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THE INFLUENCE OF TRANSFORMATIONAL LEADERSHIP, ORGANIZATIONAL SUPPORT, PROACTIVE PERSONALITY, AND AI LITERACY ON TASK PERFORMANCE: THE MEDIATING ROLE OF WORK ENGAGEMENT IN CHINA

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Abstract:

As artificial intelligence (AI) increasingly transforms the manufacturing industry, understanding the human factors that influence task performance is vital. This research explores how transformational leadership, perceived organizational support, proactive personality, and AI literacy influence task performance among employees in manufacturing companies in Hunan Province, China. Grounded in Self-Determination Theory (SDT), the research examines the satisfaction of employees' needs for autonomy, competence, and relatedness promote work engagement, which serves as a mediator in these relationships. The study adopts a quantitative methodology, with the intention of collecting the data through structured surveys from employees in AI-integrated manufacturing companies in China. Statistical Package for the Social Sciences (SPSS) and Structural Equation Modelling (SEM) will be utilized to analyse the direct and indirect impacts of the independent variables on task performance via work engagement. The data will be collected and analysed, and the results are expected to indicate that transformational leadership, organizational support, proactive personality, and AI literacy significantly enhance task performance, both directly and indirectly, by boosting work engagement as hypothesized in this research. This research advances current knowledge by applying SDT in AI-enabled workplaces and is expected to offer practical recommendations for managers seeking to enhance employee motivation and task performance amid technological change.

Keywords:

Transformational Leadership, Organizational Support, and AI Literacy.

Introduction

In 2025, the global manufacturing industry is expected to show six major development trends, including accelerated digital transformation, decentralised manufacturing, continuous improvement of intelligence and automation, green manufacturing, supply chain restructuring and globalisation, as well as talent training and skills transformation (Xu et al, 2022). In its latest annual analysis of manufacturing statistics, Make UK, a UK-based manufacturers' organisation, reveals that China will become the world's largest manufacturing country by 2022, with the world's largest manufacturing output (Make UK, 2022). As a pillar industry of the national economy, the development of the manufacturing sector not only directly affects the country's economic growth rate, but also determines its competitive position in the global value chain. Significant changes have taken place in the workplace due to technological advancements and rapid globalisation, which has forced businesses across industries to adapt to the changing needs of demographics, technology, and socio-economic systems. Among these, Artificial Intelligence (AI) has emerged as a major force driving industrial growth (Chen et al., 2025). In this context, breakthroughs in AI, smart manufacturing and automation technologies are particularly compelling. These technologies are reshaping every aspect of manufacturing: from the intelligent transformation of production processes, to the digital transformation of management models, to the structural adjustment of talent demand (Industrial Digital Talent Research and Development Report, 2023). The latest data from China's National Bureau of Statistics (2024) shows that the high-tech manufacturing sector achieved 8.9% year-on-year growth in 2024, a figure that not only reflects the rapid pace of technological upgrading in the sector, but also highlights the fact that digital transformation has become an inevitable choice for the development of the manufacturing industry.

However, technological change brings with it opportunities as well as significant challenges. As the penetration rate of smart manufacturing technologies continues to rise, enterprises are faced with a key paradox: while new technologies can theoretically improve productivity significantly, the actual effect often depends on the adaptability of employees. In the face of international industrial restructuring and changes, China's Ministry of Education, in conjunction with the Ministry of Human Resources and Social Security and the Ministry of Industry and Information Technology, has jointly compiled the Guidelines for Talent Development Planning in the Manufacturing Sector (Ministry of Education, Ministry of Human Resources and Social Security, & Ministry of Industry and Information Technology. 2017), which aims to benchmark against the traditional manufacturing powerhouses, to design the institutional mechanism for talent development at the top level, and to strengthen the construction of manufacturing talent teams.

Problem Statement

Due to organizational structure changes, technical advancements, and the incorporation of AI into day-to-day operations, China's manufacturing sector has experienced a substantial transition in recent years. Employees must, however, exhibit proactive behaviours, adjust to AI-driven workflows, and receive sufficient organizational and leadership support as their workplaces become more dynamic to sustain high performance levels (Zhang et al., 2019). One of the primary factors influencing task performance in manufacturing is the function of proactive personalities. Employees that are proactive are more likely to address problems, take initiative, and pursue ongoing improvement—all of which are essential for innovation and operational effectiveness. However, rather than proactively optimizing operations, many workers in the manufacturing sector continue to operate in a reactive manner, executing jobs primarily step-by-step. This begs the question of how proactive personalities impact work engagement and, in turn, task performance in the industrial sector (Dai et al., 2024). Organizational support has a significant impact on employees' achievement as well. Lack of resources, subpar training programs, and limited opportunities for professional advancement are common problems experienced by employees in many industrial organizations. Reduced employee motivation, lower work engagement, and subpar task performance might result from a lack of organizational support (Huntington, 2005). Workers may struggle to adjust to new technologies, feel undervalued, and grow increasingly dissatisfied with their jobs without sufficient support networks, all of which eventually lower productivity.

Meng et al. (2020) found that transformational leadership enhances employees perceived meaningfulness of work, which in turn increases their engagement. Similarly, Nurtjahjani et al. (2022) demonstrated that transformational leadership is positively associated with work engagement, particularly when moderated by psychological ownership and belief in a just world. Since previous research on task performance has tended to focus on managerial or technical positions, there is a lack of research on task performance of frontline manufacturing workers in the digital era. This study seeks to fill this gap by examining the main variables affecting task performance in China's manufacturing industry, focusing on the mediating function of work engagement. Filling these research gaps will contribute to theoretical knowledge and practical applications. The findings of this study will help manufacturing companies develop effective training programs, implement supportive leadership strategies, improve employee AI literacy, and create work environments that promote engagement and high performance. Ultimately, these insights will support the sustainable development and global competitiveness of China's manufacturing industry.

Research Gaps

Lack Of Research on Manufacturing Task Performance

Much of the research on task performance has focused on managerial, academic, or service-oriented positions, with limited attention to manufacturing employees. For example, previous studies have examined the antecedents of organizational commitment and its impact on job performance (Kazmi & Javaid, 2022) or explored leadership and engagement in other sectors (Aboramadan et al.,2021). However, manufacturing employees face unique challenges such as high task complexity, technological integration, and changing job expectations, making it necessary to need for a sector-specific investigation of their task performance determinants.

Insufficient Consideration of Proactive Personality and AI Literacy as Predictors

While studies have explored traditional predictors of task performance such as job autonomy, engagement, and supervisor support (Caniels et al., 2018), given the increasing use of AI-driven tools in manufacturing, proactive employees are more likely to proactively adapt to technological developments. Similarly, AI literacy has become critical in the contemporary workplace, but little is known about how it affects work engagement that leads task

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performance. This leaves a gap in our understanding of how AI literacy affects employee's engagement and productivity in the manufacturing industrial sector.

Research Objectives
From the background of the study, a few research objectives were developed:
(1) To examine the relationship between transformational leadership, organizational support, proactive personality, AI literacy and work engagement among Chinese manufacturing employees.
(2) To examine the relationship between transformational leadership, organizational support, proactive personality, AI literacy and task performance among Chinese manufacturing employees
(3) To examine the relationship between work engagement and task performance among Chinese manufacturing employees.
(4) To examine the mediating effect of work engagement on the relationship between transformational leadership, organizational support, proactive personality, and AI literacy and task performance of Chinese manufacturing employees.

Research Questions
Therefore, the research questions were developed as follows:
(1) Is there any relationship between transformational leadership and work engagement among Chinese manufacturing employees?
(2) Is there any relationship between organizational support and work engagement among Chinese manufacturing employees?
(3) Is there any relationship between proactive personality and work engagement among Chinese manufacturing employees?
(4) Is there any relationship between AI literacy and work engagement among Chinese manufacturing employees?
(5) Is there any relationship between transformational leadership and task performance among Chinese manufacturing employees.?
(6) Is there any relationship between organizational support and task performance among Chinese manufacturing employees?
(7) Is there any relationship between proactive personality and task performance among Chinese manufacturing employees?
(8) Is there any relationship between AI literacy and task performance among Chinese manufacturing employees?
(9) Is there any relationship between work engagement and task performance among Chinese manufacturing employees?
(10) Is there a mediating effect of work engagement on the relationship between transformational leadership, organizational support, proactive personality, AI literacy, and task performance among Chinese manufacturing employees?
(11) Is there a mediating effect of work engagement on the relationship between transformational leadership, and task performance among Chinese manufacturing employees?
(12) Is there a mediating effect of work engagement on the relationship between organizational support, and task performance among Chinese manufacturing employees?
(13) Is there a mediating effect of work engagement on the relationship between AI literacy, and task performance among Chinese manufacturing employees?

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Literature Review

Task performance is a critical topic in organizational behaviour, management, and human resource research. As global competition intensifies, organizations are increasingly focused on enhancing employees' task performance to achieve strategic goals and sustainability. Task performance is essential to the success of the organization as a whole and shows how well an employee can carry out their duties. Task performance can be greatly impacted by several factors, including individual traits, organizational support, and leadership style. Understanding these determinants is essential for organizations seeking to foster a high-performance work environment and maintain a competitive edge in the evolving business landscape. Task performance has long been a primary area of study in organizational behaviour and management. Frederick W. Taylor in 1911 laid the groundwork for performance assessment by introducing the idea of "efficiency as performance" through quantitative and standardized techniques of measuring employee productivity (Taylor, 1911). This is where performance studies got their start. To accomplish strategic objectives and maintain long-term success, companies are placing a greater emphasis on task performance as global competition heats up (Demerouti et al., 2014).

Task performance is an essential component of overall task performance since it demonstrates how successfully an individual carries out responsibilities related to their role. Organizational elements (such as leadership, job design, and culture), individual characteristics (such as cognitive ability, personality, and motivation), and environmental factors (including more recent one like AI literacy) all have an effect. In the digital age, AI literacy is increasingly recognized as a crucial enabler, even while organizational support and transformative leadership have long been recognized as significant performance drivers. High-level AI-literate employees are more equipped to foster innovation, optimize output, and adapt to emerging technologies. The definition and measurement of AI literacy are still up for debate, though, which makes it challenging to include in frameworks for standardized training and assessment.

Self-Determination Theory (SDT), developed by Deci and Ryan (2000), provides a robust framework for understanding the motivational processes that drive employees' engagement and performance. SDT posits that individuals are most motivated and perform optimally when their basic psychological needs for autonomy, competence, and relatedness are fulfilled. Within this study, transformational leadership is seen as a key factor that promotes autonomy through empowering employees, supports competence via coaching and feedback, and enhances relatedness by fostering trust and shared goals (Deci & Ryan, 2017). Perceived organizational support similarly satisfies employees' needs for competence—by providing resources and recognition—and relatedness, by affirming that the organization values their contributions (Eisenberger et al., 1986).

The theoretical framework for this research is underlain by the Self-Determination Theory (SDT) (Deci & Ryan, 1985). This model is taken as the grand theoretical foundation for this research. Nevertheless, the generalizability of the underlying theory in much-published research on employees' engagement and performance is complex. As such, the evidence gathered from extensive literature reviews on employee motivation and work resources illustrates that the theoretical continuum of these studies is diverse but remains interconnected (Deci & Ryan, 2000; Bakker & Demerouti, 2017). The interrelated nature of these studies has made the SDT model strong base for any forthcoming research on employee engagement and performance in the manufacturing and service industry. The underlying theory and framework

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used for this research were further broken down based on the conceptualization of proactive personality, organizational support, transformational leadership, and AI literacy as independent variables, the role of work engagement as a mediating variable, and task performance as the dependent variable. As previously mentioned in the literature review, the underlying theory employed in this study has a significant influence on comprehending employee motivation, resource allocation, and performance improvement. The variable system in this study's framework is built using the reasoning of "individual-environment-psychological mechanism-behavioural outcome," which mirrors the usual resource-motivation-performance path.

In particular, the variables were separated into the following four groups by the study. There are two types of external environmental factors: behavioural motivational resources at the management level, such as transformational leadership, and institutional support resources at the organizational level, such as perceived organizational support (POS). While the latter highlights the role of direct supervisors in inspiring employees through inspirational vision, individual care, and role modelling, the former shows employees' general positive assessment of the organization in terms of system, development opportunities, and emotional care. Even though they are both external resources, their levels and methods are different. A proactive personality reflects an individual’s intrinsic tendency to take initiative and control over their work environment, thus fulfilling the need for autonomy and competence (Crant, 2000). AI literacy contributes to the need for competence by increasing employees’ confidence in navigating AI-integrated tasks, reducing anxiety, and improving their perceived effectiveness in technologically advanced settings (Dwivedi et al., 2021). When these psychological needs are met, employees are more likely to experience work engagement—a motivational state characterized by vigor, dedication, and absorption—which acts as a mediating mechanism between the independent variables and task performance (Ryan & Deci, 2017; Bakker & Demerouti, 2008). Consequently, higher engagement leads to increased persistence, creativity, and effectiveness in completing work tasks. Thus, SDT offers a coherent explanation of how psychological, organizational, and individual factors jointly influence employees’ motivation and task performance in the context of AI-enabled manufacturing environments. The theory of this research was underlain based on SDT.

Leadership style, particularly transformational leadership, has a significant impact on employee performance. Nonetheless, transformational leadership besides transactional continue to rule the leadership of many Chinese manufacturing companies. (Hong et. al, 2018) Employee engagement may be affected by the limited use of transformational leadership, which reduces overall job performance. To improve labour productivity in the industrial sector, it is important to understand how transformational leadership affects performance and work engagement. In addition, due to the increasing use of AI-driven technologies in the manufacturing industry, the employment roles of employees have changed, requiring them to develop AI-related competencies. Currently, manufacturing operations rely heavily on AI-driven solutions such as intelligent production planning, predictive maintenance, and automated quality control (Dong, et al., 2024). However, the lack of AI knowledge among many employees makes it difficult to successfully integrate AI into routine tasks. Inadequate AI skills can lead to increased operational errors, increased work stress, and decreased efficiency (Gao, et al., 2023). Although AI applied literacy is becoming increasingly important, little is known about how it affects work engagement and task performance in manufacturing.

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With notable variations in the kinds of resources and methods of action, the external resources that employees rely on in the workplace can be roughly categorized as behavioural motivation at the leadership level and institutional support at the organizational level. Employees' perceptions of the organization's overall attention, respect, and care are the focus of Perceived Organizational Support (POS), which is a type of structural and institutional situational resource (Eisenberger et al., 1986). These resources are primarily represented in training and development opportunities, fair management systems, and reasonable performance evaluations. The dynamic and individualized leadership resource known as transformational leadership, on the other hand, is more focused on the impact of direct supervisors in day-to-day management (Avolio & Bass, 1994). Its goal is to stimulate employees' internal motivation and development potential with role models, individual care, inspiration, and vision shaping capacity for growth and motivation (Bass,1985).

Perceived organizational support (POS), which is frequently derived from institutional levels of fairness, developmental opportunities, and working conditions (Rhoades & Eisenberger, 2002), focuses on employees' overall perceptions of whether the organization values their contributions and cares about their well-being (Eisenberger et al., 1986). On the other hand, transformational leadership is more of a behavioural, interactive, and situational resource that focuses on the behavioural traits of supervisors in their everyday interactions, such as role modelling, motivational visioning, individual caring, and intellectual stimulation (Avolio & Bass, 1994). Despite being work resources, they differ greatly in terms of motivational persistence, methods of action, and resource provision levels (Bakker & Demerouti, 2007). They can be compared in a model to examine independent or synergistic paths of influence.
Although artificial intelligence (AI) technologies have been rapidly adopted by over 60% of manufacturing firms in China (China Academy of Information and Communications Technology, 2023), many organizations have yet to achieve the anticipated enhancements in employee task performance. This gap is primarily due to insufficient employee preparedness, low levels of AI literacy, and inadequate work engagement (McKinsey & Company, 2022; Deloitte, 2023).

While technical skills are undoubtedly important, psychological, and organizational elements—such as transformational leadership, perceived organizational support, and proactive personality traits—are also crucial in driving employee motivation and performance. Nonetheless, existing research has not sufficiently explored how these factors collectively affect task performance in AI-driven manufacturing environments, especially within the Chinese setting. Moreover, the potential mediating effect of work engagement in these relationships remains largely unexplored. Considering the significance of meeting employees' intrinsic psychological needs for autonomy, competence, and relatedness as outlined by Self-Determination Theory (Deci & Ryan, 2000), it is vital to investigate how these variables interplay to influence task performance. Addressing this gap will offer valuable guidance for managers striving to enhance workforce effectiveness in the face of rapid technological advancements.

A key mediator between task performance and proactive personality, organizational support, transformational leadership, and AI literacy is work engagement. On the other hand, factors such as excessive workloads, skill mismatches, and unclear career paths often lead to work disengagement, all of which can adversely affect task performance. Examining job engagement as a mediator can yield important information about ways to improve manufacturing

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employee's performance. Despite the increasing complexity of industrial work roles, the combined benefits of proactive personality, organizational support, transformational leadership, and AI literacy on task performance through the mediating function of work engagement have not been thoroughly studied. Work engagement is commonly acknowledged as a crucial psychological conduit between performance and resources. Task performance, the result variable, is the calibre, effectiveness, and achievement of the tasks that employees complete as part of their official job duties. This metric is frequently utilized as a key indicator of the efficacy of HR procedures in addition to reflecting the exogenous behavioural outcomes of individual outputs. In summary, the goal of the research model is to uncover the logic of the fundamental chain of "internal and external resources-psychological drive-behavioural results" by investigating how to boost employees' psychodynamic energy to improve their work output performance from the perspective of multidimensional resources. From the literature reviewed, the theoretical framework was developed as follows:

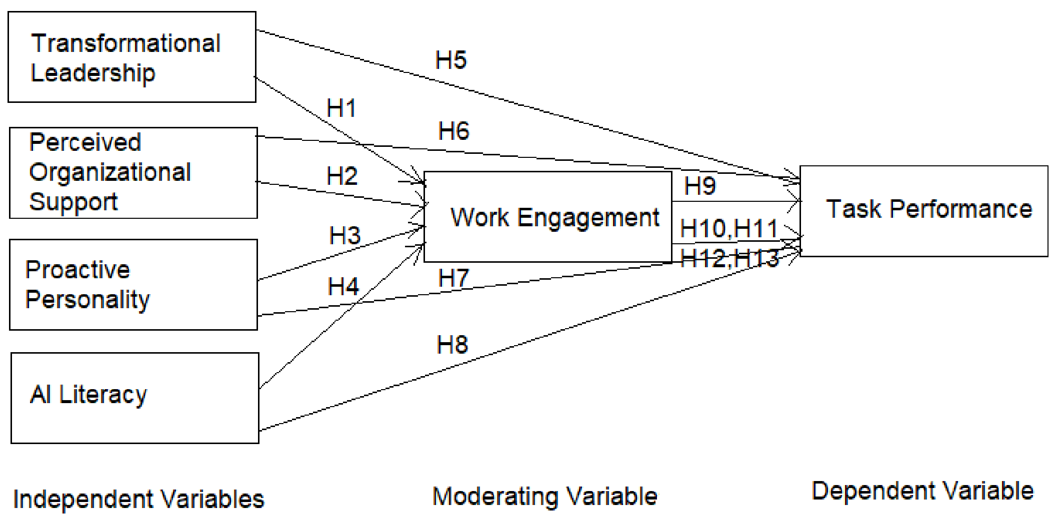

Figure 1: The Theoretical Framework of The Research

Research Hypotheses
The following hypotheses from the respective pioneers are included in the framework and interpreted as below:

H1: There is a significant relationship between transformational leadership and work engagement among Chinese manufacturing employees.

H2: There is a significant relationship between perceived organizational support and work engagement among Chinese manufacturing employees.

H3: There is a significant relationship between proactive personality and work engagement among Chinese manufacturing employees.

H4: There is a significant relationship between AI literacy and work performance among Chinese manufacturing employees.

H5: There is a significant relationship between transformational leadership and task performance among Chinese manufacturing employees.

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H6: There is a significant relationship between perceived organizational support and task performance among Chinese manufacturing employees.

H7: There is a significant positive relationship between proactive personality and task performance among Chinese manufacturing employees.

H8: There is a significant positive relationship between AI literacy and task performance among Chinese manufacturing employees.

H9: There is a significant relationship between work engagement and task performance among Chinese manufacturing employees.

H10: Work engagement significantly mediates the relationship between transformational leadership and task performance among Chinese manufacturing employees.

H11: Work engagement significantly mediates the relationship perceived organization support and task performance among Chinese manufacturing employees.

H12: Work engagement significantly mediates the relationship between proactive personality and task performance among Chinese manufacturing employees.

H13: Work engagement significantly mediates the relationship between AI literacy and task performance among Chinese manufacturing employees.

Research Methodology

This study will use descriptive and correlational research methodology to accomplish its objectives. Descriptive research describes and explains the characteristics of the variables under study (Sekaran & Bougie, 2016). Since this study examines the relationships between task performance, job engagement, transformational leadership, proactive personality, perceived organizational support, and AI literacy, a correlational research approach is appropriate. This method allows the researchers to identify correlations between variables while maintaining measurement objectivity and precision. A correlational study will be carried out to ascertain the relationships among the mediating variable (work engagement), the dependent variable (task performance), and the independent variables (transformational leadership, proactive personality, perceived organizational support, and AI literacy). According to Sekaran and Bougie (2016), correlational research is suitable when the goal is to examine how several factors interact and determine how they interact in a certain context.

The cross-sectional research methodology used in this study collects data at a specific moment in time throughout a predetermined length of time. According to Sekaran and Bougie (2016), a cross-sectional study is appropriate for examining correlations between variables without the need for long-term monitoring. To ensure that there are enough replies to test the research hypotheses, data collecting is scheduled to take place across a few months. The individual employees in Chinese manufacturing industry serves as the study's unit of analysis. Data is gathered at the individual level because the study intends to investigate the effects of work engagement, leadership style, ai literacy, individual personality, and perceptions of organizational support on employees' task performance. To give a thorough analysis of the

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research model, employees from a variety of manufacturing industries, such as automotive, electronics, machinery, tea production and processing and textiles, will be polled.

The study guarantees methodological rigor and permits a methodical investigation of the connections between the major constructs by using this research methodology. The study's goal of validating and expanding on current theoretical knowledge in the context of China's manufacturing sector is in line with the application of a cross-sectional and correlational approach. Employees in China's manufacturing sector make up the research population for this study, which primarily focuses on Hunan province with some data from other areas. Workers in medium and large-sized businesses in the mechanical manufacturing sector are the study's specific target population. Standardized management structures, structured performance review processes, and relatively sophisticated technologies set these companies apart. By concentrating on this area, the study hopes to provide a comprehensive understanding of the dynamics of job performance in structured and technologically advanced organizational environments, while also taking generational differences into account.

According to data from the National Bureau of Statistics, a sizable portion of China's labour force is employed in the manufacturing sector, which continues to be a crucial pillar of the nation's economy. Given the substantial workforce in the mechanical manufacturing industry, selecting an adequate sample size is essential to ensuring the generalizability of the study's findings. Studying the effects of proactive personality, organizational support, transformational leadership, work engagement, and AI literacy on task performance is a great way to learn about employees in this sector. Focusing solely on mechanical manufacturing industry allows for a more concentrated analysis of task performance in a physically diverse and technologically complex industrial environment. The study's target group consists of employees from large and medium-sized companies in the mechanical manufacturing industry. The primary objective is to investigate how task performance is affected by transformational leadership, proactive personality, organizational support, AI literacy, and mediated by work engagement. Because of the high degree of uniformity in performance management, organizational systematicity, and technological complexity within the mechanical manufacturing sector, the study purposefully selected significant companies that are representative of this industry as sample sources.

This study specifically focuses on five Changsha, Hunan province-based businesses—Sany Heavy Industry, Zoom Lion Heavy Industry Science & Technology Co., Ltd., CRCHI Heavy Industry Co., Ltd., Sunward Intelligent Equipment Co., Ltd., and Sinoboom Intelligent Equipment Co., Ltd.—that are listed among the top 50 manufacturers of construction equipment worldwide. These businesses, which span several subsectors such construction machinery, aerial work platforms, tunnel boring machines, and green intelligent manufacturing, have long been at the forefront of the worldwide construction machinery manufacturing industry. They have the following advantages in research: Strong industry representation: China construction machinery magazine and the global top 50 construction machinery manufacturers summit jointly released the 2024 "global top 50 construction machinery manufacturers list," which featured all five companies and demonstrated the sophisticated state of the Chinese and even international machinery manufacturing industries; Full organizational scale: the corporations mentioned above are all medium-sized to large businesses with a sizable workforce, a variety of job kinds, and sophisticated management systems that allow for thorough coverage of workers in various roles and responsibilities; High

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research convenience: Changsha-based researchers make it possible to distribute and collect questionnaires, conduct in-depth interviews, and verify data more quickly, guaranteeing sample quality and information accuracy; Unambiguous theoretical generalizability: despite the Changsha origin of the sample, the chosen businesses are widely represented and have exemplary importance in the sector. Their organizational culture, managerial backgrounds, and degrees of AI application provide theoretical benchmarks for medium- to large-scale machinery manufacturing companies.

Furthermore, there is significant variation within the employee groups in the organizations regarding gender, age, and job functions, especially regarding age structure. Based on the questionnaire, the study divides participants into five age groups: “18 years old to 25 years old”, "26–30 years old," "31–35 years old," "36–40 years old," and "41 years old and above", this allows for a more thorough comparison of generational disparities. Employees in the mechanical manufacturing industry, which falls under category C: manufacturing (National Bureau of Statistics of China, 2017), are particularly included in the research population. Businesses are further divided into the following size groups: big businesses (≥1000 workers), medium-sized businesses (300–999 workers) and small businesses (less than 300 workers).

Sampling Design and Procedures
To ensure the representativeness and relevance of the sample, this study used a structured, multi-stage sampling technique, concentrating on employees of five reputable mechanical manufacturing enterprises in Changsha, Hunan Province. These firms are excellent representations of China's advanced manufacturing sector; they are all large or medium-sized enterprises that are listed in the Top 50 Global Construction Machinery Manufacturers Ranking (International Construction, 2024).

The Sampling Technique Consists of The Following Three Steps:
First, the purposive sampling will be employed. The five mechanical manufacturing firms in Changsha were picked on purpose due to their substantial operations, industry influence, and worldwide repute. This selection technique ensures that the study focuses on employees who work in core production, technology development, and organizational operations—groups most relevant to studying task performance, leadership effect, AI literacy, and proactive work behaviours. Then stratified sampling will be used. The employees in each selected organization are grouped by department or function (e.g., R&D, production, quality control, administration) and job level (e.g., operational staff, technicians, mid-level managers). This stratification allows for adequate representation of each type of employee and allows for the investigation of the potential impact of occupational or structural disparities on the linkages under study. Lastly, simple random sampling will be employed where employees from every stratum are selected at random to participate in the survey. This approach will reduce selection bias and improve the findings' generalizability. Employees from a variety of job roles and demographic backgrounds in the mechanical manufacturing sector make up the final sample, which offers a strong basis for investigating how task performance is impacted by transformational leadership, proactive personality, perceived organizational support, AI literacy and word engagement as mediating variable.

The questionnaire will be distributed using internal company communication channels, WeChat, and Wenjuanxing. With sporadic follow-up communications to promote participation and increase the response rate, the poll will be available for two months. The study will improve

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methodological rigor and fortifies the validity and relevance of its conclusions in the context of China's upscale mechanical manufacturing industry by utilizing this structured sample techniques.

Locations Of Data Collection and Sampling Plan
Five prominent machinery manufacturing companies that were included in the 2024 Top 50 Global Construction Machinery Manufacturers Ranking—which was co-published by China Construction Machinery magazine and the Global Construction Machinery Manufacturers Summit—are the focus of this study, which focuses on data collection in Changsha City, Hunan Province. Sany Heavy Industry, Zoom Lion Heavy Industry, Sunward Intelligent Equipment, Sinoboom Intelligent Equipment, and CRCC (China Railway Construction Heavy Industry) are some of these businesses. These companies are categorized as large or medium-sized businesses with significant innovation capabilities and a global market presence. They represent a variety of product segments in the high-end manufacturing machinery industry.
To guarantee sufficient data coverage and organizational variety, the sampling plan is organized as follows:
(1) Changsha, Province of Hunan. Employees of the following five businesses will have their data gathered:
1. Sany Heavy Industry (large company; 7th in the world).
2. Zoom Lion Heavy Industry is a sizable company that is ranked 10th in the world.
3. China Railway Construction Heavy Industry (CRCHI) is a major company that is ranked 33rd in the world.
4. Sunward Intelligent Equipment is a medium-sized business that is ranked 43rd in the world.
5. Sinoboom Intelligent Equipment is a medium-sized business that is ranked 44th in the world.

(2) Online distribution of questionnaires.

The survey will be disseminated electronically using WeChat, Wenjuanxing, and internal company communication channels to increase accessibility and response rates (Questionnaire Star). Participants will be drawn from a variety of departments and levels of staff, including management, R&D, production, and quality control. To guarantee enough response volume and representativeness, the survey will be opened for two months with frequent reminders. The study can examine how transformational leadership, proactive personality, organizational support, AI literacy, and work engagement affect task performance in a strategically important cluster of China's high-end manufacturing sector thanks to this targeted but varied sampling approaches.

Questionnaire
The questionnaire consists of four sections (A, B, C, and D) to assess the study variables comprehensively:

Section A: Basic Information, Respondents' gender, age, position level, years of work Experience, highest education level, industry type, job type and AI training experience within China's manufacturing sector are among the background data gathered in this section. These elements guarantee sample representativeness and provide context for the results. Section B: Independent Variables include Proactive personality, perceived organizational support, transformational leadership, and AI literacy are the independent factors that are measured in

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this section. Validated measuring scales from the body of existing literature are used to evaluate each construct. Section C: Mediating variable act as a mediating variable where work engagement is assessed by evaluating employees' levels of involvement with their tasks using a pre-established scale. While Section D: Dependent Variable, the Task Performance is the dependent variable in this study, evaluated using a reliable and widely used scale.

For Sections B, C, and D, a Likert scale will be used to guarantee uniformity and simplicity of response. Respondents can indicate how much they agree or disagree with each statement using a scale that goes from 1 (strongly disagree) to 5 (strongly agree). The use of validated structured questionnaires guarantees that the information gathered can be measured and used for statistical analysis. To ensure clarity and dependability, the questionnaire will be both pre-tested or pilot-tested to improve the phrasing and structure of the questions. The following section of this chapter covers the specific sections involved in instrument validation as shown in Table 1 below.

Table 1: Variable Composition and Questionnaire

Section	Rating Scale	Variable	Scale Basis
A	Dichotomous Scale	Gender	
	Dichotomous	Age	
		Position	
		Working Experience	
		Highest Education Level	
		industry sector	
		Job Type	
		Salary Level	
		AI Training Experience	
B	Likert Scale	Transformational Leadership	Carless et al. (2000).
		Perceived Organization Support	Oubibi, M., Fute, A., Xiao, W., Sun, B., & Zhou, Y. (2022) ; Rhoades, L., & Eisenberger, R. (2002).
		Proactive personality	Seibert, S. E., Crant, J. M., & Kraimer, M. L. (1999).
		AI Literacy	Carolus, A., Koch, M. J., Straka, S., Latoschik, M. E., & Wienrich, C. (2023).
C		Work Engagement	Oubibi, M., Fute, A., Xiao, W., Sun, B., & Zhou, Y. (2022) ; Schaufeli and Bakker (2003).

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D		Task Performance	Han Y, Liao Jianqiao, Long Lirong. (2007).

Tools and Techniques

SPSS and SmartPLS Version 3 are the main data analysis tools that will be used in this study. With Partial Least Squares Structural Equation Modelling (PLS-SEM), these software applications allow the researchers to perform preliminary data analysis, validity and reliability tests, and hypotheses testing. One well-liked program for analyzing data from social science research is the Statistical Analysis Software Package, or SPSS. Its wide variety of capabilities includes outlier detection, reliability testing, normality tests, descriptive statistics, common method bias analysis, and missing value analysis (Mat-Roni, 2015). To ensure data accuracy, SPSS Version 27 will be used for this study's initial data screening before proceeding to structural equation modelling. This study will employ Partial Least Squares Structural Equation Modeling (PLS-SEM) using Smart PLS Version 3. PLS-SEM, a variance-based structural equation modeling technique, is particularly useful for doing exploratory research and formulating hypotheses (Hair et al., 2017). With Smart PLS for hypothesis testing and SPSS for preliminary data analysis, this study is hoped to guarantee a thorough and methodical approach to examining the correlations between variables in the context of the Chinese manufacturing industry.

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References

Aboramadan, M., Dahleez, K., & Hamad, M. H. (2021). Servant leadership and academics outcomes in higher education: The role of job satisfaction. *International Journal of Organizational Analysis, 29*(3), 562–584.

Avolio, B. J., & Bass, B. M. (2004). Multifactor leadership questionnaire: Third edition manual and sampler set. Mind Garden, Inc.

Bakker, A. B., & Demerouti, E. (2007). The Job Demands-Resources model: State of the art. *Journal of Managerial Psychology*, 22(3), 309–328. https://doi.org/10.1108/02683940710733115

Bass, B. M. (1985). Leadership and performance beyond expectations. Free Press.

Caniels, M. C. J., Semeijn, J. H., & Renders, I. H. M. (2018). Mind the mindset! The interaction of proactive personality, transformational leadership, and growth mindset for engagement at work. *Career Development International, 23*(1), 48–66. https://doi.org/10.1108/cdi-11-2016-0194

Carolus, A., Koch, M. J., Straka, S., Latoschik, M. E., & Wienrich, C. (2023). MAILS - Meta AI literacy scale: Development and testing of an AI literacy questionnaire based on well-founded competency models and psychological change- and meta-competencies. *Computers in Human Behavior: Artificial Humans*, 1(2), 100014. https://doi.org/10.1016/j.chbah.2023.100014

Volume 8 Issue 31 (September 2025) PP. 719-734
DOI: 10.35631/IJEMP.831049
Chen, K., Zhao, S., Jiang, G., He, Y., & Li, H. (2025). The green innovation effect of the digital economy. *International Review of Economics & Finance, 99*, Article 103970. https://doi.org/10.1016/j.iref.2024.103970

China Academy of Information and Communications Technology. (2023). *Annual report on AI adoption in Chinese manufacturing*. [Report].

Carless, S. A., & De Paola, C. (2000). The measurement of cohesion in work teams. Small Group Research, 31(1), 71–88. https://doi.org/10.1177/104649640003100104

Crant, J. M. (2000). Proactive behavior in organizations. *Journal of Management*, 26(3), 435–462.

Dai, K., Yang, X., & Chen, A. (2024). How does functional industrial policy promote green innovation? Empirical evidence from manufacturing development strategies. Modern Economic Science, 46(6), 116–131. https://doi.org/10.20069/j.cnki.DJKX.202406009

Deci, E. L., & Ryan, R. M. (1985). Intrinsic motivation and self-determination in human behavior. Plenum.

Deci, E. L., & Ryan, R. M. (2000). The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Demerouti, E., Bakker, A. B., & Leiter, M. P. (2014). Burnout and job performance: The moderating role of self-efficacy. *Journal of Occupational Health Psychology*, 19(1), 53–65. https://doi.org/10.1037/a0033900

Dong, H., et al. (2024). Research on technology and application of artificial intelligence enabling the whole process of manufacturing. *ICT & Policy*, 50(12), 42.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Constantiou, I., & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management,* 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2020.101994

Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. *Journal of Applied Psychology*, 71(3), 500–507. https://doi.org/10.1037/0021-9010.71.3.500

Gao, Z., & Zhang, H. (2023). Paths and countermeasures for optimizing the talent support system of manufacturing enterprises driven by high-quality development. Journal of Technology Economics, 42(12), 45–55. https://doi.org/10.3969/j.issn.1003-1398.2023.12.005

Ge, Y., Tian, Y., Li, M., & Wang, C. (2011). Application of structural equation modeling in management research: Comparative analysis of PLS-SEM and CB-SEM. *Journal of Industrial Engineering and Engineering Management*, 25(4), 112–118.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107–123.

Han, Y., Liao, J., & Long, L. (2007). Model of development and empirical study on employee job performance construct. *Journal of Management Sciences in China, 10*(5), 62–77. https://doi.org/10.3969/j.issn.1007-9807.2007.05.008

Hong, S.-P. (2018). A study on the impact of leadership style on green innovation performance: Green open innovation activities as a mediating variable (Master’s thesis). National Taiwan Normal University, Taiwan.

Huntington, R. (2025). Perceived organizational support. *Journal of Applied Psychology, 71*(3), 500-507.

EISSN : 2600-8750
Volume 8 Issue 31 (September 2025) PP. 719-734
DOI: 10.35631/IJEMP.831049

International Construction. (2024). Ranking of the top 50 global construction machinery manufacturers in 2024. https://www.cm-sv.com/news/ranking-of-the-top-50-global-construction-machinery-manufacturers-in-2024/

Kazmi, S. W., & Javaid, S. T. (2022). Antecedents of organizational identification: Implications for employee performance. *RAUSP Management Journal, 57*(2), 111–130.

Make UK. (2022). UK Manufacturing: The Facts 2022. Make UK. Retrieved from https://memuknews.com/business/government-legislation/uk-manufacturing-slips-to-twelfth-in-world-rankings/

Mat Roni, S. (2015). Preliminary data analysis: An analysis before the analysis. Edith Cowan University. Retrieved from https://www.researchgate.net/publication/262151892_Introduction_to_SPSS

Meng, F., Wang, Y., Xu, W., Ye, J., Peng, L., & Gao, P. (2020). The diminishing effect of transformational leadership on the relationship between task characteristics, perceived meaningfulness, and work engagement. *Frontiers in Psychology*, 11, 585031. https://doi.org/10.3389/fpsyg.2020.585031

McKinsey & Company. (2022). *The state of AI adoption in manufacturing*. [Report].

Ministry of Education, Ministry of Human Resources and Social Security, & Ministry of Industry and Information Technology. (2017). Guidelines for manufacturing talent development planning.

National Bureau of Statistics of China. (2017). What are the criteria for the division of large, small, medium, and micro enterprises. https://www.stats.gov.cn/zs/tjws/tjbz/202301/t20230101_1903367.html

Nurtjahjani, F., Batilmurik, R. W., Puspita, A. F., & Fanggidae, J. P. (2022). The relationship between transformational leadership and work engagement: Moderated mediation roles of psychological ownership and belief in just world. *Organization Management Journal*, 19(2), 47–59. https://doi.org/10.1108/OMJ-03-2021-1169

Oubibi, M., Fute, A., Xiao, W., Sun, B., & Zhou, Y. (2022). Mobile-optimized AI-driven personalized learning: A case study at Mohammed VI Polytechnic University. *Sustainability, 14*(4), 2045. https://doi.org/10.3390/su14042045

Rhoades, L., & Eisenberger, R. (2002). Perceived organizational support: A review of the literature. *Journal of Applied Psychology, 87*(4), 698–714. https://doi.org/10.1037/0021-9010.87.4.698

Ryan, R. M., & Deci, E. L. (2017). Self-determination theory: Basic psychological needs in motivation, development, and wellness. Guilford Press.

Seibert, S. E., Crant, J. M., & Kraimer, M. L. (1999). Proactive personality and career success. *Journal of Applied Psychology, 84*(3), 416–427.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach* (7th ed.). John Wiley & Sons.

Taylor, F. W. (1911). The principles of scientific management. Harper & Brothers.

Xu, G., Zeng, J., Wang, H., Qian, C., & Gu, X. (2022). How transformational leadership motivates employee involvement: The roles of psychological safety and traditionality. *SAGE Open, 12*(1). https://doi.org/10.1177/21582440211069967

Zhang, Y., & Zhang, L. (2019). Artificial intelligence: Angel or devil of human destiny—Also discussing new technology and youth development. *China Youth Social Science, 38*(1), 1–23. https://doi.org/10.16034/j.cnki.10-1318/c.2019.01.003