Does Generative Artificial Intelligence Appropriation (GAIA) influence employees' internal states, and what moderating factors affect this relationship?

Abstract

This study investigates the impact of Generative Artificial Intelligence Appropriation (GAIA)—defined as the extent to which users actively adapt and integrate AI into their work—on occupational self-efficacy. Addressing the gap regarding quality of utilization versus quantity, we employed a mixed-methods approach combining qualitative interviews and a quantitative survey of 149 Japanese employees. Results demonstrate that GAIA significantly enhances occupational self-efficacy. Furthermore, hierarchical regression analysis reveals that this positive relationship is strengthened by corporate AI education and usage frequency. Mediation analysis further indicates that GAIA indirectly improves job satisfaction via self-efficacy. These findings suggest that to maximize human capital, organizations must foster appropriation rather than relying on mere adoption.

Keywords: GAIA, Occupational Self-efficacy, AI education, AI usage

Numbers of words: 7997 words

1. Introduction

To sustain competitive advantage, firms must appropriately leverage new technologies and effectively integrate them into their business processes (Melville et al., 2004; Teece et al., 1997). In today's competitive global market, the ability to utilize technology shapes individual performance, thereby determining firm competitiveness. (Ahearne et al., 2008).

Within this context, digital technologies have attracted increasing attention in recent years. In particular, the emergence of Generative Artificial Intelligence (GenAI) has had a notable impact on task execution and decision-making processes (Jeong et al., 2025), and its adoption in organizational settings has been accelerating. GenAI enhances operational efficiency, making it a vital foundation for international business (Feuerriegel et al., 2024). Consequently, research examining its influence on employee behavior has expanded (Han et al., 2025; Zhang et al., 2025).

However, much of the existing literature has focused on quantitative aspects, such as the "presence or absence" of GenAI usage or its "frequency of use" (Brynjolfsson et al., 2023). This approach failed to capture the qualitative dimension of GenAI utilization—how employees integrate AI into their work and extract value from it. To address this research gap, Khatri et al. (2026) developed the Generative Artificial Intelligence Appropriation (GAIA) scale to measure the qualitative GenAI usage and demonstrated its validity. GAIA is significant in that it captures deep integration and advanced application of GenAI, rather than mere usage experience. However, empirical research on how GAIA affects employees' psychological responses and potential moderating factors remains unexplored.

This study aims to fill these theoretical and empirical gaps by posing the following research question: "Does GAIA influence employees' internal states, and what moderating factors affect this relationship?" To address this question, we first conduct exploratory case analyses with practitioners actively using GenAI. This investigation reveals the potential influence of GAIA on individuals' self-efficacy and identifies AI education and usage intensity as possible moderating factors. Building on these insights, we develop hypotheses grounded in Wood and Bandura's (1989) Social Cognitive Theory (SCT). We then test these hypotheses using a survey of Japanese practitioners. Our analysis clarifies the impact of qualitative GenAI use, as measured by GAIA, on task self-efficacy and examines the conditions under which this effect is strengthened.

2. Theoretical Background

2-1. GenAI in Business Management and Its Impact on Employee

In recent years, GenAI has been rapidly introduced into global firms as a tool to support business operations. Like previous technological innovations, GenAI increases efficiency and productivity significantly by automating many tasks that were previously performed by humans (Feuerriegel et al, 2024). For instance, Noy and Zhang (2023) found that college-educated professionals using ChatGPT for writing tasks reduced task completion time by 40%. Brynjolfsson et al. (2023) reported that the introduction of a GenAI-based conversational assistant in customer support increased the number of issues resolved per hour by 14% on average. These findings suggest that GenAI contributes to operational efficiency by automating routine tasks, thereby enhancing both processing speed and volume, which leads to allowing humans to engage in more creative activities.

At the same time, GenAI possesses a unique aspect that distinguishes it from traditional automation technologies: it functions not merely as an automation tool but as a "thinking partner" (Tseng & Warschauer, 2023:259) that supports work through collaboration with humans and augments human intelligence and capabilities, which complements humans rather than replacing them. (Brynjolfsson, 2022) It enables people to solve complex problems or even achieve what was previously impossible, improving employees' productivity, efficiency, and even creativity (Dwivedi et al, 2023). Dell'Acqua et al. (2023) demonstrated in a field experiment with consultants that those using GenAI produced results of over 40% higher quality compared to those working alone, confirming that human-AI collaboration significantly elevates creative performance.

Given this unique nature, numerous studies have examined not only the external performance outcomes of GenAI usage but also its impact on the internal psychological states of employees. Some research consistently indicates that AI usage positively improves employees' self-efficacy, which subsequently has been shown to promote employees' willingness to take risks (Han et al., 2025) and innovative behavior (Zhang et al., 2025). Beyond competence-related beliefs, recent scholarship explains broader psychological impacts drawing on the Job Demands-Resources (JD-R) model. Cambra-Fierro et al. (2025) and Filippelli et al. (2026) suggest that when GenAI functions as a job resource that supports work processes and facilitates goal achievement, it significantly enhances employees' work engagement and well-being, thereby fostering a positive work experience.

2-2. Generative Artificial Intelligence Appropriation (GAIA)

Despite the valuable insights provided by the studies, existing research has limitations. A critical inadequacy lies in the measurement of AI usage; most studies have focused predominantly on the quantity of usage or simple adoption. For instance, Han et al. (2025) and Zhang et al. (2025) measured AI Usage using a 5-point Likert scale with items such as "I use artificial intelligence to perform most of my work tasks," focusing primarily on the frequency or extent of reliance. Furthermore, Cambra-Fierro et al. (2025) operationalized GenAI adoption using a 7-point Likert scale focused on attitudinal beliefs, such as "I believe that ChatGPT can help improve things."

While these scales successfully capture how often a tool is used or how positively it is viewed, they largely neglect how employees utilize GenAI in their daily workflows. Since GenAI is an interactive technology where the quality of outputs varies significantly depending on the user's input and customization, it is highly probable that "how deeply one has integrated GenAI into their own work and mastered the tool (=quality)," rather than merely frequency of use or general acceptance, has the decisive impact on employees.

The limited progress in research regarding the quality of AI usage may be attributed to the difficulty in comprehensively defining and measuring the degree of integration or quality of use. The concept of Generative Artificial Intelligence Appropriation (GAIA) and its measurement scale, newly developed by Khatri et al. in 2025, address this methodological challenge.

GAIA is defined as "how users adopt Generative Artificial Intelligence tools, adapt them according to their needs, and integrate them into their work" (Khatri et al., 2026:1). In other words, it refers to a state where users go beyond mere usage to utilize the GenAI tool effectively and "make it their own" (Bar et al., 2016:617), which constitutes high-quality utilization. Khatri et al. also established a scale that measures holistically the degree of GAIA comprising the following five dimensions:

1. Integrative Appropriation: The degree to which AI is integrated into daily work practices.
2. Adoptive Appropriation: The user's acceptance and willingness to utilize the technology.
3. Customised Appropriation: The active adaptation of the technology to meet

specific personal or task needs.

4. Interface Appropriation: The user's ability to adapt to and navigate the specific interface.
5. Ethical Appropriation: The application of ethical judgment regarding the usage and outputs of the tool.

This GAIA scale allows for the quantification of the engagement between users and AI at an individual level by offering a comprehensive measure that captures the full spectrum of appropriation—from adoption and customization to integration— which could not be captured by traditional measures of frequency alone.

2-3. Research Gap

However, GAIA scale has only recently been developed, and there remains room for further validation regarding its application. While Khatri et al. (2026) demonstrated that GAIA influences "Individual Creative Performance", literature on technology appropriation suggests that appropriation is deeply connected to internal psychological states. Therefore, verifying the impact of GAIA on employees' internal states must be a critical next step for future research. Furthermore, it is also unclear under what circumstances this impact might be strengthened or weakened.

Based on the above, this study poses the following research question:

RQ: Does GAIA influence employees' internal states, and what moderating factors affect this relationship?

3. Exploratory Qualitative Research

3-1. Purpose and Methodology

Prior GenAI research has focused on quantitative adoption, leaving qualitative and psychological implications underexplored. Specifically, the GAIA construct (Khatri et al., 2026) lacks empirical grounding regarding how it manifests in concrete workplace behaviors and which components contribute to psychological outcomes. Given this gap, qualitative research is necessary to clarify actual conditions before proceeding to hypothesis development (Knight & Cavusgil, 2004). We conducted semi-structured interviews (60–90 minutes) between August and November 2025 with four practitioners leading GenAI-based transformation or possessing a broad overview of workplace practices. The interviews covered usage modes, psychological changes, organizational support, and frequency. The aim was to identify high-quality usage characteristics, explore their link to psychological outcomes, and conditions strengthening this relationship (See Appendix for interviewee attributes).

3-2. Findings: Observed Patterns of GenAI Usage

First, while GenAI usage often begins with simple automation such as translation, advanced users have progressed to tailoring the role of GenAI to fit their own work structures. A management consultant uses multiple tools for different purposes, suggesting a personalized usage pattern. He also contrasted a mode of use in which documents are simply input and summarized with a mode in which issues are structured and questions are posed for each point, stating that the latter clearly produces higher-quality output. Furthermore, a practitioner involved in corporate DX and GenAI utilization support cited an example of an advanced company where employees break down their own workflows and design GenAI as an agent to handle inquiries and routine decision-making, entrusting it with semi-autonomous handling of part of their daily tasks. The GenAI utilization manager at the large IT firm also stated that while the initial use of GenAI in their company focused on general-purpose tasks, it later progressed to customization, such as building systems connected to department-specific knowledge bases and designing team-specific prompt sets. These observations suggest usage quality depends on the degree to which users adjust GenAI's role to their specific goals and work structures, consistent with the Customized Appropriation (CUA) dimension of GAIA (Khatri et al., 2026).

Second, this customized usage was accompanied by concrete accounts of psychological change, especially reductions in anxiety and shifts in confidence and self-evaluation. A DX support practitioner explained that using GenAI for English emails or peer reviews significantly lowered stress; he felt that GenAI-mediated content would fall within an acceptable range, thereby increasing his occupational self-efficacy. The manager responsible for the GenAI utilization at the large IT firm stated that, through using GenAI, it had become possible to tentatively try working in domains that they had previously given up on as being outside their area of expertise. By navigating uncertainties with GenAI, they accumulated experiences of actually completing finished products, and described a sense of "being able to return to things I once gave up on in my life," which they said was linked to heightened self-esteem and a greater sense of fulfilment in their daily life. Additionally, a management consultant linked high-volume output to psychological shifts, whereas an IT specialist observed that generating content through GenAI fosters a subjective sense of capability extension. These accounts suggest that the increase in output and the opportunities for new challenges arising from CUA may be linked to changes in subjective feelings of competence and self-evaluation.

Third, practitioners customizing GenAI emphasized the importance of a continuous learning cycle. The manager responsible for the GenAI utilization at the large IT firm focused not only on initial education but also on personally testing and sharing impactful use cases to promote effective usage. She emphasized that while skills develop naturally with use, the process does not end at adoption; continuous education remains essential. The management consultant noted that proficient users, including himself, continue to experiment daily, investing heavily in multiple subscriptions and high-performance devices. Through such intensive use, new prompts and ideas emerge, creating a cycle where capabilities naturally expand. The IT specialist explained the case of an initially inexperienced user who, triggered by training, began to use GenAI and then became immersed in application development using GenAI, building mechanisms that replaced their own work tasks through trial and error with multiple tools. Although this user started using GenAI after receiving formal education, they dramatically enhanced their understanding and skills regarding GenAI by continuing to learn on their own through repeated use, thereby making substantial use of GenAI in their work. These observations suggest that, once a certain level of quality in GenAI usage has been secured, receiving education and continuing to practice through one's own trial and error make it possible to further expand what can be accomplished with GenAI. They further suggest that continually learning through education or practice is important not only for enhancing the quality of GenAI usage itself but also for improving practitioners' occupational self-efficacy and performance.

3-3. Summary and Implications for Hypothesis Development

The case analyses highlight three points. First, advanced practitioners do not merely use GenAI as a generic tool but customize it to their work. This empirical phenomenon is consistent with the characteristics of Customized Appropriation (CUA), one of the subdimensions of GAIA as defined by Khatri et al. (2026), and suggests that the GAIA concept can also manifest in practice.

Second, customization appeared associated with perceived capability gains. These narratives suggest that using GenAI as a tool may raise occupational self-efficacy.

Third, these practitioners understand the importance of continuous learning. Some practitioners sought to create a situation in which many employees could use GenAI more effectively by providing in-house education not only in the form of initial training intended simply to get people to start using GenAI, but also in the form of education on high-quality ways of using GenAI and advanced use cases. In addition, by proactively continuing to use GenAI themselves, they changed their own work processes and expanded what they were able to do in their work. Taken together, these case analyses suggest that GAIA (in particular its CUA dimension) is positively related to occupational self-efficacy, and that this relationship may be strengthened by GenAI-related education and continuous GenAI usage. Based on these findings, we construct hypotheses for subsequent quantitative testing.

4. Hypotheses Development

Qualitative research has suggested that GAIA may improve occupational self-efficacy (OSE). Self-efficacy was defined as "people's beliefs about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives"(Bandura, 1994:71). Bandura (1977) argues that this belief is a major determinant of people's behavioral choices, the amount of effort they expend, and their persistence in the face of difficulties. However, applying a generalized concept of self-efficacy is considered inappropriate for capturing the specific impacts of GenAI in a business context. Given that self-efficacy is a context-dependent concept, Bandura (1977) emphasizes the importance of measuring it at a specific task level. In this context, OSE is characterized as a "domain-specific" (Rigotti et al., 2008:239) construct and defined as "the competence that a person feels concerning the ability to successfully fulfill the tasks involved in his or her job" (Rigotti et al., 2008:239). Thus, this study adopts OSE to assess the impact of GAIA.

In the interview, it was revealed that GenAI appropriation enhances users' OSE. One interviewee stated, "GenAI fills the gaps in my abilities and raises my average job performance." By utilizing GenAI as a complementary tool to bridge gaps in their proficiency and knowledge, employees are enabled to handle tasks outside their area of expertise, effectively expanding the scope of their capabilities. This experience directly fosters employees' confidence in their ability to successfully execute work tasks and achieve desired results in their jobs, thereby enhancing their overall OSE.

This observation is consistent with existing literature, particularly Social Cognitive Theory (Wood & Bandura, 1989). According to this, "mastery experiences" (Wood & Bandura, 1989:364) constitute the most effective means of developing a sense of self-efficacy. Therefore, the employees' self-evaluation that they are successfully mastering and utilizing GenAI (i.e., high GAIA) functions as a continuous source of successful experiences. This perception directly contributes to the enhancement of their OSE. Thus, the following hypothesis is established:

H1: GAIA is positively correlated with OSE.

The first moderating variable is AI education. Appropriate education is considered essential for the organizational assimilation of technology. Existing research emphasizes the importance of training as a key managerial intervention to promote acceptance (Venkatesh et al., 2003). This holds true in the context of GenAI. Morandini et al. (2023) point out that to maintain competitiveness, organizations must not only introduce AI tools but also strategically provide upskilling and reskilling opportunities for employees to acquire these new skills. Furthermore, Basri (2024) demonstrated that knowledge and understanding of AI have a significant positive effect on employees' AI self-efficacy, suggesting the importance of enhancing knowledge through high-quality education and training programs provided by companies.

Such education provides opportunities for "modeling," which Wood and Bandura (1989) identify as a factor in enhancing self-efficacy. Modeling is the activity of learning from the behavior of others. It refers to the process of guiding your own actions by observing how others have succeeded and comparing yourself to them. Applying this theory to the context of this study, AI education can be perceived as an opportunity to learn successful methods of using GenAI, and thus, serves as an opportunity for modeling.

In this process, the learner's existing level of appropriation (GAIA) is thought to differentiate how the presented model is accepted. For learners who have already incorporated AI into their work (i.e., high GAIA), the expert principles acquired through education serve as validation that their prior trial-and-error efforts were correct. By confirming that their strategies align with those of experts, their self-efficacy is likely to be reinforced more significantly than through self-study alone. On the other hand, for learners whose utilization is limited (i.e., low GAIA), their own rules for comparison are either not established or they merely recognize the divergence between their current state and that of the experts; therefore, this amplification effect on self-efficacy is less likely to occur. Thus, the following hypothesis is established:

<u>H2: More frequent AI education strengthens the positive relationship between GAIA and OSE.</u>

The next factor that may strengthen the relationship between GAIA and OSE is the extent to which individuals actually utilize GenAI. The value of advanced digital technologies, including GenAI, depends not merely on their adoption but on the depth of their practical use. Prior research on information technology (IT) implementation has similarly shown that the introduction of technology alone is insufficient to generate meaningful outcomes. For example, Bhattacherjee (2001) argues that the success of information systems is determined not by initial adoption but by continued use. Likewise, Jasperson et al. (2005) emphasize that the degree to which users engage with an IT system after its introduction and embed it into their work processes is a critical determinant of performance and effectiveness. These insights suggest that technologies such as GenAI—characterized by diverse functions and rapid change—continuous usage accompanied by appropriate application is essential, rather than mere adoption or occasional use.

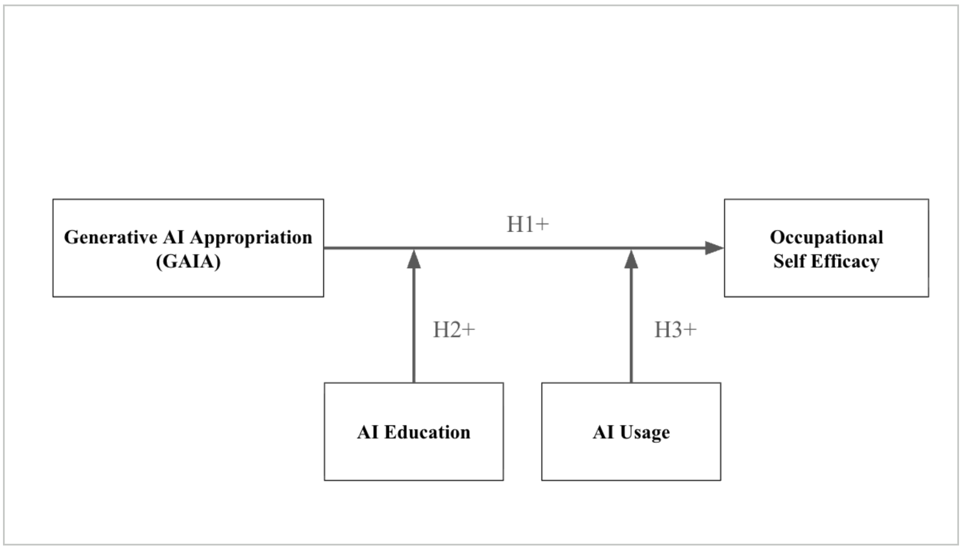
Such experiences of proper utilization can serve as a source of self-efficacy. Wood and Bandura (1989) noted that mastery experiences are a primary source of self-efficacy. Self-efficacy refers to an individual's belief in their ability to accomplish a task, and the accumulation of successful experiences contributes to psychological resources and self-affirmation. Individuals with high GAIA are likely to use GenAI more competently; thus, through continued use, they may accumulate successful experiences and enhance their self-efficacy. Exploratory interviews also suggested that individuals who effectively utilize GenAI may increase their self-efficacy through sustained engagement with GenAI.

These findings indicate that not only high-quality use of GenAI but also the frequency and duration of actual use amplify its positive impact on OSE. In other words, individuals who can apply GenAI appropriately and continue to utilize it over time are more likely to accumulate successful experiences in their jobs and consequently improve their OSE. Thus, the following hypothesis is established:

H3: Greater AI usage strengthens the positive relationship between GAIA and OSE

The Conceptual Framework of this study is modeled in Figure 1.

Figure 1 Conceptual Framework of this study



5. Methodology

5-1. Data Collection

In November 2025, a questionnaire survey was conducted among employees in Japan. Responses were collected through snowball sampling, leveraging the networks of team members and affiliated individuals. The survey was administered using Google Forms, with the questionnaire details provided in the appendix. A total of 176 responses with exclusion of 27 responses for the non-use of GenAI were collected, resulting in 149 valid responses for analysis. Analysis reveals that the sample obtained is not biased towards the attributes such as industry or gender, implicating that the problem of sample bias from snowball sampling may not be as significant as anticipated.

The dependent variables reflect the respondents' current situation, while the independent variables pertain to their experiences of using GenAI from the past. This approach mitigates concerns about reverse causality. For the survey items originally developed in English, a single back-translation procedure was conducted.

5-2. Measurement

Dependent Variable

Occupational Self-Efficacy (OSE)

In this study, OSE is set as the dependent variable. This construct was measured using a shortened version of the Occupational Self-Efficacy Scale validated by Rigotti et al. (2008). This scale consists of six items selected from the original version developed by Schyns and von Collani (2002). Each item was rated on a 6-point Likert scale, where (1) indicates "strongly disagree" and (6) indicates "strongly agree." The mean of these six items was used as the OSE score. The Cronbach's alpha coefficient was 0.841, indicating that the scale's reliability was adequate.

Independent Variable

GAIA

GAIA was measured using the GAIA scale, a multidimensional measure developed and validated by Khatri et al. (2026). Each item was rated on a 7-point Likert scale, where (1) indicates “strongly disagree” and (7) indicates “strongly agree.” The average of these 19 items was used for analysis. Cronbach's alpha was 0.838, indicating no reliability issues.

Moderator Variable

AI Education

Following Saleh & Azimi (2025), who focused on the frequency of training, we measured the number of learning opportunities (study sessions, workshops, training programs, etc.) related to GenAI that the respondent's company had conducted over the past year.

AI Usage

To measure GenAI usage levels, we asked: (1) “How many days per week do you use GenAI?” and (2) “On days you use GenAI, how many minutes do you use it on average?” In the analysis, we used the “total weekly usage time” calculated by multiplying the reported “number of usage days per week” and “average daily usage time” as an indicator.

Control Variables

This paper incorporated individual-level, job-level, and organizational-level variables as control variables to eliminate differing interpretations of the relationship between independent and dependent variables. Variables related to GenAI were also added. At the individual level, demographic factors such as age, gender, and educational background were used as control variables. For age, respondents were categorized into five groups (25 years old or younger = 1, 26–30 years old = 2, 31–40 years old = 3, 41–50 years old = 4, 51 years old or older = 5) (*Age*). For gender, a dummy variable was used, with males coded as 1 (*Gender*). For educational background, we coded university or graduate school graduates as 1 and others as 0 (*Education*).

Furthermore, at the organizational level, we controlled three job-related factors. First, we measured the length of service at the current company in months (*Working Experience*). Next, to control for job position, we referred to 1 as managerial roles and to 0 as non-managerial roles (*Management*). Following Kawaguchi and Motegi (2021), we measured the proportion of routine work in assigned duties on a 0–100% scale (*Routine*).

At the organizational level, the company size was controlled. Specifically, companies with 1,000 or more employees were coded as 1, and those with fewer than 1,000 employees as 0 (*Company Size*). Finally, to control GenAI experience, we added a variable measuring the duration of GenAI usage in months (*AI Experience*). Table 1 shows the descriptive statistics for the above variables.

As an additional verification in this study, we attempted to control "Industry (Business Type)" at the company level and "Job Type" at the individual level. However, incorporating these variables into the model did not result in any substantial changes to the main findings, so they were excluded from the final analysis.

5-3. Common Method Bias

Moreover, we checked for common method bias by Harman's single-factor test (Podsakoff & Organ, 1986). We included all items from the two constructs (OSE and GAIA) in a factor analysis. The first factor accounted for only 12% of variance, below the generally accepted threshold of 50%. Accordingly, the extent of common method variance in this study is significantly limited.

5-4. Analysis Method

This study conducted hierarchical multiple regression analysis based on the variables described above. All independent, moderating, and control variables were z-standardized.

Table 1 Descriptive statistics

	Variables	Mean	Std. Dev.	Min	Max
1	Age	3.70	0.80	1.00	5.00
2	Gender	0.64	0.48	0.00	1.00
3	Education	0.92	0.27	0.00	1.00
4	Working Experience	71.80	102.23	1.00	480.00
5	Management	0.22	0.42	0.00	1.00
6	Routine	26.81	21.20	0.00	90.00
7	Company Size	0.59	0.49	0.00	1.00
8	AI Experience	13.72	8.98	1.00	40.00
9	OSE	3.90	0.87	1.67	6.00
10	GAIA	4.66	0.74	3.05	6.63
11	AI Education	4.44	7.75	0.00	50.00
12	AI Usage	244.83	376.90	5.00	3500.00

6.Results

The correlation matrix is presented in Table 2, and the results of the hierarchical regression analysis are shown in Table 3. The analysis began with Model 1, which included only control variables (Age, Gender, Education, Working Experience, Management, Routine, Company Size, AI Experience). It then proceeded to Models 2 and 3, which introduced the main effects, and finally to models including interaction terms (Models 4, 5, and 6).

The variance inflation factor values of all the explanatory variables are below the threshold of 5 (Hair et al., 1998), suggesting that multicollinearity is not a critical statistical issue in our sample.

Table2 The correlation matrix

#	Variables	1	2	3	4	5	6	7	8	9	10	11	12
1	Age	1											
2	Gender	0.024	1										
3	Education	-0.02	0.141	1									
4	Working Experience	0.242 **	0.095	-0.32 **	1								
5	Management	0.137	0.160	-0.080	0.205 *	1							
6	Routine	-0.02	-0.16	-0.09	0.107	-0.07	1						
7	Company Size	0.068	0.066	0.205 *	-0.01	-0.12	0.056	1					
8	AI Experience	-0.14	0.117	0.098	-0.1	0.000	-0.230 **	-0.09	1				
9	OSE	0.001	0.112	0.142	0.030	0.183 *	-0.15	-0.06	0.178 *	1			
10	GAIA	-0.1	0.191 *	0.123	-0.03	-0.01	-0.17 *	-0.08	0.307 **	0.275 **	1		
11	AI Education	-0.09	0.061	0.122	0.102	0.126	0.012	0.256 **	0.130	0.060	0.028	1	
12	AI Usage	-0.1	-0.03	0.040	-0.1	-0.07	-0.060	-0.06	0.225 **	0.086	0.367 **	-0.05	1

**p<0.01, *p<0.05

Table3 The results of the hierarchical regression analysis

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.	Coef.	Std. Dev.
Age	-0.016	0.084	0.000	0.083	0.001	0.084	0.010	0.084	0.014	0.082	0.028	0.081
Gender	0.03	0.084	-0.002	0.083	-0.002	0.085	0.011	0.084	-0.006	0.083	0.011	0.081
Education	0.166	0.088 †	0.145	0.087 †	0.143	0.088	0.144	0.087	0.136	0.086	0.136	0.084
Working Experience	0.073	0.090	0.062	0.088	0.060	0.090	0.040	0.090	0.048	0.088	0.018	0.087
Management	0.165	0.084 †	0.174	0.082 *	0.172	0.084 *	0.163	0.084	0.203	0.083	0.197	0.081 *
Routine	-0.088	0.084	-0.068	0.083	-0.068	0.083	-0.075	0.083	-0.085	0.082	-0.097	0.080
Company Size	-0.063	0.083	-0.046	0.082	-0.049	0.086	-0.068	0.086	-0.068	0.084	-0.098	0.083
AI Experience	0.138	0.084	0.083	0.085	0.083	0.088	0.070	0.087	0.120	0.086	0.109	0.085
GAIA (H1)			0.220	0.085 **	0.224	0.091 *	0.239	0.090 **	0.203	0.089 *	0.220	0.087 *
AI Education					0.010	0.086	0.010	0.085	0.028	0.084	0.032	0.083
AI Usage					-0.009	0.087	0.005	0.087	-0.184	0.105	-0.199	0.103
GAIA×AI Education (H2)							0.200	0.106†			0.273	0.104 **
GAIA×AI Usage (H3)									0.262	0.094 **	0.314	0.094 ***
R2	0.050		0.087		0.074		0.091		0.118		0.154	
F-Value	1.964 †		2.566**		2.072*		2.233*		2.645**		3.075***	

***p<0.001, **p<0.01, *p<0.05, †p<0.1

The results of the hypothesis testing are described sequentially below. First, Hypothesis

1 (H1) was tested using Model 2 and Model 6. As a result, a significant positive correlation between GAIA and OSE was confirmed in Model 2 ($p < 0.01$). This significant positive relationship was maintained in Model 6, which included all variables ($p < 0.05$). Thus, the results indicate that employees who appropriate GenAI in a way suitable for their work demonstrate higher occupational self-efficacy. Therefore, H1 was supported.

Second, Hypothesis 2 (H2) was tested using Model 4 and Model 6. The results indicate that the interaction term of GAIA and AI Education has a positive effect on OSE. While the interaction in Model 4 was marginally significant ($p < 0.1$), the full model (Model 6) revealed a significant positive correlation at the $p < 0.01$ level. This suggests that for employees receiving AI-related education, the positive effect of GAIA on self-efficacy is strengthened. Therefore, H2 was supported.

Third, Hypothesis 3 (H3) was tested using Model 5 and Model 6. The analysis showed that the interaction term of GAIA and AI Usage demonstrated a significant positive correlation with OSE in Model 5 ($p < 0.01$). Furthermore, in Model 6, the significance level increased ($p < 0.001$), indicating a strong positive moderating effect. This implies that the beneficial impact of GAIA on self-efficacy is maximized when actual AI usage frequency is high. Therefore, H3 was supported.

To interpret the significant interaction effects observed in H2 and H3 in more detail, a simple slope analysis was conducted. The interaction effects were plotted based on the mean plus/minus one standard deviation of the moderator variables.

Figure 2 Interaction Effects

Figure 2 (A)

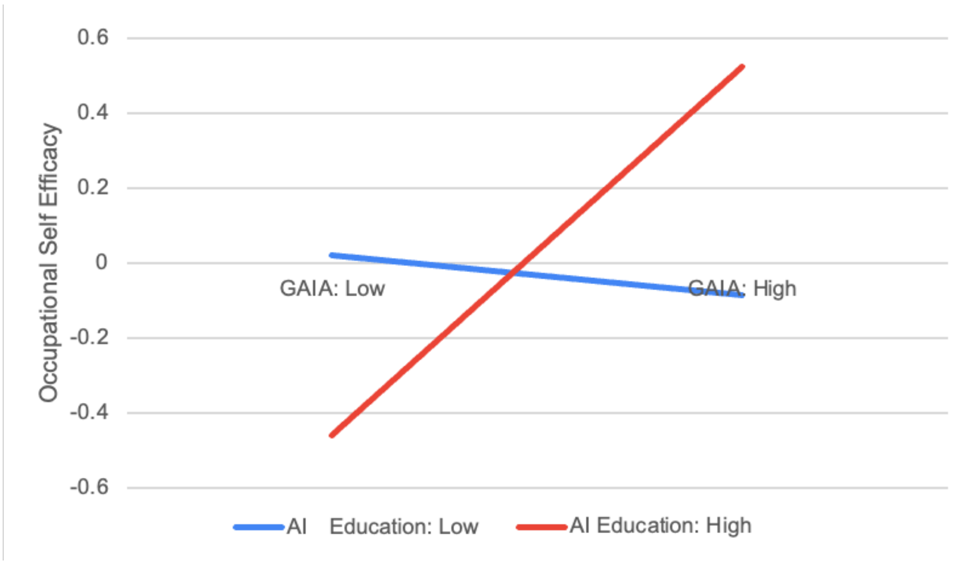
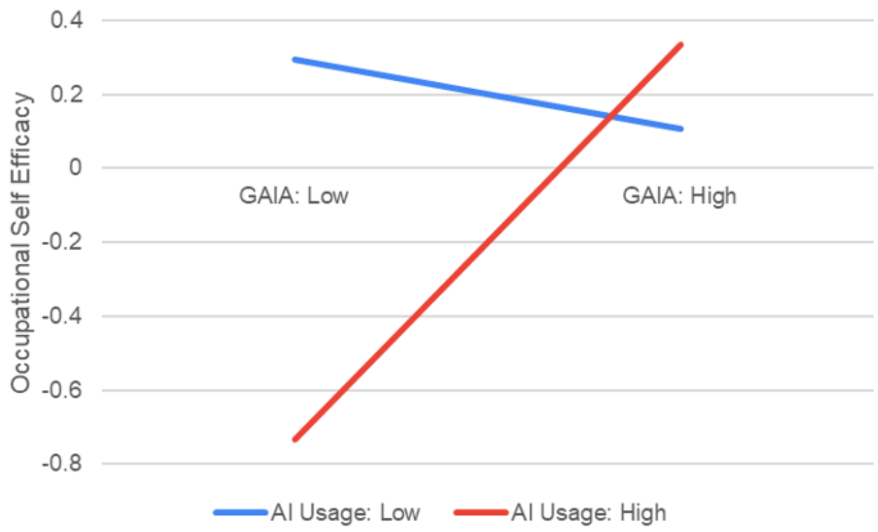


Figure 2 (B)



As shown in Figure 2 (A), the positive relationship between GAIA and OSE is confirmed to be stronger when AI Education is high compared to when it is low. Similarly, Figure 2 (B) indicates that the positive relationship between GAIA and OSE becomes more pronounced when AI Usage is high. These plots further support the moderating roles of AI Education and AI Usage.

Regarding other variables, AI Experience and AI Usage (as main effects) yielded non-significant results. This reveals that simply using AI does not necessarily increase OSE. Similarly, AI Education alone does not directly lead to OSE. Regarding personal variables, "Management" showed a significant positive effect in many models, indicating that holding a managerial position is associated with higher occupational self-efficacy.

Additional Analysis: Relationship with Job Satisfaction

In this study, we have clarified the impact of GAIA on OSE, an individual internal variable. This focus was based on variable selection derived from qualitative research and hypothesis construction, which yielded significant results. However, internal variables other than OSE exist. Therefore, there remains room for verification regarding whether the influence of GAIA extends to internal variables other than OSE, or whether enhanced OSE exerts additional influence on other important factors. To verify these relationships from a more multifaceted perspective, an additional investigation was conducted using another internal variable as the dependent variable.

Here, Job Satisfaction (JS) was adopted as the additional dependent variable. JS was selected because employee attitudes, including job satisfaction, are directly linked to organizational performance, positioning it as one of the most representative variables for measuring individual internal states and organizational effectiveness (Ko et al., 2021). In this survey, JS was measured using the scale adopted by Ko et al. (2021) The analysis results are shown in Table 4.

Table4: Results of Hierarchical Regression Analysis on Job Satisfaction

	Model 7		Model 8	
	Coef.	Std. Dev.	Coef.	Std. Dev.
OSE			0.438	0.084 ***
Age	0.039	0.086	0.027	0.079
Gender	-0.128	0.086	-0.133	0.079 †
Education	0.161	0.090 †	0.101	0.083
Working Experience	0.095	0.092	0.087	0.085
Management	0.048	0.086	-0.038	0.081
Routine	-0.156	0.085 †	-0.114	0.078
Company Size	-0.202	0.088 *	-0.159	0.081 †
AI Experience	0.089	0.090	0.042	0.083
GAIA (H1)	0.082	0.093	-0.014	0.087
AI Education	1.045	0.298	0.078	0.08
AI Usage	-0.027	0.979	0.084	0.102
GAIA×AI Education (H2)	0.128	0.899	-0.105	0.104
GAIA×AI Usage (H3)	0.120	0.904	-0.125	0.095
Adjusted R2	0.046		0.202	
F-Value	1.550		3.678***	

***p<0.001, **p<0.01, *p<0.05, †p<0.1

First, to verify the direct effect of GAIA on JS, Model 7 (excluding OSE) was constructed. The results showed that the direct path from GAIA to JS was not significant, and none of the models including moderator variables showed significance. Furthermore, the adjusted coefficient of determination (Adjusted R^2) for the overall model remained low. Subsequently, Model 8, which introduced OSE into the model, was tested. The results confirmed that OSE has a significant positive effect on JS ($p < 0.001$). Additionally, the Adjusted R2 increased, and the model fit was improved.

Interpreting these results suggests that GAIA does not correlate with just any internal variable; rather, it held a strong correlation specifically because the variable was OSE. Furthermore, since this additional analysis suggests that higher OSE may enhance JS, it implies a potential pathway where GAIA enhances OSE, which in turn enhances JS. While detailed analysis remains a topic for future research, this additional analysis demonstrates the potential for the effect of GAIA enhancing OSE to bring about further ripple effects.

7. Discussion

This study examined the impact of GAIA on employees' OSE. The results of a hierarchical multiple regression analysis based on a questionnaire survey of 149 individuals revealed that GAIA has a significant positive effect on OSE. Furthermore, this relationship was found to be positively moderated by "AI Education" and "AI Usage." Additionally, supplementary analysis suggested that while GAIA does not have a direct effect on Job Satisfaction, it enhances Job Satisfaction indirectly through the mediation of OSE.

These results suggest that in the utilization of GenAI, it is critical not merely to use the technology but to position and integrate it effectively within work processes. In management research concerning GenAI, attention has shifted from mere usage to the quality of usage, leading to the proposal of the GAIA concept. Aligning with this research stream, one of the significant findings of this study is the clarification that it is the *quality* of usage (GAIA), rather than the *quantity* (AI Usage), that contributes to individual self-efficacy.

In addition, this study demonstrates that there are boundary conditions (contingencies) for these relationships. The mechanism by which the quality of GenAI usage enhances self-efficacy is less likely to function effectively if AI education is not provided or if the frequency of GenAI usage is low. Another critical discovery of this study is that the effect of GenAI quality can be moderated by other management variables.

7-1. Implications for Scholars

This study offers academic contributions primarily in two areas. First is the contribution to the field of technology management. Felicetti et al. (2024) emphasize the importance of user "Appropriation" in the utilization of generative AI and call for the elucidation of moderating factors involved in the outcome creation process. Responding to this call, this study contributes to the field by focusing on OSE as a psychological outcome and clarifying the moderating mechanisms that enhance this effect. To the best of the authors' knowledge, there are almost no studies globally that have investigated the relationship between GAIA and individuals' internal states, positioning this study at the forefront of this research area.

Second, this study contributes to management research regarding self-efficacy. By applying Bandura's Social Cognitive Theory (SCT) to the novel context of GenAI utilization, this study demonstrates that SCT remains applicable in the context of

GenAI. Extending the discussion of classical SCT within the cutting-edge context of GenAI utilization constitutes the second contribution of this study.

7-2. Implications for Practitioners

Based on the results of this study, the following three practical recommendations are offered to companies aiming to introduce GenAI and maximize its effects. First, it is insufficient for companies to merely recommend the "free use" of GenAI. In this study, it was not the history or frequency of GenAI usage, but rather whether the technology was appropriately integrated into work that influenced self-efficacy. In other words, simply allowing employees to use GenAI may not positively impact their internal states unless business processes are designed to ensure appropriate integration. The insight that practitioners should focus on the *quality* rather than the *quantity* of GenAI utilization is a critical suggestion from this study.

Second, this study showed that GenAI education and usage do not lead to employee self-efficacy on their own; rather, they strengthen the relationship between high-quality GenAI Appropriation and self-efficacy. While companies are currently promoting GenAI education and usage, these initiatives bring positive effects to employees' internal states only when correct appropriation is achieved. Conversely, this suggests that if education and usage promotion are conducted without achieving appropriation, they may not influence employees' sense of competence. Practitioners must consider this point carefully.

Third, there is the potential for GenAI utilization to aid in improving employee self-efficacy. Possessing self-efficacy is considered important for employees (Bandura, 1977), and this study also indicates that it leads to job satisfaction. The importance of raising self-efficacy is frequently discussed in the context of Japanese companies as well (Ministry of Health, Labour and Welfare, 2019). Therefore, the result that GenAI—a technology that extends individual capabilities—leads to self-efficacy suggests a new possibility for GenAI. Consequently, practitioners should consider positioning GenAI as a tool for enhancing self-efficacy and promoting its utilization accordingly.

7-3. Relationship with International Business

The analytical results of this study also contain important implications from the perspective of International Business (IB). First, this study provides the latest findings regarding the management of GenAI utilization, which is being discussed globally. The utilization of GenAI is a global trend and is indispensable for future international business. Consequently, discussions on AI utilization in the IB field are becoming active as of 2025 (Lindner et al., 2025; Schmeisser et al., 2026). Within this context, discussing how GenAI utilization affects employees will serve as an empirical and theoretical foundation for developing research on GenAI utilization in the IB field. Furthermore, since GenAI has become unavoidable in facing international business, the arguments of this study offer useful suggestions for practitioners executing international business.

Second, this study provides a new perspective on methods to improve self-efficacy, which is valued even in the context of multinational enterprises (MNEs). According to Luthans et al. (2006), self-efficacy is related to organizational commitment and intention to turnover across cultures. In other words, in MNEs employing staff from various countries, self-efficacy is an important management item that influences employees' attitudes toward the organization beyond cultural backgrounds. Additionally, self-efficacy has been shown to be important in the context of expatriate adaptation and effectiveness (Black et al., 1991; Chen et al., 2010). Thus, this study, which proposes measures that may improve self-efficacy—considered important in MNEs—from the context of GenAI utilization, makes a significant contribution to the IB field.

Third, the analysis results of this study could influence GenAI diffusion policies in various countries. The results of this study are based on analysis in Japan, a relatively economically developed country where GenAI is spreading to some extent. However, it is known that there are various challenges regarding how to diffuse GenAI in developing countries (Mannuru et al., 2025). This study may have implications for the diffusion of GenAI in developing nations. By identifying the situation where GenAI utilization leads to self-efficacy, this study suggests that GAIA is essential. Therefore, even when introducing GenAI in developing countries, promoting usage in a form adapted to the country's situation (Appropriation) first, and then providing opportunities for education and usage in that state, may improve the self-efficacy of the population. If such effects are observed, many citizens will likely use GenAI more actively. The implications of this study can be said to be relevant to policies for the development of such developing countries.

7-4. Limitations and Future Research

Several limitations remain. First, there is the issue of data measurement. All variables in this study are based on self-reports, and the influence of Common Method Bias (CMB) may not have been completely eliminated. Although this study employed measures to exclude the possibility of CMB as much as possible, it has not been completely removed. Future research needs to enhance objectivity by utilizing actual GenAI usage data obtained from system logs or by using time-series data.

Second, there is the limitation of outcome indicators. Through interviews, this study focused on self-efficacy as a psychological indicator and clarified the relationship with job satisfaction in additional analyses. However, there are other important variables indicating employees' psychological states and attitudes, such as Organizational Commitment (Allen & Meyer, 1990), which indicates attachment and sense of belonging to the organization. Furthermore, there is a possibility to verify various variables beyond internal variables. It is desirable for future research to examine other outcome variables and quantitatively verify how GAIA influences them and what the moderating factors are.

Third, there is the verification of causality. Since this study is based on cross-sectional data, there is a limit to the strict identification of causal relationships. For instance, a reverse causal relationship where employees with high self-efficacy are more likely to promote GAIA is also conceivable. To clarify this point, longitudinal surveys tracking changes before and after AI introduction or experimental approaches involving educational interventions are required.

Addressing these challenges and further advancing the elucidation of the mechanism will lead to a deeper understanding of the management of new technologies and the collaboration between humans and AI currently under discussion.

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9.Appendix

9-1. Details of questionnaire

Dependent variables		
GAIA	Integrative Appropriation (IA)	Generative AI helps me develop problem-solving skills.
		Generative AI helps me to finish my work quickly.
		I feel confident that Generative AI aligns with our organization's goals.
		I trust the reliability of the responses generated by Generative AI.
	Adoptive Appropriation (AA)	I'm interested in using Generative AI functions.
		I'm willing to use Generative AI functions.
		I can validate my thought process through Generative AI.
	Customised Appropriation (CUA)	I have modified Generative AI to leverage its potential.
		I can't wait to invent new uses of Generative AI.
		I proactively seek updates to ensure optimal usage of Generative AI.
		I feel in control over Generative AI functions.
		I feel comfortable experimenting with different settings of Generative AI.
		I've modified my everyday work practices to leverage the possibilities of Generative AI.
	Interface Appropriation (IFA)	I find Generative AI user-friendly.
		Generative AI interface is very smooth.
		I think Generative AI can be used in multiple ways constructively.
	Ethical Appropriation (EA)	I think it is okay to use technology to suit to your benefit.
		I think it is okay to improperly use Generative AI if it suits the organization.
		I think it is okay to use Generative AI even beyond its general intent.

Independent variables		
Occupational Self Efficacy		I can remain calm when facing difficulties in my job because I can rely on my abilities.
		When I am confronted with a problem in my job, I can usually find several solutions.
		Whatever comes my way in my job, I can usually handle it.
		My past experiences in my job have prepared me well for my occupational future.
		I meet the goals that I set for myself in my job.
		I feel prepared for most of the demands in my job.
Job satisfaction		My job enables me to feel a sense of achievement.
		I'm pleased with my job.
		Whenever I do a good job, my boss or colleagues always appreciate me.
		I'm proud of my job.
		I think that my job worth doing.
		I'm satisfied with my job.
Moderator		
AI Usage	day	The average number of days per week the participant uses generative AI at work. (Scale: 0 to 7)
	time	The average time spent using generative AI on days when it is used, measured in minutes. (Continuous variable)
AI Education		How many times a year does your company hold formal education and training (seminars, study sessions, e-learning, etc.) on the use of AI tools?

Control		
Age		Participants selected their age group from categorical options (e.g., 25 or under, 26–30, 31–40, 41–50, 51 or older).
Gender		Participants indicated their gender. (Options: Male, Female, Prefer not to answer)
Education		Participants indicated their highest level of education completed (e.g., High school, Vocational school, University, Graduate school).
Working Experience		Participants reported the total duration of their employment at the current organization in months.
Management		Participants indicated their management level(e.g., Frontline staff, General employees, Technical specialists)
Routine		Participants estimated the percentage of their working hours spent on repetitive or routine tasks (Response range: 0–100%).
Company Size		The size of the organization categorized by the number of employees. (Options: Large enterprise (≥1,000), Medium-sized enterprise (100–999), Small enterprise (≤99))
AI Experience		Participants reported the total duration of their AI usage duration .
Industry		Participants selected the industry in which their company worked.
Job Type		Participants selected their job types.

9-2. Attributes of the interviewees of exploratory qualitative research

year/month/date	mode	Gender	Job description
2025/8/17	Face-to-Face	Male	Corporate DX and AI utilisation support
2025/10/24	Face-to-Face	Female	Generative AI promotion in a large IT company
2025/10/27	Online	Male	Management consulting and business management
2025/11/6	Online	Male	IT specialist engaged in AI education and application development