INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES
Vol 16, Issue 3, (2026) E-ISSN: 2222-6990

The Impact of Transformational Leadership on the Task Performance of Elderly Care Workers: The Mediating Role of Work Engagement and the Moderating Role of Attitudes toward Artificial Intelligence

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DOI Link: http://dx.doi.org/10.6007/IJARBSS/v16-i3/27962

Published Date: 16 March 2026

Abstract

Purpose: This study investigates the impact of transformational leadership (TL) on the task performance (TP) of elderly care workers in Beijing, examining the mediating role of work engagement (WE) and the moderating effect of attitudes towards artificial intelligence (AAI). **Design/methodology/approach:** A quantitative design was adopted, using purposive sampling of 268 elderly care workers in Beijing, China. Data were analysed using SPSS and SmartPLS, with 5,000 resampling bootstraps employed within the Job Demands-Resources (JD-R) model to test the hypothesised relationships. **Findings:** TL positively influenced TP through WE, indicating a full mediation effect, as the direct relationship between TL and TP was not significant. AAI significantly moderated the relationship between WE and TP, with favourable AAI strengthening this link. These findings support the motivational processes proposed by the JD-R model and demonstrate that AAI, as a personal resource, can enhance the connection between engagement and performance. **Research limitations/implications:** This study is confined to elderly care institutions in Beijing, which may limit the generalisability of the findings. The cross-sectional design restricts causal inference, while self-reported data may introduce common method bias. Future research may adopt longitudinal or multi-source methodologies. **Practical implications:** Research findings indicate that while care service providers strengthen TL and employee engagement, they should prioritise fostering positive AAI. Systematic training, organisational support, and open communication can further enhance engagement, thereby improving AI application and TP. **Originality/value:** Within the context of elderly care, research examining the incorporation

of AAI into the JD-R model remains scarce. This study contributes to understanding how TL and AAI jointly shape employees' WE and TP.
Keywords: Transformational Leadership, Work Engagement, Task Performance, Ai Attitudes, Elderly Care Workers, JD-R Model

Introduction

China is experiencing one of the most rapid population ageing processes globally. As of the end of 2023, there were over 297 million individuals aged 60 and older, representing 21.1% of the total population (National Bureau of Statistics of China, 2024). This figure is projected to exceed 400 million by 2035, accounting for more than 30 per cent of the total population and marking the onset of a deeply ageing society (Xinhua, 2025). Unlike the nearly century-long demographic transition experienced by many European countries, China has accomplished this shift in just two decades (Yuan & Gao, 2020). The World Bank has further noted that population ageing is becoming an urgent concern in developing countries, calling for timely policy and institutional responses (World Bank, 2021).

This demographic shift has exerted unprecedented pressure on China's elderly care system, particularly in institutional care, where growing demand is compounded by a pronounced shortage of skilled workers (Hung, 2023; Yuan & Gao, 2020; Zhao & Li, 2024). Despite the nationwide expansion of institutional care services, significant structural challenges persist. Although the number of facilities has expanded, the misalignment between service supply and demand persists, with ongoing concerns about service quality and workforce capacity (Zhang & Zhang, 2023).

Beijing presents a particularly critical case study. According to the Beijing Municipal Working Committee on Ageing, Beijing Association on Ageing, and China Philanthropy Research Institute at Beijing Normal University (2024), adults aged 60 and above accounted for 30.12% of the city's registered residents by the end of 2023, which was well above the national average. The report also shows that during the same period, 42,000 registered care workers were employed across the city. Of these, approximately 11,000 were employed by 571 registered elderly care institutions, which collectively provided 112,000 certified care beds. Despite this, occupancy rates remain relatively low. This paradox of low occupancy coexisting with persistent staffing shortages highlights a profound structural mismatch between service provision and actual demand. Concurrently, labour shortages have increased workloads, intensified job pressures, and undermined service performance (Zhang & Zhang, 2023). Factors such as high job intensity, limited career progression opportunities, and relatively low remuneration further exacerbate recruitment and retention challenges (Zhao & Li, 2024).

To address these challenges, the Chinese government has elevated smart elderly care (SEC) to a national strategic priority within the broader smart health and elderly care (SHEC) initiatives (National Health Commission of the People's Republic of China, 2021; Xinhua, 2025). These programmes promote the integration of AI, big data, and Internet of Things (IoT) technologies to enhance service efficiency and quality while alleviating labour shortages. Within this framework, AI-enabled elderly care (AIEC) has emerged as a practical reform pathway (National Health Commission of the People's Republic of China, 2021). Rather than replacing human labour, AIEC seeks to optimise resource allocation, support frontline workers, and enhance the effective use of human capital (Wong et al., 2024; Topol, 2019).

Evidence suggests that digital platforms and AI applications can enhance efficiency, improve resource coordination, and improve the care experience for institutional residents (Chen et al., 2025; Zhao & Li, 2024).

Importantly, the successful implementation of AIEC depends not only on technological readiness but also on frontline employees' willingness to engage with such innovations (Chen et al., 2025; Hung, 2023). Research indicates that team leaders play a pivotal role in motivating staff to embrace AI, while employees' AAI influences whether this engagement translates into improved TP (Wong et al., 2024). However, empirical evidence regarding how TL and employees' AAI jointly influence WE and TP in elderly care institutions, particularly in China, remains limited. Against this backdrop, this study examines the impact of TL on TP among care workers in Beijing's elderly care institutions, using WE as a mediating variable and AAI as a moderating variable. This research contributes to expanding the JD-R model (Bakker & Demerouti, 2017; Bakker & de Vries, 2021) and offers practical insights for promoting sustainable performance in elderly care institutions amidst digital transformation.

Literature Review

Transformational Leadership

Transformational leadership (TL) is defined as "a job resource because this intangible asset allows the employees and managers to achieve work goals, reduce hindrance job demands and the associated costs and stimulate personal growth, learning and development" (Juyumaya & Torres, 2023, p. 36). Traditionally, TL has been conceptualised through four dimensions: "Idealized influence, inspirational motivation, intellectual stimulation, and individualized consideration" (Bass & Avolio, 1994, p. 3). However, meta-analytic evidence indicates these dimensions are highly correlated and are often regarded as indicators of a single higher-order construct (Judge & Piccolo, 2004). Consequently, recent studies have increasingly adopted a unidimensional approach to examining TL, treating it as a composite leadership style when assessing its impact on employee outcomes (Wang et al., 2022; Juyumaya & Torres, 2023). Consistent with this approach, the present study conceptualises TL as a single-factor construct to maintain parsimony and theoretical coherence within the research framework.

Within elderly care institutions, TL proves particularly crucial given the high physical exertion and intense emotional demands faced by frontline workers (Krijgsheld, Tummers, & Scheepers, 2022). Leaders who articulate a clear vision and provide personalised support can foster openness to innovation, reduce resistance to change, and cultivate a supportive atmosphere, thereby enhancing adaptability, as recent research in service and AI-enabled contexts suggests (Wang et al., 2022; Nguyen & Malik, 2022). Empirical research confirms that TL enhances WE, which in turn fosters more substantial organisational commitment and improves TP (Judge & Piccolo, 2004; Wang et al., 2022). Within the JD-R model, leadership is regarded as a key organisational resource that helps buffer job demands and stimulate motivational processes (Bakker & Demerouti, 2017; Bakker & de Vries, 2021). Consequently, recent research increasingly emphasises the value of TL in fostering engagement rather than focusing solely on its direct impact on performance (Wang et al., 2022).

TL plays a pivotal role in organisational technological transformation, particularly in AI-driven digitalisation. With the rise of digital and AI-enabled elderly care systems, leaders who articulate a clear vision for AI applications, build trust in AI tools, and integrate them into workflows can enhance staff engagement, adaptability, and ultimately achieve sustainable performance (Na, Jung, & Kim, 2023; Wang et al., 2023). However, few studies have specifically examined the role of TL during AI-driven digital transformation in elderly care institutions, particularly in the Chinese context, where smart elderly care is developing rapidly yet still faces significant challenges related to AI anxiety among elderly care workers (Hung, 2023; Zhang & Zhang, 2023).

Work Engagement

Work Engagement (WE) has emerged as a key mechanism for explaining how employees maintain positive functioning despite high job demands. WE is defined as “a positive, fulfilling, work-related state of mind characterised by vigour, dedication, and absorption” (Schaufeli et al., 2002, p. 74), representing a primary pathway within the JD-R framework through which job resources translate into performance outcomes (Bakker & Demerouti, 2017). Specifically, within labour-intensive elderly care services, WE help buffer the adverse effects of burnout and contribute to improved service quality and sustainability (Bakker & de Vries, 2021; Chiminelli-Tomás et al., 2025).

Previous research indicates that WE positively correlates with TP, organisational commitment, and innovative behaviour (Corbeanu & Iliescu, 2023), and frequently mediates the effects of leadership and organisational support (Saks, 2006; Juyumaya & Torres, 2023). Recent scholarship has increasingly examined WE within the context of technological change. During organisational technological adoption processes, engagement influences employees’ willingness to accept and utilise these innovations (Wong et al., 2024). Within AI-enabled elderly care, TL stimulates employees’ intrinsic motivation, while positive AAI determines whether engagement translates into enhanced performance (Juyumaya & Torres, 2023; Nguyen & Malik, 2022).

Recent empirical findings further reinforce this view. Wang et al. (2023) report that responsible AI implementation can enhance WE and performance, indicating that AI adoption strengthens motivational processes when it is managed ethically and strategically. Similarly, Chuang and Huang (2025) found that highly engaged employees tend to perceive AI as supportive rather than threatening, suggesting a reciprocal relationship between engagement and employees’ attitudes towards AI. However, empirical evidence on WE as a mediating mechanism in digital transformation remains limited, particularly in China, where institutions continue to face severe labour shortages and rapid pressure to adopt AI (Hung, 2023; Zhang & Zhang, 2023). To address this gap, this study conceptualises WE as a core motivational pathway through which TL enhances TP, rather than acting directly, thereby reflecting the motivational processes of the JD-R model.

Task Performance

Task Performance (TP) is defined as “the proficiency with which job incumbents perform activities that are formally recognised as part of their jobs and that contribute to the organisation’s technical core” (Borman & Motowidlo, 1993, p. 73). In elderly care services, TP encompasses both physical care responsibilities for older adults, such as assisting with daily living activities and conducting medical monitoring, as well as emotional support, both of which are crucial to the well-being of residents in elderly care institutions. Maintaining high levels of TP is vital to the reputation of elderly care institutions and maintaining public trust (Wang et al., 2023; Krijgsheld, Tummers, & Scheepers, 2022).

The advent of smart elderly care has introduced new skill requirements for elderly care workers, particularly in operating and adapting to AI-assisted systems (Wong et al., 2024; Hung, 2023). However, many care workers in China possess relatively low educational backgrounds and limited exposure to AI, constraining their capacity to adopt and utilise AI to enhance performance (Wang et al., 2023; Zhao & Li, 2024). These challenges suggest that the technological competence of care workers in contemporary elderly care institutions depends not only on their professional capabilities but also on their ability to employ technology effectively.

Positive AAI strengthens employees' confidence and willingness to integrate intelligent tools into daily work, thereby improving performance (Nguyen & Malik, 2022; Manresa et al., 2025). Supportive TL plays a pivotal role in fostering employee engagement and technological readiness, thereby translating into improved performance (Melkas et al., 2020; Na, Jung, & Kim, 2023). Within the JD-R model, TP in AI-assisted elderly care may be conceptualised as the outcome of a resource-motivational process, in which TL primarily enhances TP indirectly through WE, while AAI reinforces this motivational pathway (Bakker & Demerouti, 2017; Xanthopoulou et al., 2007; Tariq et al., 2025).

Attitudes towards AI

Attitudes towards artificial intelligence (AAI) are increasingly recognised as a factor influencing employees' adoption and use of AI technologies in the workplace. Positive attitudes foster trust in AI systems and encourage the integration of AI into daily tasks, thereby improving work efficiency and effectiveness (Tariq et al., 2025; Manresa et al., 2025). Research grounded in the Technology Acceptance Model (TAM; Venkatesh et al., 2003) reveals that positive attitudes towards AI are associated with increased trust in AI systems and higher usage intentions (Tariq et al., 2025). Although some studies indirectly link AI utilisation to enhanced perceptions of efficiency and service quality, further empirical validation of the attitudinal mechanism is needed (Nguyen & Malik, 2022).

Within elderly care services, AI is increasingly discussed as an area needing ethical oversight, while also being recognised for its potential to improve efficiency (Hung, 2023; Chen et al., 2025). In China, government policy initiatives in smart health and elderly care have promoted the implementation of AI technologies (Xinhua, 2025); however, their ultimate success depends on frontline care workers' acceptance (Chen et al., 2025; Zhao & Li, 2024). Evidence indicates that applying AI to elderly care services presents both substantial opportunities and systemic challenges, suggesting successful integration requires not only suitable technology but also supportive organisational and policy frameworks (Zhao & Li, 2024). Notwithstanding these advances, AI cannot fully substitute for the interpersonal and emotional aspects of care (Topol, 2019; Taddeo & Floridi, 2021). Accordingly, elderly care workers require ongoing training and organisational support to effectively utilise AI (Wong et al., 2024; Nguyen & Malik, 2022).

Within the JD-R model, AAI constitutes a personal resource that supports motivation and strengthens the link between WE and TP (Bakker & de Vries, 2021). Concerns regarding technological complexity, ethical implications, and sustainability continue to shape employee perceptions (Melkas et al., 2020; Wong et al., 2024). Employees with more favourable AAI are more likely to convert their WE into higher levels of TP (Tariq et al., 2025; Nguyen & Malik, 2022), although empirical evidence in the context of elderly care remains limited. This study addresses this gap by conceptualising AAI as a moderating variable in the WE-TP relationship, rather than as a direct determinant of performance.

Job Demands-Resources (JD-R) Model
The JD-R model explains how job demands and resources jointly shape employee outcomes (Demerouti et al., 2001; Bakker & Demerouti, 2017). High job demands, such as workload and emotional labour, can trigger stress, whereas job resources such as leadership and autonomy activate motivational processes that enhance WE and TP (Schaufeli, 2017; Xanthopoulou et al., 2007, 2009). Personal resources, such as self-efficacy and AAI, also sustain motivation and buffer against stress (Bakker & de Vries, 2021; Melkas et al., 2020). In elderly care services, where job demands are typically high, resources are crucial to maintaining service effectiveness (Krijgsheld, Tummers, & Scheepers, 2022). Within this framework, TL operates primarily as a job resource to promote WE, thereby enhancing TP, while AAI, as a personal resource, moderates the relationship between WE and TP (Bakker & Demerouti, 2017; Wong et al., 2024; Tariq et al., 2025).

Hypothesis Development
Transformational Leadership and Work Engagement
Transformational leadership provides employees with vision, inspiration, intellectual stimulation, and individualised support (Bass & Riggio, 2006). These behaviours act as organisational resources within the JD-R model, enabling employees to cope with work demands and sustain motivation. Previous research has shown that TL enhances engagement (Wang et al., 2022), particularly within care settings characterised by high emotional and physical demands (Krijgsheld, Tummers, & Scheepers, 2022). However, empirical evidence remains limited in the context of Chinese elderly care institutions, especially as AI-driven transformation continues to reshape leadership and employee motivation.
Hypothesis 1: Transformational leadership is positively related to work engagement.

Transformational Leadership and Task Performance
Transformational leadership may directly influence TP by aligning employees' efforts with organisational goals, fostering a sense of responsibility, and motivating them to exceed expectations (Bass & Riggio, 2006). Previous research suggests that TL fosters supportive and empowering environments, thereby enhancing employee performance (Wang et al., 2022). However, evidence regarding this direct relationship remains inconclusive, particularly in labour-intensive elderly care services undergoing technological transformation.
Hypothesis 2: Transformational leadership is positively related to task performance.

Work Engagement and Task Performance
Work engagement is defined as a positive, work-related state characterised by vigour, dedication, and absorption (Schaufeli et al., 2002) and has consistently been linked to higher TP in service industries (Corbeanu & Iliescu, 2023; McManus, Dundon, & Lavelle, 2025). In elderly care settings, engaged elderly care workers are typically more attentive to residents' needs, more proactive in problem-solving, and more resilient in the face of demanding

conditions (Chiminelli-Tomás et al., 2025). Despite substantial evidence supporting this relationship, few studies have investigated it within the context of AI-supported elderly care.
Hypothesis 3: Work engagement is positively related to task performance.

The Mediating Role of Work Engagement Between Transformational Leadership and Task Performance

Within the JD-R model, WE represents a central motivational pathway through which job resources influence employee outcomes (Bakker & Demerouti, 2017; Schaufeli, 2017). TL motivates employees and fosters higher engagement (Wang et al., 2022), which subsequently contributes to improved TP (Xanthopoulou et al., 2007, 2009). This mechanism is particularly relevant in elderly care institutions, where care workers encounter substantial job demands alongside the adoption and development of AI technologies (Chiminelli-Tomás et al., 2025). However, empirical evidence for this mediating relationship remains limited within Chinese elderly care institutions.
Hypothesis 4: Work engagement mediates the relationship between transformational leadership and task performance.

The Moderating Role of Attitudes towards AI Between Work Engagement and Task Performance

Within the JD-R model, AAI is conceptualised as a personal resource (Xanthopoulou et al., 2007) that may reinforce the motivational process by which WE enhances TP. Employees with a positive attitude towards AI are more likely to accept and effectively utilise AI tools to deliver high-quality care (Na, Jung, & Kim, 2023; Nguyen & Malik, 2022). Previous research further suggests that employees who hold a favourable attitude towards AI can improve various performance indicators, including TP (Zhao and Li, 2024; Manresa et al., 2025). However, empirical evidence from elderly care institutions experiencing increasing AI integration remains limited.
Hypothesis 5: Attitudes towards AI positively moderate the relationship between work engagement and task performance, such that the effect of work engagement on task performance is more substantial under more favourable attitudes towards AI.

Figure 1 presents the research framework developed from the proposed hypotheses.

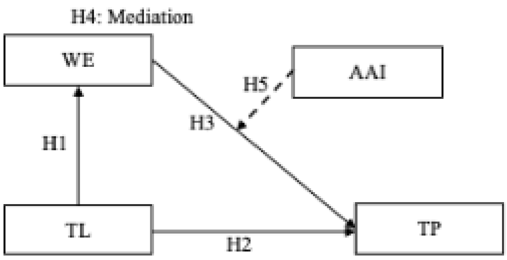

Figure 1. Research framework

Methods

This study employs a cross-sectional quantitative design using a structured questionnaire to examine the hypothesised relationships among TL, WE, TP, and AAI. This design is well-suited to testing theoretically derived relationships within the JD-R model, as it allows the simultaneous assessment of multiple latent constructs within a single model. Although cross-sectional data limit causal inference, they provide a practical means of identifying significant patterns and associations within large employee populations.

This study focused on frontline care workers in elderly care institutions in Beijing, China, using purposive sampling to ensure that only non-managerial employees directly engaged in care provision were included. The sample size adequacy was first assessed using G*Power 3.1, which indicated that 77 cases would suffice for a model with three predictors, a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, and power = 0.80 (Faul et al., 2009). Nevertheless, consistent with recommendations for PLS-SEM, a minimum of 200 cases is preferable for model stability (Hair et al., 2017). To ensure adequacy, 400 questionnaires were distributed, considering an expected response rate of approximately 50% in organisational research (Baruch & Holtom, 2008). Data collection was conducted with the support of a professional survey firm in Beijing, which identified eligible participants across multiple institutions and ensured random distribution within the inclusion criteria. The online survey platform was configured to allow only one submission per device to prevent duplicate submissions. A total of 298 questionnaires were returned (74.5% response rate), and after excluding 30 invalid responses (e.g., unusually short completion times or straight-line patterns), 268 valid responses were retained for analysis, yielding an effective response rate of 67.0%. Participation was voluntary, and informed consent was obtained from all respondents.

Measures

Transformational Leadership was measured using the 8-item unidimensional version of the Multifactor Leadership Questionnaire (MLQ; Bass & Avolio, 1995), adopted from Juyumaya and Torres (2023). This version captures core behavioural components of TL, including inspiration, motivation, ethical conduct, and support for innovation. In the original validation, Cronbach's α was reported at 0.98. This instrument was selected for its parsimony, theoretical clarity, and suitability for modelling TL as a job resource within the JD-R model (Bakker & Demerouti, 2017; Judge & Piccolo, 2004).

Work Engagement was assessed using the nine-item Utrecht WE Scale (UWES-9; Schaufeli et al., 2002), adopted from McManus, Dundon, and Lavelle (2025). This version treats WE as a unidimensional construct, with a Cronbach's α of 0.89. The UWES-9 was chosen for its conciseness and theoretical alignment with the JD-R model, where WE function as a central motivational mechanism (Bakker & Demerouti, 2017).

Task Performance was measured using the five-item TP subscale of the Individual Work Performance Questionnaire (IWPQ; Koopmans et al., 2013), adopted from Platania et al. (2024). In their validation study, Cronbach's α was 0.75. The IWPQ was selected for its brevity and applicability in service-oriented contexts, where TP is a key outcome within the JD-R model.

Attitudes towards artificial intelligence (AAI) were measured using the Attitudes Towards Artificial Intelligence in Work, Healthcare and Education (ATTARI-WHE) scale (Gnambs et al., 2025). Although the scale was originally designed to assess AI attitudes across multiple contexts, the developers state that "a total score across all items can be created to capture general attitudes towards AI" (p. 3). In accordance with this guidance, the present study operationalised AAI as a unidimensional construct. In its original validation study, the scale

demonstrated good internal consistency, with a Cronbach's α of 0.89. Given its robust psychometric properties and conceptual suitability for assessing employees' overall AAI, the scale was deemed appropriate for measuring AAI among elderly care workers in this study.
All constructs were measured using validated scales rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Across all constructs, Cronbach's α values exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency and suitability for structural equation modelling (Hair et al., 2017). All scales were initially developed in English and then translated into Chinese using a standard translation-back-translation procedure to ensure semantic and conceptual equivalence (Brislin, 1970).

To minimise the potential impact of common method variance (CMV) and social desirability bias (Podsakoff et al., 2003), several procedural safeguards were implemented in the study design. To reduce evaluation apprehension, respondents were assured of anonymity and confidentiality. Questionnaire items were interleaved across different constructs to mitigate response pattern bias. Explicit instructions emphasised that there were no correct or incorrect answers, thereby encouraging honest responses. Furthermore, a professional third-party survey firm administered the questionnaire to minimise direct interaction between researchers and respondents, thereby reducing the likelihood of demand characteristics.

Data Analysis
This study employed Partial Least Squares Structural Equation Modelling (PLS-SEM) to test the proposed theoretical model. PLS-SEM is suitable for exploratory and predictive research involving complex variable relationships, relatively small sample sizes, and data distributions that do not satisfy the assumption of normality (Hair et al., 2017). This approach is also suitable for reflective measurement models, demonstrating its applicability when research objectives involve explaining variance in key endogenous variables, such as WE and TP. Within the JD-R model, this analytical approach exhibits considerable flexibility and predictive relevance (Bakker & Demerouti, 2017).

Data analysis was performed using SPSS and SmartPLS software. First, descriptive statistics were used to summarise for respondents' demographic characteristics. Next, the recommended PLS-SEM procedure (Hair et al., 2017) was applied. The measurement model was evaluated by examining reliability, convergent validity, and discriminant validity (Hair et al., 2017; Henseler, Ringle, & Sarstedt, 2015). Subsequently, the structural model was analysed to validate the hypothesised relationships among latent variables. Finally, bootstrapping with 5,000 resamples and bias-corrected and accelerated confidence intervals (95% BCa CI) was employed to assess the significance of path coefficients and indirect effects (Hair et al., 2017).

Findings
The demographic characteristics of the respondents are presented in Table 1. Out of 268 respondents, 71 (26.5%) were male and 197 (73.5%) were female. In terms of age, 10 respondents (3.7%) were aged 20 years or below, 32 (11.9%) were aged 21-29 years, 122 (45.5%) were aged 30-39 years, 83 (31.0%) were aged 40-49 years, and 21 (7.8%) were aged 50 years or above. Regarding marital status, 46 respondents (17.2%) were single, 211 (78.7%) were married, 9 (3.4%) were divorced, and 2 (0.7%) were widowed. With respect to educational background, 62 respondents (23.1%) had completed junior high school or below,

139 (51.9%) had completed senior high, vocational, or technical school, 51 (19.0%) held an associate degree or diploma, and 16 (6.0%) held a bachelor's degree. In terms of work experience, 5 respondents (1.9%) had less than one year, 8 (3.0%) had 1-2 years, 5 (1.9%) had 3-4 years, 88 (32.8%) had 5-6 years, and 162 (60.4%) had seven years or more of experience. Analysis revealed that most respondents were female, aged 30-49, married, had completed secondary or vocational education, and had been engaged in elderly care services for over 7 years.

Table 1
Representativeness of collected samples (n=268)

Characteristic	Category	n	%
Gender	Male	71	26.5
	Female	197	73.5
Age (years)	≤ 20	10	3.7
	21-29	32	11.9
	30-39	122	45.5
	40-49	83	31.0
	≥ 50	21	7.8
Marital status	Single	46	17.2
	Married	211	78.7
	Divorced	9	3.4
	Widowed	2	0.7
Education background	Junior high school or below	62	23.1
	Senior high school / vocational / technical	139	51.9
	Associate degree or diploma	51	19.0
	Bachelor's degree	16	6.0
Work experience (years)	< 1	5	1.9
	1-2	8	3.0
	3-4	5	1.9
	5-6	88	32.8
	≥ 7	162	60.4

The measurement model was first analysed to assess the reliability and validity of the constructs, determining the degree to which the observed variables accurately represented their corresponding latent variables. The measurement model was evaluated by examining factor loadings, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2017; Henseler, Ringle, & Sarstedt, 2015). As shown in Table 2, the composite reliability (CR) values ranged from 0.896 to 0.931, exceeding the recommended threshold of 0.70 (Hair et al., 2017). Consistent with Hair et al. (2017), CR is considered a more appropriate measure of internal consistency than Cronbach's alpha in PLS-SEM. Similarly, the Cronbach's alpha values ranged from 0.855 to 0.916, surpassing the recommended level of 0.80, indicating very good reliability. With regard to indicator reliability, the factor loadings ranged from 0.719 to 0.842, well above the recommended cut-off value of 0.50 (Hair et al., 2017). Convergent validity was confirmed, as all AVE values (0.557-0.633) exceeded the minimum criterion of 0.50. Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT), and all values were below the recommended threshold of 0.90 (Henseler et al., 2015;

see Table 3). Overall, the measurement model demonstrated sound reliability, convergent validity, and discriminant validity, thereby enabling subsequent structural analysis.

Table 2
Reliability results

Constructs	Alpha	CR	AVE
Transformational leadership (TL)	0.911	0.928	0.617
Work engagement (WE)	0.916	0.931	0.600
Attitudes towards artificial intelligence (AAI)	0.901	0.919	0.557
Task performance (TP)	0.855	0.896	0.633

Table 3
Discriminant Validity (HTMT Ratio)

	AAI	TL	TP	WE
AAI				
TL	0.288			
TP	0.366	0.505		
WE	0.284	0.612	0.623	

Following the assessment of the measurement model, the structural model was evaluated. The significance of the hypothesised relationships was tested using bootstrapping with 5,000 subsamples in SmartPLS (Hair et al., 2017), which produced estimates of standard errors, t-values, p-values, and path coefficients. Descriptive statistics of the latent variables are presented in Table 4. All constructs were measured on a five-point Likert scale, with mean values above the midpoint of 3.0. The highest mean was observed for AAI (M = 3.764) and the lowest for WE (M = 3.547). Standard deviations ranged from 0.811 (AAI) to 0.966 (TP), suggesting moderate variability among responses. Correlation analysis indicated that all constructs were significantly related at the $p < 0.01$ level. Overall, the results indicate that the constructs demonstrated satisfactory reliability and discriminant validity, providing a robust foundation for subsequent structural model analyses.

Table 4
Means, standard deviations, and correlations among latent variables

	Mean	Std. Deviation	TL	WE	AAI	TP
TL	3.688	0.963				
WE	3.547	0.875	0.558**			
AAI	3.764	0.811	0.261**	0.259**		
TP	3.572	0.966	0.447**	0.552**	0.321**	

Note. TL = Transformational Leadership; WE = Work Engagement; AAI = Attitudes toward Artificial Intelligence; TP = Task Performance. All constructs were measured using a five-point Likert scale. Values represent Pearson correlation coefficients. $p < .01$ (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed).

Figure 2 presents the results of the structural model estimated using SEM. It illustrates the relationships among latent constructs by displaying path coefficients, indicator loadings, and R-squared (R^2) values (Hair et al., 2017; Henseler, Ringle, & Sarstedt, 2015).

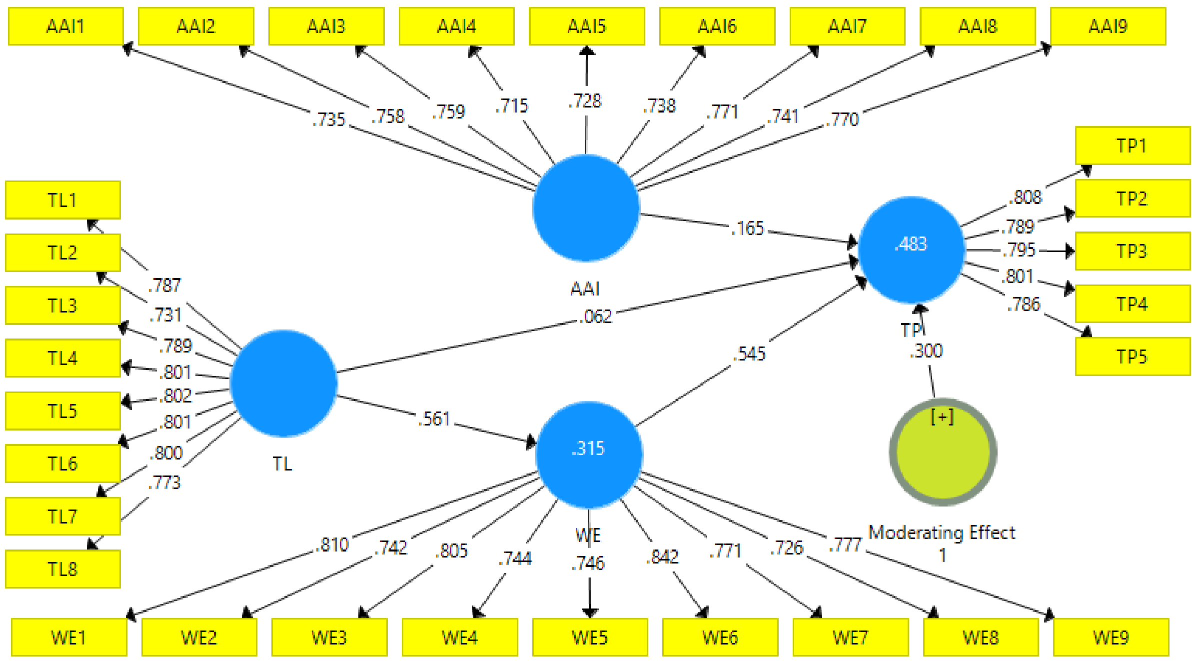

Figure 2. Structural Model Framework.

The results in Table 5 indicate that four hypothesised relationships were supported. TL had a significant positive effect on WE (β = 0.561, t = 10.887, p < 0.001, 95% BCa CI [0.450, 0.653]), supporting H1. However, TL did not show a significant direct effect on TP (β = 0.062, t = 0.897, p = 0.370, 95% BCa CI [-0.074, 0.199]), indicating that H2 was not supported. WE was positively associated with TP (β = 0.545, t = 7.771, p < 0.001, 95% BCa CI [0.398, 0.673]), providing support for H3. The bootstrapping analysis further indicated that TL affected TP indirectly through WE (β = 0.305, t = 6.573, p < 0.001, 95% BCa CI [0.219, 0.399]), confirming H4 (Hair et al., 2017). AAI also demonstrated a significant direct relationship with TP (β = 0.165, t = 2.674, p = 0.008, 95% BCa CI [0.048, 0.287]) and significantly moderated the relationship between WE and TP (β = 0.300, t = 4.499, p < 0.001, 95% BCa CI [0.166, 0.425]), supporting H5 (Manresa et al., 2025). These findings provide empirical support for the proposed model and contribute to the theoretical application of the JD-R model.

Table 5
Structural Model Results

Links	95% BCa CI	Result

Hypo-thesis		Path Coefficient	Standard Deviation	t-Value	P-Value	LLCI	ULCI	
H1	TL -> WE	0.561	0.052	10.887	0.000	0.450	0.653	Supported
H2	TL -> TP	0.062	0.069	0.897	0.370	-0.074	0.199	Not Supported
H3	WE -> TP	0.545	0.070	7.771	0.000	0.398	0.673	Supported
H4	TL -> WE -> TP	0.305	0.046	6.573	0.000	0.219	0.399	Supported
H5	Moderating Effect -> TP	0.300	0.067	4.499	0.000	0.166	0.425	Supported

Discussion and Conclusions

The findings provide empirical support for the proposed theoretical framework by elucidating the interactive mechanisms among TL, WE, and AAI within the context of elderly care institutions (Na, Jung, & Kim, 2023; Wang et al., 2023). Existing research largely supports the view that TL can directly influence employees' TP (Judge & Piccolo, 2004). However, within the JD-R model employed in this study and the highly standardised protocol-driven context of elderly care institutions, the influence of TL on routine task performance among elderly care workers is primarily mediated by psychological and motivational mechanisms. Specifically, this effect is achieved indirectly by enhancing WE, rather than exhibiting a significant direct effect (Bakker & Demerouti, 2017; Schaufeli et al., 2002; Juyumaya & Torres, 2023). This finding aligns closely with the motivational pathways outlined by the JD-R model, in which job resources stimulate employees' vigour, dedication, and focus, thereby enhancing performance outcomes (Bakker & Demerouti, 2017; Schaufeli et al., 2002). Within the context of elderly care institutions, given the persistent workload pressures and high demands for emotional labour faced by frontline care workers, the role of such leadership resources is particularly salient (Krijgsheld, Tummers, & Scheepers, 2022; Hung, 2023).

Work engagement (WE) has long been regarded as a key driver of employee performance (Schaufeli et al., 2002; Bakker & Demerouti, 2017). The findings indicate that elderly care workers with higher levels of WE exhibited greater persistence and concentration in daily care tasks. This is consistent with existing research, which highlights that engagement serves as a bridge between supportive work environments and positive performance outcomes (Corbeanu & Iliescu, 2023; Juyumaya & Torres, 2023). The findings further extend relevant theories to institutional care settings, indicating that sustained high levels of WE are associated with maintaining care service quality while reducing practitioners' susceptibility to burnout and fatigue (Bakker & de Vries, 2021; Chiminelli-Tomás et al., 2025). Overall, these findings reaffirm the critical mediating role of WE in linking organisational resources to employee performance outcomes.

The findings indicate that AAI functions as a significant contextual variable influencing TP. Frontline care workers with more positive AAI were more likely to translate their WE into higher TP levels (Chuang & Huang, 2025). Moderation analysis indicates that AAI, as an individual cognitive disposition, influences the intensity with which motivational energy generated by WE is directed towards TP (Nguyen & Malik, 2022; Manresa et al., 2025). When employees perceive AI as a supportive tool rather than a potential threat, their WE is more likely to translate into productive work behaviours (Taddeo & Floridi, 2021). This finding extends collaborative human-AI interaction research and further indicates that AAI can be regarded as a significant personal resource variable within the JD-R framework (Melkas et al., 2020; Wong et al., 2024).

The findings of this study are largely consistent with existing research linking TL, WE, and TP (Judge & Piccolo, 2004; Wang et al., 2022), while offering a more contextualised perspective on these relationships within the setting of Chinese elderly care institutions. In environments characterised by both high emotional labour demands and rapid digital transformation (Chen et al., 2025), elderly care institutions provide a distinctive empirical setting for leadership mechanisms. The findings further validate the applicability of the JD-R model in elderly care contexts, revealing the joint pathways through which leadership resources and technological attitudes collectively sustain employee work engagement (Bakker & Demerouti, 2017; Hung, 2023; Zhao & Li, 2024). Collectively, this study suggests that sustained performance improvement among elderly care workers depends on achieving a dynamic equilibrium between human and technological factors. This finding reinforces the explanatory validity and theoretical value of the JD-R model within human-machine collaborative service contexts (Manresa et al., 2025; Topol, 2019).

Theoretical Implications

This study extends the explanatory boundaries of the JD-R model within high-emotional labour service domains by applying it to the labour-intensive, emotionally demanding context of elderly care services. Although the JD-R framework has gained extensive empirical support in corporate and healthcare settings (Bakker & Demerouti, 2017; Bakker & de Vries, 2021), systematic empirical research within the context of institutional elderly care services in China remains relatively scarce (Zhang & Zhang, 2023; Hung, 2023). To address this research gap, this study constructs an integrated theoretical framework. It positions TL as a key organisational resource, defines WE as the core psychological mechanism, and introduces AAI as a contextual moderator variable. Findings indicate that within Chinese elderly care institutions, TL exerts an indirect influence on TP primarily by stimulating care workers' WE mechanisms rather than through direct pathways (Bakker & Demerouti, 2017; Schaufeli, 2017).

Building upon this foundation, the present study further incorporates AAI into the JD-R framework to address a key theoretical issue in organisational behaviour research within digital transformation contexts: how employees shape their work motivation and behavioural patterns through cognitive evaluations of technological change (Nguyen & Malik, 2022; Manresa et al., 2025; Venkatesh et al., 2003). Theoretically, this study reveals the interactive mechanism between job resources and personal resources in AI contexts, constructing an extended theoretical framework to explain the synergistic effects of psychological and technological resources. This provides a novel interpretative perspective for deepening the application of the JD-R model within intelligent service industries (Bakker & de Vries, 2021). The findings further indicate that positive AAI significantly strengthen the mechanistic linkage between WE and TP, elucidating the pivotal role of employees' cognitive evaluations and affective attitudes in the motivation-performance conversion mechanism.

Through the theoretical extension, this study systematically integrates traditional organisational behaviour theory with human-computer interaction research, incorporating AAI as a personal resource variable into the JD-R model (Melkas et al., 2020; Tariq et al., 2025; Venkatesh et al., 2003). This interdisciplinary integration not only deepens academic understanding of mechanisms underlying employee motivation and performance but also provides crucial theoretical foundations for human resource management and technological governance in the context of smart elderly care (Wong et al., 2024). Against the backdrop of China's elderly care institution sector grappling with labour shortages, high turnover rates, and pressures for intelligent transformation, this study theoretically demonstrates the importance of synergistically advancing technological innovation and human capital development (Hung, 2023; Zhao & Li, 2024; Zhang & Zhang, 2023), thereby furnishing subsequent research with an explanatory theoretical framework.

Practical and Social Implications

From a practical perspective, this study offers targeted insights for management practices within institutional care settings. Its practical significance lies primarily in establishing the working environment, technical readiness, and staff development as core operational priorities. A supportive working environment is regarded as a fundamental condition for ensuring the consistency and quality of daily care services. This can be strengthened through enhanced communication of organisational vision, provision of personalised support mechanisms, and the implementation of continuous learning systems, thereby boosting staff motivation and professional commitment (Bass & Avolio, 1995; Schaufeli et al., 2002). At the operational level, technical readiness can be elevated through transparent communication mechanisms, participatory implementation pathways, and systematic training arrangements. This supports care workers' adaptation to technology-enabled care processes and enhances overall operational efficiency (Wong et al., 2024; Manresa et al., 2025). Through optimising workload allocation, moderately expanding job autonomy, and establishing structured career progression pathways, sustainable human resource development becomes a critical institutional foundation for enhancing organisational resilience. This approach also helps mitigate the risk of emotional exhaustion, thereby stabilising task performance outcomes (Schaufeli et al., 2002; Bakker & Demerouti, 2017).

At the policy level, this study indicates that the state should establish sustained investment in technological infrastructure and systematic guidance for human capital development as equally important strategic objectives within its smart ageing strategy (Hung, 2023; Zhao & Li, 2024; National Health Commission of the People's Republic of China, 2021). Beyond strengthening the structural deployment of intelligent hardware and system platforms, institutional policy instruments should explicitly convey a long-term orientation towards enhancing practitioners' professional capabilities and technological literacy. This approach facilitates the establishment of a stable and sustainable governance system for institutional elderly care services (Zhao & Li, 2024). At the societal level, continuously enhancing the professional competence and technical literacy of care personnel strengthens public institutional trust in the institutional care system (Chen et al., 2025; Hung, 2023). As population ageing accelerates, this trust assumes increasing strategic significance in shaping family decisions about long-term care and in maintaining the social legitimacy of institutional care services.

Limitations and Suggestions for Future Research

This study has several limitations. The cross-sectional design restricts inferences regarding causal relationships among TL, WE, TP, and AAI. Data were derived solely from a sample of Beijing-based elderly care workers, potentially limiting the generalisability of findings to other regions and institutional contexts. Furthermore, within the JD-R model, this study primarily operationalised AAI as an enabling construct, without fully accounting for its potential negative or ambivalent dimensions. Additionally, reliance on self-reported questionnaire data, despite procedural controls, may still be susceptible to social desirability bias and common method variance.

Future research may address these limitations through several approaches. Longitudinal or experimental designs could provide stronger causal evidence and elucidate how leadership, engagement, and AAI evolve over time. Broader sampling across provinces, urban and rural areas, and diverse institutional types would enhance external validity and capture contextual variation within China's elderly care system. Examining the negative impacts of AI-assisted elderly care would contribute to a more comprehensive understanding of employees' responses to AI integration. In addition, the use of multi-source or mixed-method data, including supervisor evaluations, objective performance indicators, and qualitative interviews, could provide deeper insights into how organisational and technological factors jointly shape elderly care workers' performance in AI-assisted elderly care services.

References

Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. *Journal of Occupational Health Psychology, 22*(3), 273–285. https://doi.org/10.1037/ocp0000056

Bakker, A. B., & de Vries, J. D. (2021). Job Demands–Resources theory and self-regulation: New explanations and remedies for job burnout. *Anxiety, Stress, & Coping, 34*(1), 1–21. https://doi.org/10.1080/10615806.2020.1797695

Baruch, Y., & Holtom, B. C. (2008). Survey response rate levels and trends in organizational research. *Human Relations, 61*(8), 1139–1160. https://doi.org/10.1177/0018726708094863

Bass, B. M., & Avolio, B. J. (1994). *Improving organizational effectiveness through transformational leadership.* Thousand Oaks, CA: Sage Publications.

Bass, B. M., & Avolio, B. J. (1995). *MLQ Multifactor Leadership Questionnaire: Technical report.* Redwood City, CA: Mind Garden.

Bass, B. M., & Riggio, R. E. (2006). *Transformational leadership* (2nd ed.). Mahwah, NJ: Lawrence Erlbaum Associates.

Borman, W. C., & Motowidlo, S. M. (1993). Expanding the criterion domain to include elements of contextual performance. In N. Schmitt & W. C. Borman (Eds.), *Personnel selection in organizations* (pp. 71–98). San Francisco, CA: Jossey-Bass.

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology, 1*(3), 185–216. https://doi.org/10.1177/135910457000100301

Chen, Y., Wu, F., Zhang, W., Xing, W., Zhu, Z., Huang, Q., & Yuan, C. (2025). Perspectives on AI-driven nursing science among nursing professionals from China: A qualitative study. *Nursing Reports, 15*(6), 218. https://doi.org/10.3390/nursrep15060218

Chiminelli-Tomás, V., Tutte-Vallarino, V., Ferreira-Umpiérrez, A., Hernández-Morante, J. J., & Reche-García, C. (2025). Impact of nursing practice environments in work engagement and burnout: A systematic review. *Healthcare, 13*(7), 779. https://doi.org/10.3390/healthcare13070779

Chuang, L.-M., & Huang, S.-H. (2025). AI-supported healthcare technology resistance and behavioral intention: A serial mediation empirical study on the JD-R model and employee engagement. *Systems, 13*(4), 268. https://doi.org/10.3390/systems13040268

Corbeanu, A., & Iliescu, D. (2023). The link between work engagement and job performance: A meta-analysis. *Journal of Personnel Psychology, 22*(3), 111–122. https://doi.org/10.1027/1866-5888/a000316

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology, 86*(3), 499–512. https://doi.org/10.1037/0021-9010.86.3.499

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Gnambs, T., Stein, J.-P., Appel, M., Griese, F., & Zinn, S. (2025). An economical measure of attitudes towards artificial intelligence in work, healthcare, and education (ATTARI-WHE). *Computers in Human Behavior: Artificial Humans, 3*, 100106. https://doi.org/10.1016/j.chbah.2025.100106

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). SAGE Publications.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*, 115-135. doi: 10.1007/s11747-014-0403-8

Hung, J. (2023). Smart elderly care services in China: Challenges, progress, and policy development. *Sustainability, 15*(1), 178. https://doi.org/10.3390/su15010178

Judge, T. A., & Piccolo, R. F. (2004). Transformational and transactional leadership: A meta-analytic test of their relative validity. *Journal of Applied Psychology, 89*(5), 755–768. https://doi.org/10.1037/0021-9010.89.5.755

Juyumaya, J., & Torres, J. P. (2023). Effects of transformational leadership and work engagement on managers' creative performance. *Baltic Journal of Management, 18*(1), 34–53. https://doi.org/10.1108/BJM-11-2021-0449

Koopmans, L., Bernaards, C. M., Hildebrandt, V. H., Schaufeli, W. B., de Vet, H. C. W., & van der Beek, A. J. (2013). Development of an individual work performance questionnaire. *International Journal of Productivity and Performance Management, 62*(1), 6–28. https://doi.org/10.1108/17410401311285273

Krijgsheld, M., Tummers, L. G., & Scheepers, F. E. (2022). Job performance in healthcare: A systematic review. *BMC Health Services Research, 22*(1), 149. https://doi.org/10.1186/s12913-021-07357-5

Manresa, A., Sammour, A., Mas-Machuca, M., Chen, W., & Botchie, D. (2025). Humanizing GenAI at work: bridging the gap between technological innovation and employee engagement. *Journal of Managerial Psychology, 40*(5), 472-492. https://doi.org/10.1108/JMP-05-2024-0356

McManus, H., Dundon, T., & Lavelle, J. (2025). "Workin for a livin": Mediating the role of perceived support, work engagement, and organizational citizenship behavior in the hospitality sector. *International Journal of Hospitality Management,* 126, 103983. https://doi.org/10.1016/j.ijhm.2024.103983

Melkas, H., Hennala, L., Pekkarinen, S., & Kyrki, V. (2020). Impacts of robot implementation on care personnel and clients in elderly-care institutions. International *Journal of Medical Informatics,* 134, 104041. https://doi.org/10.1016/j.ijmedinf.2019.104041

Ministry of Human Resources and Social Security of the People's Republic of China, & Ministry of Civil Affairs of the People's Republic of China. (2019). *National occupational skill standards: Elderly care worker (2019 edition)*. Beijing, China.

Na, E., Jung, Y., & Kim, S. (2023). How do care service managers and workers perceive care robot adoption in elderly care facilities? *Technological Forecasting and Social Change,* 187, 122250. https://doi.org/10.1016/j.techfore.2022.122250

National Bureau of Statistics of China. (2024, February 29). *Statistical communiqué of the People's Republic of China on the 2023 national economic and social development.* Retrieved from http://www.stats.gov.cn/sj/zxfb/202402/t20240228_1947915.html

National Health Commission of the People's Republic of China. (2021). *Action plan for the development of the smart health and elderly care industry (2021–2025)*. Beijing, China: National Health Commission. Retrieved from https://www.nhc.gov.cn/lljks/c100158/202110/a871dfd3e1fd45b89e9af1f40e44ba12/files/1733127377368_21866.pdf

Nguyen, T.-M., & Malik, A. (2022). Impact of knowledge sharing on employees' service quality: The moderating role of artificial intelligence. *International Marketing Review, 39*(3), 482–508. https://doi.org/10.1108/IMR-02-2021-0078

Office of Beijing Municipal Working Committee on Ageing, Beijing Association on Ageing, & China Philanthropy Research Institute, Beijing Normal University. (2024, October 11). *Beijing elderly career development report (2023).* Beijing Municipal Civil Affairs Bureau. Retrieved from https://mzj.beijing.gov.cn/attach/0/e579da4186d440e7890d97711cc87d91.pdf

Platania, S., Morando, M., Gruttadauria, S. V., & Koopmans, L. (2024). The individual work performance questionnaire: Psychometric properties of the Italian version. European Journal of Investigation in Health, *Psychology and Education, 14*(1), 49–63. https://doi.org/10.3390/ejihpe14010004

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Saks, A. M. (2006). Antecedents and consequences of employee engagement. *Journal of Managerial Psychology, 21*(7), 600–619. https://doi.org/10.1108/02683940610690169

Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies, 3*(1), 71–92. https://doi.org/10.1023/A:1015630930326

Schaufeli, W. B. (2017). Applying the Job Demands-Resources model: A "how to" guide to measuring and tackling work engagement and burnout. *Organizational Dynamics, 46*(2), 120–132. https://doi.org/10.1016/j.orgdyn.2017.04.008

Taddeo, M., & Floridi, L. (2021). How AI can be a force for good: An ethical framework to harness the potential of AI while keeping humans in control. In B. C. Stahl, V. Yaghmaei, & M. Jirotka (Eds.), *The ethics of artificial intelligence* (pp. 9–28). Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-030-81907-1_7

Tariq, K., Tahir, H., Malik, U., Shafiq, A., & Khan, M. (2025). Attitudes and readiness to adopt artificial intelligence among healthcare practitioners in Pakistan's resource-limited settings. *BMC Health Services Research, 25*, 1031. https://doi.org/10.1186/s12913-025-13207-5

Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine, 25*(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Wang, J., Wang, Z., Alam, M., Murad, M., Gul, F., & Gill, S. A. (2022). The impact of transformational leadership on affective organizational commitment and job performance: The mediating role of employee engagement. *Frontiers in Psychology, 13*, 831060. https://doi.org/10.3389/fpsyg.2022.831060

Wang, W., Chen, L., Xiong, M., & Wang, Y. (2023). Accelerating AI adoption with responsible AI signals and employee engagement mechanisms in health care. *Information Systems Frontiers, 25*, 2239–2256. https://doi.org/10.1007/s10796-021-10154-4

Wong, K. L. Y., Hung, L., Wong, J., Park, J., Alfares, H., Zhao, Y., Mousavinejad, A., Soni, A., & Zhao, H. (2024). Adoption of artificial intelligence-enabled robots in long-term care homes by health care providers: Scoping review. *JMIR Aging, 7*(1), e55257. https://doi.org/10.2196/55257

World Bank. (2021). *World Bank support to aging countries: An independent evaluation.* Independent Evaluation Group. Washington, DC: World Bank. Retrieved from https://documents1.worldbank.org/curated/en/672701626792774286/World-Bank-Support-to-Aging-Countries-An-Independent-Evaluation

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2007). The role of personal resources in the job demands–resources model*. International Journal of Stress Management, 14*(2), 121–141. https://doi.org/10.1037/1072-5245.14.2.121

Xanthopoulou, D., Bakker, A. B., Demerouti, E., & Schaufeli, W. B. (2009). Work engagement and financial returns: A diary study on the role of job and personal resources. *Journal of Occupational and Organizational Psychology, 82*(1), 183–200. https://doi.org/10.1348/096317908X285633

Xinhua. (2025, January 10). *China accelerates elderly care reforms as population ages.* The State Council of the People's Republic of China. https://english.www.gov.cn/news/202501/10/content_WS67805ca4c6d0868f4e8eea64.html

Yuan, X., & Gao, Y. (2020). Demographic transition and economic miracles in China: An analysis based on demographic perspective. *International Journal of Economic Policy Studies, 14*(1), 25–45. https://doi.org/10.1007/s42495-019-00030-0

Zhang, S., & Zhang, Z. (2023). Human resource dilemma and intelligent choice of elderly care service in China. *Journal of Xi'an Jiaotong University (Social Sciences), 43*(3), 152–163. https://doi.org/10.15896/j.xjtuskxb.202306013

Zhao, Y., & Li, J. (2024). Opportunities and challenges of integrating artificial intelligence in China's elderly care services. *Scientific Reports, 14*, 9254. https://doi.org/10.1038/s41598-024-60067-w