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Influencing Mechanism of Digital Literacy on Innovative Job Performance, The Mediating Role of Job Crafting

Junfeng Cheng
Universiti Sains Malaysia
Email: chengjf1243@student.usm.my

Shankar Chelliah*
Universiti Sains Malaysia
*Corresponding Author Email: shankar@usm.my

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Abstract

Purpose: This study employed the Job Demands-Resources (JD-R) model to examine how digital literacy influenced innovative job performance (IJP) through dual mediating mechanisms of promotion-focused and prevention-focused job crafting. It sought to clarify how digital literacy shaped the innovation outcomes of STTs via distinct job crafting orientations. **Design/methodology/approach:** Using a sample of 692 STTs from Specialized Refinement Differential Innovation (SRDI) “little giant” companies in China’s Yangtze River Delta region, this study employed Smart-PLS 4.1.1 for partial least squares structural equation modeling. The PLS-Predict procedure was used to assess out-of-sample predictive accuracy, ensuring analytical robustness and theoretical validity. **Findings:** Digital literacy enhanced IJP, positively shaping promotion-focused but negatively influencing prevention-focused job crafting. While promotion-focused crafting strengthened IJP, prevention-focused job crafting weakened it. Both mediating effects were significant, and the model exhibited strong predictive validity. **Research limitations/implications:** The sample focused on China’s SRDI “little giant” companies restricts generalizability. Future research should broaden contexts, adopt multidimensional digital literacy constructs, and apply longitudinal or multi-source designs to strengthen causal inference and cross-industry applicability. **Practical implications:** Findings provide empirical guidance for enhancing employee digital capabilities and IJP. Companies should integrate digital literacy development into talent strategies by refining training, task design, and resource allocation to foster promotion-focused job crafting while reducing prevention-focused behaviors. **Originality/value:** This study considered digital literacy as a critical individual resource within the JD-R model, revealing its dual mechanism of resource gain and obstacle avoidance, influencing IJP. It expanded theoretical boundaries and empirical evidence on employee innovation performance in the digital era.

Keywords: Digital Literacy, Innovative Job Performance, Job Crafting, Srdi "Little Giant" Companies

Introduction

As we enter the new era of IR 5.0 and accelerated digital and intelligent transformation in industries, digital intelligence technologies are penetrating multiple critical sectors such as manufacturing, services, and R&D at an unprecedented pace (Bag et al., 2021; Huang & Rust, 2018), driving systemic restructuring of production methods, organizational structures, and value creation logic. This trend not only significantly enhances production efficiency and operational capabilities but also imposes new demands on organizational innovation models, talent structures, and core competitiveness (Anthony et al., 2023). Especially for Specialized Refinement Differential Innovation (SRDI) "little giant" companies, their competitive advantages heavily rely on continuous technological breakthroughs and product innovations in niche markets. The innovative job performance (IJP) of scientific and technological talents (STTs) has become a critical source for companies to maintain sustained competitiveness (Li & Yao, 2024; Sullivan, 2024). However, the opportunities and challenges brought by digitalization coexist, employees must continuously adapt and improve IJP in a rapidly changing technological environment, which imposes higher demands on their cognition, motivation, skills, and organizational support systems (Liang et al., 2022; Yin et al., 2024).

In the context of digital and intelligent transformation, employees with high digital literacy are often proficient in using digital tools for data analysis, product testing, and optimization. This not only improves the efficiency of problem identification and resolution but also significantly enhances the quality of product and service development (Sasmoko et al., 2019). Digital literacy not only directly enhances employees'perception of the usability and usefulness of technology but also promotes digital innovation behavior by shaping positive attitudes toward technology and willingness to apply it (Cetindamar et al., 2021; Nikou et al., 2022). Employees with high levels of digital literacy are more likely to proactively acquire knowledge, integrate information, share resources, and demonstrate stronger innovative momentum in team collaboration (Caroline et al., 2025; Huu, 2023). In the context of SRDI "little giant" companies, which are characterized by technology intensiveness and limited resource, digital literacy is not only a prerequisite for employees to adapt to emerging technologies and digitalized work models but also a crucial safeguard for driving technology transfer, enhancing organizational innovation capabilities, and improving market competitiveness. However, empirical research on the digital literacy and IJP of STTs in SRDI "little giant" companies is still in its infancy, with limited deep exploration of the digital and intelligent transformation context.

In this context, employees need to flexibly switch between traditional and digital work modes, which places higher demands on their ability to proactively adjust work styles and resource allocation. Digital literacy, digital leadership, transformational leadership, and organizational support can all enhance employees' ability to proactively adjust tasks and resource allocation, thereby optimizing the work environment and stimulating creative potential(Huu, 2023). The importance of the dual-dimensional job crafting perspective lies in the fact that different types of job crafting not only reflect employees' differentiated coping strategies in the face of challenges and pressures but also reveal the distinct mechanisms through which positive and negative pathways influence IJP (Bindl et al., 2019; Gui et al., 2024).

Therefore, this paper will explore the following core question, how does STTs' digital literacy in China's SRDI "little giant" companies further influence their innovation work performance by both ProJC and PreJC?

Literature Review

Job Demands-Resources (JD-R) Model

The JD-R model was first proposed by organizational behavior scholars (Demerouti et al., 2001), aiming to examine how stressors and motivational factors in the work environment influence employees' work experiences and performance, and it has been extensively applied in research on employee motivation and organizational management. Within this theoretical framework, employee performance is determined by the dynamic equilibrium between demands and resources. Recent research indicates that individuals do not passively accept their environment but can actively reshape resources and demands through proactive behaviors, with job crafting serving as a key pathway (Bakker et al., 2023). Huu (2023) emphasize that digital literacy is a key personal resource that empowers employees with digital competence and autonomy, thereby having a significant positive impact on their innovative job behavior, demonstrating its resource-enhancing characteristics. Simultaneously, it reduces pressure by mitigating the demanding needs arising from technological complexity and enhances employees' information processing and resource integration capabilities, thereby strengthening self-efficacy and situational control (Blanka et al., 2022). Specifically, STTs with high digital literacy tend to adopt promotion-focused job crafting (ProJC), actively expanding resources and challenging tasks to stimulate growth motivation. They also employ PreJC to reduce hindering demands and conserve limited resources (Geldenhuys et al., 2021). Together, these approaches optimize resource-demand matching, enabling employees to maintain engagement and adaptability in high-intensity and uncertain environments. This transformation into heightened creativity and problem-solving capabilities drives improved IJP. Consequently, the JD-R model provides robust theoretical support for this study, revealing the underlying mechanism through which digital literacy influences IJP via ProJC and PreJC.

Innovative Job Performance (IJP)

IJP is the critical foundation for enterprises to maintain sustained competitive advantage and dynamic adaptability(Jin & Peng, 2024). Based on the needs of this study, we focused on the antecedents of employee IJP and found that employees' individual self-efficacy, intrinsic motivation, knowledge and skills, psychological state, and personality traits, as well as the organizational environment, leadership behavior, external circumstances, and human resource management, all have a significant impact on IJP.

Al-Abbadi et al. (2020) demonstrated that knowledge functions as a strategic resource at both organizational and individual levels, with core management processes, such as acquisition, sharing, and application, serving as critical enablers of IJP. They further note that knowledge hoarding, treated as private intellectual capital, significantly shapes innovation outcomes. Expanding this perspective, Luo and Zhang (2021) argue that employees' capacity for knowledge recombination and exposure to diverse domains enhance integration and application, thereby improving IJP. Huu (2023) highlights digital literacy as a vital competence enabling effective use of digital tools and fostering innovative behaviors. Yet, Cetindamar et al. (2021) caution that research has insufficiently examined employees' digital intelligence and the mechanisms through which it influences innovation, indicating a need for deeper inquiry.

Digital Literacy

With the accelerated development of Industry 5.0, digital intelligence technologies is increasingly integrated into corporate operations and daily management. Murawski and Bick (2017) point out that the core challenge of digital and intelligent transformation lies not in technological trends or disruptive innovations, but in aligning organizational culture, cognitive patterns, and core competencies with digital work practices. This transformation must be employee-centric, with a particular focus on enhancing digital literacy. Otherwise, employees may face significant adaptation and survival pressures (Khan & Vuopala, 2019). Companies are increasingly recognizing that employee digital literacy has become a key factor in the success of digital and intelligent transformation and the enhancement of competitiveness (Nikou et al., 2022). Also, Maddikunta et al. (2022) emphasize that Industry 5.0 requires the development of a composite talent pool that combines cutting-edge digital intelligence technologies skills with deep technical understanding.

Cetindamar et al. (2021) pointed out that digital literacy, as a precursor to employee cognitive behavior, has a positive relationship with the willingness to adopt cloud technology. Nikou et al. (2022) revealed that digital literacy not only directly shapes employees'perceived ease of use of technologies, but also indirectly strengthens their intention to adopt digital tools by influencing their attitudes. Regarding the generative mechanisms of innovative behavior, Pilav-Velić et al. (2021) confirmed that digital literacy drives employees' sustained engagement in opportunity identification, idea generation, and implementation through the mediating effects of digital practices and attitudes toward digital innovation. Huu (2023) highlighted that employees'digital literacy, particularly digital competence and autonomy, has a significant positive influence on their engagement in innovative work behavior. Drawing on a systematic review, Caroline et al. (2025) affirmed a close association between digital literacy, employability, and innovative work behavior. However, some scholars have pointed out that future research still needs to conduct more studies to examine the relationship between employees' digital literacy and innovative work behavior, as well as their underlying mechanisms, across different industries and contexts (Caroline et al., 2025; Huu, 2023). Furthermore, no studies have yet conducted empirical research on the relationship between employees'digital literacy and their IJP in the context of digital transformation in SRDI "little giant" companies. Therefore, this study holds significant theoretical and practical implications.

Job Crafting

In today's increasingly complex and continuously evolving organisational context, job crafting has gradually emerged as a critical managerial approach for addressing external uncertainties and internal adaptability challenges (Brenninkmeijer & Hekkert-Koning, 2015). At its core, job crafting involves employees' rapid and proactive adaptation to their work environments, and it is widely recognized as a key driver of organizational sustainability. Empirical evidence suggests that job crafting serves as a crucial mediating mechanism linking individual cognition, competencies, and perceived organizational support to innovation performance (He et al., 2023; Nikou et al., 2022; Tomas et al., 2023; Zhu et al., 2022). Especially in the context of Industry 5.0 and the acceleration of digital transformation, complex environments and diverse tasks require employees to adapt flexibly through job crafting (Klus & Müller, 2021; Zhu et al., 2022).

Recent scholarship distinguishes two outcome-oriented forms of job crafting: promotion-focused (expanding and optimizing work) job crafting and prevention-focused (avoiding potential risks) job crafting, aimed at mitigating potential risks, together illustrating its dual-edged nature (Bindl et al., 2019; Cheng et al., 2023; Mo et al., 2024; Wang et al., 2025).

Huang and Li (2025) emphasized that digital literacy, as a key condition for employees to master digital tools and cope with tasks, was an important foundation for effective job crafting to cope with the cognitive and technical demands of digital work. Tomas et al. (2023) confirmed that employee job crafting and innovative job behaviors exhibit a dynamic reciprocal relationship, with resource acquisition and innovative performance mutually reinforcing each other. In digital and intelligent context, research indicates that digital literacy and challenging evaluations of artificial intelligence can enhance performance through job crafting, while hindering evaluations and insecurity lead to decreased performance (He et al., 2023; Nikou et al., 2022).However, the distinction and empirical evidence regarding promotive and preventive job crafting remain in the exploratory stage (Bindl et al., 2019; Gui et al., 2024). In summary, this study will combine JD-R model to further examine the mechanisms underlying the roles of promotion-focused and prevetion-focused job crafting between digital literacy and IJP.

Hypothesis Development

Digital Literacy and IJP

Digital literacy Refers to individuals' capability to proficiently use information and communication technology, accurately obtain the information they need, and effectively analyse and apply it to meet the demands of work and study (Nikou et al., 2022). Digital literacy functions as both a personal trait resource and an energy resource, enabling precise opportunity recognition, effective problem solving and the reinforcement of goal-directed behaviors (Halbesleben et al., 2014).

Extensive empirical research confirms the positive impact of digital literacy on IJP. Nikou et al. (2022) demonstrate that digital literacy not only directly enhances perceived ease of use of digital technologies but also, via attitude improvement, indirectly fosters the adoption and innovative application of emerging digital tools. Huu (2023) in a systematic review, finds that digital capability and autonomy significantly bolster innovative work behaviors. Santoso et al. (2019) validate the positive moderating role of digital literacy on the relationship between innovative behaviors and performance within the Indonesian telecommunications sector. Zahoor et al. (2023) show that, in UAE SMEs, managerial digital literacy effectively drives organisational innovation and performance.

Accordingly, in SRDI "little giant" companies, employees with high digital literacy will be able to skilfully utilise digital tools for research and development, efficiently gather and analyse information, markedly enhancing their innovation performance. Therefore, the following hypothesis is proposed:
H1: Digital literacy is positively associated with IJP.

Digital Literacy and Job Crafting

The JD-R model pointed out that, as a core personal resource, digital literacy not only motivated employees intrinsically but also significantly enhanced their emotional commitment and work engagement (Bakker et al., 2023; Bakker & Xanthopoulou, 2013).

In empirical research, Huu (2023) found that employees with high digital literacy were more likely to proactively use digital tools for knowledge acquisition and information integration. Caroline et al. (2025) also noted that employees with high digital literacy perform better in adapting to emerging technologies, coping with flexible work arrangements, and team communication and knowledge sharing. Huang and Li (2025) argued that digital literacy was a key prerequisite for employees to implement effective job crafting to meet digital task requirements: employees with high digital literacy were more capable and confident in adopting a ProJC to access more resources. Conversely, employees with lower digital literacy may be more inclined to adopt a PreJC to avoid resource depletion and potential risks.

It can be inferred that, in the context of SRDI "little giant" companies, employees with high digital literacy are more likely to adopt ProJC. Conversely, they may tend to adopt PreJC. Therefore, the following hypotheses are proposed:
H2: Digital literacy is positively associated with ProJC.
H3: Digital literacy is negatively associated with PreJC.

Job Crafting and IJP

In the JD-R model, job resources are regarded as key elements in the process of motivating employees, enhancing work engagement and positive emotional experiences, thereby directly improving employee performance (Bakker & Demerouti, 2007). As a critical output of knowledge intensive tasks, innovative performance particularly depends on employees utilizing additional resources to engage in creative endeavours and take on certain risks (Tims & Bakker, 2010).

In empirical research, through a study based on a Belgian sample, Tomas et al. (2023) found that there was a dynamic reciprocal relationship between employees'job redesign behaviors and innovative work behaviors: more job resources and development opportunities can stimulate employees' sustained innovative behaviors, and vice versa. Dar et al. (2023) further noted that employees with higher levels of autonomy and structural design capabilities were more likely to exhibit innovative tendencies. However, current research on the relationship between job crafting and employee innovation had largely failed to distinguish between promotion-focused and prevention-focused crafting pathways, and lacks empirical validation (Bindl et al., 2019; Gui et al., 2024). Gui et al. (2024) only theoretically proposed that promotion-focused human-machine job crafting could positively influence employee innovation performance, while prevention-focused human-machine job crafting might have a negative impact on employee innovation performance.

Based on this, in the context of SRDI "little giant" companies, this study proposed that employees adopting ProJC can help improve their innovation performance. Conversely, implementing PreJC might inhibit their innovation performance to a certain extent. Therefore, the following hypotheses are proposed:
H4: ProJC is positively associated with IJP.

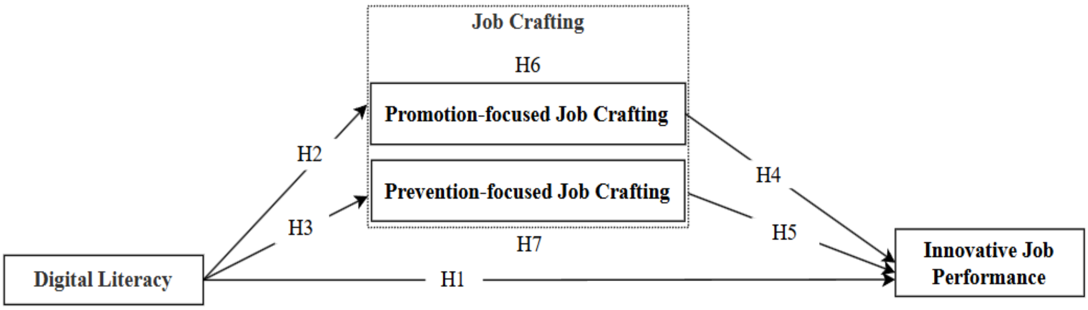
H5: PreJC is negatively associated with IJP.

The Mediating Role of Job Crafting in the Relationship between Digital Literacy and IJP

Huang and Li (2025) found that employees with high digital literacy were more capable and confident in undertaking ProJC to obtain more resources, while those with low digital literacy may be more inclined to adopt PreJC to avoid resource depletion and potential risks. Through empirical research, Nikou et al. (2022) proposed that digital literacy can indirectly enhance work efficiency by positively influencing employee attitudes and behaviors. Huu (2023) further proposes that employees with high digital literacy are more likely to proactively use digital tools for knowledge acquisition and information integration, thereby significantly enhancing their innovative work behavior. However, current research on the relationship between job crafting and employee innovation often fails to distinguish between these two pathways and lacks empirical testing of their underlying mechanisms (Bindl et al., 2019; Gui et al., 2024).

Based on this, drawing on the JD-R model's "dual-path" hypotheses, this study proposed that among SRDI "little giant" companies, ProJC plays a positive mediating role between employees' digital literacy and IJP, while PreJC may play a negative mediating role between the variables. Therefore, the following hypotheses are proposed:
H6: ProJC mediates the relationship between digital literacy and IJP.
H7: PreJC mediates the relationship between digital literacy and IJP.

Figure1 presents the conceptual framework that forms the theoretical foundation of this study.



Note: H6, H7 represent mediating hypotheses.
Figure 1 Research Model

Research Methodology

Research Context

This study focuses on STTs within SRDI "little giant" companies. This group exhibits the following characteristics: Firstly, these companies are at a critical stage of digital transformation and independent innovation, where STTs play a central role in knowledge conversion and technological breakthroughs. Secondly, with relatively compact company scales and flexible organizational structures, STTs often juggle both R&D and innovation tasks, thereby better highlighting the role of digital literacy in driving innovation performance. Thirdly, the Chinese government's ongoing policy support for "little giant" companies subjects their STTs to significant resource pressures and environmental challenges in practice. Related research indicates that the innovation capabilities of SRDI "little giant" companies primarily stem from STTs, including R&D personnel, designers, and highly skilled workers (Li & Yao, 2024; Sullivan, 2024). Therefore, this study focuses on exploring how the digital literacy of this group shapes innovation job performance through both ProJC and PreJC, holding significant theoretical value and practical implications.

Research Instruments

This survey consisted three parts: preliminary screening items, measurement of core constructs, and collection of demographic information. To ensure scientific validity and reliability of the measurement, the study employed established scale items from existing literature. IJP was assessed using a seven-point likert scale ranging from one= "never" to seven= "always", whereas all other variables were measured on five-point likert scales ranging from "strongly disagree" to "strongly agree". IJP was operationalized through nine items which were adapted from Janssen and Van Yperen (2004). The measurement of digital literacy was adapted from a ten-item scale described by Nikou et al. (2022). This study adopted the 16-item scale from Mo et al. (2024) to measure ProJC, while adopting the 12-item scale from Mo et al. (2024) to measure PreJC. To ensure the quality of the questionnaire, we incorporated feedback from two academic experts in management and six industry practitioners during a pre-test phase. Their evaluations informed several revisions to the measurement items. In addition, a back-translation procedure was conducted to ensure equivalence between the English and Chinese versions of the instrument (Brislin, 1986). Then, a subsequent pilot test with 35 participants confirmed the instrument's reliability, as all Cronbach's alpha values exceeded the recommended threshold of 0.7 (Hair et al., 2021).

Data Collection

This study gathered data via an online survey administered to participants, a method widely recognized for its efficiency in gathering large-scale quantitative data. Compared with traditional paper-based surveys, online questionnaires reduce costs, improve response rates, and allow researchers to access geographically dispersed samples within shorter timeframes, while providing respondents the flexibility to fill out the questionnaire independently and without time constraints (Bougie & Sekaran, 2019; Descamps et al., 2023). Data collection methods consisted of several rigorously implemented steps. At first, we conducted systematic questionnaire design to ensure measured content effectively reflects research objectives. Subsequently, pre-testing was performed to verify the instrument's reliability and validity, with structural and item refinements made accordingly. Finally, the formal questionnaire distribution and retrieval were completed via the third-party platform "Wen Juan Xing" (https://www.wjx.cn/). This online system streamlined data collection while ensuring a secure and efficient process for participant engagement. This series of standardized procedures was crucial for ensuring data robustness and integrity.

This study adopted a purposive non-probability sampling approach. Given the lack of comprehensive data and lists of STTs in SRDI "little giant" companies, this strategy enhanced both sample representativeness and data consistency. Sampling was conducted along two dimensions, regional distribution and job position. Regionally, the Yangtze River Delta, where "little giant" companies are most concentrated, was prioritized. Job position, ensuring including R&D personnel, engineering designers and experimental testers, who together constitute the core STTs of these companies. Prior to questionnaire completion, all respondents were informed of the study objectives and key variable definitions. Eligibility was determined through screening questions, with only qualified individuals incorporated into the final sample. Ultimately, 692 valid responses were collected for subsequent multivariate analyses. The specific demographic characteristics of the respondents are shown in Table 1.

Table 1
Sample Demographics (N=692).

Category	Item	Frequency	Percentage (%)
Gender	Male	434	62.7%
	Female	258	37.3%
Age	20-30 (inclusive)	99	14.3%
	30-35 (inclusive)	273	39.5%
	35-40 (inclusive)	230	33.2%
	40-50 (inclusive)	84	12.1%
	Above 50	6	0.9%
Education Level	Associate degree or below	73	10.5%
	Bachelor	271	39.2%
	Master	254	36.7%
	Doctor	94	13.6%
Job level	General Employee	500	72.3%
	Frontline Manager	91	13.2%
	Departmental Manager	89	12.9%
	Senior Manager	12	1.7%

Findings

To evaluate both the measurement and structural models, this study employed Partial Least Squares (PLS) modeling techniques, utilizing Smart-PLS version 4.1.1 as the statistical analysis tool (Sarstedt et al., 2020). The reason why chose it is that it offers a user-friendly interface, is widely applied in both explanatory and predictive analyses, and does not necessitate an assumption of normality (Hair Jr et al., 2019; Sarstedt et al., 2020; Wijayanti, 2025).

Common Method Variance

Cross-sectional data gathered from one source covering a range of variables carries the potential risk of Common Method Variance (CMV), making it crucial to examine CMV. This study employed a marker variable (MV) technique to control for the influence of CMV (Lindell & Whitney, 2001; Podsakoff et al., 2003). Incorporating the marker variable into the model did not significantly alter the R^2 and β values of the endogenous constructs ($\Delta < 0.10$), as shown in Table 2. These results confirm the absence of CMV risk in this study.

Table 2
CMV Testing with MV

Endogenous variable	R^2 without MV	R^2 with MV	β without MV	β with MV
ProJC	0.438	0.451	0.189	0.198
PreJC	0.308	0.308	-0.249	-0.240
IJP	0.546	0.542		

Note: ProJC=Promotion-focused Job Crafting, PreJC=Prevention-focused Job Crafting, IJP=Innovative Job Performance.

Measurement Model Assessment

When assessing the measurement model, we followed the criteria proposed by Ramayah et al. (2018) and Hair et al. (2023), carefully examining outer loadings, average variance extracted (AVE), and composite reliability (CR). Specifically, loadings ≥ 0.50 are regarded as acceptable, AVE values ≥ 0.50 indicate sufficient convergent validity, and CR values ≥ 0.70 demonstrate adequate reliability. As shown in Table 3, all of outer loadings and AVE values exceeded the 0.50 threshold, while all CR values were above 0.70. Subsequently, discriminant validity was assessed using Heterotrait-Monotrait ratio (HTMT) criterion (Hair et al., 2023). A more conservative cut-off of ≤ 0.85 was applied, and, as presented in Table 4, all HTMT values satisfied this stricter requirement. Overall, these results confirm that the measurement items exhibit both reliability and validity.

Table 3
Measurement Model

Variable	Item	Loadings	CR	AVE
IJP	IJP1	0.82	0.936	0.66
	IJP2	0.81		
	IJP3	0.81		
	IJP4	0.821		
	IJP5	0.811		
	IJP6	0.823		
	IJP7	0.798		
	IJP8	0.815		
	IJP9	0.802		
DL	DL1	0.826	0.947	0.674
	DL2	0.823		
	DL3	0.812		
	DL4	0.824		
	DL5	0.802		
	DL6	0.833		
	DL7	0.816		
	DL8	0.838		
	DL9	0.815		
	DL10	0.823		
ProJC	ProJC1	0.792	0.959	0.618
	ProJC2	0.778		
	ProJC3	0.8		
	ProJC4	0.769		
	ProJC5	0.788		
	ProJC6	0.79		
	ProJC7	0.787		
	ProJC8	0.78		

Variable	Item	Loadings	CR	AVE
	ProJC9	0.775		
	ProJC10	0.798		
	ProJC11	0.783		
	ProJC12	0.778		
	ProJC13	0.778		
	ProJC14	0.818		
	ProJC15	0.778		
	ProJC16	0.784		
PreJC	PreJC1	0.805	0.948	0.632
	PreJC2	0.776		
	PreJC3	0.796		
	PreJC4	0.788		
	PreJC5	0.786		
	PreJC6	0.8		
	PreJC7	0.805		
	PreJC8	0.796		
	PreJC9	0.792		
	PreJC10	0.799		
	PreJC11	0.794		
	PreJC12	0.801		

Note: IJP=Innovative Job Performance, DL=Digital Literacy, ProJC=Promotion-focused Job Crafting, PreJC=Prevention-focused Job Crafting.

Table 4
Discriminant Validity (HTMT ratio).

Variable	DL	IJP	PreJC	ProJC
DL				
IJP	0.551			
PreJC	0.461	0.499		
ProJC	0.538	0.509	0.313	

Note: IJP=Innovative Job Performance, DL=Digital Literacy, ProJC=Promotion-focused Job Crafting, PreJC=Prevention-focused Job Crafting.

Structural Model Assessment

Following the methodological guidelines of Kline (2023) and Cain et al. (2017), we examined the collected data for multivariate skewness and kurtosis. The analysis revealed deviations from multivariate normality, as indicated by Mardia's multivariate skewness (β =4.885, $p<$ 0.01) and kurtosis (β = 81.540, $p>$0.01). In response, consistent with the guidelines of Hair et al. (2019), the structural model's path coefficients, standard errors, t-values, and p-values were estimated using a bootstrapping procedure with 5,000 resamples (Hair et al., 2019; Ramayah et al., 2018). In addition, acknowledging Hahn and Ang (2017) critique concerning excessive reliance on p-values, this study employed a more integrative inferential approach combining p-values, confidence intervals, and effect sizes. Table 5 presents a summary of the methodological procedures adopted to ensure rigor in testing the proposed hypotheses.

Table 5
Hypothesis Testing Direct Effects

Hypo-thesis	Relationship	Std Beta	Std Error	t-values	p-values	BCI-LL	BCI-UL	f²
H1	DL -> IJP	0.145	0.040	3.622	0.000	0.064	0.221	0.025
H2	DL -> ProJC	0.329	0.034	9.620	0.000	0.261	0.396	0.149
H3	DL -> PreJC	-0.265	0.038	6.893	0.000	-0.336	-0.185	0.078
H4	ProJC -> IJP	0.189	0.041	4.641	0.000	0.112	0.271	0.039
H5	PreJC -> IJP	-0.249	0.035	7.049	0.000	-0.317	-0.181	0.093

Note: IJP=Innovative Job Performance, DL=Digital Literacy, ProJC=Promotion-focused Job Crafting, PreJC=Prevention-focused Job Crafting.

Firstly, the effects of the predictors on ProJC and PreJC were examined. The analysis produced R^2 values of 0.438 and 0.308. These results indicate that the predictors collectively explained 43.8% and 30.8% of the variance in ProJC and PreJC. Digital literacy ($\beta = 0.145$, $p< 0.01$) showed a positive effect on IJP, thereby supporting H1. Moreover, digital literacy ($\beta=0.329$, $p<0.01$) exhibited a positive relationship with ProJC, while digital literacy ($\beta=-0.265$, $p<0.01$) demonstrated a negative relationship with PreJC, thereby supporting H2 and H3. In addition, ProJC ($\beta = 0.189$, $p< 0.01$)and PreJC ($\beta =-0.249$, $p< 0.01$) were both significantly related to IJP, confirming H4 and H5.

To test the mediation hypotheses, this study adhered to the procedures recommended by Hayes (2009), utilizing a bootstrapping approach to assess indirect effects. Mediation is considered significant when the corresponding confidence interval excludes zero. As shown in Table 6, the indirect mechanisms DL->ProJC->IJP ($\beta=0.062$, $p< 0.05$) and DL->PreJC->IJP ($\beta = 0.066$, $p< 0.05$) were both statistically significant. Furthermore, The 97.5% adjusted confidence intervals with bias correction excluded zero, providing additional support for these effects. Accordingly, both H6 and H7 were supported.

Table 6
Hypotheses Testing Direct Effects

Hypo-theses	Relationship	Std Beta	Std Error	t-values	p-values	BCI-LL	BCI-UL
H6	DL->ProJC->IJP	0.062	0.016	3.998	0.000	0.035	0.097
H7	DL->PreJC->IJP	0.066	0.014	4.549	0.000	0.039	0.097

Note: IJP=Innovative Job Performance, DL=Digital Literacy, ProJC=Promotion-focused Job Crafting, PreJC=Prevention-focused Job Crafting.

Furthermore, in line with the guidelines proposed by Shmueli et al. (2019), the PLS-Predict procedure was utilized to evaluate the model's predictive capability. This technique employs a holdout sample approach to generate case-level predictions for both indicators and latent constructs, using the PLS-Predict algorithm with a 10-fold cross-validation process to evaluate predictive relevance. As noted by Shmueli et al. (2019), predictive power is determined by $Q^2_{predict}$ and comparing the prediction errors between the PLS model and a linear model (LM). When $Q^2_{predict} > 0$, all PLS item errors are smaller than those of the LM, the model demonstrates strong predictive power; if most are smaller, predictive power is moderate; and if most are larger, predictive relevance is weak. As shown in Table 7, $Q^2_{predict}>0$, all root mean square errors (RMSE) derived from the PLS model were lower than those obtained from the

LM benchmark, indicating that the proposed model demonstrates robust out-of-sample predictive capability.

Table 7
PLS-Predict

Item	Q^2predict	PLS_RMSE	LM_RMSE	PLS-LM
IJP1	0.288	0.901	0.921	-0.020
IJP2	0.284	0.843	0.852	-0.009
IJP3	0.285	0.826	0.844	-0.018
IJP4	0.296	0.879	0.902	-0.023
IJP5	0.278	0.723	0.732	-0.009
IJP6	0.279	0.816	0.819	-0.003
IJP7	0.278	0.862	0.875	-0.013
IJP8	0.299	0.737	0.741	-0.004
IJP9	0.271	0.83	0.843	-0.013

Discussion and Conclusion

This study systematically examines the mediating effects of both ProJC and PreJC on the relationship between digital literacy and IJP, grounded in the JD-R model. Results indicate that digital literacy has a significant positive effect on IJP, digital literacy significantly enhances ProJC while markedly inhibiting PreJC tendencies, ProJC further elevates IJP, whereas PreJC exerts a negative impact on IJP, both mediation pathways achieve statistical significance. Additionally, PLS-Predict results demonstrate the model's robust out-of-sample predictive capability, indicating strong robustness and external validity. These findings align closely with recent empirical research on the digital literacy, innovative behavior and performance continuum, in which digital literacy enhances individuals' ability to identify opportunities, integrate information, and reorganize knowledge in digital contexts, thereby boosting innovative outputs (Zahoor et al., 2023). Concurrently, a positive feedback loop emerges between job crafting and innovative behavior (Tomas et al., 2023), as individuals proactively shape task and resource boundaries to achieve dynamic alignment between person, role, and resources, thereby stimulating creativity and intrinsic motivation(Zhu et al., 2022). In summary, digital literacy enhances innovative job performance through a dual mechanism of reducing impeding demands and increasing resource supply endowments, further validating the explanatory power and applicability of JD-R model in the digital era.

Theoretical Implications

Firstly, this study defines digital literacy as a core individual resource and systematically integrates it into the JD-R model. This approach addresses the resource transmission logic of digital competence, motivation and performance enhancement, thereby expanding the explanatory scope of individual resources for innovative job performance. Secondly, the study refines the construct of job crafting through a dual-dimensional perspective of promotion-focused and prevention-focused approaches. It reveals significant differences in the influence mechanisms and directional effects between the resource expansion pathway (ProJC) and the obstacle avoidance pathway (PreJC), demonstrating opposite-signed mediating effects. This deepens the intrinsic mechanism underlying the job crafting and innovation performance relationship. Thirdly, by sampling STTs from SRDI "little giant" companies, this study enhances the contextual external validity of research on digital literacy and innovative job performance. Through out-of-sample predictive analysis to validate the model's robustness and explanatory power, it further elevates the theoretical universality and practical applicability of the findings, offering new analytical perspectives and empirical evidence for human resource management research in the digital era.

Practical and Social Implications

For companies, digital literacy should be regarded as a core area for strategic human capital investment, with systematic planning of digital capability development pathways. Companies can implement tiered, role-specific training systems centered on key competency modules such as data analysis, digital collaboration, and intelligent tool application to continuously enhance employees'resource integration capabilities and self-efficacy. Simultaneously, they should redesign roles and processes to optimize task structures, expand access to challenging and growth-oriented resources, and incentivize STTs to engage in ProJC. By reducing process burdens, building digital support systems, and fostering psychological safety, organizations can effectively mitigate triggers for PreJC, thereby enhancing innovation resilience and vitality. For governments, it is recommended to embed a coordinated cultivation mechanism, digital literacy, job crafting and innovative job performance, into STTs development programs for SRDI "little giant" companies, thereby establishing a composite STTs cultivation system suited to the digital era. By strengthening the dynamic synergy among technology, organization and talents, this approach builds an innovation ecosystem grounded in digital literacy and driven by job crafting. This will foster continuous enhancement of company innovation capabilities, propelling a comprehensive leap in regional industrial competitiveness and social innovation capacity.

Limitations and Suggestions for Future Research

Although this research contributes significantly to both theoretical enrichment and practical relevance, several limitations must be acknowledged. These shortcomings also provide directions and opportunities for future research. Primarily, the sample scope has certain limitations. This study focuses on STTs from SRDI "little giant" companies in China's Yangtze River Delta region. While this sample is highly representative in terms of digitalization and innovation capabilities, its geographical and industry-specific characteristics somewhat limit the external validity of the findings. Future research could expand the sample to include different regions and industries, such as advanced manufacturing, modern services, and research institutions, to test the robustness and universality of the research model across cultural, industrial, and organizational contexts.

Moreover, the variable constructs are relatively singular. This study primarily examines the overall level of digital literacy without delving into its multidimensional structure, such as cognitive, technical, and social dimensions. Subsequent research could refine these constructs and introduce moderating variables like digital leadership, psychological safety climate, or organizational learning culture to reveal interactions among dimensions and their distinct pathways in shaping innovation performance.

Additionally, data and methodology face certain limitations. The cross-sectional self-report questionnaire design provides empirical support for the theoretical model but remains subject to CMV and limitations in causal inference. Future investigations should implement longitudinal or multi-informant data gathering techniques, integrating emerging analytical techniques like hierarchical structural equation modeling and machine learning to capture dynamic interactions and temporal evolution across individual, team, and organizational levels. This approach will systematically reveal the complexity and developmental patterns of digital literacy's operational mechanisms.

References

Al-Abbadi, L., Alshawabkeh, R., & Rumman, A. (2020). Knowledge management processes and innovation performance: The moderating effect of employees' knowledge hoarding. *Management Science Letters*, *10*(7), 1463-1472. https://doi.org/10.5267/i.ms1.2019.12.021.

Anthony, C., Bechky, B. A., & Fayard, A.-L. (2023). "Collaborating" with AI: Taking a system view to explore the future of work. *Organization science*, *34*(5), 1672-1694.

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting and Social Change*, *163*, 120420. https://doi.org/10.1016/j.techfore.2020.120420.

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.

Bakker, A. B., Demerouti, E., & Sanz-Vergel, A. (2023). Job demands–resources theory: Ten years later. *Annual review of organizational psychology and organizational behavior*, *10*(1), 25-53. https://doi.org/110.1146/annurev-orgpsych-120920-053933.

Bakker, A. B., & Xanthopoulou, D. (2013). Creativity and charisma among female leaders: The role of resources and work engagement. *The International Journal of Human Resource Management*, *24*(14), 2760-2779. https://doi.org/10.1080/09585192.2012.751438.

Bindl, U. K., Unsworth, K. L., Gibson, C. B., & Stride, C. B. (2019). Job crafting revisited: Implications of an extended framework for active changes at work. *Journal of Applied psychology*, *104*(5), 605. https://doi.org/10.1037/ap10000362.

Blanka, C., Krumay, B., & Rueckel, D. (2022). The interplay of digital transformation and employee competency: A design science approach. *Technological Forecasting and Social Change*, *178*, 121575.

Bougie, R., & Sekaran, U. (2019). *Research methods for business: A skill building approach*. john wiley & sons.

Brenninkmeijer, V., & Hekkert-Koning, M. (2015). To craft or not to craft: The relationships between regulatory focus, job crafting and work outcomes. *Career Development International*, *20*(2), 147-162. https://doi.org/10.1108/CD1-12-2014-0162.

Brislin, R. W. (1986). The wording and translation of research instruments. In W. J. L. J. W. Berry (Ed.), *Field methods in cross-cultural research* (pp. 137–164). Sage Publications.

Cain, M. K., Zhang, Z., & Yuan, K.-H. (2017). Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation. *Behavior research methods*, *49*, 1716-1735. https://doi.org/10.3758/s13428-016-0814-1.

Caroline, A., Coun, M. J., Gunawan, A., & Stoffers, J. (2025). A systematic literature review on digital literacy, employability, and innovative work behavior: emphasizing the contextual approaches in HRM research. *Frontiers in Psychology*, *15*, 1448555. https://doi.org/10.3389/fpsyg.2024.1448555.

Cetindamar, D., Abedin, B., & Shirahada, K. (2021). The role of employees in digital transformation: a preliminary study on how employees' digital literacy impacts use of digital technologies. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2021.3087724.

Cheng, B., Lin, H., & Kong, Y. (2023). Challenge or hindrance? How and when organizational artificial intelligence adoption influences employee job crafting. *Journal of Business Research*, *164*, 113987. https://doi.org/10.1016/j.jbusres.2023.113987.

Dar, N., Kundi, Y. M., & Soomro, S. A. (2023). Leader–member exchange and innovative work behavior: a 2-1-1 model. *Management Decision*, *61*(9), 2629-2644. https://doi.org/10.1108/MD-08-2022-1113.

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. https://doi.org/10 1037//0021-9010 86 3 499.

Descamps, J., Le Hanneur, M., Bouché, P.-A., Boukebous, B., Duranthon, L.-D., & Grimberg, J. (2023). Do web-based follow-up surveys have a better response rate than traditional paper-based questionnaires following outpatient arthroscopic rotator cuff repair? A randomized controlled trial. *Orthopaedics & Traumatology: Surgery & Research*, *109*(2), 103479. https://doi.org/10.1016/j.otsr.2022.103479.

Geldenhuys, M., Bakker, A. B., & Demerouti, E. (2021). How task, relational and cognitive crafting relate to job performance: A weekly diary study on the role of meaningfulness. *European Journal of Work and Organizational Psychology*, *30*(1), 83-94.

Gui, C., Zhao, X., Zhang, P., Liu, Z., & Zhou, R. (2024). The Influence Mechanism of Employees' AI Awareness on Their Innovative Performance under the Background of Digital Intelligence. *Human Resources Development of China*, *41*(8), 6-22. https://doi.org/10.16471/j.cnki.11-2822/c.2024.8.001.

Hahn, E. D., & Ang, S. H. (2017). From the editors: New directions in the reporting of statistical results in the Journal of World Business. In (Vol. 52, pp. 125-126): Elsevier.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature. https://doi.org/10.1007/978-3-030-80519-7.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. S. (2023). *Advanced issues in partial least squares structural equation modeling(2nd ed.)*. Sage. https://www.researchgate.net/publication/375891260_Advanced_Issues_in_Partial_Least_Squares_Structural_Equation_Modeling_2nd_ed.

Hair Jr, J., Page, M., & Brunsveld, N. (2019). *Essentials of business research methods*. Routledge.

Halbesleben, J. R., Neveu, J.-P., Paustian-Underdahl, S. C., & Westman, M. (2014). Getting to the "COR" understanding the role of resources in conservation of resources theory. *Journal of management*, *40*(5), 1334-1364. https://doi.org/10.1177/0149206314527130.

Hayes, A. F. (2009). Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication monographs*, *76*(4), 408-420. https://doi.org/10.1080/03637750903310360.

He, C., Teng, R., & Song, J. (2023). Linking employees' challenge-hindrance appraisals toward AI to service performance: the influences of job crafting, job insecurity and AI knowledge. *International Journal of Contemporary Hospitality Management*, *36*(3), 975-994. https://doi.org/10.1108/IJCHM-07-2022-0848.

Huang, H., & Li, J. (2025). Master or Escape: Digitization-Oriented Job Demands and Crafting and Withdrawal of Chinese Public Sector Employees. *Behavioral Sciences*, *15*(3), 378. https://doi.org/110.3390/bs15030378.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of service research*, *21*(2), 155-172. https://doi.org/10.1177/1094670517752459.

Huu, P. T. (2023). Impact of employee digital competence on the relationship between digital autonomy and innovative work behavior: a systematic review. *Artificial Intelligence Review*, *56*(12), 14193-14222. https://doi.org/10.1007/s10462-023-10492-6.

Janssen, O., & Van Yperen, N. W. (2004). Employees' goal orientations, the quality of leader-member exchange, and the outcomes of job performance and job satisfaction. *Academy of Management Journal*, *47*(3), 368-384. https://doi.org/10.5465/20159587.

Jin, H., & Peng, Y. (2024). The impact of team psychological safety on employee innovative performance a study with communication behavior as a mediator variable. *Plos one*, *19*(10), e0306629.

Khan, F., & Vuopala, E. (2019). Digital competence assessment across generations: A Finnish sample using the digcomp framework. *International Journal of Digital Literacy and Digital Competence (IJDLDC)*, *10*(2), 15-28. https://doi.org/10.4018/IJDLDC.2019040102.

Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.

Klus, M. F., & Müller, J. (2021). The digital leader: what one needs to master today’s organisational challenges. *Journal of Business Economics*, *91*(8), 1189-1223. https://doi.org/10.1007/s11573-021-01040-1.

Li, D., & Yao, Q. (2024). A pathway towards high-quality development of the manufacturing industry: Does scientific and technological talent matter? *Plos one*, *19*(3), e0294873. https://doi.org/10.1371/journal.pone.0294873.

Liang, X., Guo, G., Shu, L., Gong, Q., & Luo, P. (2022). Investigating the double-edged sword effect of AI awareness on employee's service innovative behavior. *Tourism Management*, *92*. https://doi.org/10.1016/j.tourman.2022.104564.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied psychology*, *86*(1), 114. https://doi.org/10.1037//0021-9010.86.1.114.

Luo, T., & Zhang, Z. (2021). Multi-network embeddedness and innovation performance of R&D employees. *Scientometrics*, *126*(9), 8091-8107. https://doi.org/10.1007/s11192-021-04106-7.

Maddikunta, P. K. R., Pham, Q.-V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T. R., Ruby, R., & Liyanage, M. (2022). Industry 5.0: A survey on enabling technologies and potential applications. *Journal of industrial information integration*, *26*, 100257. https://doi.org/10.1016/j.jii.2021.100257

Mo, Z., Liu, M. T., & Ma, Y. (2024). How AI awareness can prompt service performance adaptivity and technologically-environmental mastery. *Tourism Management*, *105*, 104971. https://doi.org/10.1016/j.tourman.2024.104971.

Murawski, M., & Bick, M. (2017). Digital competences of the workforce–a research topic? *Business Process Management Journal*, *23*(3), 721-734. https://doi.org/10.1108/BPMJ-06-2016-0126.

Nikou, S., De Reuver, M., & Mahboob Kanafi, M. (2022). Workplace literacy skills—how information and digital literacy affect adoption of digital technology. *Journal of Documentation*, *78*(7), 371-391. https://doi.org/110.1108/D-12-2021-0241.

Pilav-Velić, A., Černe, M., Trkman, P., Wong, S. I., & Kadić-Abaz, A. (2021). Digital or innovative: Understanding "Digital Literacy–practice–innovative work behavior" chain. *The South East European Journal of Economics and Business*, *16*(1), 107-119. https://doi.org/10.2478/jeb-2021-0009

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. https://doi.org/10.1037/0021-9010.88.5.879.

Ramayah, T., Cheah, J.-H., Chuah, F., Ting, H., & Memon, M. A. (2018). *Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 3.0: An Updated and Practical Guide to Statistical Analysis*. Pearson Singapore.

Santoso, H., Abdinagoro, S. B., & Arief, M. (2019). The role of digital literacy in supporting performance through innovative work behavior: The case of indonesia's telecommunications industry. *International Journal of Technology*, *10*(8), 1558-1566. https://doi.org/10.14716/ijtech.v10i8.3432

Sarstedt, M., Ringle, C. M., Cheah, J.-H., Ting, H., Moisescu, O. I., & Radomir, L. (2020). Structural model robustness checks in PLS-SEM. *Tourism Economics*, *26*(4), 531-554.

Sasmoko, S., Mihardjo, L., Alamsjah, F., & Elidjen, E. (2019). Dynamic capability: The effect of digital leadership on fostering innovation capability based on market orientation. *Management Science Letters*, *9*(10), 1633-1644. https://doi.org/10.5267/i.ms1.2019.5.024.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322-2347. https://doi.org/10.1108/EJM-02-2019-0189.

Sullivan, F. (2024). *2024 White Paper on the Development and Global Expansion of China Specialized and Sophisticated Enterprises that Produce New and Unique Products*. https://www.frost.com/china-sme-2024-report.

Tims, M., & Bakker, A. B. (2010). Job crafting: Towards a new model of individual job redesign. *SA Journal of Industrial Psychology*, *36*(2), 1-9. https://doi.org/10.4102/sajip.v36i2.841.

Tomas, J., Lee, H. J., Bettac, E. L., Jenkins, M. R., De Witte, H., Probst, T. M., & Maslić Seršić, D. (2023). Benefiting the organization while helping yourself: a three-wave study of reciprocal effects between job crafting and innovative work behaviour. *European Journal of Work and Organizational Psychology*, *32*(6), 761-776. https://doi.org/10.1080/1359432X.2023.2250094.

Wang, Q., Yuan, Y., Dierdorff, E. C., & Liu, J. (2025). How promotion-oriented job crafting affects job performance: exploring the role of job-crafting motives. *Journal of Vocational behavior*, 104151. https://doi.org/10.1016/j.jvb.2025.104151.

Wijayanti, C. A. (2025). *PLS-SEM SmartPLS 3 dan 4: Panduan Praktis bagi Pemula*. Penerbit NEM. https://books.google.com.my/books?id=A-VcEQAAQBAJ

Yin, M., Jiang, S., & Niu, X. (2024). Can AI really help? The double-edged sword effect of AI assistant on employees' innovation behavior. *Computers in Human Behavior*, *150*. https://doi.org/10.1016/j.chb.2023.107987.

Zahoor, N., Zopiatis, A., Adomako, S., & Lamprinakos, G. (2023). The micro-foundations of digitally transforming SMEs: How digital literacy and technology interact with managerial attributes. *Journal of Business Research*, *159*, 113755. https://doi.org/10.1016/j.jbusres.2023.113755.

Zhu, J., Zhang, B., Xie, M., & Cao, Q. (2022). Digital leadership and employee creativity: The role of employee job crafting and person-organization fit. *Frontiers in Psychology*, *13*, 827057. https://doi.org/10.3389/fpsyg.2022.827057.