%) with low technological knowledge demonstrated low achievement. This relationship indicates a positive correlation between technological knowledge and achievement, suggesting that individuals who have a good understanding of ChatGPT's functionalities and applications tend to achieve positive outcomes, demonstrate strong task performance within given timelines, and possess effective problem-solving abilities in their work. A total of 20 respondents (83.33%) demonstrated a proportional relationship between TK and Achievement, so "

H1.1 Employees with higher TK (Technological knowledge) of ChatGPT will have higher motivational factors" is supported by the result.

Table 6. Ratio between Achievement & TK

	Achievement		
TK (Technological Knowledge)	**Share (%) (n)**	**High (≥ 4)**	**Low (< 4)**
	High (≥ 4)	62.5% (15)	8.33% (2)
	Low (< 4)	8.33% (2)	20.83% (5)

Table 7 shows the ratio between TK and Recognition, with 15 respondents (62.5%) scoring above 4 on both factors and 4 respondents (16.67%) scoring below 4 on both factors, totaling 19 respondents (79.17%) who demonstrated a proportional relationship between TK and Recognition. This suggests that employees' technological knowledge of ChatGPT can positively impact factors such as rewards and praise. Therefore, **"H1.2. Employees with higher TK of ChatGPT will have higher recognition."** can be supported by the results.

Table 7. Ratio between Recognition & Technological Knowledge

	Recognition		
TK (Technological Knowledge)	**Share (%) (n)**	**High (≥ 4)**	**Low (< 4)**
	High (≥ 4)	62.5% (15)	8.33% (2)
	Low (< 4)	12.5% (3)	16.67% (4)

Table 8 shows the ratio between TK and Possibility of Growth, with 16 respondents (66.66%) scoring above 4 on both factors and 4 respondents (16.66%) scoring below 4 on both factors, totaling 20 respondents (83.32%) who demonstrated a proportional relationship between TK and Possibility of Growth. Similar to TK and other motivational factors, TK and PG also show a predominantly proportional relationship. This indicates that employees with higher technological knowledge of ChatGPT had more growth opportunities during the previous year. Therefore, **H 1.3: "Employees with higher TK of ChatGPT will have higher possibility of growth"** can be supported by the results.

Table 8. Ratio between Possibility of Growth & TK

	Possibility of Growth		
TK (Technological Knowledge)	**Share (%) (n)**	**High (≥ 4)**	**Low (< 4)**
	High (≥ 4)	66.66% (16)	4.16% (1)
	Low (< 4)	12.5% (3)	16.66% (4)

The ratio of EK (Empirical Knowledge) to motivational factors shows an inverse relationship, unlike the ratio of TK (Theoretical Knowledge) to motivational factors. Table 9 illustrates the ratio between EK and Achievement. Among the total, 9 individuals (37.5%) had all elements either above or below 4 points, while 15 individuals (62.5%) had one element above 4 points and the others below 4 points, indicating a higher proportion of inverse relationships.

Table 9. Ratio between Achievement & EK

	Achievement		
EK (Empirical Knowledge)	**Share (%) (n)**	**High (≥ 4)**	**Low (< 4)**
	High (≥ 4)	12.5% (3)	4.16% (1)

	Low (< 4)	58.33% (14)	25% (6)

Table 10 shows the ratio between EK and Recognition, and Table 11 shows the ratio between EK and Possibility of Growth. The results between EK and Recognition show an inverse relationship in 16 individuals (66.76%), and the inverse relationship between EK and Possibility of Growth is observed in 15 individuals (62.5%). Both of these proportions are higher than those showing a proportional relationship. Since the relationship between EK and all motivational factors exhibited an inverse trend, the hypothesis "H2. Employees with higher EK (Empirical Knowledge) of ChatGPT will have higher motivational factors" is rejected based on these results.

Table 10. Ratio Between Recognition & EK

	Recognition		
EK (Empirical Knowledge)	**Share (%) (n)**	**High (≥ 4)**	**Low (< 4)**
	High (≥ 4)	12.5% (3)	4.16% (1)
	Low (< 4)	62.5% (15)	20.83% (5)

Table 11: Ratio between Possibility of Growth & EK

	Possibility of Growth		
EK (Empirical Knowledge)	**Share (%) (n)**	**High (≥ 4)**	**Low (< 4)**
	High (≥ 4)	16.66% (4)	0%
	Low (< 4)	62.5% (15)	20.83% (5)

By disaggregating the EK factors into the EK1 (frequency of use) & EK2 (number of applications), we can find different patterns emerge. Examining the relationship between each EK question and motivational factors, EK 2 shows a higher proportion of inverse relationships with motivational factors, similar to Tables 9-11. On the other hand, the relationship between EK 1 and motivational factors, as shown in Tables 12-14, indicates a higher proportion of positive relationships. These results suggest that the frequency of using ChatGPT can have a more positive impact on motivational factors compared to the wider range of applications of GAI.

Table 12: Ratio between Achievement & EK1

	Achievement		
EK1	**Share (%) (n)**	**High (≥ 4)**	**Low (< 4)**
	High (≥ 4)	54.16% (13)	8.33% (2)
	Low (< 4)	16.66% (4)	20.83% (5)

Table 13. Ratio between Recognition & EK1

	Recognition		
EK1	**Share (%) (n)**	**High (≥ 4)**	**Low (< 4)**
	High (≥ 4)	54.16% (13)	8.33% (2)
	Low (< 4)	20.83% (5)	16.66% (4)

Table 14. Ratio between Possibility of Growth & EK1

	Possibility of Growth		
EK1	**Share (%) (n)**	**High (≥ 4)**	**Low (< 4)**
	High (≥ 4)	54.16% (13)	8.33% (2)
	Low (< 4)	25% (6)	12.5% (3)

In summary, TK (Technological Knowledge) is significantly related to Motivational factors compared to EK (Empirical Knowledge). Tables 6-8 compare TK with Achievement, Recognition, and Possibility of Growth, respectively, showing that respondents with high TK also possess high motivational factors. In contrast, the analysis of the ratio between EK (Empirical Knowledge) and motivational factors through Tables 9-11 shows that empirical knowledge and motivational factors have an inverse relationship. Based on this analysis, the hypothesis that employees with high technical knowledge have higher motivational factors is validated, whereas the hypothesis that employees with high empirical knowledge have higher motivational factors is not supported.

Discussion

As AI technology advances rapidly, it is integrated into various aspects of business management and work processes.

AI can enhance productivity across multiple industries through automation, particularly in jobs requiring high levels of expertise, where it holds the potential to complement human labor (Maliphol & Walter, 2023; Pizzinelli, 2023). From the interaction between AI and human resources perspective, this study explores the relationship between AI knowledge and employees' motivational factors. Specifically, this study aimed to compare the relationship between employees' knowledge of ChatGPT and motivational factors such as achievement, recognition, and growth potential. A survey was conducted among workers in various industries in South Korea to measure their technological and empirical knowledge of ChatGPT, as well as their motivational factors. The hypotheses tested in the study found that technological knowledge can influence motivational factors.

The results demonstrated that employees with higher technological knowledge—tested through hypotheses H1.1, H1.2, and H1.3-tend to experience greater achievement, recognition, and growth potential. These higher motivational factors contribute to improving employee job satisfaction (Alshallah, 2004). Since previous studies suggest that higher job satisfaction can lead to improved job performance, it can be inferred that employees who are familiar with and have a thorough understanding of AI's concepts and operations may experience both higher satisfaction and better job performance (Hoboui et al., 2017; Katebi et al., 2021).

In addition to the relationship between TK and employee motivational factors, this study revealed a proportional relationship between the frequency of AI usage and employee motivation. The more frequently employees used ChatGPT, the more positively they perceived their job motivation. These findings suggest that prolonged use of AI tools like ChatGPT can enhance employees' skills and competencies. It implies that frequent usage of AI technology, rather than its application across a wide range of tasks, has a more positive impact on employee motivation. This result further suggests that specializing in a limited number of tasks using AI, rather than utilizing it for a variety of tasks, may potentially be more efficient in enhancing motivation.

To understand why Technological Knowledge (TK) has a more direct relationship with employee motivation factors compared to Empirical Knowledge (EK), it is important to compare the characteristics of both types of knowledge. TK represents the understanding of functions and operation of technology, and it can be relatively easily and directly communicated to employees through manuals and lectures. Employees with high TK possess a clear comprehension of how AI is supposed to work, allowing them to perceive that they are effective at using AI tools.

In contrast, Empirical Knowledge (EK) is a type of knowledge acquired through experience, similar to know-how, and is obtained through undocumented sources such as trial and error and personal experiences. Acquiring EK typically requires prolonged use of the technology and employees developing their EK by applying AI in various real-world contexts. For example, a ChatGPT user may come to realize through experience that the way questions are phrased affects the results, and they can refine their questioning techniques based on feedback. Consequently, EK requires a longer acquisition period compared to TK, which may result in a relatively lesser impact on motivational factors.

Additionally, Technological Knowledge (TK) allows individuals to directly recognize their improvement as it involves learning the functions and operational methods of technology. In contrast, Empirical Knowledge (EK) is acquired over a long period, making it difficult for individuals to immediately perceive the acquisition of knowledge. In other words, the difference in how individuals perceive their knowledge acquisition can also influence motivational factors. Employees who learn and apply the operational methods and functionalities of AI can clearly recognize that their job skills have improved. On the other hand, it is challenging for employees to immediately realize when they have acquired EK. This difference in employees' perception of knowledge acquisition can have varying impacts on their motivation.

Implications and Limitations

Practical Implications

The findings of this study offer several practical concepts for managers who must consider the integration of AI and its impact on employee motivation:

First, this study highlights that technological knowledge of AI plays an important role in enhancing employee motivation. AI tools such as ChatGPT, Bing, and Copilot are increasingly being applied in business environments. However, without a proper understanding of their specific functionalities or operational methods, employees may achieve unexpected or undesired outcomes. By providing employees with education on AI's technological knowledge (e.g., Prompt Engineering, Customized Chatbot) through seminars and lectures, employees can become more proficient in utilizing AI, allowing them to obtain desired results more efficiently. Ultimately, this improved competence in AI usage can have a positive impact on their job motivation.

Second, the study found a proportional relationship between the frequency of ChatGPT use (EK1) and employee motivation factors. Through long-term use of AI tools in their work, employees can acquire valuable and practical knowledge necessary to effectively utilize ChatGPT. For instance, in the manufacturing sector, prolonged use of specific technology enables employees to gain critical techniques and know-how related to that technology. Similarly, by supporting the use of AI technologies, managers can encourage employees to use and experience AI more frequently. By facilitating these experiences, employees can build familiarity and expertise with AI, which significantly enhances their motivation as they gain confidence in their ability to apply AI effectively in their work. Increasing the number of applications that an employee uses may actually lower an employee's motivation.

Theoretical Implications

This study explored how employees' understanding of AI relates to their motivational factors. To evaluate AI knowledge, both Technological Knowledge (TK) and Empirical Knowledge (EK) were considered. For motivational factors, the most commonly mentioned elements based on job satisfaction theories—achievement, recognition, and possibilities of growth—were set as dependent variables. By investigating and analyzing the correlations between these factors, the study found that employees with higher TK have a more positive perception of motivational factors related to their jobs.

While these findings enhance the understanding of the relationship between AI knowledge and employee motivation, the study has several theoretical limitations. First, although the study demonstrated that TK and EK1 are strongly related to motivation, it did not discover the underlying mechanisms behind the question, "Why does higher TK positively influence employee motivation?" Future research should aim to uncover the reasons behind these findings. Additionally, the study did not find a strong relationship between EK and motivational factors. Understanding this discrepancy is essential for future studies. Researchers should explore why EK does not exhibit the same level of influence as TK to motivation. Possible explanations could include individual limitations (Koohborfardhaghighi et al., 2017), the context in which the knowledge is developed (Kim et al., 2024), or the time required to acquire and apply empirical knowledge. Furthermore, cognitive differences in how employees perceive their knowledge acquisition may also lead to variations in motivational factors. Examining these aspects could provide a more comprehensive understanding of how different types of knowledge influence motivation.

Conclusion

This study discussed the relationship between employees' understanding of AI and their motivational factors. Based on the concepts of technological knowledge and empirical knowledge, the study analyzed the impact of these knowledge types on employees' motivation. The hypotheses were tested through a survey conducted with 24 employees, and the results supported the hypothesis that employees with higher technological knowledge tend to exhibit higher job motivation. Ultimately, these findings suggest practical ways for companies to foster efficient coexistence between AI and employees in the industrial context. This study aims to contribute effectively to providing guidelines for companies and organizations to adapt to the rapidly changing technological landscape brought about by AI adoption.

Limitations

This study has several limitations that should be addressed in future research. First, the sample size was notably small, consisting of only 24 participants from various industries in South Korea, such as IT, manufacturing, environmental services, and construction. Due to the limited number of respondents, the findings may not completely represent the broader workforce, and the generalizability of the results is constrained. Future research should aim to increase the sample size by including a larger group of participants across various industries and regions. A larger sample would provide stronger statistical power and yield results that can be applied more broadly to a wider range of organizational contexts.

Second, this study employed descriptive statistical analysis to compare and interpret the survey data. While descriptive statistics are useful for providing a general overview of the data, this approach has limitations in identifying deeper and more nuanced relationships between variables. For example, descriptive statistics are limited in precisely identifying correlations or causal relationships between employees' AI knowledge and motivational factors. Therefore, future research should utilize more advanced statistical methods, such as factor analysis and regression models, to establish clear and definitive correlations between variables. These methods would allow researchers to explore potential mediating factors that may influence the relationship between AI knowledge and employee motivation.

By addressing these limitations, future research can contribute to a more comprehensive understanding of how AI impacts employee motivation and organizational performance.

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