Exploring Job Happiness Across Asian Countries: Factors, Challenges, and Strategies for Enhancing Employee Well-Being and Organizational Performance

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Abstract. With the generalized usage of artificial intelligence (AI) in the workplace, the influence on the efficiency, Human–AI trust, and task suitability of knowledge workers has become increasingly profound. Through literature analysis and theoretical exploration, this study develops an integrated model of AI tools and knowledge worker performance, examining how AI enhances the performance of knowledge workers. The findings indicate that AI tools can enhance efficiency in tasks of low complexity and AI tools in high complexity tasks tend to function as assistive tools. The establishment of Human–AI trust depends on the interpretability, transparency and feedback mechanisms of AI systems, which promote greater willingness of using AI tools. Excessive reliance on AI may weaken the capacity of knowledge workers for independent thinking and innovation. By dynamically allocating decision authority and establishing Human–AI trust, organizations can promote collaborative development between humans and AI and improve the performance of the employees.

Keywords: Artificial intelligence; Machine learning; Natural language processing.

1 Introduction

Due to the capabilities of artificial intelligence (AI) systems in machine learning and natural language processing, these systems have been widely adopted in the workplace, providing employees with an efficient and effective tool for accomplishing tasks from drafting documents to assisting with various supportive work activities. AI can automatically generate text in accordance with specific requirements and perform a variety of functions in professional settings. For example, it can facilitate the drafting of documents, preparation of meeting minutes and the retrieval and organization of knowledge across different domains. The multifunctionality of AI tools has led to their extensive integration into routine work tasks, necessitating a deeper understanding of the interaction between such tools and employee productivity. With the increasing involvement of AI tools in work related activities, the manner and efficiency with which employee complete tasks are undergoing significant changes. According to 2023

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data, approximately 8.2% of employees worldwide have used AI tools at least once in their work [1].

Unlike innovations in automated machinery that replace manual labor, artificial intelligence tools directly influence specialized knowledge work [2]. Knowledge work is a defining characteristic of industrial society [3], in which capitalist production has shifted toward producing goods and developing services driven primarily by technological knowledge [4]. Knowledge work enables the transformation of informational and technological resources into marketable goods and services, generating greater benefits for enterprises [5]. Knowledge workers refer to individuals who possess specialized knowledge, which encompass not only those who have completed higher education and those holding licenses or professional certifications in particular fields of physicians, lawyers and teachers [6], but also those whose core activities center on information, data and ideas and who apply these to create products and develop services [7].

Knowledge workers can enhance relevant capabilities with artificial intelligence (AI) tools, which includes improving accuracy, numerical computation, work patterns and recognition skills [8]. In various workplace, AI can perform repetitive tasks with high precision and knowledge workers are not required to spend substantial amounts of time on the routine activities and can instead focus their attention on critical decision making and complex analysis [9]. Knowledge workers and AI tools can each leverage their respective strengths in a complementary manner and form a symbiotic relationship [10]. The purpose of incorporating artificial intelligence (AI) tools into work processes is to assist knowledge workers, rather than to replace their analytical and decision making functions [11]. Compared with knowledge workers or AI operating independently, the collaboration between knowledge workers and AI tools can enhance work efficiency, improve product development capabilities and reduce organizational costs [12]. Based on the above research context, this study addresses the following research questions: the impact of AI tools on knowledge worker efficiency remains inconclusive. Employee trust strongly shapes engagement with AI, and the suitability of AI varies under different levels of task complexity. These considerations highlight the need to examine the conditions under which AI can effectively enhance workplace productivity.

2 Analysis

This section will analysis the reasons of arising of research questions based on three main aspects.

2.1 Efficiency Limitations

The alignment between AI tools and the tasks of knowledge workers remains relatively low. AI tools are mainly employed to optimize general tasks, but the work of knowledge employees is specialized labor, performed through the using of theoretical and analytical skills acquired via higher education [13]. Hence, AI tools may not fully substitute for the knowledge professionals. The tasks of the professionals typically involve multidisciplinary knowledge, decision making and innovative activities. In creative industries, generative artificial intelligence has not yet been able to replace the professional practitioners [14]. Knowledge workers can integrate expertise from various domains to produce creative products or services, which is that AI cannot complete through data collection and information retrieval. In the field of education, although artificial intelligence demonstrates strong information processing capabilities that enable the generation of higher quality reading questions to enhance students reading abilities, it remains incapable of replacing educators in the creative tasks of teaching [15]. Professionals in the advertising industry worried that solutions generated by AI tools may violate copyright regulations and lawyers were concerned that AI tools could produce fabricated legal cases [16]. Knowledge officers often recognize the AI limitations and avoided to depend on AI in complex situations. Under high uncertainty, the officers tend to return to traditional approaches that offer stability and reliability.

2.2 Trust Dynamics

The study shown that 37% of respondents do not believe artificial intelligence performs well in the daily work [17]. Public attitudes toward AI are not entirely negative, but positive perceptions do not constitute the majority, reflecting polarization of opinions, which indicates a general lack of trust in AI tools [18]. The factors including reliability, transparency, interpretability, and modes of interaction determine the performance of AI tools and influencing knowledge workers motivation.

Table 1. Key Dimensions of Human–AI Trust

FEATURE	EXPLANATION
RELIABILITY	The information provided by AI tools should maintain consistency and stability, and AI systems be capable of performing tasks repeatedly and accurately.
EXPLAINABILITY	In the work process, AI systems should not only deliver solutions but also disclose the underlying processes and logic of the decision making.
FAIRNESS	AI decision making should remain neutral and objective, avoiding the undue influence of specific variables.
PREDICTABILITY	The responses of AI systems should be predictable and their behavior should align with the expectations of knowledge workers.
INTERACTION QUALITY	AI tools adapt to user needs through feedback provided by knowledge workers and delivering more accurate and tailored services.

As showing Table 1, the degree of trust of knowledge workers place in AI tools determines their willingness to adopt using AI tools. When the reasoning processes and underlying logic of the solution generated by AI are made transparent, knowledge workers can better understand how AI systems operate and make decisions, which can reduce uncertainty and enhance Human–AI trust [19]. There is a report presented that overestimating the capabilities of AI tools may lead to diminished trust in AI systems and reduced enthusiasm for AI tools using [20].

2.3 Task Suitability

When knowledge workers rely on AI tools over extended periods to handle complex tasks, opportunities for deep thinking and problem solving are reduced, which results a growing AI dependency of workers. The research indicates that long term reliance on AI tools for decision making may diminish the agency of knowledge workers, which leads to decreased motivation, a diminished sense of meaning at work and lowers overall well-being [21]. When the solutions generated by AI tools rapidly, knowledge workers need only to execute prescribed actions to solve problems, knowledge workers may forgo depth exploration of issues because of higher efficiency. The reduction of deep cognitive engagement can reduce critical thinking and creativity, which leads to skill degradation.

3 Solutions

In response to the challenges identified in the preceding analysis, this section proposes a set of strategies aimed at optimizing Human–AI collaboration, which focus on enhancing efficiency alignment, building trust in Human–AI interaction and improving task suitability while preventing overreliance.

3.1 Enhancing Efficiency Alignment

The development of artificial intelligence (AI) reveals that the demands placed on human skills are constantly changing as AI technology continues to evolve, and the impact of AI on soft skills is primarily felt in daily tasks primarily involving textual communication. Because the ability of AI to process large amounts of text data and provide automated feedback, human participation in these tasks is decreasing, which leads to a reduction in demand for certain soft skills centered on interpersonal interaction of daily communication and basic teamwork. If employees are unable to quickly adapt and learn new technologies to improved efficiency, they are likely to be marginalized within the organization and even face the risk of being eliminated. However, the emotional understanding of AI is still based on data and algorithms, and AI tools lack true emotional experience and deep empathy, when dealing with highly personalized and complex emotional interactions, AI still cannot completely replace human soft skills. Furthermore, the impact of AI errors cannot be ignored, while AI can efficiently process data and provide feedback, its current decision-making process still has the potential for errors. For example, biased data input or limitations in model algorithms can lead to seemingly rigorous conclusions that are actually erroneous or biased. Please help me translate the above content, paying attention to avoid duplicate checks, plagiarism, AI generation, and using academic style.

Formally, Deming and Noray describe career earnings as a race between learning and skill obsolescence [22, 23]:

$$\omega_t = \omega_0 (H + (T-1)a)(1-\emptyset)^{t-1} \tag{1}$$

Where H is initial human capital, a is the learning rate, and ϕ is the rate of task change. When ϕ is low (stable, repetitive tasks), automation yields higher cumulative returns; when ϕ is high (dynamic, creative tasks), human expertise remains essential. At the occupational level, task volatility can be measured by skill-change:

$$SkillChange_0 = \sum_{s=1}^{S} \left\{ Abs \left[\left(\frac{Skill_o^s}{JobAds_0} \right)_{2019} - \left(\frac{Skill_o^s}{JobAds_0} \right)_{2007} \right] \right\} \tag{2}$$

Which captures the net turnover of skills required in job postings. Higher values signal reduced suitability for full automation and greater need for human–AI collaboration. Based on these insights, AI has strong substitution capabilities in low- and medium-complexity tasks but needs to be mainly used as an auxiliary in high-complexity tasks. At the same time, training and skills improvement programs should help knowledge workers adapt to AI tools rather than create AI tools.

3.2 Building Trust in Human–AI Interaction

For ordinary users, machine learning models, especially deep neural network (DNN) models, are a black box, making it difficult to understand the underlying decision-making mechanisms. The lack of interpretability poses a serious threat to many real-world DNN-based applications, particularly in security-sensitive tasks. For example, a lack of interpretability in medical diagnostic models may lead to incorrect treatments, potentially threatening patients' lives. To improve the interpretability and transparency of machine learning models and enhance user trust, academia and industry need conducted extensive research and proposed a series of interpretability methods. The resulting products may harm user interests in the pursuit of optimal engineering metrics, such as excessive collection of user information, which in turn infringes on privacy or disrupts life experiences. For building Human-AI trust, AI product should prioritize user experience and ethical considerations beyond functional requirements. The goal of AI systems are developed to enhance human capabilities, not replace or threaten them. Humans and machines work as collaborative partners to achieve a common goal.

Transparency, explainability and ethical standards are the three essential pillars of trustworthy AI (As shown in Figure 1). AI will play an increasingly important role in healthcare, transportation, scientific research and other fields. For example, in the medical field, AI can assist doctors in making more accurate diagnoses and treatments; in the transportation field, AI can achieve safer and more efficient autonomous driving; in the scientific research field, AI can help scientists analyze massive amounts of data and accelerate scientific discovery. These applications are inseparable from safe, explainable and ethical AI technology.

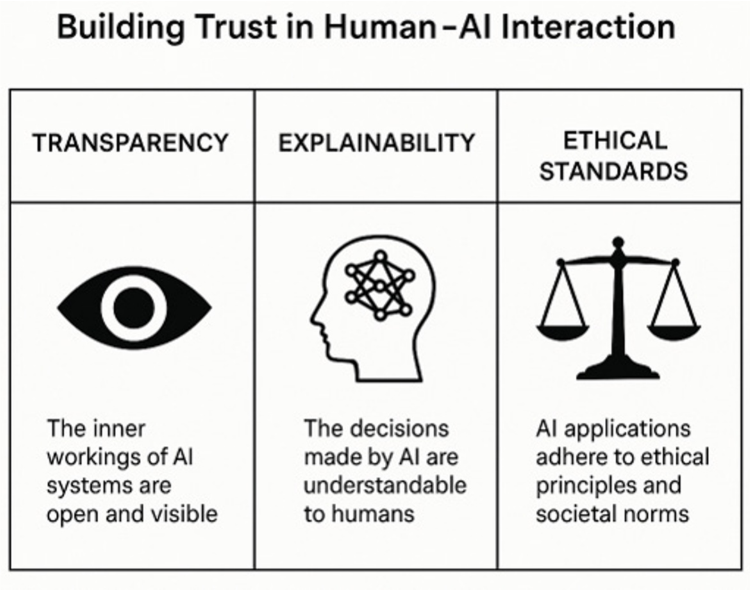

Fig. 1. Building Trust in Human -AI Interaction

3.3 Improving Suitability of Task and Avoiding Overreliance

Table 2. Task Complexity Framework and AI Tool Suitability

COMPLEXITY	FEATURE	EXAMPLE	AI MODEL
LOW	The tasks are clearly defined, highly repetitive, and standardized, requiring minimal subjective judgment.	Data entry, information retrieval, schedule planning, and basic document generation.	Fully automated, with AI capable of independent execution while human intervention is limited to supervision or handling exceptions.
MEDIUM	These tasks require a degree of analysis and synthesis, involve some uncertainty, yet still rely on partially established rules.	Strategic planning, organizational change, cross-cultural negotiation, innovation and research & development, and brand design.	AI is responsible for providing data-driven insights and solutions, while humans interpret the results and apply domain knowledge to make informed judgments.
HIGH	These tasks are unstructured, heavily reliant on professional expertise, and require creativity, contextual judgment, and ethical considerations.	Strategic planning, organizational transformation, cross-cultural negotiation, innovative research and development, and brand design.	AI provides support through multiple scenario simulations, while humans conduct comprehensive evaluations, apply creative thinking, and make final decisions.

By employing a task-classification framework combined with an AI-assisted recommendation model, tasks of varying complexity can be matched with the most suitable types of AI tools, which can significantly enhance both the efficiency and value of AI utilization.

One of the primary advantages of this model is its potential to enhance the efficiency of knowledge workers by allowing AI tools to perform tasks for which they are well-suited, while employees focus on creative and strategic activities (As shown in Table 2). In the background of human–AI symbiosis, the central concern should not be anxiety about replacement but rather how AI can be harnessed to augment human capabilities, serving as a catalyst for innovation rather than a constraint on thought. Meanwhile, cultivating interdisciplinary thinking, enhancing creativity, developing empathy and actively participating in AI ethical governance could promote humans maintain uniqueness and irreplaceable value in the intelligent age.

4 Discussion

In human–AI collaboration, decision-making authority should not be uniformly assigned; rather, it should be dynamically allocated based on task characteristics, risk levels, and the limitations of AI capabilities.

Table 3. Dynamic Allocation of Decision-Making Authority in Human–AI Collaboration

ALLOCATION	DECISION-MAKING	SCENE	EXAMPLE
AI-DRIVEN	AI executes tasks directly, with humans performing only supervisory functions.	Tasks that are clearly defined, low-risk, and highly repetitive.	Automated financial reimbursements and customer service chatbots.
HUMAN-COMPUTER INTERACTION	AI provides solutions, while humans make the final confirmation or adjustments.	Tasks that require analysis and judgment, for which AI can provide valuable support.	Recruitment resume screening and corporate strategic analysis.
HUMAN DOMINANCE	AI functions as an advisor, with humans retaining ultimate decision-making authority.	Tasks characterized by high complexity, high uncertainty, and risk sensitivity.	Clinical medical diagnostics and major investment decisions.

In the collaboration between AI tools and knowledge workers, corporate management increasingly focus enhancing Human–AI trust and establishing rational distribution of decision authority (As shown in Table 3). By the data processing and knowledge integration of AI tools, knowledge workers can focus more effectively on strategy making and innovative solutions, which can improve the performance. To establish a symbiotic relationship between employees and artificial intelligence, organizations should provide continuous training and workplace reskilling initiatives. Knowledge workers need to participate in training programs to acquire theoretical knowledge related to AI and to promote their practical application skills, and AI systems can use data generated during the training process to optimize the accuracy of the services, which can create a positive feedback loop. However, there are limitations in AI tools. Human–AI trust directly influences knowledge workers willingness to engage with AI tools. When AI systems lack transparency, interpretability and feedback mechanisms, knowledge workers cannot trust the information provided by AI tools.

5 Conclusion

In the interaction of technological innovation and economic uncertainty, the attitudes of knowledge workers influence how artificial intelligence can be used. This study analyzes the impact of AI tools on the performance of knowledge workers across three dimensions: efficiency, the establishment of Human–AI trust, and task suitability. The findings suggest that AI tools have a substitutive effect in tasks of low to medium complexity, in highly complex and creative work, knowledge workers act as primary decision makers and AI tools is supportive instruments. The development of human–AI trust effectively enhances knowledge workers willingness in AI tools through the systems interpretability, reliability and feedback mechanisms.

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