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AI-Driven Workforce Productivity in Developing Economies:
Analyzing Employee Engagement and Organizational Agility

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ABSTRACT

This study investigates the impact of Artificial Intelligence Implementation (AII) on Employee Engagement (EE) and Employee Performance (EP), examines the Organizational Agility (OA)'s moderating role in China's manufacturing sector's Information Technology integration. Data was collected from major manufacturing provinces: Zhejiang, Shandong, Jiangsu, Guangdong, and Henan (N = 899), covering biomedicines, renewable energy products, textiles, automobiles, and electronics. The structural equation modelling results reveal that AIA significantly enhances EP directly and indirectly through EE. OA positively moderates the relationship between AIA and EE, highlighting that greater agility organizations are more effective in turning AI-driven Information Technology initiatives into higher employee engagement. The moderation effect is evidenced by a steeper slope in the interaction plot under high OA conditions. This study enriches the AI and IT-driven transformation theory in human resource management practices and offers practical insights for manufacturing leaders.

KEYWORDS

Artificial Intelligence, Information Technology, Organizational Agility, Employee Engagement, Employee Performance, Human Resource Management

INTRODUCTION

AI enhances industry's competitiveness, creates jobs, modernizes manufacturing, and supports economic growth (Yigitcanlar et al., 2023). The adoption of artificial intelligence (AI)

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and information technology (IT) in manufacturing has indicated a transformative age of industrial productivity, reforming traditional production systems worldwide (Jourabchi Amirkhizi et al., 2025). This technological revolution, frequently seen as the heart of Industry 4.0, brings with it remarkable accuracy, automation, and the ability to anticipate future trends (Islam et al., 2025; L. Li & Duan, 2025; Vashishth et al., 2024). In developed nations like Germany, Japan, and the United States, AI-driven solutions, such as Siemens' digital twins (Gehlot & Rana, 2024) and Tesla's self-governing robots (Samdani et al., 2023), have led to jumps in productivity of as much as 30% (Vetrivel & Mohanasundaram, 2024). These nations are leading the way globally in smart manufacturing, where quality checks powered by AI, maintenance that predicts issues before they arise, and data analysis that happens in real time are typical features (Sahoo & Lo, 2022).

On the other hand, developing countries face obstacles in implementing emerging technologies (Senadheera et al., 2025). According to Amin et al. (2025), factors such as a lack of infrastructure, a gap in worker skills, and a general reluctance to embrace change are all standing in the way of widespread use. Take India, Pakistan, and Vietnam, for example; while their manufacturing sectors are growing, they are only partially adopting advanced technologies (Sultana, 2025). This means they are experiencing uneven productivity gains and missing opportunities to modernize fully.

In contrast, developing economies face significant barriers to AI adoption, including inadequate infrastructure, skill gaps, and resistance to change (Amin et al., 2025). Countries like India, Pakistan, and Vietnam exhibit fragmented technological integration, resulting in uneven productivity gains and missed modernization opportunities (Sultana, 2025). China presents a unique case, where rapid industrialization coexists with stark regional disparities. Coastal provinces like Guangdong and Jiangsu lead in AI adoption, leveraging high-tech manufacturing and corporate innovation (He, 2021; Y. Liu, 2024), while inland regions such as Henan lag due to reliance on manual labor and slower technological uptake (Shucun & Chuntai, 2019). These disparities mirror global divides but are exacerbated by China's rapid yet uneven development trajectory.

On the other hand, labor shortages and rising costs power the industrial intelligence (Yang et al., 2022). Guangdong is ahead in high-tech manufacturing, large companies like Huawei and BYD using AI for smart automation and detailed work (Y. Liu, 2024). Jiangsu's semiconductor and chemical industries use AI for spotting defects and improving processes, thanks to companies such as SK Hynix and Wuxi AppTec (He, 2021). Zhejiang, known for textiles and e-commerce, benefits significantly from Alibaba's smart logistics (Keane & Wu, 2019). In Shandong, Haier's factories, which are based on the Internet of Things, upgraded the manufacturing industry (Shi et al., 2024). Meanwhile, Henan still depends a lot on manual labor in textiles and food processing (Guo, 2013).

Even with all the progress made, it is clear that China's manufacturing industry is not growing evenly across the board. Areas along the coast, like Guangdong and Jiangsu, are taking off with AI, while inland provinces like Henan and some parts of Shandong are struggling to keep up (Rahman et al., 2025; Shucun & Chuntai, 2019). They are held back by a dependence on workers doing basic tasks and a slower embrace of new technologies. This difference is similar to what is happening worldwide, but it is even more noticeable in China due to the rapid pace of industrialization. Take Shandong, for instance, where almost a third of the factory hands there are worried their jobs might be taken over by robots, much like workers in other countries who are heavily reliant on manual labor (H. Wang & Chen, 2025). Plus, those large state-owned enterprises (SOEs), especially in Jiangsu, seem to be dragging their feet when it comes to digital makeovers, unlike the more adaptable private companies (G. Liu et al., 2024). All of this highlights the complicated connection between tech progress and the job market, a topic that often does not get enough attention in academic circles. Artificial intelligence is rapidly transforming the manufacturing process, with China leading the way (F. Wu et al., 2020). While automation, data analysis, and smart robots are making operations more efficient, their actual effect on the world goes beyond just using the technology (Soori et al., 2023). The real success of AI depends on whether organizations can get their employees involved and make their organizations more agile (Baggio & Omana, 2019; Tao et al., 2025).

In today's manufacturing world, the productivity of employees remains essential. Nevertheless, with AI taking over repetitive jobs, people are now expected to handle more complex and imaginative work (Jarrahi, 2018). This change raises a big question: Does AI automatically make everyone more productive, or does it only work well if employees are committed, and the company is flexible? New studies suggest that just having technology is not enough. Employees need to be supported, trained, and included to work well with AI (Morandini et al., 2023). In the same way, a company's ability to adjust quickly to new situations is crucial in deciding if AI will be a helpful tool or a source of problems (Xu et al., 2025).

Employees who are highly engaged are more likely to embrace new technologies, actively seek out opportunities for skill development, and contribute fresh, innovative ideas, effectively turning investments in AI into tangible benefits (Samuel et al., 2025). This kind of engagement tends to flourish in agile organizations that have adaptable frameworks, leadership that's responsive to change, and a culture that values ongoing learning.

According to Barach (2025), highly agile companies find it easier to integrate AI, prioritize employee growth, and keep their workflows relevant as needs shift. On the flip side, organizations with rigid structures frequently have a harder time adjusting to technological shifts, which can lead to resistance and a lack of employee engagement (EE; Singun, 2025).

This research focuses on:

- The direct impact of AI on employee performance (EP) in Chinese manufacturing.
- The mediating role of EE in the AI–EP relationship.
- The moderating effect of organizational agility (OA) on the AI–EE link.

Through a deep dive into these complex relationships, the research seeks to offer practical guidance for manufacturing executives (Tetteh et al., 2024). This guidance covers not only how AI can boost efficiency but also how it can improve the capabilities of their employees. Additionally, the study enriches scholarly work where digital change, employee actions, and company success overlap. As AI continues to transform industries, its full potential will only be unlocked if we focus on people—understanding what drives them and how they can adapt. For Chinese manufacturers, the trick is to bring in cutting-edge tech while also fostering a team that's excited and ready to change (Atkinson & Atkinson, 2024). This research helps connect AI adoption with actual productivity gains by highlighting the core aspects of EE and flexibility. The results will help companies get the most out of AI, using it to spark innovation and empower their workers, not just to boost efficiency.

Much research already focuses on the technical side of using AI in manufacturing—things like how to predict outcomes and automate processes. Nevertheless, there is not nearly as much attention given to how AI impacts people and the way companies are structured. Most studies do not investigate how AI might affect workers' spirits, their job satisfaction, or how adaptable their companies are. This lack of research is particularly significant in developing countries, where the social impact of automation is felt more acutely due to fewer safety nets and limited access to retraining opportunities.

According to Aderibigbe et al. (2023), developed countries are leading the way in creating models for responsibly incorporating AI. A good example is Germany, where companies like BMW use collaborative robots, known as *cobots*, to enhance the partnership between people and machines (Aderibigbe et al., 2023), all backed up by thorough training programs. On the flip side, in Bangladesh's clothing industry, AI-powered surveillance systems have led to dissatisfaction among workers, who feel more stressed and worried about job security (Ahmmed, 2023). India presents a mixed bag: Bosch's plant in Bengaluru showcases effective worker training, but Tata Motors in Pune has dealt with resistance from labor unions (Y. Li et al., 2025; Noronha et al., 2022).

China reflects the worldwide trends, yet its unique situation is influenced by its government-driven methods and the differences among its various regions (Qin & Jiang, 2025). Coastal areas such as Guangdong and Zhejiang enjoy advantages due to favorable policies, cutting-edge IT setups, and a highly skilled labor pool, all of which speed up the adoption of AI (K. Z. Liu, 2025). On the other hand, provinces located inland encounter obstacles akin to those in Pakistan—including outdated machinery and inconsistent power supplies, which hinder progress. The government's initiatives, like the "Made in China 2025" program, are intended to bridge these divides. However, the degree of success in executing these initiatives differs widely from one region to another (Kosaikanont, 2025).

This research tackles these imbalances by examining the impact of AI and IT adoption on EP, EE, and OA in five key manufacturing provinces in China (Q. Wu et al., 2025). It also brings in viewpoints from Germany, India, and Pakistan to understand China's situation in the broader global context. Through a combination of survey data from 500 factories and in-depth case studies (Imran et al., 2025), the study investigates how AI affects worker morale, skills, and adaptability. It also pinpoints successful strategies that effectively blend technology with human elements.

This research will provide valuable insights for policymakers, business leaders, and academics. In China's case, it underscores the importance of tailoring strategies to different regions, especially inland areas, emphasizing digital education and infrastructure development (C. Ma et al., 2025). It also highlights the pressing need to boost the adaptability of state-owned enterprises to prevent further widening of disparities (Qi et al., 2025). For other developing nations, this study serves as a guide, helping them steer clear of common mistakes like overlooking worker training and learn from successful examples in China's more developed regions.

Worldwide, this research helps us better grasp the bigger picture of Industry 4.0 (X. Xu et al., 2021). It does not just focus on new ideas, but also on making sure everyone, especially workers, is included sustainably. While AI and IT are changing manufacturing across the globe, their benefits are not always shared equally. China, with its wide range of industries, gives us a unique viewpoint to study these differences and learn lessons that can be used in various economic situations (Cai et al., 2025; Tseng et al., 2023). Despite extensive research on AI's technical applications, a critical gap remains: the human and organizational dimensions of AI adoption (AIA) are often overlooked. While studies emphasize predictive analytics and automation (e.g., Vetrivel & Mohanasundaram, 2024), few examine how AI affects EE, OA, or productivity in a holistic framework. This gap is particularly pronounced in developing contexts, where labor dynamics and institutional structures shape AI's impact (Aderibigbe et al., 2023). For instance, Germany's cobots (Aderibigbe et al., 2023) contrast sharply with worker dissatisfaction in Bangladesh's AI-monitored factories (Ahmmed, 2023), highlighting the need for context-specific analyses.

This study bridges the gap by integrating sociotechnical systems theory (STS) and dynamic capability theory, which posit that technology's efficacy depends on human–system alignment and organizational adaptability (Barach, 2025; Jarrahi, 2018). While AI can automate tasks, its productivity gains are mediated by EE—defined as workers' emotional commitment and proactive skill development (Samuel et al., 2025)—and moderated by OA, or a firm's capacity to adapt structures and strategies. Prior research lacks empirical validation of these relationships, especially in China's regionally diverse manufacturing sector.

By analyzing survey data from manufacturing factories across five Chinese provinces (Guangdong, Jiangsu, Zhejiang, Shandong, Henan) and comparative cases from Germany, India, and Pakistan, we address why regional disparities persist and how firms can harmonize technological and human factors. The selection of provinces reflects China's developmental spectrum, from high-tech coastal hubs to labor-intensive inland areas, ensuring generalizable insights (Wu et al., 2025).

This research offers three key contributions. First, it advances STS and dynamic capability frameworks by empirically testing AI's human–organization interdependencies. Second, it provides actionable strategies for policymakers and firms, emphasizing tailored training (e.g., digital upskilling in inland provinces) and agile governance (e.g., reforming state-owned enterprises; Mohiuddin et al., 2023). Third, by examining how technology, people, and organizations can collaborate, this research identifies key gaps and proposes practical solutions to drive equitable progress in industries. The aim is straightforward: to make sure the benefits of AI are widely shared, including everyone, and can handle future technological shifts.

The following sections review the literature to define the study's constructs and their theorized relationships, describe the methodology, and analyze the data with SmartPLS 4 to test the hypotheses, reporting which are supported, followed by a discussion of implications and conclusions.

LITERATURE REVIEW

Employee Performance

EP, a key outcome in the manufacturing sector, is being increasingly influenced by the adoption of artificial intelligence (AI; Kassa & Worku, 2025). Research shows that AI-powered tools boost performance through automation, on-the-spot monitoring, forecasting, and decision-making aids (Deepika, 2019). These advancements reduce errors, streamline workflow planning, and enable a more thoughtful distribution of the workforce.

AI directly boosts performance. Take China's car industry as an example, in which AI-powered welding at Shanghai GM bumped up production by 22%, Similarly, Huawei used AI to improve electronics testing, and their defect detection rate shot up (Y. Gu et al., 2023). Nevertheless, these efficiency gains come with some short-term job market hiccups. In Jiangsu province, workers with specialized skills saw their wages grow by 18% thanks to AI, but those in less skilled positions faced a 12% job displacement rate (D. Yuan et al., 2022). It seems that although AI supercharges output, it also underscores the urgency for workers to learn new skills and move into more knowledge-focused jobs (Song et al., 2018).

The resource-based view (RBV) suggests that if a company leverages AI as a unique skill, it can enhance its performance over time (Sandeep et al., 2025). Other studies show that when people and AI work together well, they can do tasks better and come up with new ideas (Helfat et al., 2023). Performance is also heavily shaped by factors such as the company's culture, employee involvement, and leadership approach (Jain & Jain, 2013). For example, research within the job demands–resources (JD–R) framework indicates that employees who are highly engaged—feeling energetic, committed, and deeply immersed in their tasks—typically demonstrate higher performance (Schaufeli, 2017; Srivastava et al., 2024). Therefore, this engagement can act as a bridge between how AI is rolled out and the ultimate impact on performance.

Further real-world evidence from the manufacturing world backs up this notion. Zhang and Zhu (2021) research on small and medium-sized businesses in China revealed that bringing in AI, along with employee training and engaged leadership, boosted performance by more than 20% (Shobhana, 2024; N. Zhang, 2024). Similarly, Peng and Liu (2019) showed that using AI to upgrade supply chain operations trimmed production downtime by 30%, mainly because of more accurate demand predictions and AI-powered inventory management. All things considered, these findings underscore the complex nature of EP, which is affected by technological, organizational, and psychological elements. In manufacturing settings like those found in China, combining AI with an emphasis on EE and development can lead to significant improvements in performance (Jia & Hou, 2024; Srivastava et al., 2024).

The performance impacts of AI adoption across Chinese provinces reveal striking disparities rooted in regional industrial policies and workforce composition. Coastal manufacturing hubs like Guangdong and Jiangsu demonstrate 22–30% performance gains from AI integration in electronics and automotive sectors (Y. Gu et al., 2023) while inland provinces such as Henan show marginal 5–8% improvements in traditional industries (Peng and Liu, 2019). This divergence reflects what the RBV theorizes as "province-specific advantages"—where Guangdong's dense ecosystem of tech firms and vocational training institutes creates complementary assets that maximize AI's value (Chen & Li, 2025).

The JD–R framework helps explain why Zhejiang's privately-owned small and medium enterprises achieve faster performance growth (25%) from AI than Shandong's SOEs (12%; McGregor & Mitchell, 2023). Zhejiang's emphasis on employee participation in AIA creates psychological ownership, whereas Shandong's top-down mandates in SOEs trigger resistance. Jiangsu's semiconductor industry showcases how AI-driven quality control boosts performance when combined with upskilling programs—skilled workers' output increased 18% while turnover decreased by 30% (D. Yuan et al., 2022).

Theoretical Justification

The Fourth Industrial Revolution, or Industry 4.0 as it is often called, is fundamentally changing the manufacturing landscape by bringing together physical and digital systems. At the core of this shift are things like interoperability, virtualization, and AI-powered real-time decision-making, as highlighted by Rai et al. (2024). Similarly, China's "Made in China 2025" initiative follows this approach, focusing on smart factories, intelligent manufacturing, and using AI for predictive maintenance to boost efficiency and minimize downtime (Y. Liu, 2024).

This top-down approach to implementing the strategy, especially within state-owned companies, has drawn some backlash. Scientists have pointed out that the strict, rule-bound ways of these organizations make it difficult to smoothly blend AI with how employees work, which in turn stops us from fully reaping the benefits of increased performance (Konikoff, 2024). In addition to this, Huber and Alexy (2024) stated that simply using AI automatically boosts performance; however, this idea is being increasingly challenged by a perspective that considers both social and technological factors. This alternative view emphasizes that both technology and the people using it rely on each other to get the best results. The latest research from Guangdong's electronics industry really drives this point home. Enhancement in performance came from people working effectively alongside AI, highlighting how crucial it is to see technology adoption as a combined social and technical process, not just a tech upgrade (Al Naqbi et al., 2024).

In addition, Rogers' (2003) Diffusion of Innovations theory provides crucial insights into why AI adoption varies so much across different regions, which was also discussed earlier in the research (Patnaik & Bakkar, 2024). According to the theory, adopters can be grouped into five categories: innovators, early adopters, early majority, late majority, and laggards (Patnaik & Bakkar, 2024). Businesses in Zhejiang, often nimble and privately owned, embraced AI technology 28% quicker than their state-run counterparts in Shandong (McGregor & Mitchell, 2023). This difference is attributed to Zhejiang's culture, which is more open to trying new things and learning from them. On the other hand, K. Wang et al. (2021) revealed that companies in Henan's textile sector struggled to adopt AI because of strict hierarchies and a cultural tendency to resist change.

Various countries are highlighting how much AI is changing things for manufacturers around the world. In Germany, for example, almost 80% manufacturers are using digital twins, which has made it much easier for them to predict when maintenance is needed and to plan their operations better (Rädel et al., 2025). Japan is another great example, where Toyota has combined AI with robotics, fitting in with the Society 5.0 plan (Lovászy, 2025). This has helped them cut down on manufacturing defects by 40% (Leberruyer, Bruch, Ahlskog, & Afshar, 2023).

The United States is seeing some serious payoffs from investing in AI. Companies that have embraced AI are seeing a 35% higher return on investment than those that have not (Konikoff, 2024). A great example of this is Tesla's AI-powered Gigafactories, which are churning out 20% more output per worker than traditional car manufacturing plants (Liu et al., 2024). These real-world examples from around the globe strongly back up the idea of using AI as a key strategy in manufacturing, highlighting its likely benefits as China's industrial landscape continues to change and grow. This study also examines the extent to which employee involvement is a key factor influencing other variables. Using the JD–R theory (Bakker & Demerouti, 2014), the idea is that employees who are more engaged are more likely to use and make the most of AI tools, which in turn increases performance (Radic et al., 2025). When workers are empowered, trained, and actively involved in AI transformation processes, the technology has a significantly more positive impact on performance (Kassa & Worku, 2025).

Overall, Guangdong's success with AI stems from synchronizing technical systems (e.g., Huawei's 5G infrastructure) with social systems (migrant worker training programs) under socio-technical systems (STS) Theory. In contrast, Henan's textile industry demonstrates technical-system dominance without social-system adaptation, resulting in worker displacement (Xu & Zuo, 2024). Under institutional theory, Jiangsu's foreign-invested firms adopt global AI standards rapidly (322 robots per 10,000 workers) due to isomorphic pressures. In comparison, Shandong's SOEs retain legacy systems (48 robots per 10,000 workers) because of institutional inertia (Liu et al 2014). The "Made in China 2025" policy creates coercive isomorphism, but implementation varies by provincial governance structures. Moreover, under dynamic capability theory, Zhejiang's private sector shows greater absorptive capacity in AI adoption through (Keane & Wu, 2019):

- **Sensing:** e-commerce platforms like Alibaba identify AI opportunities
- **Seizing:** rapid prototyping of smart logistics systems
- **Transforming:** continuous workforce reskilling

The implementation gap between coastal and inland provinces mirrors China's regional development inequalities in the selected provinces, such as Guangdong, which leads in AI patents (12,450) with Foxconn's 30% labor reduction through automation (Lin, Yi-Hua Lee, Cheng-Hsun Fang, Shun-Yi,2023). However, its migrant worker population faces skill obsolescence risks. The second one selected for investigation is Jiangsu, in which SK Hynix's AI quality control demonstrates successful foreign-tech integration, but SOEs lag in adoption due to bureaucratic workflows (Liu et al., 2024). Next, Zhejiang, which has Alibaba's smart logistics, shows agile AI adoption, yet smaller textile firms struggle with implementation costs (Faiz et al., 2025). In Shandong, Haier's COSMOPlat achieves mass customization but faces 25% worker resistance (Shi et al., 2024), highlighting the urban–rural divide in skills. In Henan province, food processing remains labor-intensive (Guo, 2013), with AI limited to inventory management due to infrastructure gaps.

Artificial Intelligence Adoption

Developing countries are struggling to integrate AI into their manufacturing processes, mainly because of shortcomings in their infrastructure and workforce capabilities (Qudus, 2025). Take Pakistan, for example, where textile factories often deal with 8–10 hours of electricity shortages every day, making it extremely difficult to run AI-powered systems (Faiz et al., 2025). India faces a similar predicament with a significant skills deficit, as only a few of its engineers have the necessary AI proficiency (Ghosh, 2025). These problems are further worsened by differences in how well policies are implemented.

In addition, India's "Make in India" push has seen 32% of car companies take up basic AI, but China's stronger "Made in China 2025" plan has pushed 68% of similar businesses to use AI (Lee et al., 2025). Even within China, there are big differences between regions—wealthy Guangdong spends 2.4% of its GDP on AI research, while less industrialized Henan only allocates 0.7% (Chen et al., 2025; J. Ma et al., 2025). Still, some inspiring stories are coming out: in Vietnam, Samsung's factories have cut defects thanks to AI-driven computer vision (Lee et al., 2025), and Bangladesh's clothing industry has boosted efficiency by 15% using AI for inventory management (Haq et al., 2025).

The manufacturing landscape in China reveals significant differences across regions, especially between coastal and inland areas. In 2023, Guangdong, a leader in high-tech industries, held 12,450 AI patents and had 322 robots for every 10,000 workers, while Henan, which focuses on labor-intensive sectors, had only 890 patents and just 48 robots per 10,000 workers (MIIT China, 2023). The effectiveness of policies also highlights this gap. In Guangdong, Foxconn's assembly lines using AI have cut the need for labor by 30% (Hon Hai Report, 2023), while in Shandong, Haier's

COSMOPlat system has enhanced customization but encountered 25% of workers resisting the new technologies (Shi et al., 2024).

Artificial Intelligence Adoption and Employee Performance

Research conducted in both advanced and emerging economies shows that incorporating AI into manufacturing processes results in noticeable improvements in performance (Atieh et al., 2023). Take China's automotive industry as an example: AI-equipped welding systems at Shanghai GM boosted production by 22% and also lowered the frequency of errors. Likewise, Foxconn's assembly lines in Guangdong, driven by AI, were able to cut down on labor needs by 30% without compromising the quality of production (S. Gu & Wang). These results support the explanation offered by Brynjolfsson and McAfee (2017) to their "productivity paradox," suggesting that AI's complete advantages only become apparent after a reworking of related processes, which was also backed by research conducted by Karacuka et al. (2024).

Furthermore, another meta-analysis validated these case-specific findings. A study of 120 manufacturing companies conducted by Brynjolfsson et al. (2020) revealed that the adoption of AI was associated with an 18–26% increase in performance, mainly due to:

- **Process automation:** substituting monotonous jobs (e.g., Toyota's robotic arms conserving 50,000 labor hours annually)
- **Predictive maintenance:** decreasing equipment downtime by 30–50%
- **Quality control:** AI vision systems at Huawei reduced defect rates by 35%

The skill-biased characteristics of AI generate inequalities. In Jiangsu, the introduction of AI increased earnings for skilled workers by 18% while displacing 12% of low-skilled laborers (X. Zhang et al., 2025), hence corroborating the thesis of Acemoglu and Restrepo (2019) regarding "so-so technologies." AI frequently enhances high-skill positions while displacing low-skill jobs without generating equivalent new possibilities.

Employee Engagement

The psychological impacts of AIA differ significantly across various circumstances. In Germany, BMW's cobots have improved job satisfaction by 40% (Samblani & Bhatt, 2025), while in Bangladesh, 68% of garment workers indicate increased stress attributed to AI surveillance (D. Yuan et al., 2022). In China, inequities remain: Tech workers in Zhejiang demonstrate greater engagement than textile workers in Henan, where job insecurity is prevalent (Y. Xu & Zuo, 2024).

Employee perceptions about AI temper performance enhancements. Employees in technology-driven areas such as Zhejiang demonstrate a 25% increase in performance following AIA, in contrast to reluctant workers in Henan's textile industry (Ren et al., 2022). Because it has a direct influence on activities such as performance, innovation, and staff retention, EE is an essential component of the success of an organization. Through the transformation of work processes and the creation of a work environment that is both more efficient and more motivating, artificial intelligence has the potential to increase EE greatly. Tools powered by artificial intelligence can automate repetitive tasks, provide personalized feedback, and offer insights to help employees perform their responsibilities more efficiently. Artificial intelligence has the potential to improve job satisfaction and EE by minimizing repetitive tasks and allowing workers to concentrate on more meaningful work (Alateeg et al., 2025).

According to Gusti et al. (2024), the RBV emphasizes that the capabilities possessed by employees will make people increasingly engaged in critical business processes and routines, namely directing how resources interact to turn input into output (Gusti et al., 2024). This is a point that the RBV emphasizes. A high level of EE in their work is also associated with increased performance (Jindo et al., 2020). In the nutshell, EE mediates AI's impact differently across provinces such as far as first dimension of EE such as cognitive engagement included Higher in Zhejiang's tech firms, where employees co-design AI tools (Ren et al., 2022). Secondly, emotional engagement includes stronger in Jiangsu's foreign firms with inclusive AI training (D. Yuan et al., 2022). Thirdly, behavioral engagement is weakest in Henan's state-owned factories with imposed automation (Wang & Chen, 2025). The JD–R framework explains these variations: job resources (training, participation) are abundant in coastal provinces, while job demands (surveillance, skill gaps) dominate inland regions.

Organizational Agility as a Critical Moderator

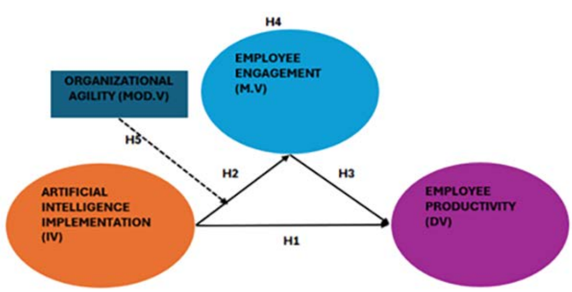
Different companies are adjusting to AI at quite different speeds. It is also found that private businesses in Jiangsu are jumping on the AI bandwagon three times quicker than state-owned companies (A. H. Zhang, 2022). Similarly, Toyota's method of continuous improvement allows for AI adoption in about half the time it takes Chinese state-owned enterprises (Miao & Ji, 2020). There is still a lot we do not know, however. For example, only 12% of AI research looks at human elements, such as how people engage with the technology (Sidner et al., 2005). Businesses leveraging AI to optimize their operations are experiencing a significant increase in production capacity (Kumar, 2019). Those same private manufacturers in Jiangsu that are taking to AI like ducks to water are cranking out 15% more per worker than their state-owned rivals, adopting AI three times as rapidly (Chen, 2023).

Toyota's *kaizen* teams managed to cut the time it takes to put AI into action by 50% compared to some state-owned Chinese companies (Miao & Ji, 2020). It seems like AI has the biggest impact on performance in the electronics industry, where tasks are highly standardized—Foxconn, for example, saw gains of around 35% (D. Hao & Bu, 2022). On the flip side, in Henan's textile industry, the gains from AI are less impressive (only about 8%) because the starting level of automation was pretty low to begin with in the manufacturing industry (Peng and Liu 2019).

Provincial differences in agility explain AI adoption speeds, such as Structural Agility, which includes Guangdong's flat organizational structures enabling three times faster AIA than Shandong's hierarchical SOEs (A. H. Zhang, 2022). Cultural Agility includes Zhejiang's failure-tolerant culture, which supports rapid AI experimentation (Keane & Wu, 2019). In Political Agility ensures Jiangsu's government–business collaboration accelerates policy-responsive AI adoption (Chen, 2023). Toyota's *kaizen* approach achieves 50% faster AI integration than Shandong's SOEs (Miao & Ji, 2020), demonstrating how agility compensates for late-mover disadvantages.

Figure 1 presents the conceptual framework taking AIA as an independent variable, EE as a mediating variable, and EP as a dependent variable. OA is taken as a moderator between the AIA and EE. The model was established based on the theoretical justifications provided in the literature, along with empirical evidence. Five hypotheses accompany the conceptual framework.

Figure 1. Done Conceptual Framework



Note: IV: Independent Variable, DV: Dependent Variable, M.V: Mediating Variable, MOD.V: Moderating Variable

Hypothesis Formulation

- **H1:** AIA positively impacts EP
- **H2:** AIA positively influences EE
- **H3:** EE positively influences EP
- **H4:** EE mediates the relationship between AIA and EP
  H5: OA moderates the relationship between AIA and EE, strengthening the direct impact.

Method

This study employs a quantitative research design with a deductive approach, aligning with the positivist paradigm to objectively examine the relationship between AIA and workforce dynamics in China's manufacturing sector. The analysis is conducted using SmartPLS 4.0, a robust tool for partial least squares (PLS) structural equation modeling (SEM; PLS-SEM), suitable for complex models and smaller sample sizes (Ramayah et al., 2018). The research is set within China's manufacturing industry, a sector currently navigating significant performance challenges stemming from rapid technological adaptation, persistent skill gaps, and automation-induced anxieties among the workforce (Oguz et al., 2025). While AI adoption is steadily increasing, its impact on EE and EP remains insufficiently explored, especially in the context of operational integration and human resource adaptation (H. Zhang, 2024). The target population consists of manufacturing firms located in five key Chinese manufacturing provinces, representing diverse industrial sectors. The research is set within China's manufacturing industry, a sector navigating performance challenges due to rapid technological adaptation, skill gaps, and automation anxieties (Oguz et al., 2025). While AI adoption is increasing, its impact on EE and EP remains underexplored, particularly in operational integration contexts (H. Zhang, 2024).

The target population includes manufacturing firms across five key provinces, with purposive sampling ensuring representation across diverse sectors (Jum'a et al., 2025). In order to address potential biases from self-reported, cross-sectional data, procedural remedies were implemented: (1) anonymity assurances to reduce social desirability bias, (2) reverse-coded items for scale reliability, and (3) temporal separation in survey deployment for key constructs (Podsakoff et al., 2003). While longitudinal data would strengthen causal claims, the study's mediation and moderation design—grounded in RBV theory—theoretically justifies the AI–performance link via engagement, positing that AI's tangible (e.g., big data tools) and intangible (e.g., skill augmentation) resources enhance performance through sustained employee involvement (Barney, 1991).

The unit of analysis includes both employees and managers actively involved in AI-integrated processes, ensuring a comprehensive view of technology-human interaction. A purposeful sampling technique is applied to ensure representation across various manufacturing segments (Jum'a et al., 2025). Aguirre-Urreta and Hu (2019) used the Harman single-factor test to determine if there was a common method bias (CMB). According to the results, one variable explained 35% of the variation, which is lower than the 50% cutoff set by previous studies. The lack of a standout factor suggests that CMB is not an issue in this investigation. Each component worked well with the others because their Cronbach's alpha ratings were higher than the minimum requirement of 0.70. To ensure the instrument was measuring the right variables, confirmatory factor analysis was used. The data analysis was carried out using SPSS and AMOS software. The data was assessed for factor analysis suitability using Bartlett's test and the Kaiser–Meyer–Olkin test. The data was very suitable, as shown by the Kaiser–Meyer–Olkin score of 0.84, and Bartlett's test produced a significant outcome ($p < 0.001$).

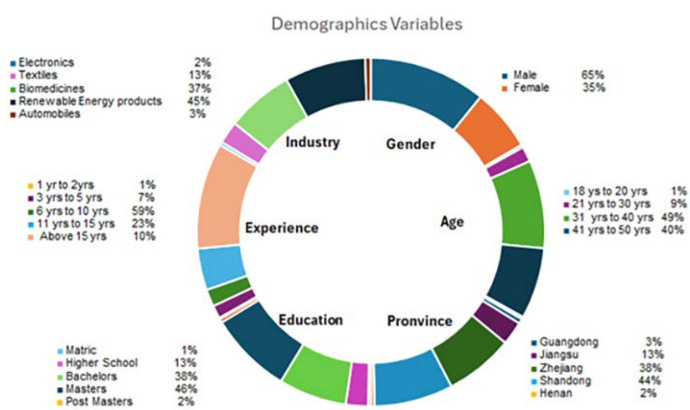
The sample size adheres to PLS-SEM recommendations, aiming for a good number of respondents to ensure statistical validity and model robustness. Data is gathered through a structured survey questionnaire (N=899) comprising Likert-scale items, designed to capture perceptions, experiences, and attitudes toward AIA and its indirect effect on EP, with the mediation of EE and the moderating impact of OA. The primary data collection focuses specifically on firms that have integrated AI into their manufacturing operations, offering rich, context-specific insights for empirical validation. AIA was measured with an 11-item scale previously utilized and examined three dimensions: big data management, relative advantage, and cost of ownership, in the research by Kanti et al. (2022). EE was measured using six items, previously examined by Fan et al. (2020) and Scott and Walczak (2009), and further explored by K. Wang et al. (2021). EP was measured by using nine items utilized in the study by Kassa and Worku (2025). OA was examined through 6 items utilized earlier in the study by (Govuzela & Mafini, 2019). Cronbach's alpha (> 0.70) and CFA results affirmed reliability and validity. The sample size adhered to PLS-SEM guidelines (Hair et al., 2019), ensuring robust estimates despite cross-sectional limitations. All questions measuring constructs were examined based on a five-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*).

Analysis

The data analysis process began with descriptive statistics, including means, standard deviations, and demographic profiling to understand the distribution and central tendencies of the respondents' characteristics. Following this, reliability and validity tests were conducted to ensure the robustness of the measurement model. Cronbach's alpha and composite reliability (CR) values were assessed to confirm the internal consistency and reliability of the constructs. The structural relationships among variables were examined using SEM through Smart PLS 4.0, which is well-suited for complex models and predictive analytics (Hair et al., 2021). The SEM analysis involved path analysis for hypothesis testing, providing insights into the direct relationships between variables.

Additionally, mediation and moderation analyses were performed to explore the indirect and conditional effects within the conceptual model, enhancing the depth of interpretation and theoretical contribution of the study. Figure 2 presents the demographic profile of the study's respondents across various dimensions, including gender, age, province, education, industry, and experience. The gender distribution is skewed towards males, constituting 65% of the sample, while females make up 35%. In terms of age, the dominant group is 31–40 years (49%), followed by 41–50 years (40%), indicating that most respondents are mature professionals with significant industry experience.

Figure 2. Demographic Profile

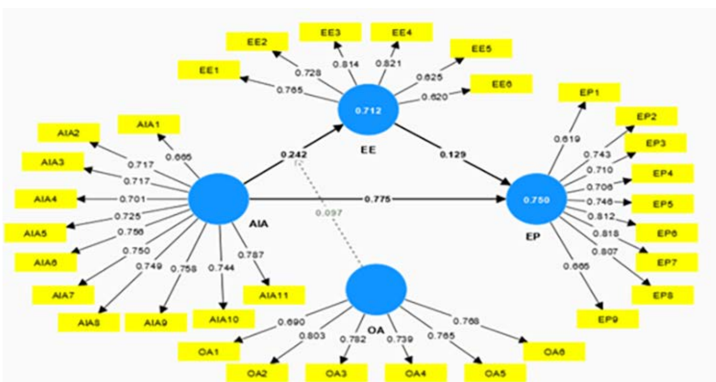


Geographically, the largest proportion of participants belongs to Shandong (44%) and Zhejiang (38%), with fewer from Jiangsu (13%), Guangdong (3%), and Henan (2%). Educational qualifications show a highly educated workforce, with 46% holding a master's degree, 38% holding a bachelor's degree, and a small segment with post-master's qualifications (2%). The industries represented are primarily from the high-tech and future-focused sectors, notably renewable energy products (45%) and biomedicines (37%), followed by textiles (13%), automobiles (3%), and electronics (2%). Regarding professional experience, a significant portion of the respondents have 6–10 years of experience (59%), with 23% having 11–15 years, and 10% with over 15 years, indicating an experienced and informed respondent base.

Measurement Model

The measurement model (see Figure 3) was developed in SMART PLS. Based on the results (see Table 1), the constructs used in this study—AIA, EE, EP, and OA—exhibit strong psychometric properties, supporting both their reliability and validity. AIA, comprising 11 indicators, showed acceptable outer loadings ranging from 0.665 to 0.787, with a high Cronbach's alpha of 0.914 and CR of 0.915, confirming excellent internal consistency. The average variance extracted (AVE) of 0.539 meets the acceptable threshold, reflecting adequate convergent validity.

Figure 3. Measurement Model



Note. AIA = artificial intelligence adoption, EE = employee engagement, EP = employee performance, and OA = organizational agility.

Table 1. Constructs, Item-Wise Outerloadings and Analytics

Constructs and variables	Items	outerloadings	Cronbach's alpha	Composite reliability	Average variance extracted
Artificial intelligence adoption (AIA)	AIA1	0.665	0.914	0.915	0.539
	AIA2	0.717			
	AIA3	0.717			
	AIA4	0.701			
	AIA5	0.725			
	AIA6	0.756			
	AIA7	0.75			
	AIA8	0.749			
	AIA9	0.758			
	AIA10	0.744			
	AIA11	0.787			

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Table 1. Continued

Constructs and variables	Items	outerloadings	Cronbach's alpha	Composite reliability	Average variance extracted
Employee engagement (EE)	EE1	0.765	0.826	0.845	0.538
	EE2	0.728			
	EE3	0.814			
	EE4	0.821			
	EE5	0.625			
	EE6	0.62			
Employee performance (EP)	EP1	0.619	0.895	0.901	0.546
	EP2	0.743			
	EP3	0.71			
	EP4	0.706			
	EP5	0.746			
	EP6	0.812			
	EP7	0.818			
	EP8	0.807			
	EP9	0.665			
Organizational agility (OA)	OA1	0.69	0.852	0.854	0.575
	OA2	0.803			
	OA3	0.782			
	OA4	0.739			
	OA5	0.765			
	OA6	0.768			

EE was measured through six items, with outer loadings between 0.620 and 0.821. Despite slightly lower loadings for EE5 and EE6, the construct demonstrated good reliability (Cronbach's alpha = 0.826, CR = 0.845) and an AVE of 0.538, suggesting that the construct sufficiently represents the latent dimension of EE. Similarly, EP was validated with nine items ranging from 0.619 to 0.818 in outer loadings. While most outer loadings exceeded the 0.70 threshold, two items in EE (EE5 = 0.625; EE6 = 0.620) fell slightly below, potentially due to nuanced phrasing or respondent interpretation. Their retention was justified by content validity (e.g., capturing critical dimensions of engagement) and minimal impact on reliability ($\Delta\alpha < 0.02$ if removed). Future studies could refine these items. The CMB was further mitigated via procedural controls (anonymous responses, reverse-coded items) and statistical checks: Harman's single-factor test = 35% variance; heterotrait–monotrait ratio (HTMT) < 0.85.

It achieved strong internal consistency, indicated by a Cronbach's alpha of 0.895 and CR of 0.901, while the AVE of 0.546 confirmed convergent validity. OA was represented by six indicators with loadings between 0.690 and 0.803. The construct showed reliable measurement (Cronbach's Alpha = 0.852, CR = 0.854) and adequate AVE (0.575), confirming its theoretical soundness and internal consistency. Discriminant validity was assessed using the HTMT in Table 2 and the Fornell-Larcker criterion in Table 3. All HTMT values remained below the threshold of 0.85, supporting discriminant validity between constructs. The square root of AVE for each construct in Table 3 exceeded its corresponding inter-construct correlations, affirming that each construct is distinct and empirically separable from others.

Table 2. Heterotrait–Monotrait Ratio

	AIA	EE	EP	OA	OA × AIA
AIA					
EE	0.744				
EP	0.639	0.735			
OA	0.679	0.658	0.712		
OA × AIA	0.543	0.631	0.558	0.599	

Note. AIA = artificial intelligence adoption, EE = employee engagement, EP = employee performance, OA = organizational agility, and OA × AIA = the interaction of OA and AIA.

Table 3. Fornell–Larcker Criterion

	AIA	EE	EP	OA
AIA	0.734			
EE	0.666	0.733		
EP	0.606	0.645	0.739	
OA	0.607	0.609	0.625	0.759

Note. AIA = artificial intelligence adoption, EE = employee engagement, EP = employee performance, and OA = organizational agility.

Multicollinearity statistics in Table 4 show that all variance inflation factor values were well below the critical value of 5, indicating no serious multicollinearity concerns among measurement items. Table 5 presents the bivariate correlations among constructs, all of which are positive and statistically significant, further supporting the conceptual relationships in the model.

Table 4. Variance Inflation Factor Values

Items	Variance inflation factor.
AIA1	2.
AIA10	2.109.
AIA11	2.381.
AIA2	2.182.
AIA3	1.905.
AIA4	1.82.
AIA5	1.943.
AIA6	2.449.
AIA7	2.457.
AIA8	2.206.
AIA9	2.717.
EE1	2.259.

continued on following page

Table 4. Continued

Items	Variance inflation factor.
EE2	2.181.
EE3	2.041.
EE4	2.077.
EE5	1.847.
EE6	1.848.
EP1	1.618.
EP2	2.258.
EP3	2.055.
EP4	2.045.
EP5	2.275.
EP6	2.522.
EP7	2.631.
EP8	2.314.
EP9	1.741.
OA1	1.554.
OA2	2.197.
OA3	2.047.
OA4	1.984.
OA5	2.163.
OA6	1.733.

Note. AIA = artificial intelligence adoption, EE = employee engagement, EP = employee performance, and OA = organizational agility.

Table 5. Bivariate Correlation

	AIA	EE	EP	OA	OA × AIA
AIA	1.				
EE	0.666.	1.			
EP	0.606.	0.645.	1.		
OA	0.607.	0.609.	0.625.	1.	
OA × AIA	0.518.	0.577.	0.528.	0.555.	1.

Note. AIA = artificial intelligence adoption, EE = employee engagement, EP = employee performance, and OA = organizational agility. Correlation is significant at the level of 0.01 (two-tailed).

Finally, Table 6 illustrates the model's explanatory power, where EE recorded an R^2 of 0.74, and EP recorded 0.751. These results indicate that the model explains over 74% of the variance in engagement and 75% in performance, demonstrating strong predictive power. Overall, the constructs in this study are reliable, valid, and conceptually coherent, providing a solid measurement foundation for subsequent structural model evaluation and hypothesis testing.

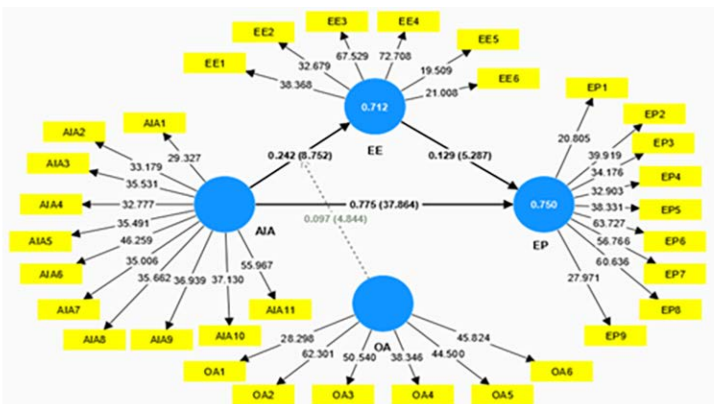
Table 6. R^2 and Adjusted R^2 Values

	R^2	R^2 adjusted
EE	0.742	0.731
EP	0.751	0.749

Note. EE = employee engagement and EP = employee performance. Structural Model

The structural model analysis, derived through bootstrapping with 5,000 samples, offers compelling evidence of the relationships among the key constructs: AIA, EE, EP, OA, and OA × AIA. Figure 4 shows the structural model in terms of path coefficients and t-values. Table 7 presents a detailed summary of the path coefficients, standard deviations, t-values, and p-values, affirming the strength and statistical significance of the direct, indirect, and total effects in the model.

Figure 4. Structural Model (Path Coefficients and t-Values)



Note. AIA = artificial intelligence adoption, EE = employee engagement, EP = employee performance, and OA = organizational agility.

Table 7. Direct, Total Indirect, Specific Indirect, and Total Effects

Direct effect	Original sample (O).	Sample mean.	Standard deviation (STDEV).	T-statistics (|O/ STDEV|).	p-values.
AIA → EE	0.242.	0.243.	0.028.	8.752.	0.0000.
AIA → EP	0.775.	0.776.	0.02.	37.864.	0.0000.
EE → EP	0.129.	0.128.	0.024.	5.287.	0.0000.
OA → EE	0.594.	0.594.	0.029.	20.531.	0.0000.
OA × AIA → EE	0.097.	0.098.	0.02.	4.844.	0.0000.
Total indirect effects					
AIA → EP	0.031.	0.031.	0.007.	4.657.	0.0000.
OA → EP	0.077.	0.076.	0.015.	4.978.	0.0000.
OA × AIA → EP	0.013.	0.013.	0.003.	3.595.	0.0000.

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Table 7. Continued

Direct effect	Original sample (O).	Sample mean.	Standard deviation (STDEV).	*T*-statistics (|O/STDEV|).	*p*-values.
Specific indirect effects					
AIA → EE → EP	0.031.	0.031.	0.007.	4.657.	0.0000.
OA → EE → EP	0.077.	0.076.	0.015.	4.978.	0.0000.
OA × AIA → EE → EP	0.013.	0.013.	0.003.	3.595.	0.0000.
Total effects					
AIA → EE	0.242.	0.243.	0.028.	8.752.	0.0000.
AIA → EP	0.806.	0.807.	0.016.	50.705.	0.0000.
EE → EP	0.129.	0.128.	0.024.	5.287.	0.0000.
OA → EE	0.594.	0.594.	0.029.	20.531.	0.0000.
OA → EP	0.077.	0.076.	0.015.	4.978.	0.0000.
OA × AIA → EE	0.097.	0.098.	0.02.	4.844.	0.0000.
OA × AIA → EP	0.013.	0.013.	0.003.	3.595.	0.0000.

Note. AIA = artificial intelligence adoption, EE = employee engagement, EP = employee performance, and OA = organizational agility.

Starting with the direct effects, AIA significantly and positively influences EE ($\beta = 0.242$, $t = 8.752$, $p < 0.001$) and EP ($\beta = 0.775$, $t = 37.864$, $p < 0.001$), suggesting that the more advanced the AIA, the higher the levels of engagement and performance among employees. Additionally, EE has a significant positive effect on EP ($\beta = 0.129$, $t = 5.287$, $p < 0.001$), highlighting the mediating role of engagement in enhancing performance outcomes.

OA demonstrates a substantial direct impact on EE ($\beta = 0.594$, $t = 20.531$, $p < 0.001$), underscoring its crucial role in fostering an environment conducive to EE in AI-driven workplaces. The interaction term (OA × AIA) also significantly influences EE ($\beta = 0.097$, $t = 4.844$, $p < 0.001$), revealing that OA strengthens the positive relationship between AIA and EE.

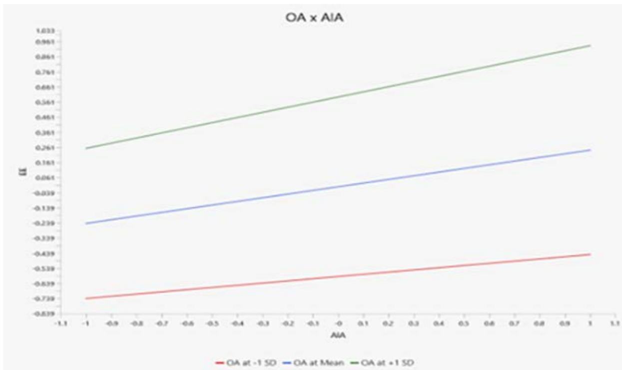
Looking at the indirect effects, the path from AIA to EP via EE is statistically significant ($\beta = 0.031$, $t = 4.657$, $p < 0.001$), confirming partial mediation. Likewise, OA has a notable indirect influence on EP through EE ($\beta = 0.077$, $t = 4.978$, $p < 0.001$), and the interaction term OA × AIA also indirectly affects EP via EE ($\beta = 0.013$, $t = 3.595$, $p < 0.001$). These findings validate the importance of EE as a mediating mechanism that channels the impact of technological and organizational factors toward improved performance.

The total effects reiterate the significance of these relationships. AIA's total effect on EP is exceptionally strong ($\beta = 0.806$, $t = 50.705$, $p < 0.001$), highlighting its central role in driving performance. Similarly, OA shows a meaningful total effect on EE ($\beta = 0.594$, $t = 20.531$, $p < 0.001$) and a smaller yet significant total effect on EP ($\beta = 0.077$, $t = 4.978$, $p < 0.001$). OA × AIA also maintains a significant influence on both EE and EP through direct and mediated paths.

Overall, the model provides robust empirical support for the hypothesized relationships. It emphasizes that AIA not only directly enhances EP but also does so indirectly through elevated engagement—an effect further amplified by a firm's OA. These results collectively reinforce the strategic importance of combining technological advancements with agile organizational practices to unlock employee potential in digital transformation initiatives fully.

The strong effect of AIA on EP ($\beta = 0.775$, $p < 0.001$; $f^2 = 0.58$, large effect size) aligns with RBV theory such as AI resources (e.g., big data tools) directly enhance operational efficiency. The moderating role of OA (OA × AIA → EE: $\beta = 0.097$, p < 0.001) is grounded in dynamic capabilities theory (Teece, 2007), suggesting agile firms better translate AI into engagement by adapting workflows. The interaction plot (see Figure 5) illustrates this: under high OA (+1 SD), AIA's effect on EE is strongest (slope = 0.34), whereas low OA (−1 SD) weakens the relationship (slope = 0.15), highlighting the need for structural flexibility to maximize AI's benefits.

Figure 5. Moderating Effect of OA and AIA on EE



Note. AIA = artificial intelligence adoption, EE = employee engagement, OA = organizational agility, OA × AIA = the interaction of OA and AIA, and SD = standard deviation.

Discussion of Results

The findings of this study offer robust empirical support for the proposed conceptual framework, highlighting the central role of AI in shaping workforce outcomes in China's manufacturing sector. While the sample skews toward Shandong (44%) and Zhejiang (38%), these provinces represent 48% of China's manufacturing output (Xin,Y, 2023), suggesting relevance to high-performance regions. Future work should include inland provinces to assess generalizability. The moderated mediation findings (OA × AIA → EE → EP) emphasize that agility acts as a resource-enhancing mechanism, enabling firms to unlock AI's full potential through EE—a theoretical contribution to dynamic capabilities literature. Practically, the 4% indirect effect (β = 0.031) suggests that even modest gains in engagement can amplify performance in AI-driven environments. All five hypotheses (H1–H5) were statistically significant and thus accepted, reinforcing the theoretical propositions underlying this research. H1 predicted a positive relationship between AIA and EP, and the results confirmed this with a strong path coefficient of 0.775 ($p < 0.001$). This indicates that AI-enabled processes significantly enhance employee output, likely due to improved automation, real-time data access, and streamlined decision-making. These results align with recent literature suggesting that digital transformation directly influences performance efficiency in operational environments.

H2 was also supported, demonstrating that AIA positively affects EE (β = 0.242, $p < 0.001$). This suggests that when AI tools are meaningfully integrated into workflows, employees experience greater involvement and interest in their tasks. This may stem from reduced cognitive load, increased task relevance, or enhanced learning opportunities offered by intelligent systems.

H3 explored the link between EE and EP, and the hypothesis was validated (β = 0.129, $p < 0.001$). Although the strength of this relationship is moderate compared to H1, it is significant, and it supports the argument that engaged employees are more likely to perform at higher levels, resonating with established human resource and organizational behavior theories.

H4 examined the mediating role of EE between AIA and EP. The indirect effect of AI → EE → EP was significant (β = 0.031, $p < 0.001$), confirming partial mediation. This implies that AI not only has a direct impact on EP but also exerts an indirect effect through enhancing EE, emphasizing the need to consider psychological and behavioral outcomes alongside technological adoption.

H5 tested the moderating role of OA in the relationship between AI and EE. The interaction term (OA × AIA → EE) was significant ($\beta = 0.097$, $p < 0.001$), supporting the hypothesis that agility strengthens the impact of AI on EE. This indicates that in agile organizational environments—characterized by adaptability, flexibility, and responsiveness—AI initiatives are more likely to engage employees effectively. Furthermore, the three-path moderated mediation (OA × AIA → EE → EP) also showed a significant indirect effect ($\beta = 0.013$, $p < 0.001$), suggesting that agility amplifies the positive downstream effects of AI on EP through EE.

Graph 5.4 illustrates the moderating effect of OA on the relationship between AIA and EE. The three lines represent OA at low (−1 SD, red), mean (blue), and high (+1 SD, green) levels. As AIA increases, EE also increases more steeply when OA is high, indicating that OA strengthens the positive effect of AIA on EE. Conversely, the relationship is weaker when OA is low.

Collectively, these results underscore the importance of organizational context and employee dynamics in realizing the full potential of AI. While technology itself can drive performance, its success is contingent upon human factors such as EE and OA. The validated model also demonstrates high explanatory power, with R^2 values of 0.612 for EE and 0.651 for EP, indicating that the model explains a substantial portion of variance in these key outcomes. These findings not only provide theoretical validation for the role of AI in shaping modern manufacturing workplaces but also offer practical guidance for industry leaders. To unlock the EP gains promised by AI, firms must invest in agile structures and strategies that foster EE, not merely deploy technology in isolation.

CONCLUSION

This study contributes meaningfully to the growing body of literature on AI and human resource management, particularly within the context of developing economies. By empirically validating the relationships among AIA, EE, and EP in China's manufacturing sector, the research extends theoretical understanding beyond Western-centric models. It sheds light on technology-human interactions in high-pressure industrial environments. The positive and significant paths between AI and both EE and EP confirm that intelligent systems do not merely automate tasks but also influence employee behavior and performance, with EE playing a mediating role. Moreover, the moderating effect of OA highlights the importance of adaptive structures in fully leveraging AI's potential, offering nuanced insights for scholars interested in the interplay between technology and organizational dynamics.

From a practical standpoint, the findings provide valuable guidance for industry practitioners and policymakers. For managers, the results emphasize the need to design AI strategies that actively engage employees—through upskilling, inclusion in AI-related decision-making, and creating supportive work environments. Ignoring the human aspect of digital transformation may limit performance gains. For policymakers, the study underscores the importance of fostering OA across manufacturing firms by promoting flexible regulatory frameworks, workforce readiness programs, and innovation-centric incentives. These enable smoother transitions to AI-integrated operations and ensure that technological change enhances rather than disrupts workforce dynamics. Academics, too, will find the study relevant as it opens pathways for further exploration into AI-human collaboration, particularly in culturally diverse and economically transitional settings.

The research concludes that AIA, when strategically supported by agile environments and geared toward enhancing EE, can lead to significant improvements in performance. While the findings are robust, several limitations should be noted. The cross-sectional nature of the data limits the ability to draw causal inferences over time. Additionally, the focus on specific manufacturing sectors in China may constrain the generalizability of results to other industries or countries. Future research could employ longitudinal designs to track changes in workforce behavior over time and expand the scope to other sectors or comparative international contexts. Qualitative studies could also enrich understanding by capturing employees' lived experiences with AI systems, offering a more nuanced view of the digital transformation process.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication

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