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# How Does the Use of Generative Artificial Intelligence Affect Employees' Cognitive and Non-Cognitive Abilities? A Study Based on Social Learning Theory

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## Abstract

Enterprises are vigorously promoting the deep integration of generative artificial intelligence into knowledge work scenarios, placing employees under realistic pressure regarding job adjustments. This pressure stems from AI beginning to intervene in employees' cognitive processes, which may serve as a lever for capability enhancement or may induce job substitution. Against this backdrop, whether generative AI helps employees improve their abilities or encourages them to outsource their thinking processes has become a core issue that urgently needs to be addressed. Based on social learning theory, this study treats AI as a virtual modeler and empirically examines the impact of AI usage intensity on employees' cognitive and non-cognitive abilities through an analysis of 677 questionnaire responses. The results show that AI usage intensity has a significant positive effect on employees' cognitive abilities, specifically across five dimensions: knowledge comprehension, text processing, information gathering, office software application, and language expression. This effect further transfers to the personality level, significantly enhancing employees' openness, extraversion, agreeableness, and conscientiousness, while inhibiting neurotic tendencies. Organizational type plays a moderating role, with the positive effect being significant only in non-public enterprises and institutions. This study extends social learning theory to the context of human–machine interaction, revealing the internalization pathway through which AI, as a virtual modeler, influences employees' ability development. It also examines the transfer effect of capabilities from cognition to personality, providing theoretical support and practical implications for the capability-enhancing effects of human–machine collaboration.

## Keywords

generative artificial intelligence, cognitive ability, non-cognitive ability, social learning theory

## 1. Introduction

In February 2026, Block Inc. laid off more than 4,000 employees under the pretext of using AI to improve quality and efficiency. Job adjustments aimed at cost reduction and efficiency gains continue to occur, placing employees under real pressure from layoffs, hiring freezes, and workforce downsizing. A 2025 Pew Research Center survey found that 52% of American workers are concerned about the impact of AI on their future jobs, and 32% believe it will reduce long-term employment opportunities. It is evident that AI has shifted from an auxiliary technology to a real force influencing organizational and labor structures [1]. For knowledge workers, the direct impact of AI comes from generative tools such as Doubao, Gemini, ChatGPT, and Copilot. Unlike algorithms embedded in the background, generative AI directly intervenes in employees' cognitive processes through dialogue, writing, searching, summarizing, translation, analysis, and creative generation. This means that its impact may not first manifest as job substitution, but rather in how employees use it to accomplish information acquisition, content generation, problem analysis, and decision support. Therefore, we should not only focus on changes in the number of jobs but also pay attention to the reshaping of cognitive processes, human–machine interaction patterns, changes in thinking habits, and the evolution of ability structures. A fundamental question thus emerges: Does generative AI help employees enhance their cognitive abilities and personality traits, or does it encourage them to outsource their thinking processes, thereby weakening independent judgment and intrinsic motivation? The answer to this question not only concerns the direction of AI application in organizations but also determines the fundamental adjustment of human resource management strategies.

Although existing studies have found that generative AI can improve the efficiency and quality of certain tasks [2–5], there remains a lack of systematic analysis regarding how it affects the process of employees' ability formation, particularly the differences in cognitive and non-cognitive abilities resulting from different usage patterns. Past scholars have mostly treated artificial intelligence as a technological object with fixed effects, believing that its utility is unilaterally determined by its technical attributes [6], while neglecting the agency of users. In fact, the actual utility of technology is continuously constructed and reshaped by users during the usage process [7]. Specifically, if employees regard AI as a partner that inspires thinking and maintain deep cognitive engagement during interaction, their abilities are more likely to develop positively. Conversely, if they merely treat AI as a tool to replace thinking and directly adopt its outputs without reflection, the autonomous development of their abilities may be inhibited [6]. This shift in perspective moves the analytical focus from the technology itself to the usage process, offering a new possibility for resolving existing theoretical divergences.

Based on the above analysis, this study starts from the employees' usage process and systematically explores the impact mechanism of artificial intelligence use on employees' ability development. It specifically focuses on three core questions: (1) how employees achieve ability enhancement through interaction with artificial intelligence; (2) whether this enhancement transfers from the cognitive level to the personality level; and (3) whether this process differs across different organizational contexts. To answer these questions, this study is grounded in social learning theory and treats generative artificial intelligence as a virtual modeler to examine the impact mechanism of intelligent tool use on employees' cognitive and non-cognitive abilities. Bandura's social learning theory posits that humans learn not only through direct experience but also by observing the behaviors and consequences of models, thereby acquiring new cognitive patterns and behavioral strategies. In human–machine interaction, generative artificial intelligence, through continuous linguistic interaction, demonstrates information processing methods, expression strategies, and cognitive behavioral styles to employees, providing observable and imitable learning materials. Whether employees can internalize these external models into their own abilities depends on the degree of cognitive engagement during interaction [8,9] and the learning atmosphere provided by organizational culture [10,11]. Based on this theoretical framework, this paper will sequentially examine the direct impact of generative AI usage intensity on employees' cognitive abilities, the transfer effect on non-cognitive abilities, and the moderating role of organizational type in the above pathways. The contributions of this study lie in extending social learning theory to the human–machine interaction context, revealing the transfer effect of generative AI on employees' cognitive and non-cognitive abilities, and clarifying the contextual boundaries of organizational learning culture. This provides actionable management insights for addressing corporate layoff dilemmas, optimizing human–machine collaboration models, and designing pathways for employee ability development.

## 2. Theoretical Foundation and Research Hypotheses

### 2.1 Human–Machine Interaction and Ability Reshaping from the Perspective of Social Learning Theory

Generative artificial intelligence is a computer technology that creates new content based on training with massive datasets. Its core feature lies in generating content with high-order logical thinking through interaction with external information [12,13]. As this technology becomes deeply embedded in knowledge work scenarios, a core question gradually emerges: When artificial intelligence takes on more and more cognitive tasks, are employees' cognitive abilities enhanced or gradually replaced? Existing research shows clear divergence. On the one hand, some scholars emphasize the augmentation effect of AI, arguing that human–machine collaboration can enhance humans' text comprehension, processing, and expression abilities [14,15]. On the other hand, some studies warn of the automation risks of AI, pointing out that over-reliance on algorithmic outputs can lead to cognitive laziness, skill degradation [16], and even algorithm confirmation bias [17,18].

This divergence implies a key issue: Why does artificial intelligence's impact on employees' abilities produce such diametrically opposed conclusions? The traditional technology-function perspective often treats AI as a technological object with fixed effects, assuming its utility is unilaterally determined by its technical attributes. Some scholars have found that the actual effects of technology largely depend on the agency users exercise during the technology usage process [7]. Social learning theory provides a critical perspective for understanding this interactive process. Bandura argues that humans learn not only through direct experience but also by observing models' behaviors and their consequences to acquire new cognitive patterns and behavioral strategies. In traditional contexts, models are usually "human"; in employees' interactions with generative AI, generative AI plays the role of a "modeler" through continuous linguistic interaction. To understand how employees achieve cognitive transformation from this interaction, it is necessary to further unpack the specific content output by AI as a "modeler" and the intermediate process by which employees internalize it into their own abilities.

First, as a modeler, the modeling content of generative artificial intelligence can be categorized into three types. (1) Information processing paradigms. This is reflected in AI's screening, classification, integration, and structured presentation of external information. For example, AI extracts key elements from complex information and organizes them logically; employees learn efficient information processing methods by observing this process. (2) Expression and execution strategies. At the linguistic level, AI adjusts tone, wording, and sentence structure according to the communication context to achieve effective delivery. At the task level, AI demonstrates a complete operational chain from problem identification to outcome completion and recommends corresponding tools and steps. Employees gradually improve communication quality and work efficiency by imitating its expression methods and execution paths. (3) Cognitive behavioral styles. This is the deepest level of modeling content, reflected in the stable behavioral tendencies and thinking habits that AI exhibits during interaction. For example, when facing open-ended questions, it explores multiple possibilities, demonstrating creative tendencies; when handling tasks, it follows systematic steps and repeated refinement, demonstrating systematic thinking; it maintains calm, emotion-free responses during interaction, demonstrating emotional stability; and it shows respect and cooperative attitudes in communication, demonstrating cooperative tendencies. The above content provides employees with observable and imitable thinking patterns and behavioral styles.

Second, the process by which employees transform external models into their own abilities involves three progressive stages. The first is attention and recognition. According to social learning theory, observational learning begins with the attention process. Whether individuals can learn from a model depends on whether they can capture the key features of the modeled behavior. Driven by tasks, employees actively allocate attentional resources to screen and identify the content of the demonstration. The second stage is encoding and storage. This stage corresponds to representational and symbolic encoding processes, in which individuals transform modeled behaviors into symbolic representations, internalizing external models into stable cognitive resources. Employees symbolically encode the identified demonstration content, forming memorable and reusable cognitive schemas or behavioral scripts. The final stage is the realization of ability acquisition through transfer and practice. This process corresponds to behavioral reproduction and motivational reinforcement. In subsequent independent tasks, employees consciously invoke the formed cognitive templates, and through repeated attempts, adjustments, and corrections, integrate them with their own knowledge structures, ultimately completing the transformation from external models to internal abilities. Among these, the first two stages focus on cognitive absorption and storage, while the third stage solidifies the model into stable abilities through repeated practice.

In the above process, employees' cognitive engagement plays a critical role. Cognitive engagement refers to the level of attentional resource allocation and cognitive effort during task execution. Research shows that activities with high cognitive engagement can significantly improve children's attention and executive function, thereby promoting cognitive development [19,20]. Accordingly, we can infer that when employees maintain high cognitive investment and reflective processing during interaction with artificial intelligence, they are more likely to achieve positive transfer of abilities and positive personality development across the full chain of attention, encoding, and transfer. Conversely, when employees merely treat artificial intelligence as a task execution tool and directly adopt its outputs without deep processing, their cognitive engagement decreases, and the autonomous development of abilities and self-shaping of personality may be inhibited. Thus, the impact of artificial intelligence on employees' ability development ultimately depends on the depth of users' engagement in interaction with generative AI, rather than the functional strength of the technology itself.

A large body of research confirms that cognitive abilities are malleable and can be enhanced through systematic training and interaction [21,22]. First, at the level of information processing paradigms, artificial intelligence demonstrates how to decompose complex problems, locate core information, and cross-verify multi-source content. For example, when studying "the impact of remote work on employee performance," AI demonstrates breaking down the problem into sub-problems, retrieving key information, and integrating it into an analytical framework. Employees internalize information literacy through repeated imitation [23]. Second, at the level of expression and execution strategies, AI demonstrates how to optimize communication expression and efficiently complete tasks. For instance, when writing project summary reports, AI adjusts expression style according to the audience, and employees master standardized expression by comparison [14]. In pivot table analysis, AI gradually demonstrates operational steps, and employees improve their application skills through imitation [11]. Finally, at the level of cognitive behavioral styles, AI demonstrates imitable thinking patterns and behavioral styles. In knowledge comprehension, AI explains complex concepts in multiple ways and shows their internal connections. For example, when explaining "diminishing marginal utility," AI uses definitions, examples, charts, and other multidimensional explanations. Through repeated observation, employees acquire systematic and creative thinking, thereby deepening knowledge understanding [15].

Based on the above analysis, this paper proposes the following hypotheses:

H1: Generative AI usage intensity has a significant positive effect on employees' cognitive abilities.

H1a: Generative AI usage intensity has a significant positive effect on employees' knowledge comprehension ability.

H1b: Generative AI usage intensity has a significant positive effect on employees' text processing ability.

H1c: Generative AI usage intensity has a significant positive effect on employees' information gathering ability.

H1d: Generative AI usage intensity has a significant positive effect on employees' office software application ability.

H1e: Generative AI usage intensity has a significant positive effect on employees' language expression ability.

## 2.2 From Cognition to Personality: The Transfer Effect of Generative AI on Employees' Non-Cognitive Abilities

Definitions of non-cognitive abilities vary across disciplines, yet considerable commonalities exist among the concepts [24]. Non-cognitive abilities generally refer to personality traits unrelated to intellectual factors, including openness, extraversion, conscientiousness, agreeableness, and neuroticism [25]. They play a role in individuals' work performance, career development, and life satisfaction that is equally important as cognitive abilities [26]. Unlike the relative stability of cognitive abilities, research in personality psychology has revealed that personality traits are malleable and undergo systematic changes through interactions with social experiences and environments [27–29]. There exists a long-term, bidirectional, and dynamic interaction between personality and work: personality not only influences job performance and career choices, but work experiences themselves also shape the evolutionary trajectory of personality traits [30]. In other words, the work context constitutes an important domain for personality development. Through prolonged task practice and interpersonal interactions, employees' behavioral patterns and emotional response styles continue to be adjusted and reshaped.

Bandura's social cognitive theory provides the core mechanism for understanding this shaping process: self-efficacy, that is, individuals' beliefs about their ability to successfully complete a given task. The enhancement of self-efficacy not only affects performance in specific tasks but also gradually alters individuals' overall self-perception of their capabilities through the "generalization of efficacy beliefs," thereby influencing their behavioral tendencies and emotional patterns [31]. A large body of empirical research has confirmed a stable association between self-efficacy and the Big Five personality traits: individuals with high self-efficacy typically exhibit higher levels of openness, extraversion, and conscientiousness, as well as lower neuroticism [32–34].

In human–machine interaction, generative AI enhances employees' self-efficacy through three pathways, thereby promoting positive development of personality traits. First, immediate reinforcement from task completion experiences. Studies have shown that self-efficacy plays a significant mediating role between generative AI use and learning achievement [35,36]. According to social cognitive theory, individuals obtain the most effective enhancement of self-efficacy through "mastery experiences." The rapid responses and high-quality outputs of AI enable employees to receive continuous positive feedback. For example, when using AI to complete complex analytical reports, the structured output framework leads employees to feel "I can accomplish this task," thereby significantly boosting self-efficacy. Second, the release of cognitive load and reallocation of resources. AI undertakes low-creativity tasks such as information retrieval, preliminary screening, and formatting, thereby liberating employees from routine operational labor [23]. When employees redirect their cognitive resources toward higher-order thinking and decision-making, their perception of their own abilities also improves. Third, the generalization of efficacy beliefs and personality transfer. As self-efficacy at the specific task level accumulates continuously, employees form a generalized belief that "I can effectively cope with challenges." This belief, drawing on the cognitive behavioral styles demonstrated by AI, permeates broader behavioral domains: creative thinking fosters the belief that "I can explore new possibilities," enhancing openness; systematic thinking reinforces the belief that "I can complete tasks systematically," strengthening conscientiousness; emotionally stable responses cultivate the belief that "I can handle pressure stably," reducing neuroticism; cooperative attitudes shape the belief that "I can interact cooperatively," improving agreeableness; and clear logical expression builds the belief that "I can express myself effectively," enhancing extraversion. Through the above mechanisms, employees internalize the behavioral styles exhibited by AI into their own thinking habits and interaction patterns, achieving positive development of personality traits.

Based on the above analysis, this paper proposes the following hypotheses:

H2: Generative AI usage intensity has a significant positive effect on employees' non-cognitive abilities.

H2a: Generative AI usage intensity has a significant positive effect on employees' openness.

H2b: Generative AI usage intensity has a significant positive effect on employees' extraversion.

H2c: Generative AI usage intensity has a significant positive effect on employees' agreeableness.

H2d: Generative AI usage intensity has a significant positive effect on employees' conscientiousness.

H2e: Generative AI usage intensity has a significant negative inhibitory effect on employees' neuroticism, that is, a significant positive effect on employees' emotion management ability.

### 2.3 The Moderating Role of Organizational Type: The Contextual Boundary of Modeling Effects

The pathway through which employees enhance their abilities through interaction with generative AI does not operate uniformly across all organizations. Organizational learning culture is a key contextual factor influencing learning behavior and knowledge transfer. Organizations with different ownership structures have developed differentiated institutional arrangements and cultural orientations over long-term development. Empirical studies have found that private enterprises exhibit a stronger learning atmosphere than state-owned enterprises [37]. This difference stems from the fundamentally different operational logics of the two types of organizations: public enterprises and institutions emphasize procedural compliance, risk avoidance, and outcome predictability, forming a culture centered on rule compliance with limited space for exploratory learning; non-public enterprises and institutions face market competition and rely on continuous innovation and rapid response, internalizing encouragement for exploratory learning, knowledge sharing, and independent thinking, thereby forming a more open and error-tolerant culture.

Differences in organizational learning culture regulate the dominant types of motivation employees exhibit in human–machine interaction by shaping their value perceptions of learning activities. According to self-determination theory, when the social environment supports the need for autonomy, individuals are more inclined to develop intrinsic motivation [38]. In organizations with a strong learning culture, learning is regarded as an intrinsically valuable activity; employees interact with AI to explore new knowledge and deepen understanding, making them more likely to engage in deep cognitive processing and treat AI outputs as resources for reflection and integration. In contrast, in organizations with a weak learning culture, learning is instrumentalized as a means to achieve performance goals; employees use AI out of tool-oriented motives aimed at pursuing efficiency and avoiding risks, tending to treat AI as an "answer generator" and use it in a shortcut manner, thereby weakening the beneficial effects of cognitive engagement. In summary, the systematic differences in organizational learning culture between public enterprises/institutions and non-public enterprises/institutions shape the level of cognitive engagement employees exhibit when using AI. In non-public enterprises and institutions, organizational learning culture is stronger, employees' motivations are more oriented toward intrinsic exploration, and they are more likely to achieve substantial improvement in cognitive abilities through deep interaction. In public enterprises and institutions, organizational learning culture is relatively weaker, employees' motivations are more oriented toward instrumental task completion, and even frequent use of AI yields relatively limited ability enhancement effects.

H3: Organizational type moderates the relationship between generative AI usage intensity and employees' cognitive abilities, such that the positive effect of generative AI usage intensity on employees' cognitive abilities is stronger in non-public enterprises and institutions.

# 3. Research Design

## 3.1 Data Sources and Sample Selection

This study employed a questionnaire survey method to collect data, targeting employees from various enterprises and public institutions in China. Employees were selected as the survey subjects rather than their supervisors, subordinates, or colleagues because the core issue of this study concerns the impact of generative artificial intelligence use on individuals' cognitive and non-cognitive abilities. Employees are both the direct users of artificial intelligence and the primary agents of ability change. According to the "first-person authority" theory, individuals' first-person statements regarding their own psychological states carry indisputable authority [39]. In psychology, ability is defined as the psychological characteristics necessary for an individual to successfully complete a certain activity [40]. Therefore, data obtained from the employees' perspective can most accurately reflect changes in their abilities. The questionnaire was distributed through the Credamo online survey platform. This platform is a leading online survey service in China, possessing a mature sample pool covering all provinces, industries, and age groups across the country. It has been widely used by domestic and international scholars in academic research in fields such as management and psychology [41], and can provide reliable sample data for this study.

The survey was conducted from September to December 2025. A total of 800 questionnaires were distributed. During the data cleaning stage, samples with missing values, obvious response patterns, abnormal completion times, or those that failed the attention check questions were removed. Ultimately, 677 valid questionnaires were obtained, yielding an effective response rate of 84.6%.

## 3.2 Variable Design and Measurement

### 3.2.1 Dependent Variables

**(1) Employees' Cognitive Ability**

The measurement of cognitive ability is primarily divided into scientific measurement and related-factor measurement. The former often employs standardized neurodevelopmental assessment tools, such as the Wechsler Scales and Raven's Progressive Matrices [42]; the latter is mostly based on Cattell's theory of fluid and crystallized intelligence [43]. Existing studies have found that working memory capacity tasks are highly correlated with fluid intelligence [44], and thus cognitive ability is often measured indirectly through the former [45]. Scholars define cognition as a series of mental processes involving the encoding, storage, retrieval, and use of sensory input [46]. Drawing on Anderson's classic definition, this study defines employees' cognitive ability as the set of mental activities that workers engage in during information processing, encompassing the acquisition, storage, processing, and application of knowledge. Referring to the measurement logic of the aforementioned related factors and combining the application characteristics of generative artificial intelligence in work scenarios, this study further divides cognitive ability into five dimensions: knowledge comprehension, text processing, information gathering, office software application, and language expression.

Knowledge comprehension and text processing abilities belong to the knowledge processing dimension, measuring the level of understanding of complex textual content and the efficiency of text drafting and polishing, respectively. Information gathering ability belongs to the knowledge acquisition dimension and is used to measure the speed of online information retrieval and screening. Office software application ability belongs to the knowledge application dimension and assesses the ability to use tools such as PPT, Excel, and Python to complete work tasks. Language expression ability belongs to the knowledge storage and application dimension and measures the clarity of verbal expression. Each dimension was measured using a single-item 7-point Likert scale. A composite index of cognitive ability was constructed using the mean method. Specific variable definitions are presented in Table 1.

**(2) Employees' Non-Cognitive Ability**

Non-cognitive ability is a rich and comprehensive concept. To date, the academic community has not reached a unified consensus on its definition and systematic measurement methods. Existing studies have applied more than ten approaches to measure non-cognitive abilities, including the Big Five personality framework, social-emotional competence framework, transferable skills framework, ACT behavioral skills, and KIPP framework [47]. Most studies draw upon the Big Five personality theory framework from personality psychology to derive and construct corresponding measurement indicators [48]. Based on the most widely used and authoritative Big Five personality indicators both domestically and internationally, and in conjunction with the specific dimensions through which generative AI influences employees' abilities, this study constructs the following proxy indicators:

Roccas argues that individuals high in openness are more creative and exploratory [49]; therefore, this study uses creativity as the measure of openness. Individuals high in extraversion are sociable, so communication skills are used as the measure of extraversion. Individuals high in agreeableness are typically friendly, helpful, and exhibit prosocial behavior; thus, empathy and altruistic behavior are selected as two indicators to measure agreeableness. Conscientiousness relates to goal setting, planning, and execution ability; therefore, reliability and time management ability are used as two indicators. Neuroticism concerns individuals' emotional stability; hence, negative emotion management ability is adopted as the measurement indicator. Items for each dimension were measured using a 7-point Likert scale. A composite index of non-cognitive ability was constructed using the mean method. Specific variable definitions are presented in Table 1.

*Table 1: Definition of Dependent Variables*

| Variable Dimension | Quantum Variable Dimension | Variable Definition | Variable Symbol | Variable Dimension | Quantum Variable Dimension | Variable Definition | Variable Symbol |
|---|---|---|---|---|---|---|---|
| Cognitive Ability | Knowledge comprehension ability | The ability of the occupant to understand the connotation of knowledge text. | CO1 | Non -cognitive Ability | Openness to Experience | Creativity: the ability to generate new ideas and create new things. | NCO1 |
| | Text processing ability | The text processing ability of the incumbent in their work. | CO2 | | Extraver -sion | Communication skills: the ability to understand others and to adapt your communication to the person and the situation. | NCO2 |
| | Information gathering ability | The ability of the occupant to find and screen a large amount of information through the Internet. | CO3 | | Agreeableness | Empathy: The cognitive awareness, grasp, and understanding of others' emotions and feelings from their perspective. | NCO3 |
| | Office software application ability | The candidate's ability to complete tasks using professional software including PowerPoint, Excel, PAD, and Python. | CO4 | | | Altruism: Voluntary acts of helping others without expecting anything in return. | NCO4 |
| | | | | | Conscien -tiousness | Reliability: The ability to complete tasks with high quality. | NCO5 |
| | | | | | | Time management ability: The ability to complete work tasks within a specified time. | NCO6 |
| | Language expression ability | The ability of a person to express his or her thoughts clearly in words. | CO5 | | Neuroticism | Negative emotion processing ability: The ability to process negative emotions such as anxiety, hostility, vulnerability, and stress. | NCO7 |

### 3.2.2 Independent Variable

Generative AI usage intensity refers to the frequency with which employees invoke generative AI tools in work scenarios. This study adopted a single-item measure, asking respondents about the average number of times they used it per day.

### 3.2.3 Moderating Variable

Organizational type refers to the ownership nature of the organization in which the employee works. This study divides organizational type into two categories: “public enterprises and institutions” and “non-public enterprises and institutions.” According to China’s regulations on the disclosure of government information, public enterprises and institutions refer to enterprises and public institutions that undertake social public service functions in accordance with the law. Public enterprises and institutions include government agencies, public institutions, and state-owned enterprises. Non-public enterprises and institutions include private enterprises, foreign-funded enterprises, Hong Kong-, Macao-, and Taiwan-funded enterprises, joint ventures, and other economic entities that do not undertake public service functions.

### 3.2.4 Control Variables

Referring to studies by Venkatesh, Kim, Liu Fangyuan, and others, and taking into account the specific context of generative AI use [50–52], this study selected the following variables that may influence employees’ cognitive and non-cognitive abilities as control variables: gender, age, position type, and usage manner. The definitions and coding of the independent variable, moderating variable, and control variables are shown in Table 2.

*Table 2: Definition of Independent Variables, Controlled Variables and Moderating Variables*

| Type of Variable | Variable Name | Variable Definition | Variable Symbol | Options Settings |
|---|---|---|---|---|
| Independent variable | Usage intensity | Frequency of using generative AI | FU | 1=less than once daily, 2=once daily or more |
| Controlled variable | Gender | Gender | Gender | 1=male, 2=female |
| | Age | Age | Age | 1=18-34 years old, 2=35-54 years old<br>3=≥55 years old |
| | Job Type | Job type in the organization | Position | 1=Organizational Coordination and Comprehensive Management<br>2=Science and Technology, R&D, and Innovation<br>3=Modern Services and Professional Support<br>4=Frontline Operations and Practical Operations |
| | Usage manner | Use and methods of generative AI | MU | 1=Outsourcing of cognition.<br>Quickly search for concepts, knowledge, or data you don't know.<br>Summarize and condense complex information. For example, provide complex text to AI, and AI will generate a summary.<br>Find instant solutions or steps for common work issues.<br>2=Human-machine collaboration.<br>Generate drafts of emails, reports, and proposals based on the points you provided.<br>Optimize, polish, expand, simplify, or translate your text.<br>Provide a specific framework or outline for your ideas.<br>For complex projects, you and AI engage in multiple rounds of dialogue to brainstorm and refine execution details.<br>Use AI to simulate specific roles for practice or analyze different perspectives. |

| Type of Variable | Variable Name | Variable Definition | Variable Symbol | Options Settings |
|---|---|---|---|---|
| | | | | Hand over long documents, data, or meeting minutes to AI to help analyze problems, insights, or risks.<br>3=Partially intelligent agent.<br>Create custom AI program templates for repetitive tasks.<br>Use AI APIs or advanced features to build decision-support or automation systems.<br>Guide other team members to use your custom AI program templates more effectively. |
| Moderating variable | Type of Organization | Nature of the organization | Orga_type | 1=Enterprises and Institutions,<br>2=Non-public Enterprises and Institutions |

### 3.3 Model Design

To test the research hypotheses, this study constructed multiple linear regression models for analysis. All regression models employed robust standard errors to address potential heteroscedasticity issues. Data analysis was conducted using SPSS 27.0 statistical software.

To examine the impact of generative AI usage intensity on employees' cognitive abilities, Model 1 was constructed:

$$Cognitive\_Ability=\beta_0+\beta_1\text{intensity}+\beta_2\text{gender}+\beta_3\text{age}+\beta_4\text{position}+\beta_5\text{manner}+\epsilon \quad (1)$$

where the dependent variable Cognitive_Ability represents each of the five dimensions of cognitive ability as well as the composite score of cognitive ability. The independent variable intensity denotes generative AI usage intensity. Control variables include gender, age, position type, and usage manner.

To examine the impact of generative AI usage intensity on employees' non-cognitive abilities, Model 2 was constructed:

$$Non\_Cognitive\_Ability=\beta_0+\beta_1 intensity+\beta_2 gender+\beta_3 age+\beta_4 position+\beta_5 manner+\varepsilon \quad (2)$$

where the dependent variable Non_Cognitive_Ability represents each of the five dimensions of non-cognitive ability as well as the composite score of non-cognitive ability. The settings for the independent variable and control variables are the same as in Model 1.

To test the moderating role of organizational type in the relationship between generative AI usage intensity and employees' cognitive abilities, Model 3 was constructed:

$$\begin{aligned} Cognitive\_Ability &=\beta_0+\beta_1 intensity+\beta_2 gender+\beta_3 age+\beta_4 position \\ &+\beta_5 manner+\beta_6 organization + \beta_7 intensity\times organization+\varepsilon \end{aligned} \quad (3)$$

where organization represents organizational type, and intensity × organization is the interaction term between usage intensity and organizational type. If the coefficient $\beta_7$of the interaction term is significant, it indicates that organizational type exerts a moderating effect between usage intensity and cognitive ability. To further examine the direction of the moderating effect, simple slope analysis will be conducted to test the predictive effect of usage intensity on cognitive ability in the two subsamples of public enterprises/institutions and non-public enterprises/institutions, respectively.

## 4. Data Analysis Results

### 4.1 Descriptive Statistics and Correlation Analysis

This study is based on 677 valid questionnaire responses. The sample covers employees across different genders, age groups, position types, organizational types, and generative AI usage behaviors. The specific distribution is presented in Table 3. Among the respondents, females accounted for 60.6%, and the 35–54 age group constituted the main body, accounting for 81.1%. In terms of position types, organizational coordination and comprehensive management positions had the highest proportion at 32.3%. Non-public enterprises and institutions accounted for 68.7%. High-frequency generative AI use (on average once or more per day) accounted for 45.2%, and the primary usage manner was task collaboration, accounting for 66.2%. The sample distribution aligns well with the actual structure of China's employed population and organizational types, demonstrating good representativeness.

*Table 3: Descriptive Statistics*

| Variables | | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 267 | 39.4 |
| | Female | 410 | 60.6 |
| Age | 18-34 years old | 56 | 8.3 |
| | 35-54 years old | 549 | 81.1 |
| | ≥55 years old | 72 | 10.6 |
| Job Type | Organizational Coordination and Comprehensive Management | 219 | 32.3 |
| | Science and Technology, R&D, and Innovation | 177 | 26.1 |
| | Modern Services and Professional Support | 186 | 27.5 |
| | Frontline Operations and Practical Operations | 95 | 14.0 |
| Type of Organization | Enterprises and Institutions | 212 | 31.3 |
| | Non-public Enterprises and Institutions | 465 | 68.7 |
| Usage Intensity | less than once daily | 371 | 54.8 |
| | once daily or more | 306 | 45.2 |
| Usage Manner | Outsourcing of Cognition | 197 | 29.1 |
| | Human-machine Collaboration. | 448 | 66.2 |
| | Partially Intelligent Agent | 32 | 4.7 |

Table 4 presents the correlations among the research variables. It can be seen that generative AI usage intensity is significantly correlated with cognitive abilities—including knowledge comprehension, text processing, information gathering, office software application, and language expression—as well as non-cognitive abilities, including openness, extraversion, agreeableness, conscientiousness, and neuroticism.

*Table 4: Correlation Analysis of Variables*

| | Usage intensity | Knowledge comprehension | Text processing | Information gathering | Office software application | Language expression | Openness to Experience | Extra-version | Agreeableness | Conscientious-ness | Neuroticism | Cognitive | Non-cognitive |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Usage intensity | -- | | | | | | | | | | | | |
| Knowledge comprehension | .210** | -- | | | | | | | | | | | |
| Text processing | .180** | .274** | -- | | | | | | | | | | |
| Information gathering | .190** | .279** | .137** | -- | | | | | | | | | |
| Office software application | .135** | .277** | .235** | .146** | -- | | | | | | | | |
| Language expression | .117** | .295** | .315** | .198** | .283** | -- | | | | | | | |
| Openness to Experience | .109** | .341** | .337** | .196** | .264** | .357** | -- | | | | | | |
| Extraversion | .098* | .257** | .214** | .100** | .281** | .448** | .262** | -- | | | | | |
| Agreeableness | .150** | .356** | .226** | .216** | .327** | .482** | .381** | .415** | -- | | | | |
| Conscientious-ness | .191** | .283** | .322** | .255** | .334** | .332** | .320** | .232** | .296** | -- | | | |
| Neuroticism | .153** | .189** | .142** | .093* | .279** | .329** | .266** | .348** | .415** | .243** | -- | | |
| Cognitive | .260** | .644** | .630** | .550** | .614** | .699** | .477** | .423** | .517** | .487** | .335** | -- | |
| Non-cognitive | .211** | .428** | .364** | .264** | .442** | .580** | .635** | .633** | .797** | .634** | .653** | .668** | -- |

*Note: **. Significance at the 0.01 level (two-tailed). *. Significance at the 0.05 level (two-tailed).*

## 4.2 Main Effect Test: The Impact of Generative AI Usage Intensity on Cognitive Ability

Logistic multiple regression analysis was employed to examine the main effects of generative AI usage intensity on overall cognitive ability and its various dimensions, while controlling for variables including gender, age, position type, and usage manner. Table 5 reports the regression results for overall cognitive ability. The regression coefficient is 0.302 and is significant at the 0.001 level, indicating that generative AI usage intensity has a significant positive effect on overall cognitive ability. Thus, Hypothesis H1 is empirically supported. Regarding the regression results for each dimension of cognitive ability: In the knowledge comprehension model, the coefficient of usage intensity is 0.336 and significant at the 0.001 level, supporting H1a. In the text processing model, the coefficient is 0.330 and significant at the 0.001 level, supporting H1b.

In the information gathering model, the coefficient is 0.356 and significant at the 0.001 level, supporting H1c. In the office software application model, the coefficient is 0.236 and significant at the 0.01 level, supporting H1d. In the language expression model, the coefficient is 0.251 and significant at the 0.01 level, supporting H1e.

*Table 5: Regression Analysis of Cognitive Ability with Generative AI Usage Intensity*

| Variables | Knowledge comprehension | | Text processing | | Information gathering | | Office software application | | Language expression | | Cognitive | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M1 | M2 | M1 | M2 | M1 | M2 | M1 | M2 | M1 | M2 | M1 | M2 |
| Constant | 5.398*** | 5.011*** | 5.665*** | 5.156*** | 5.687*** | 5.323*** | 5.958*** | 5.440*** | 5.871*** | 5.322*** | 5.716*** | 5.250*** |
| | (0.320) | (0.343) | (0.283) | (0.301) | (0.274) | (0.294) | (0.239) | (0.252) | (0.274) | (0.290) | (0.175) | (0.182) |
| Controlled variable | | | | | | | | | | | | |
| Gender | -0.081 | -0.067 | -0.043 | -0.025 | -0.059 | -0.045 | -0.174** | -0.155* | -0.012 | 0.008 | -0.074 | -0.057 |
| | (0.085) | (0.084) | (0.075) | (0.074) | (0.073) | (0.072) | (0.063) | (0.062) | (0.072) | (0.071) | (0.046) | (0.045) |
| Age | 0.201* | 0.207* | 0.104 | 0.112 | 0.018 | 0.024 | 0.009 | 0.017 | -0.001 | 0.008 | 0.066 | 0.073 |
| | (0.096) | (0.096) | (0.085) | (0.084) | (0.083) | (0.082) | (0.072) | (0.071) | (0.083) | (0.081) | (0.053) | (0.051) |
| Job type | -0.069 | -0.059 | -0.044 | -0.032 | -0.049 | -0.040 | -0.012 | 0.000 | 0.023 | 0.036 | -0.030 | -0.019 |
| | (0.040) | (0.040) | (0.035) | (0.035) | (0.034) | (0.034) | (0.030) | (0.029) | (0.034) | (0.033) | (0.022) | (0.021) |
| Usage manner | -0.049 | -0.068 | 0.127 | 0.102 | 0.081 | 0.063 | -0.014 | -0.039 | 0.032 | 0.005 | 0.035 | 0.013 |
| | (0.079) | (0.079) | (0.070) | (0.069) | (0.068) | (0.068) | (0.059) | (0.058) | (0.068) | (0.067) | (0.043) | (0.042) |
| Independent variable | | | | | | | | | | | | |
| Usage intensity | | 0.251** | | 0.330*** | | 0.236*** | | 0.336*** | | 0.356*** | | 0.302*** |
| | | (0.083) | | (0.073) | | (0.071) | | (0.061) | | (0.070) | | (0.044) |
| $R^2$ | 0.014 | 0.027 | 0.010 | 0.039 | 0.007 | 0.023 | 0.011 | 0.054 | 0.001 | 0.038 | 0.010 | 0.074 |
| $\Delta R^2$ | 0.014* | 0.013** | 0.010 | 0.029*** | 0.007 | 0.016*** | 0.011 | 0.043*** | 0.001 | 0.037*** | 0.010 | 0.064*** |
| F | 2.433* | 3.795** | 1.732 | 5.506*** | 1.115 | 3.102** | 1.952 | 7.663*** | 0.170 | 5.269*** | 1.764 | 10.803*** |
| N | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 |

*Note: Standard error is shown in parentheses; dependent variable is cognitive ability; *p <0.05, **p <0.01, **p <0.001.

## 4.3 Main Effect Test: The Impact of Generative AI Usage Intensity on Non-Cognitive Ability

Consistent with the analysis of cognitive ability, logistic multiple regression analysis was used to test the main effect of generative AI usage intensity on overall non-cognitive ability and its various dimensions, controlling for gender, age, position type, and usage manner. The results in Table 6 show that the regression coefficient of usage intensity for non-cognitive ability is 0.248, significant at the 0.1% level, indicating that generative AI usage intensity has a significant positive effect on overall non-cognitive ability.

At the dimensional level: In the openness model, the coefficient of usage intensity is 0.202 and significant at the 5% level, indicating a significant positive effect on openness. In the extraversion model, the coefficient is 0.212 and significant at the 1% level, showing a significant positive effect on extraversion. In the agreeableness model, the coefficient is 0.237 and significant at the 0.1% level, verifying the positive effect on agreeableness. In the conscientiousness model, the coefficient is 0.257 and significant at the 0.1% level, indicating a significant positive effect on conscientiousness. In the neuroticism model, the coefficient is 0.334 and significant at the 0.1% level, suggesting that the positive effect of usage intensity on neuroticism is the most pronounced. In summary, Hypotheses H2, H2a, H2b, H2c, H2d, and H2e are all supported.

*Table 6: Regression Analysis of Non-Cognitive Ability with Generative AI Usage Intensity*

| Variables | Openness to Experience | | Extra version | | Agreeableness | | Conscientiousness | | Neuroticism | | Non-cognitive | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M1 | M2 | M1 | M2 | M1 | M2 | M1 | M2 | M1 | M2 | M1 | M2 |
| **Constant** | 5.732*** | 5.421*** | 5.845*** | 5.518*** | 5.458*** | 5.092*** | 5.820*** | 5.424*** | 5.571*** | 5.055*** | 5.672*** | 5.290*** |
| | (0.321) | (0.345) | (0.309) | (0.332) | (0.260) | (0.278) | (0.207) | (0.220) | (0.338) | (0.361) | (0.184) | (0.195) |
| **Controlled variable** | | | | | | | | | | | | |
| Gender | -0.197* | -0.186* | -0.087 | -0.075 | -0.155* | -0.141* | -0.049 | -0.035 | -0.214* | -0.195* | -0.129** | -0.116* |
| | (0.085) | (0.085) | (0.082) | (0.082) | (0.069) | (0.068) | (0.055) | (0.054) | (0.090) | (0.089) | (0.049) | (0.048) |
| Age | 0.131 | 0.136 | 0.018 | 0.023 | 0.072 | 0.078 | 0.057 | 0.063 | 0.067 | 0.075 | 0.068 | 0.074 |
| | (0.097) | (0.097) | (0.093) | (0.093) | (0.079) | (0.078) | (0.063) | (0.062) | (0.102) | (0.101) | (0.056) | (0.055) |
| Job type | -0.119** | -0.111** | -0.045 | -0.037 | -0.089** | -0.080* | -0.036 | -0.027 | -0.073 | -0.060 | -0.070** | -0.061** |
| | (0.040) | (0.040) | (0.038) | (0.038) | (0.032) | (0.032) | (0.026) | (0.025) | (0.042) | (0.042) | (0.023) | (0.023) |
| Mode of use | 0.142 | 0.127 | -0.153* | -0.169* | 0.118 | 0.100 | 0.071 | 0.052 | 0.007 | -0.018 | 0.053 | 0.035 |
| | (0.080) | (0.080) | (0.077) | (0.077) | (0.065) | (0.064) | (0.051) | (0.051) | (0.084) | (0.083) | (0.046) | (0.045) |

| Variables | Openness to Experience | | Extra version | | Agreeableness | | Conscientiousness | | Neuroticism | | Non-cognitive | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M1 | M2 | M1 | M2 | M1 | M2 | M1 | M2 | M1 | M2 | M1 | M2 |
| **Independent variable** | | | | | | | | | | | | |
| Usage intensity | | 0.202* | | 0.212** | | 0.237*** | | 0.257*** | | 0.334*** | | 0.248*** |
| | | (0.084) | | (0.081) | | (0.067) | | (0.053) | | (0.088) | | (0.047) |
| R² | 0.030 | 0.038 | 0.009 | 0.019 | 0.026 | 0.043 | 0.009 | 0.042 | 0.014 | 0.035 | 0.029 | 0.067 |
| Δ R² | 0.030*** | 0.008* | 0.009 | 0.010** | 0.026*** | 0.018*** | 0.009 | 0.033*** | 0.014 | 0.021*** | 0.029*** | 0.038*** |
| F | 5.125*** | 5.290*** | 1.589 | 2.664* | 4.450*** | 6.090*** | 1.475 | 5.852*** | 2.331 | 4.809*** | 5.027*** | 9.666*** |
| N | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 | 677 |

**Note: Standard error is shown in parentheses; dependent variable is cognitive ability; *p <0.05, **p <0.01, **p <0.001.*

## 4.4 Moderating Effect Test: The Moderating Role of Organizational Type

To examine the moderating role of organizational type in the relationship between generative AI usage intensity and cognitive ability, the moderating variable (organizational type) and the interaction term "usage intensity × organizational type" were added to the main effect model. As shown in Table 7, the change in $\Delta R^2$ is 0.0090 and significant at the 0.05 level. The coefficient of the interaction term "usage intensity × organizational type" is 0.2437, which is significantly positive at the 0.05 level ($p = 0.0105$). This indicates that organizational type exerts a significant positive moderating effect between generative AI usage intensity and cognitive ability.

To further clarify the specific effects under different organizational types, simple slope analysis was conducted. The results show that when the organizational type is public enterprises and institutions, the predictive effect of generative AI usage frequency on cognitive ability is not significant (Effect = 0.1347, $p = 0.0873$). When the organizational type is non-public enterprises and institutions, generative AI usage frequency has a significant positive predictive effect on cognitive ability (Effect = 0.3784, $p < 0.001$). These findings indicate that the positive impact of generative AI usage intensity on employees' cognitive abilities is contingent upon organizational type. The effect is significant only in non-public enterprises and institutions, but not significant in public enterprises and institutions. Therefore, Hypothesis H3 is supported.

*Table 7: Regulatory Effect Analysis by Type of Organization*

| Variables | Cognitive Ability | | Type of Organization |
|---|---|---|---|
| | M1 | M2 | M3 |
| Constant | 5.723*** | 5.255*** | 5.8570*** |
| | (0.195) | (0.201) | (0.3081) |
| Controlled variable | | | |
| Gender | -0.074 | -0.057 | -0.0641 |
| | (0.046) | (0.045) | (0.0448) |
| Age | 0.066 | 0.073 | 0.0698 |
| | (0.053) | (0.051) | (0.0510) |
| Job type | -0.030 | -0.019 | -0.0139 |
| | (0.022) | (0.021) | (0.0211) |
| Usage manner | 0.035 | 0.013 | 0.0148 |
| | (0.043) | (0.042) | (0.0420) |
| Independent variable | | | |
| Usage intensity | | 0.302*** | -0.1090 |
| | | (0.044) | (0.1661) |
| Moderating variable | | | |
| Type of organization | | | -0.3572*<br>(0.1460) |
| Interaction term | | | |
| Usage intensity × Type of organization | | | 0.2437*<br>(0.0950) |
| R² | 0.010 | 0.075 | 0.0835 |
| Δ R² | 0.010 | 0.064*** | 0.0090* |
| F | 1.411 | 8.990*** | 8.7093*** |
| N | 677 | 677 | 677 |

**Note: Standard error is shown in parentheses; dependent variable is cognitive ability; *p <0.05, **p <0.01, **p <0.001.*

## 5. Conclusion

Based on social learning theory, this study treats generative artificial intelligence as a virtual modeler and systematically examines the impact mechanism of employees' interaction with intelligent tools on their cognitive and non-cognitive abilities, while analyzing the contextual boundary of organizational type in this process. This study empirically investigates the effects of generative AI, viewed as a virtual modeler, on employees' cognitive and non-cognitive abilities. The findings reveal that AI usage intensity significantly and positively influences employees' cognitive abilities across the dimensions of knowledge comprehension, text processing, information gathering, office software application, and language expression. This effect further transfers to the personality level, enhancing openness, extraversion, agreeableness, and conscientiousness, while inhibiting neurotic tendencies. Organizational type plays a moderating role, with the positive effect being significant only in non-public enterprises and institutions.

At the theoretical level, this study extends social learning theory to the context of human–machine interaction. It reveals that generative AI acts as a virtual modeler through three levels—information processing paradigms, expression and execution strategies, and cognitive behavioral styles. Employees transform external demonstrations into their own abilities through processes of attention, encoding, and transfer. This addresses the gap in prior research regarding insufficient attention to micro-level usage processes. The study also identifies a cross-level transfer effect of AI use on employees' abilities: the diverse exploratory, systematic thinking, emotional stability, and cooperative attitudes demonstrated by AI provide employees with observable and imitable models. Through continuous observation, imitation, and practice, employees internalize these into their own thinking habits and behavioral patterns, achieving cross-level transfer from cognition to personality. Furthermore, by introducing organizational type as a moderating variable, the study uncovers the contextual boundary of organizational learning culture: non-public enterprises and institutions, facing market competition, develop open and error-tolerant learning cultures, leading employees to view AI more as an object for exploration and collaboration. In contrast, public enterprises and institutions emphasize procedural compliance and risk avoidance, resulting in weaker learning cultures; employees tend to use AI primarily out of task-completion motives. This provides a new explanatory logic for understanding the organizational contingency of AI effects.

At the practical level, this study offers three implications for organizations seeking to optimize human–machine collaboration models. First, the focus of evaluation should shift from usage frequency to interaction quality. Managers can establish human–machine collaborative innovation awards to recognize cases of deep interaction through multi-round dialogues, follow-up questioning, and creative iteration, and incorporate interaction quality into performance evaluation systems. Second, differentiated usage scenario guidelines should be developed. Business backbone staff and AI experts can jointly compile scenario manuals that clarify interaction strategies for different tasks—such as creative ideation, information gathering, solution optimization, and routine execution—and establish a case library to help employees learn from successful experiences. Third, a reflective communication mechanism for human–machine collaboration should be established. Regular review meetings can be held to share confusions, discoveries, and breakthroughs. Employees should be encouraged to write collaboration logs to document insights and behavioral adjustments, transforming individual interactions into organizational-level learning resources.

Future research can be extended in the following directions. Regarding the heterogeneity of generative AI tool types, this study treats various tools as relatively unified virtual modelers. Subsequent studies could refine tool categories, compare the differential roles of different tools in employees' ability development, and explore their respective influence pathways and boundary conditions. Regarding the mechanisms of organizational context, this study found that organizational type moderates the relationship between AI use and cognitive ability. Future research could employ qualitative methods to conduct in-depth interviews with employees who frequently use AI in typical organizations, or use quantitative approaches to integrate organizational-level factors (learning culture, leadership style, incentive mechanisms) with individual-level usage behavior and ability changes into a unified model, thereby revealing the deeper mechanisms through which organizational context operates. Regarding the differentiated effects of human–machine interaction patterns, this study primarily focused on the impact of usage intensity. Future studies could further examine employees' interaction modes with AI, conduct detailed analysis of interaction processes using usage logs, identify different usage patterns (e.g., exploratory, utilitarian, and collaborative), and adopt longitudinal research designs to explore the dynamic relationships between these patterns and changes in employees' abilities. This would provide more targeted guidance for organizations to optimize human–machine collaboration models.

## References


[1] Dong, Z., Aziz, M. F. A., & Wang, Y. (2025). An empirical analysis of how artificial intelligence development influences the adjustment of human capital structure. *Finance Research Letters*, 84.

[2] Brynjolfsson, E., Li, D., & Raymond, L. (2023). Generative AI at Work. *SSRN Electronic Journal*.

[3] Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 381, 187–192.

[4] Naqbi, H., Bahroun, Z., & Ahmed, V. (2024). Enhancing Work Productivity through Generative Artificial Intelligence: A Comprehensive Literature Review. *Sustainability*.

[5] Zhou, E., & Lee, D. (2024). Generative artificial intelligence, human creativity, and art. *PNAS Nexus*, 3.

[6] Li, Y. H., & Xue, J. X. (2026). How does the use of generative artificial intelligence affect employees' innovative performance? A heuristic-systematic perspective. *Nankai Business Review*, 1–39.

[7] Leonardi, P. M., Barley, S. R.. What's under construction here? *Academy of Management Annals*, 2010, 4(1): 1–51.

[8] Gibson, S. (2004). Social Learning (Cognitive) Theory and Implications for Human Resource Development. *Advances in Developing Human Resources*, 6, 193–210.

[9] Teng, D., X. Zhou, H. Al-Samarraie, and L. Fang. 2026. Enhancing Critical Thinking and Self-Efficacy With GenAI: A Social Cognitive Perspective Using Structural Equation Modelling. *Journal of Computer Assisted Learning*, 42, no. 1: e70176.

[10] Egan, T., Yang, B., & Bartlett, K. (2004). The effects of organizational learning culture and job satisfaction on motivation to transfer learning and turnover intention. *Human Resource Development Quarterly*, 15, 279–301.

[11] Callari, T. C., & Puppione, L. (2025). Can Generative Artificial Intelligence Productivity Tools Support Workplace Learning? A Qualitative Study on Employee Perceptions in a Multinational Corporation. *Journal of Workplace Learning*. Advance online publication.

[12] Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., & Varma, A. (2023) Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, 33(3): 606–659.

[13] Vanneste, B. S., Puranam, P. (2024). Artificial intelligence, trust, and perceptions of agency. *Academy of Management Review*, Advance online.

[14] Liu, Y., Park, J., & McMinn, S. (2024). Using generative artificial intelligence/ChatGPT for academic communication: Students' perspectives. *International Journal of Applied Linguistics*. 34 (4), 1437–1461.

[15]Zhang, H. , & Wang, Q. (2025). How could genai work on in-service teachers' knowledge building process? an empirical study based on epistemic network analysis. *International Journal of Educational Technology in Higher Education*, 22(1).

[16] Macnamara, B., Berber, I., Çavusoglu, M., Krupinski, E., Nallapareddy, N., Nelson, N., Smith, P., Wilson-Delfosse, A., & Ray, S. (2024). Does using artificial intelligence assistance accelerate skill decay and hinder skill development without performers' awareness? *Cognitive Research: Principles and Implications*, 9.

[17] Wang, Y. Y., Huang, P. P., Jin, Y. H., Xu, L., & Wu, W. Y. (2024). Technological hollowing-out of knowledge workers in manufacturing under the background of artificial intelligence: Conceptualization, formation, and influence mechanisms. *Advances in Psychological Science*, 32(12), 2005–2017.

[18] Natali, C., Marconi, L., Duran, L., & Cabitza, F. (2025). AI-induced Deskilling in Medicine: A Mixed-Method Review and Research Agenda for Healthcare and Beyond. *Artificial Intelligence Review*, 58.

[19] Schmidt, M., Benzing, V., & Kamer, M. (2016). Classroom-Based Physical Activity Breaks and Children's Attention: Cognitive Engagement Works. *Frontiers in Psychology*, 7.

[20] Egger, F., Benzing, V., Conzelmann, A., & Schmidt, M. (2019). Boost your brain, while having a break! The effects of long-term cognitively engaging physical activity breaks on children's executive functions and academic achievement. *PLoS ONE*, 14.

[21] Hardy, J., Nelson, R., Thomason, M., Sternberg, D., Katovich, K., Farzin, F., & Scanlon, M. (2015). Enhancing Cognitive Abilities with Comprehensive Training: A Large, Online, Randomised, Active-Controlled Trial. *PLoS ONE*, 10.

[22] Von Bastian, C., Belleville, S., Udale, R., Reinhartz, A., Essounni, M., & Strobach, T. (2022). Mechanisms underlying training-induced cognitive change. *Nature Reviews Psychology*, 1, 30–41.

[23] Balinas, E. (2025). The Impact of Generative Artificial Intelligence on University Information Literacy Education: A Systematic Review from Challenges to Changes. *International Journal of Latest Technology in Engineering Management & Applied Science*.

[24] Heckman, J. J. (2011). Integrating personality psychology into economics. *NBER Working Papers*, 33(3): 1–31.

[25] Costa JR P T, McCrae R R. (1988). From Catalogue to Classification: Murray's Needs and the Five-Factor Model. *Journal of Personality and Social Psychology*, 55(2): 258–265.

[26] Roberts, B. W., Kuncel, N. R., et al. (2007) The Power of Personality: The Comparative Validity of Personality Traits, Socioeconomic Status, and Cognitive Ability for Predicting Life Outcomes. *Perspectives on Psychological Science*, 2(4): 313–345.

[27] Specht, J., Egloff, B., & Schmukle, S. (2011). Stability and change of personality across the life course: the impact of age and major life events on mean-level and rank-order stability of the Big Five. *Journal of Personality and Social Psychology*, 101 (4), 862–82.

[28] Roberts, B. W., Luo, J., Briley, D. A., Chow, P. I., Su, R., & Hill, P. L. (2017). A systematic review of personality trait change through intervention. *Psychological Bulletin*, 143(2), 117.

[29] Bühler, J., Orth, U., Bleidorn, W., Weber, E., Kretzschmar, A., Scheling, L., & Hopwood, C. (2023). Life Events and Personality Change: A Systematic Review and Meta-Analysis. *European Journal of Personality*, 38, 544–568.

[30] Woods, S. A., Lievens, F., Fruyt, F. D., & Wille, B. (2013). Personality across working life: the longitudinal and reciprocal influences of personality on work. *Journal of Organizational Behaviour*, 34(S1): S7–S25.

[31] Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2): 191-215.

[32] Caprara, G. V., Vecchione, M., Alessandri, G., Gerbino, M., & Barbaranelli, C. (2011). The contribution of personality traits and self-efficacy beliefs to academic achievement: a longitudinal study. *British Journal of Educational Psychology*, 81(1):78–96.

[33] Stajkovic, A. D., Bandura, A., Locke, E. A., Lee, D., & Sergent, K. (2018). Test of three conceptual models of the influence of the Big Five personality traits and self-efficacy on academic performance: a meta-analytic path analysis. *Personality and Individual Differences*, 120, 238–245.

[34] Furnham, A., & Cheng, H. (2023). The Big-Five personality factors, cognitive ability, health, and social-demographic indicators as independent predictors of self-efficacy: A longitudinal study. *Scandinavian Journal of Psychology*.

[35] Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023) The relationship between student interaction with generative artificial intelligence and learning achievement: Serial mediating roles of self-efficacy and cognitive engagement. *Frontiers in Psychology*, 14.

[36] Shahzad, M., Xu, S., & Zahid, H. (2024). Exploring the impact of generative AI-based technologies on learning performance through self-efficacy, fairness & ethics, creativity, and trust in higher education. *Education and Information Technologies*, 30, 3691–3716.

[37]Wang, X. H., &Yang, B. Y. (2007). The culture of learning organizations in Chinese state-owned and privately-owned enterprises: An empirical study. *Frontiers of Business Research in China*, 1(002), 275–299.

[38] Ryan, R. M., & Deci, E. L.. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *The American Psychologist*, 55(1), 68–78.

[39] Davidson, D. (1984). First Person Authority. *Dialectica*, 38 (2/3).

[40] Guo, L. Y. (Ed.). (2002). *Psychology*. Nanjing: Nanjing University Press.

[41] Credamo Insights. (2025). Technology Empowering Research, Education and Business. *Monthly Journal of Technology Entrepreneurship*, 38(08): 2.

[42] Williams, M., Corn, E., Ransanz, S., Berl, M., Andringa-Seed, R., & Mulkey, S. (2024). Neurodevelopmental assessments used to measure preschoolers' cognitive development in Latin America: a systematic review. *Journal of Paediatric Psychology*.

[43] R.B. Cattell. (1943). The description of personality: Basic traits resolved into clusters. *The Journal of Abnormal and Social Psychology*, 38 (4), 476–506.

[44] Wilhelm, O., Hildebrandt, A. and Oberauer, K. (2013) What is working memory capacity, and how can we measure it? *Front. Psychol*. 4:433.

[45] Rozgonjuk, D., Schmitz, F., Kannen, C., & Montag, C. (2021). Cognitive ability and personality: Testing broad to nuanced associations with a smartphone app. *Intelligence*, 88, 101578.

[46] Anderson, J. R. (2010). *Cognitive Psychology and its Implications* (7th ed.). Worth Publishers.

[47]Zhou,J.Y. (2020). The concept and measurement progress of non-cognitive skills. *Global Education*, 49(5), 53–66.

[48] Gosling, S. D., Rentfrow, P. J., Swann, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, 37(6), 504–528.

[49] Roccas, S., Sagiv, L., Schwartz, S. H., Knafo, A. (2002).The big five personality factors and personal values. *Personality and Social Psychology Bulletin*, 28(6), 789–801.

[50] Venkatesh, V., Morris, M., & Ackerman, P. (2000). A Longitudinal Field Investigation of Gender Differences in Individual Technology Adoption Decision-Making Processes. *Organizational Behavior and Human Decision Processes*, 83 (1), 33–60 .

[51] Liu, F. Y., & Hu, Z. Y. (2025). Generative artificial intelligence and employees' digital creativity. *Journal of Technical Economics & Management*, (10), 116–123.

[52] Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of Generative AI System Adoption and Usage Behavior in Korean Companies: Applying the UTAUT Model. *Behavioral Sciences*, 14.



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