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업무 환경에서 생성형 AI 사용 의도에 영향을 미치는 촉진 요인과 저해 요인 분석

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Enablers and Inhibitors of Generative AI Usage Intentions in Work Environments

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ABSTRACT

Purpose: This study aims to investigate the factors influencing the adoption of Generative AI in the workplace, focusing on both enablers and inhibitors. By employing the dual factor theory, this research examines how knowledge support, customization, entertainment, perceived risk, realistic threat, and identity threat impact the intention to adopt Generative AI technologies such as ChatGPT.

Methods: Data were collected from 192 participants via MTurk, all of whom had experience using Generative AI. The survey was conducted in June 2024, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to ensure the validity and reliability of the measurement model. Attention-check questions were used to ensure data quality, and participants provided demographic information at the end of the survey.

Results: : The findings reveal that knowledge support and entertainment significantly enhance the intention to adopt Generative AI, whereas realistic threat poses a substantial barrier. Customization, perceived risk, and identity threat did not significantly affect adoption intentions.

Conclusion: This study contributes to the literature by addressing the gap in understanding the adoption mechanisms of Generative AI in professional settings. It highlights the importance of promoting AI's knowledge support and entertainment capabilities while addressing employees' concerns about job security. Organizations should emphasize these benefits and proactively mitigate perceived threats to foster a positive reception of Generative AI technologies. The findings offer practical implications for enhancing user acceptance and provide a foundation for future research in this area.

Key Words: Generative AI, Chatgpt, Dual Factor Theory, Usage Intention

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1. Introduction

In era of advancing AI technologies such as ChatGPT, there has been a transformation in how businesses engage with customers and streamline various operations. These AI systems are adopt at generating text that closely mimics language, simplifying tasks like handling customer inquiries creating content and offering support. Particularly noteworthy is ChatGPT's proficiency in engaging in conversations sharing information and aiding with writing tasks (Dwivedi et al., 2023). This technological progress has broadened the horizons for office-based industries by enabling them to leverage AI for customer service, content creation and administrative functions.

Nevertheless, the widespread adoption of AI models raises concerns and hurdles. Ethical dilemmas surrounding the use of AI generated content include risks associated with misinformation, dissemination, or misuse, well as the necessity for oversight have all gained prominence. For example, incidents such as the protests by the American Writers Guild highlight the growing apprehension about the implications of AI in creative industries (Isidore, 2023).

Consequently, organizations need to navigate these challenges when integrating AI models into work environments to ensure effective utilization. Hence, this study aims to explore the motives driving office workers utilization of Generative AI in their job responsibilities.

There is a growing interest in AI that can create content, with studies focusing mainly on its applications in education and only a few examining its impact in work settings. For example, Generative AI offers advantages in education by providing personalized instruction, adaptive learning, and automated assessments, which can deliver effective education to learners (Adıgüzel et al., 2023; Halaweh, 2023; Lim et al., 2023). These are contents that are difficult to provide effectively in traditional education due to a lack of human resources. However, at the same time, the use of AI in education raises ethical concerns, including potential biases, privacy issues, and over-reliance on technology (Adıgüzel et al., 2023). It could also signify the end of traditional forms of writing education, such as essays (Lim et al., 2023). Due to these dual characteristics, there is significant debate over the use of Generative AI in the field of education.

However, its importance in work settings is also notable, yet related research is lacking. Previous studies have discussed the impact of introducing Generative AI in the workplace and the changes required to maintain sustainable employability for workers (Adiasto, 2024). Ayinde et al. (2023) discuss the potential for Generative AI's adoption in the workplace. However, these studies are primarily theoretical, and empirical research remains limited.

To address this gap in research, our study applies the dual factor theory to identify two factors that influence people's willingness to adopt AI in the workplace, enablers and inhibitors. Through surveys and data analysis, we seek to uncover the underlying motivations for both embracing and resisting AI in environments. This initial exploration of integrating AI into work environments aims to establish a foundation for research efforts, in this field.

2. Theoretical Background and literature review

2.1. Generative Ai in the workplace

The popularity of Generative AI has grown with the emergence of ChatGPT(Hussain et al., 2024). By integrating deep learning and language models, ChatGPT has greatly improved the capabilities of traditional chatbots. Its advanced language processing skills allow it to be effectively utilized in various workplace settings. One prominent application is in customer service, where ChatGPT's ability to understand and respond to human language in real time is expected to significantly enhance efficiency. Additionally, it excels in data analysis and report generation, going beyond mere text summarization to analyze data and create detailed reports. In fields like programming, ChatGPT demonstrates impressive problem-solving abilities.

Research on Generative AI has predominantly focused on its application in educational contexts. Studies have explored its potential to aid in scientific writing (Salvagno et al., 2023) and its impact on educational environments, debating whether it would be beneficial or detrimental (Lim et al., 2023). However, most of these studies remain conceptual, with empirical research still in its early stages. Specifically, there is a lack of research examining the role and acceptance of Generative AI in workplace settings.

With the rise of AI driven automation, like ChatGPT, there's a growing fear of job instability among workers (Cao & Song, 2024). Additionally, businesses might be wary of implementing Generative AI tools due to worries about sensitive data leaks. To highlight the importance of further investigation, the upcoming section will focus on the dual factor theory.

2.2. Dual factor theory

Dual factor theory divides the determinants of technology usage intentions into two categories: enablers and inhibitors (Cenfetelli, 2004). The theory was first introduced by Herzberg et al. (1959), who discovered that job satisfaction and dissatisfaction arise from different factors. Contrary to the common belief that satisfaction and dissatisfaction are merely opposite ends of a single spectrum, this theory asserts that they are influenced by distinct variables. Traditional models of technology acceptance, such as the Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (Williams et al., 2015), attempt to explain the adoption of new systems based on their perceived usefulness (Park et al., 2022). However, they often overlook inhibitors. Considering the crucial role that barriers to innovation play in technology adoption, both enablers and inhibitors must be examined (Park and Park, 2024; Park et al., 2024). Despite the growing recognition of Generative AI, particularly ChatGPT, its professional application remains limited. This study, therefore, employs Dual Factor Theory to explore and understand the factors that influence the intention to adopt Generative AI in the workplace.

3. Research model and hypotheses development

3.1. Enablers

3.1.1. Knowledge support

One of the valuable resources provided by advanced AI models is knowledge support, which brings significant benefits to office worker industries. In this context, knowledge refers to the information and insights obtained through these AI systems(Wang et al., 2023). Generative AI and similar models have the ability to analyze vast amounts of text data, making them indispensable tools for supporting knowledge acquisition. They can extract relevant insights from diverse sources such as articles, research papers and internal documents, giving employees access to a wealth of information.

By utilizing these AI models for knowledge support, employees can experience multiple advantages. First, they can quickly find and access relevant information, saving time and effort compared to manual searches. With the help of Generative AI models, employees can efficiently locate the information they need for their work tasks.

Moreover, Generative AI models can provide real time suggestions, recommendations and summaries based on analyzed data. These models can generate concise summaries that highlight key points and offer suggestions for further exploration. By incorporating these AI generated insights into their workflow, employees can make better decisions and improve their work quality.

Also, Generative AI can be valuable for fostering creativity and innovation. Workers have the opportunity to collaborate with these systems to brainstorm ideas, create content and compile reports. Generative AI's language generation features can assist employees in expressing their ideas more clearly, ultimately enhancing the quality and productivity of their written work.

For example, a study by Jo and Park (2023) highlighted the importance of Generative AI's ability to provide knowledge support in influencing users willingness to use the system. The study revealed that users find great value in gaining new knowledge through Generative AI, which positively impacts their actual usage of the platform. Based on these insights, following hypothesis is proposed:

H1: Knowledge support has a positive impact on the adoption intention of Generative AI in the workplace.

3.1.2. Customization

Another benefit of using AI technology is the ability to provide personalized experiences. Customization involves tailoring content, products and services to meet the specific needs of users (Xiao & Benbasat, 2007). AI systems driven by machine learning algorithms can personalize recommendations, solutions and interactions based on individual preferences and requirements. By analyzing extensive datasets and utilizing advanced algorithms, AI can gather and analyze user preferences, behavior patterns and contextual information. Notably, sophisticated natural language processing algorithms like ChatGPT can process unstructured data, such as text, to deliver outputs customized to meet specific user requirements and enhance interactions (Rudolph et al., 2023).

In white-collar industries, such customization can offer numerous benefits. For example, in customer service settings, AI driven chatbots and virtual assistants can offer customized responses to customer queries that based on their specific needs. By comprehending user intent and context, these systems can provide relevant support customized for each individual, thereby improving customer satisfaction levels. Likewise in marketing and sales tasks, AI technologies leverage customer data to offer personalized suggestions and recommendations. Through analyzing previous purchase histories, browsing behaviors and demographic details, AI powered systems can predict individual preferences accurately and suggest tailored product recommendations that boost customer engagement rates leading to increased conversions. Considering these findings, this study proposes the following hypothesis:

H2: Customization has a positive impact on the adoption intention of Generative AI in the workplace.

3.1.3. Entertainment

Entertainment is another critical antecedent of technology adoption. Entertainment plays a crucial role in attracting individuals to interact with information sharing platforms like the internet and social media (Cheung et al., 2021). While customers may utilize new technologies for their practicality, they also find joy and amusement in using these tools (Bianchi & Andrews, 2018). In particular, conversation stands out as a fundamental form of entertainment for humans. It fosters emotional connections, facilitates knowledge exchange and offers pleasure. Engaging in conversations allows people to express ideas, share jokes and discuss various subjects, helping them alleviate everyday stress and expand their knowledge, thus, emphasizing the importance of conversational technologies like chatbots from an entertainment standpoint.

Several studies have highlighted the entertainment aspect of chatbots. For example, Ashfaq et al. (2020) discovered that the entertainment factor provided by chatbots significantly impacts users intention to continue using them. Similarly, Kasilingam (2020) proposed that entertainment plays a pivotal role in driving the use of chatbots in shopping scenarios. Building on these earlier findings, this research proposes the following hypothesis:

H3: Entertainment has a positive impact on the adoption intention of Generative AI in the workplace.

3.2. Inhibitors

3.2.1. Perceived risks

One of the job demands associated with the adoption of Generative AI models in workplace is privacy concern. As AI technologies handle and process large amounts of data, including personal and sensitive information, there are potential risks and challenges related to privacy protection (Shin, 2021). Privacy risks are defined as the negative impact resulting from the disclosure of users' personal information (Bouhia et al., 2022). Privacy encompasses both personal and corporate information. Traditional research has primarily focused on the infringement of personal data privacy. Customers fear that companies might misuse their personal identification or credit card information, leading to reluctance in using certain services. Privacy breaches have been a major barrier to the adoption of online services.

In the context of Generative AI, however, the potential for privacy invasion arises from the AI learning from the input data provided by users. Given Generative AI's problem-solving capabilities, users might input extensive work-related data to seek solutions, which can lead to privacy breaches (Song et al., 2022). Consequently, workers must continuously verify whether it is safe to use such data with Generative AI in their workplace. This continuous verification process is perceived as an additional task, which can act as a strain in using Generative AI. Considering these factors, we propose the following hypothesis:

H4: Privacy risks have a negative impact on the adoption intention of Generative AI in the workplace.

3.2.2. Perceived threat

The rise of new technologies brings about enhanced efficiency and advantages for people. However, some technologies also present threats to humans. A notable example is robots. When individual perceived certain threat, they tend to avoid the threat (Yoo and Park, 2023). Robots are perceived as a threat to human jobs, safety, and resources, particularly when they are capable of outperforming humans on various tasks (Yogeeswaran et al., 2016). The concern posed by robots escalates when they adopt more human like appearances rather than purely mechanical forms (Yogeeswaran et al., 2016). Although Generative AI lacks the physical embodiment of robots, it exhibits a significant linguistic resemblance to humans. This linguistic similarity could lead Generative AI to be perceived as human-like, potentially raising similar concerns as those associated with humanoid robots.

The perceived threats can be broadly classified into realistic threats and identity threats. Realistic threats encompass worries related to physical safety, job stability and material possessions (Huang et al, 2021).

For example, the more people worry about job security, the more they tend to resist using technology (Dabbous et al., 2022; Cao and Song, 2024). Therefore, the notion of Generative AI as a threat can instill apprehension in individuals who may fear losing their jobs or facing changes in their socioeconomic status.

Identity threats emerge when individuals feel that the uniqueness, values, or identity of their group is being questioned or undermined (Huang et al., 2021). In this study, identity threats are based on the definition by Craig et al. (2019), which suggests that when AI contradicts an individual's personal experiences or identity, the individual may experience a loss of self-esteem and engage in defensive behaviors to maintain their identity-related self-worth.

In the realm of Generative AI, particularly those designed to mimic human traits, there is a concern that these AI models could potentially erode the distinction between humans and machines, posing a risk to human individuality and distinctiveness. These perceived threats may trigger feelings of unease and unfavorable perceptions towards Generative AI. Research in the hospitality context supports this assumption, showing that higher levels of identity threats posed by AI systems lead to lower intentions to use them (Xu et al., 2024). Considering these factors, we propose the following hypothesis:

H5: The realistic threat of Generative AI has a negative impact on the adoption intention of Generative AI in the workplace.

H6: The identity threat of Generative AI has a negative impact on the adoption intention of Generative AI in the workplace.

4. Methodology

The conceptual framework for this research is grounded in dual factor theory. To comprehensively examine both the enablers and inhibitors influencing the intention to use Generative AI in the workplace, we have identified three enablers (knowledge support, customization, and entertainment) and three inhibitors (perceived risk, realistic threat, and identity threat) as independent variables. This study aims to understand the factors driving the adoption of Generative AI in professional settings, and therefore utilizes a survey methodology for data collection. The research model is depicted in Figure 1.

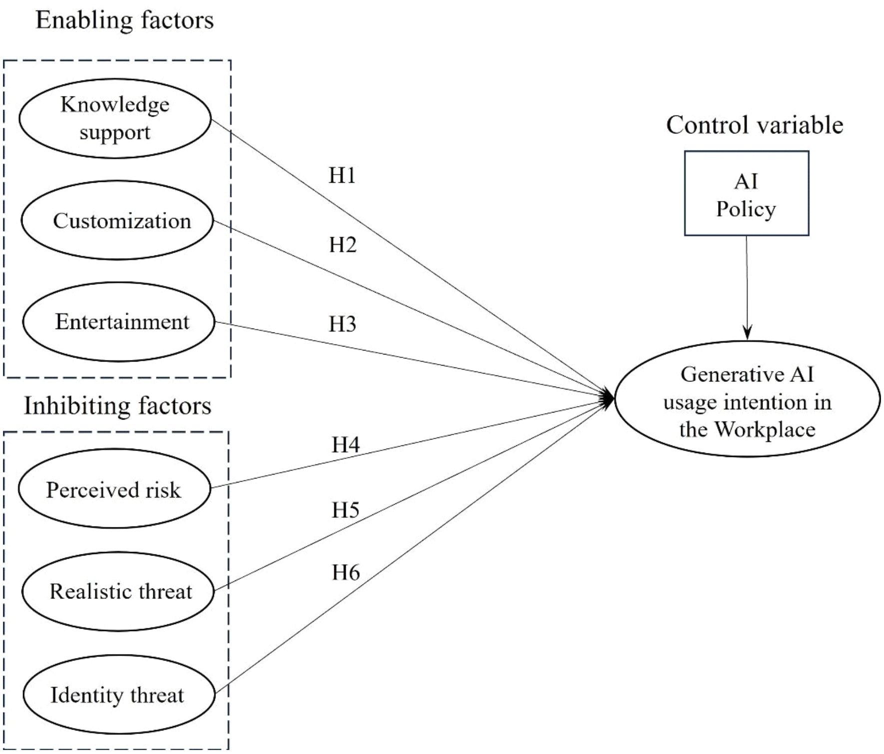

Figure 1. Proposed model framework

4.1. Survey Items

Respondents were asked to address six variables that represent the benefits and risks associated with Generative AI. The benefits include knowledge support, customization, and entertainment, while the risks encompass perceived risks, realistic threat, and identity threat. To ensure the reliability and validity of the measurements, items were adopted from previous studies.

Knowledge support was measured with three items from Wang et al. (2023). Customization was assessed using three items from Cheung et al. (2020), and entertainment was evaluated using three items from Li et al. (2013) and Wolf and Maier (2024). Perceived risk was measured with three items from Lu et al. (2011). Realistic threat and identity threat were each measured with two items from Huang et al. (2021). The intention to use Generative AI was measured with three items from Lin (2011). All items were rated on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree) to ensure high reliability. The complete list of measurement items is provided in Table 1.

Table 1. Survey items

Variables	Content	Reference
Knowledge support	SUP 1 : Using Generative AI tools like ChatGPT, I have access to more information than ever that is helpful for my job performance.	Wang et al. (2023)
	SUP 2 : Using Generative AI tools like ChatGPT, I have access to more knowledge than ever that is useful for my job performance.	
	SUP 3 : Through Generative AI, I have access to more resources than ever that help me enhance my job performance.	
Customization	CUS 1 : Generative AI tools enable customized services tailored to my needs in the workplace.	Cheung et al. (2020)
	CUS 2 : Generative AI tools provide lively and relevant information feeds that cater to my professional interests.	
Entertainment	ENT 1 : I find using ChatGPT to be enjoyable.	Li et al. (2013); Wolf and Maier (2024)
	ENT 2 : The actual process of using ChatGPT is pleasant.	
	ENT 3 : I have fun using ChatGPT.	
Perceived risks	RIS 1 : I do not feel totally safe providing personal private information over Generative AI chatbots.	Lu et al. (2011)
	RIS 2 : I am worried about using Generative AI chatbots because other people may be able to access my account	
	RIS 3 : I do not feel secure sending sensitive information through Generative AI chatbots.	
	RIS 4 : I do not feel safe providing work-related information over Generative AI chatbots.	

Variables	Content	Reference
Realistic threat	REA 1 : The increased use of Generative AI in our everyday life is causing more job loss for humans.	Huang et al. (2021)
	REA 2 : In the long run, Generative AI poses a direct threat to human safety and well-being.	
Identity threat	IDT 1 : Recent advances in Generative AI technology are challenging the very essence of what it means to be human.	Huang et al. (2021)
	IDT 2 : Technological advancements in the area of Generative AI threaten human uniqueness.	
Intention to use	INT 1 : I am very likely to adopt Generative AI tools in the future.	Lin (2011)
	INT 2 : I plan to adopt Generative AI tools in the future.	
	INT 3 : I believe it is worthwhile for me to adopt Generative AI tools.	

4.2. Data Collection

This study surveyed users experienced with Generative AI, collecting data from June 3 to June 5, 2024. A total of 210 office worker participants from the United States were recruited via MTurk, with strict criteria to ensure data reliability (Aguinis et al., 2021). Participants were required to have a 98% or higher approval rating and have completed over 500 tasks on MTurk. Only those meeting these standards were permitted to participate, and each received a $0.50 reward.

To further ensure data integrity, attention-check questions (e.g., "Please select 'Strongly disagree' for this question") were included. Respondents who failed these checks were excluded from the study. At the survey's conclusion, demographic information was gathered from all participants. Table 2 presents an overview of these demographics. After excluding 18 responses that did not pass the attention tests or provided incorrect answers to reverse-coded items, 192 valid responses were retained for analysis.

Table 2. Demographic statistics of respondents (N=192)

Measure	Value	Frequency	Percentage (%)
Gender	Male	144	75
	Female	48	25
Age group	20s	60	31.3
	30s	84	43.7
	40s	44	22.9
	50s	3	1.6
	60s	1	0.5

Measure	Value	Frequency	Percentage (%)
Education	Lower than high school	7	3.7
	High school graduate	128	66.7
	College graduate	55	28.6
	Master's degree or above	2	1.0
AI policy AI types	I do not want to use it, and it is prohibited at my workplace	3	1.6
	I want to use it, but it is prohibited at my workplace.	87	45.3
	I do not want to use it, but it is allowed at my workplace.	7	3.6
	I want to use it, and it is allowed at my workplace.	23	12
	I do not want to use it, but it is encouraged at my workplace.	1	0.5
	I want to use it, and it is encouraged at my workplace.	71	37.0
	Chat-based AI	154	80.2
	Image generation AI	12	6.3
	Audio generation AI	0	0.0
	Video generation AI	0	0.0
	Code generation AI	26	13.5
Usage frequency (per week)	0 times	99	51.6
	1-2 times	41	21.4
	3-4 times	28	14.6
	5-6 times	10	5.2
	Daily	14	7.3

5. Results

The data were analyzed using the partial least squares method (PLS) and the Smart PLS (version 4.0) statistical software package. This method is when analyzing small samples and measurement scales because of its low constraints (Chin 1998; Gefen et al. 2011). Additionally, PLS allows latent constructs as formative or reflective indicators (Fu 2011; Hsieh et al. 2012). This enables analysis of the second order variables used in this study. Considering the varying user experiences, AI Policy was included in the model as a control variable.

5.1. Measurement validity test

In this study, Smart PLS 4.0 was utilized to conduct data analysis through Partial Least Squares Structural Equation Modelling (PLS-SEM). The choice of PLS-SEM was strategic, given its robustness in handling non-normal data, a prevalent challenge in survey-based research (Hair et al., 2019). Additionally, PLS-SEM is particularly advantageous for modeling intricate structures with smaller sample sizes (Hair et al., 2019)

To ensure the reliability of our analysis, we rigorously tested the validity of the measurement items, focusing on both convergent and discriminant validity. Following the guidelines of Fornell and Larcker (1981), convergent validity was evaluated based on three criteria. Composite Reliability (CR) and Cronbach's alpha values should exceed 0.7, and an Average Variance Extracted (AVE) should be greater than 0.5.

The analysis revealed that all factor loading values ranged from 0.772 to 0.963, meeting the required criteria. The Cronbach's alpha values for all items were robust, with the lowest value being 0.777. Additionally, the lowest AVE recorded was 0.769, well above the minimum threshold of 0.5. Therefore, the convergent validity of the measurement model was confirmed, as detailed in Table 3.

For assessing discriminant validity, we employed the Heterotrait-Monotrait Ratio (HTMT) method, as recommended by Hair et al. (2019). Discriminant validity is established when HTMT values are below 0.9. As illustrated in Table 4, all variables satisfied this stringent criterion, thereby confirming the discriminant validity of the measurement model.

Table 3. Loadings and Convergent validity

	Item	Factor Loading	Cronhach's Alpha	Composite Reliability	AVE
Knowledge support	SUP1	0.912	0.878	0.925	0.804
	SUP2	0.862			
	SUP 3	0.916			
Customization	CUS1	0.915	0.777	0.899	0.817
	CUS 2	0.893			
Entertainment	ENT1	0.933	0.897	0.936	0.830
	ENT 2	0.882			
	ENT 3	0.917			
Percevied risk	RIS1	0.873	0.927	0.930	0.769
	RIS2	0.772			
	RIS3	0.911			
	RIS4	0.941			
Realistic threat	REA1	0.959	0.827	0.915	0.844
	REA2	0.876			

	Item	Factor Loading	Cronhach's Alpha	Composite Reliability	AVE
Identity threat	IDT1	0.963	0.915	0.924	0.859
	IDT2	0.848			
Usage intention	INT1	0.921	0.934	0.958	0.883
	INT2	0.947			
	INT3	0.950			

Note : SUP: Knowledge Support, CUS : Customization, ENT : Entertainment, RIS: Perceived Risk, REA : Realistic threat, IDT : Identity Threat, INT : Intention to adopt Generative AI in workplace

Table 4. Discriminant validity results (HTMT)

	SUP	CUS	ENT	RIS	REA	IDT	INT
SUP							
CUS	0.795						
ENT	0.759	0.811					
RIS	0.096	0.106	0.057				
REA	0.137	0.258	0.236	0.204			
IDT	0.146	0.15	0.076	0.751	0.151		
INT	0.629	0.443	0.601	0.044	0.063	0.076	

Note : SUP: Knowledge Support, CUS : Customization, ENT : Entertainment, RIS: Perceived Risk, REA : Realistic threat, IDT : Identity Threat, INT : Intention to adopt Generative AI in workplace

5.2. Hypotheses test

Next, we tested our hypotheses. Initially, we examined the R-square score, which stands at 0.429, indicating that our research model explains 42.9% of the variance in the intention to adopt Generative AI. We then applied the bootstrap method with 5000 samples for robust hypothesis testing. The results indicate that among the three enablers, knowledge support (β=0.411,p=0.019) and entertainment(β =0.400, p=0.026) have a significant impact on adopt intention. However, customization does not have a significant effect on adoption intention (p=0.513). Therefore, hypotheses H1 and H3 are supported while H2 is rejected.

Next, among the three inhibitors, only realistic threat has a significant impact on adoption intention (β =-0.187, p=0.019). Thus, H5 is supported. Contrary to our expectations, perceived risk (p=0.778), and identity threat (p=0.878), do not have a significant impact on adoption intention. Therefore, H4 and H6 are rejected. According to Cohen (1988), all adopted relationships showed a weak effect (f2 ≥ 0.02). Table 5 presents a summary of the results.

Table 5. Hypotheses test results

	β	Confidence interval (2.5%, 97.5%)	T-value	P-value	f^2	Hypothesis support
H1: Knowledge support → Usage intention	0.411	[0.027, 0.719]	2.348	0.019	0.137	Supported
H2: Customization → Usage intention	-0.110	[-0.432, 0.230]	0.655	0.513	0.010	Not supported
H3: Entertainment → Usage intention	0.400	[-0.008, 0.702]	2.220	0.026	0.124	Supported
H4: Perceived risk → Usage intention	0.028	[-0.201, 0.175]	0.281	0.778	0.001	Not supported
H5: Realistic threat → Usage intention	-0.187	[-0.308, 0.008]	2.345	0.019	0.055	Supported
H6: Identity threat → Usage intention	0.013	[-0.154, 0.170]	0.154	0.878	0.001	Not Supported

5. Discussion

This study provides important insights into how Generative AI can be effectively utilized in workplace settings. The findings indicate that knowledge support and entertainment are key factors in encouraging the adoption of Generative AI at work. Specifically, Generative AI's ability to assist with tasks such as automating repetitive processes, creating macros, and providing instant access to information directly enhances productivity and efficiency in the workplace. These advantages reduce the cognitive load on employees, allowing them to focus on more complex tasks, which can significantly improve overall job performance. This finding aligns with previous research emphasizing the importance of knowledge support functionalities in technology adoption (Jo & Park, 2023).

In contrast, customization was found to have no significant impact on the intention to use Generative AI. This finding contrasts with previous research in the context of chatbots, where customization has been shown to positively influence usage intention (Lee and Park, 2019). Prior studies have predominantly focused on the consumer perspective, where customization may be considered important. However, in workplace settings, factors such as efficiency, reliability, and accuracy are often prioritized over customization. This context may explain why knowledge support, which directly aids in work-related tasks, significantly influences usage intention, while customization does not.

Entertainment represents an extended feature of Generative AI. Traditional information systems operate on predefined rules, constraining users to specific questions and tasks. In contrast, Generative AI uses natural language processing to understand and respond to human communication without such constraints. The ability to engage in interactive and entertaining communication positively influences the inclination to use chatbots, aligning with previous studies (Ashfaq et al., 2020; Kasilingam, 2020).

The results also indicate that perceived risk did not significantly affect the adoption of Generative AI. Although there are concerns about potential risks, such as the leakage of personal information or corporate secrets, users seem to mitigate these risks by avoiding the direct input of highly sensitive information. Instead, they may opt to ask indirect questions or use AI for routine tasks, which helps in reducing security concerns.

Notably, the research revealed that the perception of realistic threats creates reservations about incorporating Generative AI into work tasks. Unlike previous technologies perceived as aids to human endeavors, AI advancements are regarded as potential job disruptors. This apprehension contributes to a reluctance to embrace generative AI in professional settings. These conclusions echo earlier studies suggesting that robots can be viewed as threats by colleagues.

The study by Xu et al. (2024) argues that both realistic threat and identity threat negatively impact the intention to use AI, with realistic threat being more significant. The findings of this study support these conclusions. Identity threat has been identified as a significant concern in research related to robots (Huang et al., 2021; Singh et al., 2021). These studies found that as robots appear more mechanical, the identity threat is lower due to the clear distinction from humans, whereas humanoid robots, which resemble humans, tend to evoke a higher level of identity threat. While Generative AI mimics human language, it lacks physical characteristics, unlike robots. Considering this, it can be inferred that identity threat is more influenced by visual cues rather than linguistic communication cues.

6. Conclusion

The rise of Generative AI has brought about significant changes in society, including the workplace. Despite these shifts, there are still uncertainties surrounding how these new technologies are embraced or rejected in workplace settings. This study aims to address this gap by investigating both the enablers behind and inhibitors to adopting this advanced technology, drawing on the dual factor theory. The findings of this research provide several implications.

6.1. Theoretical implication

First, it is significant as an initial exploration of how Generative AI is being used in workplaces. While the use of Generative AI in real world scenarios is on the rise, its application at work is mostly limited to a few areas like programming or entertainment. Previous studies have mainly focused on the potential downsides of Generative AI in educational settings, giving less attention to how it interacts with and is embraced by users in professional settings. This study fills this research gap by offering valuable insights for future studies.

Second, this study addresses a key issue in technology adoption research, which often concentrates solely on the advantages of new technologies. Models such as the TAM (Davis, 1989) and UTAUT

(Williams et al., 2015) provide valuable perspectives on how the benefits of new technologies affect adoption decisions. However, these models consider only the facilitators of technology adoption, undermining the importance of inhibitors. To overcome this limitation, this study adopted the dual factor theory as a framework, examining both facilitators and inhibitors. The results indicate that the perception of a tangible threat plays a crucial role in discouraging users from embracing new technologies. This thorough investigation enhances our overall comprehension and lays a solid groundwork for future studies.

6.2. Practical implication

The study's findings suggest several practical implications for effectively encouraging the adoption of Generative AI in the workplace. Organizations should emphasize features related to knowledge support and entertainment. Specifically, promoting how Generative AI can aid in tasks like automating repetitive processes or providing instant information can enhance user acceptance. Additionally, highlighting the AI's capability to engage in interactive, entertaining communication can further drive its adoption. Companies should invest in showcasing these aspects through training and communication strategies.

The significant negative impact of realistic threat on adoption intentions indicates that employees might fear AI as a potential job disruptor. Organizations need to address these concerns proactively by clarifying how Generative AI can complement rather than replace human roles. Providing clear examples of AI's role in augmenting tasks rather than replacing them, and involving employees in the implementation process, can help mitigate these fears. Moreover, transparent communication about how AI will impact job roles and create new opportunities can alleviate concerns and foster a more positive reaction.

6.3. Limitations and Future Research

The study has pointed out some interesting discoveries, but there are certain limitations that suggest areas for future investigation. First, the sample was restricted to participants from the U.S. recruited through MTurk, which may not capture the full range of perspectives among global white-collar workers. To enhance the applicability of the findings, future studies should involve a more diverse and international sample. Moreover, this study considered white-collar workers from various industries and with differing levels of experience as a single, homogeneous group, which is a limitation. In addition, the skewed nature of the data regarding Generative AI tools and usage frequency is a limitation. Most participants used chat-based AI like ChatGPT, highlighting its current dominance in Generative AI. This suggests limited adoption of other AI types, such as image and audio generation in workplaces. Over half of respondents reported no AI usage, indicating many have yet to integrate these tools into their work routines. This imbalance may affect the generalizability of the findings across AI tools and usage patterns. Future research should use control or independent variables to explore differences across industries and sectors. A more balanced sample with a wider range of AI tools and use cases would provide clearer insights into Generative AI adoption.

Furthermore, while this research delved into factors like knowledge support, customization, entertainment value, perceived risk, realistic threat, and identity threat affecting Generative AI adoption, it overlooked other potential factors. To gain a more comprehensive understanding of adoption patterns, upcoming studies should explore additional drivers and barriers such as organizational culture, user experience aspects, and specific features of AI tools.

Lastly, this study focused on Generative AI adoption in a broad workplace setting. Future investigations could narrow down to specific industries or job roles to uncover the distinct challenges and opportunities presented by AI in diverse professional contexts. Examining industry-specific applications and their varied impacts on different job functions could yield more targeted insights and practical recommendations.

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저자소개

박준성 연세대학교 산업공학과 박사학위 과정중이다. 주요 관심분야는 고객 리뷰 데이터를 활용한 서비스 품질 및 고객 이탈이다. PLS-SEM, Hayes process macro model, 자연어 처리등 다양한 방법론을 활용한다. 이러한 다양한 접근 방식을 통해 서비스 품질 평가와 고객 이탈의 이해를 심화하고자 한다.

박희준 미국 George Washington University 공학경영 박사학위를 취득하고 현재 연세대학교 산업공학과 교수로 재직 중이다. 연세대학교 융합기술경영학과 전공주임과 YTN ‘ESG코리아’ MC로도 활동하였으며, 국가별 품질 경쟁력 수준 평가방법 개발, 녹색기술 확산을 위한 기술 분석 및 소비자 수용촉진 전략에 관한 연구 등을 수행하였다. 주요 관심분야는 혁신이론, 학습이론, 조직이론, 인적자원관리이론 및 정보기술관련 이론 등을 토대로 한 혁신경영 전략수립 및 평가방법론 개발 등이다.