Human-AI Synergy Driving Performance: The Mechanism of Empowering Leadership, Human-AI Processes and Ambidextrous Innovation in Intelligent Manufacturing

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Abstract

This Article aimed to study the mechanism by which leadership style affects production performance through ambidextrous innovation and the human-AI process. The sample was intelligent manufacturing teams. Specifically, data were collected from 41 teams (203 employees) in the automotive parts, electronics assembly, and equipment manufacturing sectors. A "time-lagged + multi-source paired" hybrid design was employed. This design combined leader, member, and objective data sources across three waves. Data collection was conducted in three phases to reduce common method bias. The data were analyzed using descriptive statistics and content analysis. The research results were found as follows: (1) empowering leadership has a significantly stronger promoting effect on production flexibility and exploratory innovation than transformational and transactional leadership; (2) human-AI process (including the three dimensions of technical trust, collaborative fluency, and fault co-management) is a key moderating variable – when its level is high, the effect of empowering leadership on exploratory innovation increases by 79%; (3) The path of ambidextrous innovation is situationally differentiated: exploitative innovation is driven by transformational/transactional leadership and improves efficiency and quality, while exploratory innovation relies on the synergy of "empowering leadership + high human-AI process" to enhance flexibility. Research shows that intelligent manufacturing companies need to prioritize the development of technology-empowering leadership, simultaneously optimize the quality of human-machine collaboration, and provide a new dimension of "human-AI process" for team process theory. This study thus offers a validated

framework for enhancing performance in intelligent manufacturing through the synergistic interplay of leadership and human-AI collaboration.

Keywords: Human-AI synergy; performance; intelligent manufacturing; Human-AI processes; ambidextrous innovation

Introduction

The intelligent transformation of the global manufacturing industry is profoundly reshaping the production paradigm. Intelligent manufacturing technologies, centered around the Internet of Things, artificial intelligence, and digital twins, have become a strategic pillar for enhancing national competitiveness (Zhou et al., 2018). However, in business practice, the dilemma of a mismatch between technological input and performance output is widespread. This contradiction highlights the limitations of a purely technology-oriented approach—the human factor, particularly leadership, is severely underestimated in the critical role of technology implementation. This research raises the core question: what behavioral patterns (leadership styles) and team mechanisms (ambidextrous innovation and human-AI processes) should leaders of intelligent manufacturing enterprises adopt to ultimately drive substantial improvements in production performance (efficiency, quality, and flexibility)?

Classic leadership theories fail to consider the impact of technological autonomy on the human-machine relationship in intelligent manufacturing; There is a lack of empirical evidence linking how ambidextrous innovation mediates leadership and specific production performance dimensions (He & Wong, 2004); Team process models such as the TAR framework (Marks et al., 2001) fail to encompass the core dimension of human processes (Xu et al., 2025). This research addresses these gaps: Incorporating ambidextrous innovation and human-AI processes into the "leadership style ⟶ production performance" pathway; Revealing the causal chain through which empowering leadership, by strengthening human processes, promotes disruptive innovation and thus improves production flexibility; Combining objective performance data with multi-source evaluation (Kagermann, 2015).

This research therefore seeks to answer the following questions: (1) How do empowering, transformational, and transactional leadership styles differentially impact production performance in intelligent manufacturing? (2) How does ambidextrous innovation mediate this impact? (3) What is the role of human-AI processes in transmitting and moderating these effects?

Research Objectives

1. To verify the differential impact of leadership styles on production performance;

2. To study the mediating role of ambidextrous innovation;

3.To demonstrate the transmission and regulatory mechanisms of human-AI processes at the team level.

Literature Review

Transformational leadership enhances followers' intrinsic motivation and organizational commitment through vision motivation, intellectual motivation, personalized care, and idealized influence. Transformational leadership promotes member knowledge sharing and strategy iteration through team reflection, and improves innovation success rate in a dynamic environment (Han et al., 2025). Transactional leadership focuses on contingency rewards and exception management, and drives short-term goal achievement through a clear performance-reward exchange mechanism. Based on the self-determination theory, contingency rewards reinforce external motivation but impair internal motivation, resulting in reduced employee exploration behavior. In standardized tasks, its effectiveness is better than transformational leadership. Transformational leadership enhances subordinates' intrinsic motivation and promotes organizational citizenship behavior through visionary inspiration and personalized care. In intelligent manufacturing, this style can enhance employee acceptance of technological change, but may inhibit autonomy in human-machine collaboration due to its overemphasis on leader-centeredness (Gao & Xu, 2023). Transactional leadership embodies the " double-edged sword" effect of contingency rewards. Clear performance rewards can improve the efficiency of standardized tasks, but over-reliance on external incentives can inhibit exploratory innovation (Jansen et al., 2009). In intelligent manufacturing, this style is suitable for highly stable processes but is less adaptable to flexible production demands. Empowering leadership is a core adaptive style in intelligent manufacturing. In intelligent manufacturing, its effectiveness is moderated by " technological maturity" —when intelligent systems have high decision-making autonomy, empowerment can enhance employee trust in technology and enhance collaborative fluency (Xu et al., 2025).

Production performance has evolved from a traditional single efficiency metric to a multidimensional construct encompassing efficiency, quality, and flexibility. This technological integration has shifted performance management from passive monitoring to predictive optimization, especially in high-mixed small-batch production, which significantly improves resource utilization (Tambare et al., 2022). Overall equipment efficiency (OEE) is a core indicator, integrating three dimensions of equipment availability, performance efficiency and quality pass rate. In the food processing industry, traditional OEE overestimates the actual efficiency by 15% due to unquantitled micro-down events. The modified OEE model improves maintenance decision accuracy by 28% (Soltanali et al., 2021). Employee performance measurement needs to avoid the competitive trap of indicators: If the manufacturing workshop evaluates "per-time output" (focus on speed) and "one-time pass rate" (focus on quality), it may cause employees to sacrifice quality to achieve the output target, causing the scrap rate to rise by 12%.

Ambidextrous innovation refers to an enterprise's ability to simultaneously pursue both radical and exploitative innovation (March, 1991). Radical innovation, based on a new knowledge system, disrupts existing technological paradigms to develop new products and expand new markets. It is characterized by high risk, long cycles, and breakthroughs. Exploitative innovation, on the other hand, relies on existing knowledge to achieve incremental improvements through process optimization or functional expansion. It is characterized by low risk, short cycles, and efficiency. The relationship between these two types of innovation is a debate between the "trade-off" and "complementary" perspectives. Exploitative innovation optimizes existing processes, directly improving efficiency and quality (He & Wong, 2004). Transactional leadership reinforces this path through contingency rewards; transformational leadership indirectly promotes it through visionary incentives. The core value of exploratory innovation: it drives technological paradigm shifts, primarily improving production line flexibility (O’Reilly & Tushman, 2013). The construct of Human-AI processes is grounded in human-machine collaboration theory, which posits that effective interaction requires more than just technical functionality but also socio-technical integration (Jarrahi, 2018). Human-AI processes are increasingly playing a moderating role in organizational management, decision-making effectiveness, and innovative behavior. Existing research shows that human-AI processes significantly moderate the impact of leader behavior, resource allocation, and individual cognition on organizational outcomes through three dimensions: trust in technology, collaborative fluency, and troubleshooting capabilities.

Research Conceptual Framework

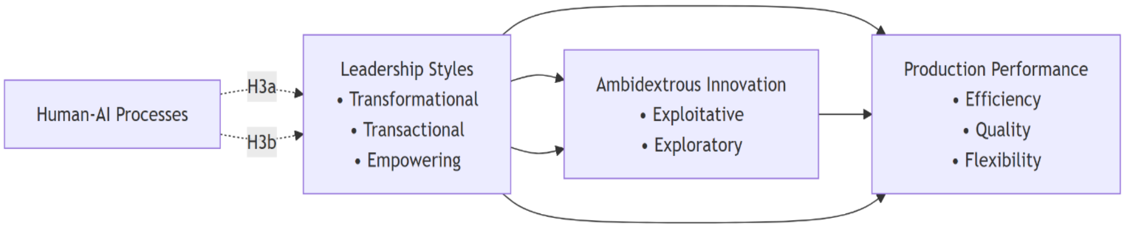

Figure 1 Conceptual Framework

H1: Direct impact of leadership style on production performance

H1a: Transformational leadership has a positive impact on quality and flexibility.

H1b: Empowering leadership has a stronger impact on flexibility than transformational and transactional leadership.

H1c: The contingency reward dimension of transactional leadership has a positive impact on efficiency, while passive-exception management has a negative impact on flexibility.

H2: The mediating role of ambidextrous innovation

H2a: Exploitative innovation mediates the relationship between transformational leadership and efficiency/quality, and between transactional leadership and efficiency.

H2b: Exploratory innovation mediates the relationship between empowering leadership and flexibility and is moderated by the human-AI process.

H3: The moderating role of the human-AI process

H3a: The quality of the human-AI process strengthens the positive impact of empowering leadership on exploratory innovation.

H3b: The human-AI process weakens the negative impact of transactional leadership (passive management by exception) on flexibility.

H4: Team-level human-AI processes indirectly enhance the willingness to engage in exploratory innovation by enhancing individual technical self-efficacy.

Research Methodology

A "time-lagged + multi-source paired" hybrid design (combining questionnaires with objective performance data) was employed. Data collection was conducted in three phases to reduce common method bias: Phase T1: Leaders completed a leadership style questionnaire and company background information; Phase T2 (1-month interval): Team members completed scales on ambidextrous innovation, team processes, and job satisfaction; Phase T3 (2-month interval): The human resources department provided objective team production performance data, and direct supervisors evaluated flexible performance. The one-month and two-month intervals between data collection phases were designed to allow sufficient time for leadership behaviors and team processes to manifest in innovation activities and subsequent performance records.

Sampling Criteria: Enterprises meeting Ministry of Industry and Information Technology "Intelligent Manufacturing Capability Maturity Model" standards of Level 3 or above (implementing ≥3 Industry 4.0 technologies, such as the Internet of Things and digital twins); teams directly involved in intelligent production line operations; team size of 5–15 members; and establishment time of >6 months.

Sample Source: Through local intelligent manufacturing industry associations, we contacted 32 companies in the Yangtze River Delta region of China, selected for their advanced adoption of intelligent manufacturing practices. We ultimately obtained 41 valid teams. The research protocol was informed consent was obtained from all participants. These included: 41 leaders, 203 employees and objective performance data.

All scales used a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree"). The developed scales were validated for reliability and validity through bidirectional translation and pre-testing (N = 127). Transformational Leadership: Using the MLQ scale, for example: "My leader explains the significance of our work to the team's goals." Transactional Leadership: Using the scale, divided into two sub-dimensions: Contingent Rewards (for example: "I receive appropriate rewards after achieving my goals") and Management by Exception (for example: "My leader intervenes only when I make mistakes"). Empowering Leadership: Using the scale, for example: "My leader encourages me to independently resolve technical issues" (α = 0.91). Ambidextrous Innovation: A modified scale (He & Wong, 2004), distinguishing between exploitative innovation (for example: "Our team often optimizes existing production processes") and exploratory innovation (for example: "Our team attempts to completely change production methods using new technologies." Human-AI Process: Based on the theory of human-machine collaboration (Jarrahi, 2018) and the requirements for the TAR model expansion (Gao & Xu, 2023), the three dimensions of "technical trust, collaborative fluency, and fault co-management" were refined. Expert Review: Three intelligent manufacturing researchers and two enterprise engineers were invited to assess item content validity. Pre-test: EFA analysis was performed to remove items with factor loadings < 0.5. Production Performance: Efficiency: Overall Equipment

Effectiveness (OEE) = Time Availability × Performance Availability × Qualified Product Rate (International Intelligent Manufacturing Alliance standard); Monthly Average Defect Rate; Flexibility: Supervisors completed a questionnaire, for example: "The team can quickly switch to produce different product models".

Research Result

The study sample consisted of 41 teams from the intelligent manufacturing sector. As detailed in Table 1.

Table 1 Sample Characteristics

Variable	Category	Frequency	Percentage
Industry Type	Auto Parts	18	43.9%
	Electronic Assembly	15	36.6%
	Equipment Manufacturing	8	19.5%
Number of Technology Applications	3	21	51.2%
	4	13	31.7%
	5	7	17.1%
Member Position Level	Grassroots Operators	126	62.1%
	Technician/Team Leader	58	28.6%
	Engineer/Technical Expert	19	9.3%

Objective 1. The research results found that empowering leadership (H1b) demonstrated a significantly stronger promoting effect on production flexibility (β = 0.35) than the positive impact of transformational leadership on quality (H1a, β = 0.27) and the action pattern of transactional leadership. This result clarifies that empowering leadership is the most critical behavioral pattern for enhancing flexibility in the intelligent manufacturing environment.

Table 2 Hypothesis Test Results

Hypothesis	Conclusion	Key Statistical Value	Practical Significance
H1a	Supported	β=0.27	Transformational leadership improves product consistency
H1b	Supported	β=0.35	Empowering leadership is key to flexible production
H2b	Supported	Indirect Effect =0.24, CI[0.12,0.39]	Exploratory innovation requires empowerment and Human–AI synergy
H3a	Supported	ΔR^2=0.07, p<0.01	Human–AI processes amplify the innovation effect of empowering leadership
H4	Supported	β=0.18, CI[0.09,0.29]	Human–machine trust drives individual innovation

Objective 2. The research results found that exploratory innovation is the key mediating mechanism through which empowering leadership influences flexibility (indirect effect = 0.24, CI[0.12, 0.39]). This indicates that empowering leadership does not directly affect flexibility, but rather achieves this by fostering exploratory innovation behaviors within the team.

Objective 3. The research results found that the Confirmatory Factor Analysis (CFA) showed a good model fit (χ^2/df = 2.37, CFI = 0.94, RMSEA = 0.06). The reliability (Cronbach's α > 0.85) and validity (AVE > 0.64) indicators for the three dimensions of Technology Trust, Collaborative Fluency, and Troubleshooting all met the standard criteria, confirming the scale's suitability for team-level analysis. The moderating effect analysis indicated that the quality of the human-AI process significantly strengthened the promoting effect of empowering leadership on exploratory innovation (H3a, ΔR^2 = 0.07, p < 0.01). The cross-level analysis results supported H4 (β = 0.18, CI[0.09, 0.29]), demonstrating that team-level human-AI processes can indirectly enhance individuals' willingness to participate in exploratory innovation by boosting their technical self-efficacy, thus revealing its intrinsic transmission mechanism.

Table 3 Formal Validity and Reliability Test of the Human-AI Processes Scale (N=41 Teams)

Module	Indicator	Technology Trust	Collaborative Fluency	Troubleshooting	Standard
CFA	χ^2/df	–	–	–	2.37 (<3)
	CFI	–	–	–	0.94 (>0.90)
	RMSEA	–	–	–	0.06 (<0.08)
Factor Range	Item Minimum-Maximum	0.75-0.83	0.77-0.86	0.78-0.85	>0.60
Reliability and Validity	Cronbach's α	0.88	0.87	0.85	>0.80
	CR	0.89	0.86	0.84	>0.70
	AVE	0.73	0.68	0.64	>0.50

Discussion

The results of the research objective 1 found that empowering leadership holds a central position in intelligent manufacturing environments. Compared to transformational and transactional leadership styles, empowering leadership demonstrates the most significant promoting effect on both production flexibility and exploratory innovation. This finding challenges the prevailing perception in traditional manufacturing where transformational leadership has been dominant. The underlying rationale is that the essence of intelligent manufacturing lies in addressing uncertainty and complexity, and empowering leadership – through granting autonomy to subordinates and encouraging self-determination – precisely activates team members' initiative to handle exceptions and experiment with new approaches within highly dynamic human-AI collaborative environments. This finding aligns with the perspective of Zhang et al. (2012), confirming that empowering leadership is particularly effective in complex and knowledge-intensive contexts.

The results of the research objective 2 found that ambidextrous innovation plays a mediating role in the "leadership-performance" relationship. Exploitative innovation, driven by transformational/transactional leadership, primarily enhances efficiency and quality through a relatively stable and linear pathway. In contrast, exploratory innovation relies on the synergistic effect of "empowering leadership + high-quality human-AI process" to drive flexibility. This finding provides a more nuanced mechanistic explanation for organizational ambidexterity theory (O'Reilly & Tushman, 2013).

The results of the research objective 3 found that the quality of the human-AI process can significantly amplify the positive impact of empowering leadership on exploratory innovation. This implies that in intelligent manufacturing, effective leadership must be coupled with positive interaction with technological systems to fully realize its value. This finding extends the traditional "Input-Process-Output" team model by expanding its core dimensions to the realm of human-AI collaboration (Marks et al., 2001). Meanwhile, the pathway through which the human-AI process promotes exploratory willingness by enhancing individual technical self-efficacy (H4) reveals its cross-level transmission mechanism from the team level to the individual level, providing a new perspective for understanding the psychological foundation of human-AI collaboration (Jarrahi, 2018).

New Knowledge from Research

The key contributions in this study are threefold. First, it establishes empowering leadership, rather than transformational leadership, as the primary driver for exploratory innovation and flexibility in high-technology manufacturing contexts. Second, it introduces and empirically validates the 'human-AI process' as a critical team-level moderator, extending traditional team process theories into the realm of human-machine collaboration. Third, it clarifies the situationally differentiated pathways of ambidextrous innovation, providing a nuanced mechanism linking leadership to multidimensional performance.

This new knowledge is particularly valuable for industrial ecosystems, such as the ASEAN region, that are actively pursuing smart manufacturing upgrades, as it emphasizes the synergistic optimization of both technological infrastructure and human-centric processes.

Conclusion

Based on the impact of leadership style on production performance in intelligent manufacturing enterprises, this study integrates ambidextrous innovation and human process theory to construct a systematic framework of " leadership behavior-team process-innovation path-performance outcomes." The results not only confirm the core role of empowering leadership in human-machine collaborative environments, but also reveal the key moderating effect of human processes as a unique interactive dimension of intelligent manufacturing teams. In the future, the success of intelligent manufacturing will depend on the coordinated optimization of " technology + human factors" rather than simply technological upgrades. Enterprises need to simultaneously promote leadership changes and human-machine collaboration capabilities during intelligent transformation in order to achieve sustainable performance improvement.

Suggestions

Based on the research findings, the researchers make the following recommendations:

1. Suggestion for Implementing the Research Findings

Leadership Development: Intelligent manufacturing companies should adjust their leadership development systems, prioritizing technology empowerment capabilities rather than simply articulating a vision. This approach should reduce reliance on traditional " command-and-control" leadership and shift toward an "empowerment-collaboration" model.

Training Design: Companies should incorporate human-AI process optimization into core KPIs for intelligent manufacturing transformation, rather than focusing solely on technology deployment. Add human-machine collaboration sandbox courses to simulate co-troubleshooting scenarios.

Technology Investment Support Strategies: Avoid the trap of prioritizing hardware over interaction. Allocate at least 15% of the smart transformation budget to the development of human-AI interaction interfaces. In creative tasks, transparent design can increase benefits.

2. Suggestion for Future Research

For future research, the focus should be on human processes in process manufacturing, such as chemical manufacturing, may be more dependent on system autonomy. And the dynamic evolution of human processes and leadership styles.

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