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The Stimulation of Employee Creativity by Artificial Intelligence Technology in Different Work Environments and Its Impact Mechanisms

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ABSTRACT
This paper focuses on the mechanism of how artificial intelligence (AI) technology affects employee creativity in different work environments. Based on Amabile's creativity component theory, a three-dimensional integrated framework of "domain skill empowerment - thinking process reshaping - motivation regulation effect" is constructed[1]. Cross-industry case studies in education, finance, technology, and manufacturing show that AI releases cognitive resources by automating repetitive tasks. Its nonlinear output characteristics can stimulate breakthrough inspirations, potentially leading to algorithmic dependence. Task substitution, while enhancing intrinsic motivation, is accompanied by the risk of technological dependence. This paper reveals the significant moderating effect of industry context on the AI action path. This paper confirms the dynamic adaptation mechanism between AI and the work environment and proposes that enterprises should build an agile iterative technology deployment framework based on the characteristics of industry knowledge, and optimize human-machine collaboration efficiency through digital literacy improvement plans and collaborative culture construction.

KEYWORDS
AI; Work Environment; Employee Creativity; Amabile's Creativity Component Theory

1 Introduction

Currently, most research focuses on the technical capabilities and application scope of artificial intelligence or the influencing factors of employee creativity, with a limited in-depth and systematic exploration of how artificial intelligence stimulates employee creativity across different work environments and its impact mechanisms. Work environment factors such as team collaboration atmosphere and leadership styles are highly likely to play critical roles in this process, yet their intrinsic connections with AI-driven creativity stimulation remain underexplored. This study holds both theoretical and practical significance: theoretically, it contributes to refining relevant theoretical frameworks and uncovering the deep-seated relationships between these elements; practically, it empowers enterprises to optimize work environments through AI, enhance employee efficiency and innovation capabilities, strengthen corporate competitiveness, while providing guidance for employees to adapt to new technological environments.

2 Literature Review, Theoretical Framework

2.1 The Multidimensional Impact of Artificial Intelligence Technology on Creativity

Based on Amabile's componential model of creativity, the impact of artificial intelligence technology on employee creativity exhibits multidimensional and dynamic interactive characteristics[1]. This paper systematically reviews existing research and uncovers theoretical gaps through three core dimensions: domain skill empowerment, cognitive process restructuring, and motivational regulation effects.

2.1.1 Domain Skill Empowerment: AI-Driven Cognitive Augmentation Mechanisms

AI technology enhances employees' professional capabilities and work efficiency through automated information processing, which enables cognitive resource reallocation. For instance, financial analysts leveraging AI tools for real-time market forecasting can significantly improve data processing efficiency[2]. The use of AI tools has been shown to substantially reduce employees' cognitive load, allowing them to focus more on higher-order tasks[3]. Further highlights that in knowledge-intensive industries such as pharmaceutical R&D, AI applications can increase innovation efficiency by over 20%[4]. This phenomenon aligns with classical theories in cognitive science, such as Sweller's cognitive load theory, which posits that reducing the burden of low-level cognitive tasks facilitates the release of higher-order thinking capacities, thereby boosting innovation efficiency[5].

2.1.2 Cognitive Process Restructuring: Nonlinear Inspiration Stimulation and Path Dependence Dilemmas

The nonlinear output characteristics of AI algorithms are reshaping human innovation pathways. When designers adopt AI tools, their creative ideation cycles are significantly shortened, and solution diversity is substantially enhanced[2]. However, this technological empowerment carries inherent risks: constrained by training data limitations, AI-generated content may exhibit a homogenization tendency, leading to creative path fixation[6]. This "inspiration-constraint paradox" is particularly prominent in creative industries such as film scriptwriting, highlighting the critical value of human critical thinking in AI collaboration[1].

2.1.3 Motivational Regulation Effects

The automation of repetitive tasks by AI can strengthen employees' intrinsic motivation. The intervention of AI tools can significantly enhance employee work efficiency, allowing them to devote more time to higher-order tasks[2]. For instance, programmers using AI-assisted tools demonstrate a notable increase in time allocation for algorithmic innovation alongside elevated self-efficacy[3]. However, technological dependency risks persist: prolonged AI usage may lead to a decline in the proposal rate of creative solutions when employees encounter unstructured problems, reflecting the inhibitory effect of "technological comfort zones" on innovation motivation[6].

This dual effect exhibits significant industry heterogeneity—manufacturing sectors prioritize efficiency gains from process optimization, while creative industries must balance the contradiction between automation tools and originality preservation[1].

2.2 Research Gaps and Theoretical Breakthrough Potential

2.2.1 Lack of Research on Multidimensional Interaction Mechanisms

Existing research predominantly focuses on investigating single dimensions such as cognitive offloading[7] or skill enhancement[8], while lacking empirical examination of the synergistic mechanisms underlying Amabile's three components. Particularly in AI intervention contexts, how skill enhancement influences innovation pathway selection through motivational regulation urgently requires the establishment of an integrated analytical framework.

2.2.2 Insufficient Research on Industry Context Specificity

Current research has yet to sufficiently reveal the industry differentiation characteristics of AI's operational mechanisms. Although Acemoglu & Restrepo proposed the hypothesis that manufacturing prioritizes efficiency enhancement while creative industries emphasize collaborative creation, related studies remain scarce and lack in-depth case analyses of vertical sectors such as healthcare and education[9].

2.2.3 Dynamic Evolutionary Perspective Requires Further Development

Existing research predominantly employs cross-sectional research designs, making it difficult to capture long-term adaptive changes in AI technology applications. Specific manifestations include: (1) At the individual level, a lack of longitudinal studies tracking skill reconstruction stages such as the AI tool learning phase, proficiency phase, and innovation phase; (2) At the organizational level, insufficient systematic explanatory frameworks for how AI-induced cultural transformations—such as establishing error-tolerance mechanisms and enhancing interdisciplinary collaboration—dynamically impact creativity[10].

3 Applications of AI in Industries

3.1 Education Sector

AI-powered teaching platforms are reshaping teachers' creative orientation through automated assignment grading and learning analytics. AI tools can significantly reduce teachers' routine administrative tasks, enabling them to devote more energy to pedagogical innovation[11]. Teachers utilizing time saved by AI tools to design "creative writing workshops" have demonstrated a marked improvement in students' creative writing scores[12]. Additionally, AI's error attribution analysis directly triggered the development of "dynamic auxiliary line visualization," resulting in class pass rates increasing from 68% to 89%, showcasing AI's strong collaborative effects[13]. Educational AI manifests creativity primarily through teaching strategy iterations, such as differentiated lesson plans, rather than process optimization seen in healthcare. Teachers' digital literacy emerges as a critical moderating variable, with digitally adapted groups adopting AI recommendations at 3.2 times the rate of traditional groups[14], confirming the positive buffering effect of industry culture on AI collaboration efficacy.

3.2 Financial Sector

AI risk control systems liberate resources for business innovation through automated credit approval and anti-fraud detection. AI tools can significantly reduce credit approval time, enabling employees to focus more on business innovation[8]. For instance, commercial bank credit officers utilizing time saved by AI tools to design "green supply chain finance" products have seen their loan portfolios show substantial growth[15]. However, financial innovation remains constrained by risk culture, with only a minority of innovations achieving breakthroughs within existing compliance frameworks[16]. Additionally, AI-driven asset allocation recommendations directly inspired the "new energy-lithium mine hedge strategy," which increased returns by 12%, demonstrating AI's collaborative effects[17]. Financial AI demonstrates creativity primarily through efficiency optimization within compliance frameworks, rather than strategic innovation seen in the education sector. Regulatory intensity exerts a negative moderating effect on AI collaboration efficacy. For instance, in derivatives businesses, AI recommendation adoption rates remain at merely 13%, primarily due to heightened manual review requirements under the Basel Accord[18].

4 Industry comparison and differences

The technology and manufacturing industries exhibit significant differences in AI role positioning, manifestations of creativity, and depth of collaboration. In the technology sector, AI serves as a "creative collaborator" that directly participates in generative processes[8]. Its creativity manifests through technologies like Generative Adversarial Networks (GANs) and Natural Language Processing (NLP) to produce market-valuable digital content such as program code, virtual avatars, and interactive narratives. This novel content output not only transforms traditional creation workflows but also restructures human-machine collaboration models, enabling designers and algorithms to form a bidirectional feedback loop of "cognitive symbiosis"[19]. However, the strong dependence of deep learning models on training data leads to continuous reinforcement of algorithmic biases, particularly in cultural product domains, potentially causing cross-cultural expression distortions and creative homogenization risks[6].

In manufacturing, AI assumes the role of "process analyst"[20], where its creativity primarily manifests through time series analysis and other technologies to achieve production rhythm optimization, predictive equipment maintenance, and efficiency improvements[21]. This value creation model relies on deep mining of operational system data, with human-machine collaboration remaining at the data support level. Engineers adjust production line configurations by interpreting AI-generated parameter optimization suggestions. However, traditional manufacturing enterprises commonly face challenges including weak industrial big data infrastructure, insufficient integration of process knowledge with algorithmic models, digital skill gaps, and persistently high costs of intelligent transformation, resulting in implementation difficulties for technology adoption.

This divergence stems from industry characteristics. The technology sector's open culture that encourages experimentation provides rapid validation scenarios for AI's agile iteration[2], enabling developers to continuously optimize generative models through testing. In contrast, manufacturing's rigid requirements for production continuity and product consistency prioritize the compatibility of AI solutions with existing quality control systems and equipment communication protocols[22]. These fundamental industrial differences directly drive distinct innovation trajectories and development speeds in AI technology across the two sectors.

5 Conclusions and Implications

AI demonstrates role-specific impacts in diverse sectors: In education, it streamlines pedagogical innovation by automating grading and learning analytics, though teacher digital literacy remains pivotal for maximizing its potential. The finance sector harnesses AI-driven risk management to enhance operational efficiency, yet must navigate regulatory compliance and risk-averse cultures through policy adaptation and organizational agility. Technology industries deploy AI as a "creative collaborator" for content generation and algorithmic design, balancing innovation outputs with homogenization risks through experimental, iteration-friendly cultures. Meanwhile, manufacturing relies on AI as a "process analyst" to optimize production systems, yet implementation barriers, including skill gaps and legacy infrastructure compatibility, demand strategic prioritization of stability and workforce upskilling. Collectively, these applications highlight AI's transformative capacity, contingent on harmonizing technological capabilities with sector-specific constraints and human-centric adaptability.

These findings demonstrate that AI's effectiveness depends not only on technical performance but also on multilevel moderations from industry traits, organizational cultures, and workforce capabilities. Future research should further explore the dynamic evolution of human-AI collaboration, particularly in cross-industry comparisons, skill reconfiguration, and organizational cultural transformation, to build a more systematic theoretical framework. This will provide academic support and practical guidance for optimizing AI applications across scenarios, maximizing its potential to enhance efficiency and stimulate creativity.

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