



Article

The impact of job substitution and job intensity on job performance in the process of enterprise digital transformation

Kang Li, Daranee Pimchangthong*

Institute of Science, Innovation and Culture, Rajamangala University of Technology Krungthep (RMUTK), Bangkok, Thailand

ARTICLE INFO

Article history:

Received 30 April 2025

Received in revised form

07 June 2025

Accepted 20 June 2025

Keywords:

Digital Transformation, Job Substitution, Job Intensity, Unemployment Insecurity, Job Mobility Insecurity, Job Performance

*Corresponding author

Email address:

daranee.p@mail.rmuth.ac.th

DOI: 10.55670/fpll.futech.4.3.23

ABSTRACT

This study explores the effects of job substitution and job intensity on employee performance in the context of digital transformation, focusing on the mediating role of job insecurity (unemployment insecurity and job mobility insecurity). Using confirmatory research methods, we analyzed 1,002 valid samples from seven Chinese furniture manufacturers. A structural equation model (SEM) developed via AMOS 27.0 revealed: (1) Job substitution (standardized coefficient = -0.254, $p < 0.001$) and job intensity (standardized coefficient = -0.264, $p < 0.001$) significantly negatively impact job performance; (2) Unemployment insecurity (mediating effect = -0.087 for job substitution; -0.10 for job intensity) and job mobility insecurity (mediating effect = -0.083 for job substitution; -0.113 for job intensity) fully mediate these relationships. This research validates relevant theories, clarifies variable relationships, and enriches digital transformation and human resource management theories. Practically, it provides HR management advice for enterprises, facilitating performance improvement and sustainable development. Methodologically, it constructs a comprehensive framework considering multiple variables, offering a new perspective to analyze the impact of transformation on employees.

1. Introduction

Enterprise DT utilizes digital and information communication technologies to redesign and optimize business processes, organizational structures, working methods, and interactions with customers, suppliers, and partners. It can improve efficiency, reduce costs, enhance innovation capabilities, and optimize the customer experience, and has thus become a strategic focus for numerous enterprises [1]. The world has fully entered the digital age. According to data from Globe Newswire [2], the DT market is expected to grow significantly at a compound annual growth rate (CAGR) of 17.42% from 2023 to 2028. In CHN, when elaborating on the Five-Year Plan for National Economic and Social Development and the Long-Range Goals for 2035 in the 2021 government report, it emphasized "accelerating digital development and building a Digital CHN", positioning digitalization as a top-level strategic priority [3]. Chinese furniture manufacturing enterprises are crucial to CHN's manufacturing industry. In the context of DT, some large-scale furniture manufacturers have launched DT and upgrading plans. These plans aim to achieve data sharing and system integration among sales, design, the Manufacturing Execution System (MES), and the Enterprise Resource

Planning (ERP) system. By leveraging digital and information technologies, they comprehensively transform their business models, operational processes, organizational structures, and corporate cultures to pursue sustainable development [4]. The success of their digital integration depends not only on technology but also on the performance of employees [5]. However, DT can lead to job displacements, triggering employee anxiety, depression, and fatigue, which reduces overall performance. The widespread use of digital tools has changed the work process. Employees need to adapt to new processes and learn new skills, and the learning curve affects work efficiency [6]. With the development of intelligence and digitalization, some jobs are being replaced, leading to unemployment. Employees have to re-evaluate their careers and often need to undergo retraining or learn new skills. Learning new skills is both time-consuming and laborious. The introduction of these technologies also reallocates job substitution and increases job intensity, which can harm their short-term job performance. Therefore, job substitution and increased job intensity during the digital transformation process pose challenges to employees' job performance. Enterprises need to address the insecurities of employees caused by job substitution and increased job intensity.

Abbreviations	
CHN	China
DT	Digital Transformation
JS	Job Substitution
JI	Job Intensity
JMI	Job Mobility Insecurity
JP	Job Performance
JSA	Task Substitution
JSB	Role Substitution
JSC	Tools Substitution
JIA	Workload
JIB	Job Difficulty
JIC	Job Urgency
JPA	Job Time
JPB	Job Quality
JPC	Job Quantity
JMIA	Changes in Responsibilities and Tasks
JMIB	Change in Skill Requirements
JMIC	Uncertainty in Career Development Opportunities
UIA	Employment Uncertainty
UI	Unemployment Insecurity
UIB	Psychological Impact
UIC	Financial Situation

These factors have long-term negative impacts on employees' mental health and career development. During DT, unemployment and job mobility insecurities are the primary psychological hurdles employees face. These not only impact daily JP but also erode loyalty and long-term commitment to the organization. When career prospects seem uncertain, employees may prioritize short-term goals, reducing their dedication to the company's long-term aims. Additionally, such insecurities create a tense workplace atmosphere, hampering team collaboration and communication, and ultimately affecting the team's overall performance and synergy [7,8]. Against this backdrop, this study constructs a comprehensive theoretical framework to explore the occupational insecurity experienced by employees in large-sized furniture manufacturing enterprises during the DT process and its related impacts. The framework encompasses variables such as JS, JI, UI, JMI, and JP. Numerous studies explore the relationships among JS, JI, and JP. In DT, JS means technology replacing traditional jobs, changing employees' roles [9]. JP, used to evaluate employees, includes productivity, quality, innovation, and customer satisfaction aspects [10]. When enterprises use automated equipment, employees may need to learn new skills, which impacts JP. Research shows a complex relationship between JS and performance. Some studies find JS may lower performance in the short term as employees adapt, but long-term, if they adapt and master new skills, performance may rise [11]. Regarding work intensity, it includes the time and energy employees invest in their work, as well as the pressure they face when completing tasks [12]. High-intensity work may cause negative emotions such as fatigue and anxiety among employees, thus affecting JP [13]. When employees are in a state of high-intensity work for a long time, work efficiency may decline, and the error rate may increase [14]. Based on these literature studies, the following hypotheses are proposed:

H1. The JS has an effect on JP.

H2. The JI has an effect on JP.

UI is the worry and anxiety about job loss or unemployment, caused by factors such as economic changes, layoffs, or

technological advancements. It can cause employees to become more anxious, stressed, and dissatisfied with their work [15]. JMI is employees' concerns about job transfers or position changes. It shows in responsibility and task changes, difficulty adapting to new job aspects, and learning - related unease. Also, it makes employees worry about promotions and career development, adding to career advancement uncertainty [16]. Tu et al. [17] explain the link between technological innovation and workers' job insecurity, showing how tech advancements can cause job displacement. Constant innovation may automate or replace traditional jobs, making employees more worried about losing their jobs. Varshney [18] claims that DT can change job content and requirements, affecting employees' job-mobility insecurity. DT may require employees to learn new skills, which can make them anxious about job mobility. Dengler and Gundert [19] found a connection between computerization levels and job insecurity. Their study showed that more computerization makes workers more worried about losing their jobs.

JI refers to the psychological and physical load that employees bear in their jobs, and it is a crucial factor influencing employee JP, occupational health, and overall quality of life. Shao et al. [20] established a negative relationship between employees' JI and their intention to stay in a job. An increase in JI leads to a decrease in the intention to stay, suggesting that high JI may be linked to employees' perceptions of occupational stability and satisfaction. Chen [21] suggested that as JI rises, employees may face greater pressure and discomfort, thereby strengthening their intention to leave the job. Karamessini et al. [22] identified several critical risk factors contributing to insecurity, including low educational levels, gender and racial discrimination, remote geographical locations, impoverished family backgrounds, economic mobility, and unfavorable policy environments. The escalation in JI can amplify the pressure and discomfort experienced by employees, subsequently diminishing their sense of occupational stability and satisfaction. Jarda and Ben Hamad [23] suggest that employees' sense of job insecurity reduces their motivation and efficiency, thereby affecting the company's performance. Therefore, during DT, it is essential for companies to address the issue of employee job insecurity and implement measures to alleviate their anxiety and stress, thereby enhancing the effectiveness of DT. Sverke et al. [24] suggest that job insecurity is a common outcome of DT and significantly increases employees' psychological pressure. If this pressure is not controlled, it may lead to a decline in employee performance. From a negative perspective, when employees perceive an inability to cope with job insecurity, it can result in diminished performance.

UI and JMI are two crucial factors that influence organizational performance. Abolade [25] establishes a certain impact of job insecurity and employee turnover rate on performance. Job insecurity can affect organizational performance in multiple ways, including reducing employee productivity, increasing turnover, and diminishing employee satisfaction. The turnover of employees can further impair organizational performance due to the loss of experienced personnel and the necessity to recruit and train new employees. Employee job insecurity emerges as a pivotal organizational concern closely tied to employee performance [26]. Both employee insecurity and turnover can significantly impact organizational performance. Employees harboring job security concerns are troubled about their economic, occupational, and personal security. Job insecurity can

adversely affect employee mental health, job satisfaction, and JP [27]. Therefore, the following hypotheses are proposed:
H3. UI is a mediator between JS and JP.
H4. JMI is a mediator between JS and JP.
H5. UI is a mediator between JI and JP.
H6. JMI is a mediator between JI and JP.
All the hypotheses were formulated according to the research framework illustrated in Figure 1.

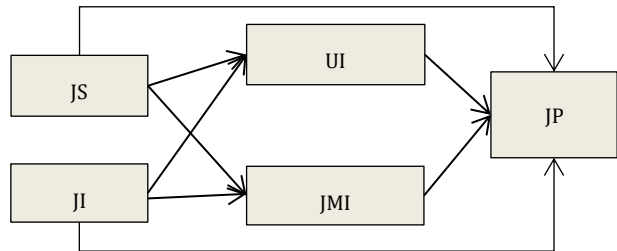


Figure 1. Research framework diagram

This study explores the impact of JS and JI on employees' JP during enterprise DT, with a focus on the mediating roles of UI and JMI. Using confirmatory research methods, it analyzes 1,002 valid sample data from seven well-known Chinese furniture manufacturers, and establishes a Structural Equation Model (SEM) to verify the direct effects of JS and JI on JP, as well as the mediating mechanisms of UI and JMI. This aims to provide references for the theory and practice of human resource management in the context of DT.

2. Methodology

2.1 Population and sample

The population in this study consisted of employees, middle-level management, and executives from seven medium-sized furniture manufacturing companies. The number of populations was 16,704, and the sample size was determined using Kline [28] as the optimal sample size for performing SEM or path analysis. The effective sample size of this study needs to be greater than 980.

2.2 Measurement

The research dimensions of all variables in the research model are taken from existing literature and slightly modified to fit the research context. Specifically, the observed indicators in the study are JS and JI. JS proposed by Barley et al. [29], which is manifested in JSA, JSB, and tool substitution. Iranmanesh et al. [30] proposed that the components of JI include JIA, task difficulty, and task urgency. The latent variable studied in this study is JP proposed by Na-Nan et al. [31], which is mainly categorized into job time, JPB, and JPC. The study's mediator variables are UI and JMI. UI proposed by De Witte [32], which mainly comprises three dimensions: UIA, UIB, and UIC impact. JMI proposed by Adekiya [16] mainly consists of three dimensions: JMIA, JMIB, and JMIC.

2.3 Questionnaire design

The design of the questionnaire mainly consists of three parts as follows:
(1) Introduction of the survey purpose, including brief instructions on respondent confidentiality and the non-biased nature of responses.
(2) Personal profile, such as gender, age, marital status, level of education, years of tenure in the current company, and current position.
(3) Survey questions designed to measure the main variables of the research model.

In this study, three dimensions were allocated to each variable, resulting in a total of 49 questions using a five-point Likert scale. The collected data were statistically analyzed for sample characteristics using SPSS 26.0 and AMOS 27.0 software. Data collection was conducted online. The survey took place from May to July 2024, and 1002 valid samples were confirmed. The effective sample rate was approximately 86.77%. This study was approved by the ethical review board of Mahachulalongkorn-rajabidyalya University, certification number R.355/2024.

2.4 Reliability and validity

Reliability analysis results, as shown in Table 1, revealed that for JS, Cronbach's Alpha was 0.832; JI was 0.813; JP was 0.859; UI was 0.823; and JMI was 0.826. The overall scale (ALL), had a Cronbach's Alpha of 0.708. A Cronbach's Alpha above 0.7 implies good scale internal consistency, meaning the measurement items consistently measure the intended constructs [33]. Regarding content validity, three experts - one academic scholar and two enterprise CEOs - rated the 49-item survey questionnaire using the IOC (Index of Content Validity). Their diverse perspectives and expertise ensured a comprehensive evaluation. Based on the scoring, four items received an average score of 0.67, indicating discrepancies or uncertainties among experts regarding the influence, importance, or assessment confidence of these items. However, 45 items had an average score of 1, indicating experts unanimously agreed on their significant influence, importance, and high assessment confidence [34].

Table 1. The reliability of the pre-survey comes from the author's analysis

NO.	Variables	Cronbach's Alpha	IOC Index	N of Items
1	JS	0.832	1	9
2	JI	0.813	1	9
3	JP	0.859	0.92	13
4	UI	0.823	1	9
5	JMI	0.826	0.96	9
6	ALL	0.708	0.97	49

3. Results and discussion

3.1 Frequency analysis of personal information

According to the statistical analysis of personal information in Table 2, the gender ratio of employees is relatively balanced, with slightly more men than women. Employees aged 31 - 40 account for the highest proportion, reaching 46.5%. 62.6% of the employees are married. 54.3% of the employees have a three-year college education background. Work experience is mainly concentrated in the range of 1 - 5 years, accounting for 70.2%. Regarding job hierarchy, operators or basic staff constitute 81.9% (the majority) of the sample. Based on the data analysis, enterprises need to pay attention to the education and skills training of employees to meet the needs during the DT process. At the same time, it is necessary to focus on the cultivation and development of management personnel to improve competitiveness.

3.2 Descriptive analysis of research variables

The mean values of the variables range from 2.864 to 3.149, as shown in Table 3, indicating that respondents' ratings for these variables tend to be neutral overall. Standard deviations range from 0.690 (JP) to 0.768 (JS), showing consistent levels of dispersion in responses. These statistical

results provide a reliable data foundation for further research and analysis [35].

Table 2. Analysis of Personal Information Distribution comes from the author's analysis

Variables	Mean	SD
JS	3.112	0.768
JI	3.149	0.738
JP	2.864	0.690
UI	3.132	0.761
JMI	3.134	0.755

Table 3. Descriptive analysis of variables from the statistical software

Category	Subcategory	Frequency	Percent	Total
Gender	Male	538	53.70%	1002
	Female	464	46.30%	
Age	21-30 Years old	383	38.20%	1002
	31-40 Years old	466	46.50%	
	41-50 Years old	135	13.50%	
	> 50 Years old	18	1.80%	
Marital	Single	335	33.40%	1002
	Married	627	62.60%	
	Divorced	34	3.40%	
	Widowed	6	0.60%	
Educational	High School or Lower	206	20.60%	1002
	3 Years College Education	544	54.30%	
	Bachelor's Degree	224	22.40%	
	Master's Degree or Higher	28	2.80%	
Length of Service in the Current Company	1-5 Years	703	70.20%	1002
	6-10 Years	254	25.30%	
	> 10 Years	45	4.50%	
Employees' Current Position	Operators/ Basic Staff	821	81.90%	1002
	Basic Managers	97	9.70%	
	Middle Management	70	7%	
	Executive	14	1.40%	

3.3 Convergent validity analysis

According to the convergent validity analysis in Table 4. The Average Variance Extracted (AVE) for all dimensions exceeds 0.5, and the Composite Reliability (CR) exceeds 0.7, demonstrating high explanatory power and internal consistency among the measurement indicators for each dimension. Specifically, the path coefficients for each dimension are also high, further confirming the strong explanatory ability of the measurement indicators for the latent variables [36].

3.4 Discriminant validity analysis

According to the data presented in the Table 5, following the Fornell and Larcker [36] criterion, which requires the square root of Average Variance Extracted (AVE) for each construct to be greater than its correlations with other constructs, the analysis reveals that each construct's square

root of AVE is indeed greater than its correlations with other constructs, as shown in both columns and rows. This indicates that constructs such as JSA, JSB, JSC, etc., are distinct from each other, reflecting the uniqueness of their measurements. Furthermore, it confirms the effectiveness of measuring latent variables, highlighting significant differences between constructs. This ensures the reliability and validity of the model, thereby enhancing the credibility and scientific rigor of the research results. Such a discriminant validity analysis provides confidence in using these latent variables for subsequent structural equation modeling or other statistical analyses. It helps ensure that research conclusions are based on a reliable and effective measurement foundation, providing solid support for theoretical validation and empirical research.

Table 4. Data of convergent validity analysis from the AMOS software

Path			Estimate	AVE	CR
Q1	<---	JSA	0.856	0.608 3	0.8226
Q2	<---	JSA	0.734		
Q3	<---	JSA	0.744		
Q4	<---	JSB	0.852	0.607	0.8218
Q5	<---	JSB	0.739		
Q6	<---	JSB	0.741		
Q7	<---	JSC	0.862	0.629 2	0.8353
Q8	<---	JSC	0.753		
Q9	<---	JSC	0.76		
Q10	<---	JIA	0.851	0.610 1	0.8237
Q11	<---	JIA	0.757		
Q12	<---	JIA	0.73		
Q13	<---	JIB	0.885	0.618 4	0.8282
Q14	<---	JIB	0.72		
Q15	<---	JIB	0.744		
Q16	<---	JIC	0.848	0.605 9	0.8212
Q17	<---	JIC	0.756		
Q18	<---	JIC	0.726		
Q19	<---	JPA	0.876	0.570 7	0.8405
Q20	<---	JPA	0.703		
Q21	<---	JPA	0.709		
Q22	<---	JPB	0.72	0.563 1	0.8647
Q23	<---	JPB	0.883		
Q24	<---	JPB	0.686		
Q25	<---	JPB	0.719	0.603 4	0.8578
Q26	<---	JPB	0.726		
Q27	<---	JPB	0.722		
Q28	<---	JPC	0.901	0.615 2	0.8271
Q29	<---	JPC	0.734		
Q30	<---	JPC	0.719		
Q31	<---	JPC	0.739	0.576 9	0.8029
Q32	<---	UIA	0.839		
Q33	<---	UIA	0.747		
Q34	<---	UIA	0.764	0.618 3	0.8286
Q35	<---	UIB	0.826		
Q36	<---	UIB	0.722		
Q37	<---	UIB	0.726	0.614 4	0.8266
Q38	<---	UIC	0.861		
Q38	<---	UIC	0.729		
Q40	<---	UIC	0.763	0.614 9	0.8265
Q41	<---	JMIA	0.843		
Q42	<---	JMIA	0.752		
Q43	<---	JMIA	0.753	0.625 5	0.8332
Q44	<---	JMIB	0.864		
Q45	<---	JMIB	0.738		
Q46	<---	JMIB	0.744	0.625 5	0.8332
Q47	<---	JMIC	0.849		
Q48	<---	JMIC	0.775		
Q49	<---	JMIC	0.745		

Table 5. Data of the discriminant validity analysis from the AMOS software

	JSA	JSB	JSC	JIA	JIB	JIC	UIA	UIB	UIC	JMIA	JMIB	JMIC	JPA	JPB	JPC
JSA	0.608														
JSB	0.244***	0.607													
JSC	0.296***	0.263***	0.629												
JIA	0.074***	0.066***	0.105***	0.610											
JIB	0.085***	0.076***	0.104***	0.217***	0.618										
JIC	0.11**	0.045***	0.091***	0.225***	0.214***	0.606									
UIA	0.181***	0.16**	0.174***	0.171***	0.123***	0.14**	0.615								
UIB	0.137***	0.097***	0.118***	0.131***	0.155***	0.116***	0.522***	0.577							
UIC	0.122***	0.158***	0.115***	0.168***	0.186***	0.119***	0.517***	0.569***	0.618						
JMIA	0.082***	0.092***	0.106***	0.068***	0.082***	0.085***	0.179***	0.165***	0.144***	0.614					
JMIB	0.08**	0.088***	0.104***	0.107***	0.061***	0.087***	0.141***	0.127***	0.181***	0.244***	0.615				
JMIC	0.073***	0.093***	0.145***	0.118***	0.083***	0.096***	0.151***	0.091***	0.173***	0.271***	0.235***	0.626			
JPA	-0.173***	-0.203***	-0.164***	-0.165***	-0.24**	-0.18**	-0.314***	-0.218***	-0.292***	-0.187***	-0.15**	-0.2**	0.571		
JPB	-0.2**	-0.227***	-0.281***	-0.198***	-0.183***	-0.187***	-0.314***	-0.326***	-0.396***	-0.226***	-0.222***	-0.223***	0.41***	0.563	
JPC	-0.133***	-0.177***	-0.249***	-0.224***	-0.207***	-0.185***	-0.296***	-0.266***	-0.413***	-0.248***	-0.206***	-0.246***	0.437***	0.535**	0.603
AVE square root	0.780	0.779	0.793	0.781	0.786	0.778	0.784	0.760	0.786	0.784	0.784	0.791	0.755	0.750	0.777

Note: *** indicates p-value less than 0.05; diagonal values represent AVE (Average Variance Extracted)

3.5 Structural validity analysis

A structural equation model (SEM) was developed, and the model fit was assessed. The results indicated that the chi-square p-value was less than 0.05. Anderson and Gerbing [37] demonstrated that researchers could systematically refine the residual correlations among measurement variables to enhance the model fit. Thus, a covariance path was established between the residuals of JS and JI. The p-value was 0.1 (> 0.05), which confirmed the adequate fit of the model to the data. Based on the model fit analysis of the structural equation model in this study, as shown in Table 6, all indicators proposed by Fornell and Larcker [36] suggest a good model fit.

3.6 Path analysis

Standardized regression weight analyses help understand model path impacts [38]. As shown in Table 7, the negative impacts of JS and JI on JP are significant, with standardized coefficients of -0.254 and -0.264, respectively, and p-values both less than 0.05. The negative impacts of UI and JMI on JP are -0.308 and -0.316, respectively, with p-values also significantly less than 0.05.

Table 6. Model fit analysis from the AMOS software

	χ^2/df	RMSEA	GFI	TLI	CFI
Standard value	<3	<0.1	>0.9	>0.9	>0.9
Actual value	1.206	0.014	0.987	0.991	0.993

Table 7. Analysis of standardized regression weights from the AMOS software

Parameter	Estimate	Lower	Upper	P
JP <--- JS	-.254	-.352	-.142	.000
JP <--- JI	-.264	-.373	-.145	.001
UI <--- JS	.283	.166	.392	.000
UI <--- JI	.325	.211	.438	.000
JMI <--- JS	.263	.148	.378	.000
JMI <--- JI	.359	.247	.477	.000
JP <--- UI	-.308	-.406	-.198	.001
JP <--- JMI	-.316	-.420	-.206	.000

3.7 Hypothesis testing

Based on the data in Figure 2, the analysis results with all p-values < 0.05 can be described as follows:

JS affects JP with an estimate of -0.254, a negative correlation confirming hypothesis H1. The confidence interval (-0.142, -0.352) in Table 8 supports this. JI affects JP with an estimate of -0.264, a negative correlation confirming hypothesis H2. The confidence interval (-0.145, -0.373) in Table 8 supports this [39]. JS impacts UI (estimate: 0.283), which in turn affects JP (estimate: -0.308). All p-values significant, confirming hypothesis H3, meaning UI mediates between JS and JP, and the value of the mediating effect is -0.087 (M3). JS impacts JMI (estimate: 0.263), which affects JP (estimate: -0.316). All p-values are significant, confirming hypothesis H4, meaning JMI mediates between JS and JP, and the value of the mediating effect is -0.083 (M4). JI impacts UI (estimate: 0.325), which affects JP (estimate: -0.308). All P-values are significant, confirming hypothesis H5, meaning UI mediates between JI and JP, and the value of the mediating effect is -0.10 (M5). JI impacts JMI (estimate: 0.359), which affects JP (estimate: -0.316). All P-values are significant, confirming hypothesis H6, meaning JMI mediates between JI and JP, and the value of the mediating effect is -0.113 (M6) [39].

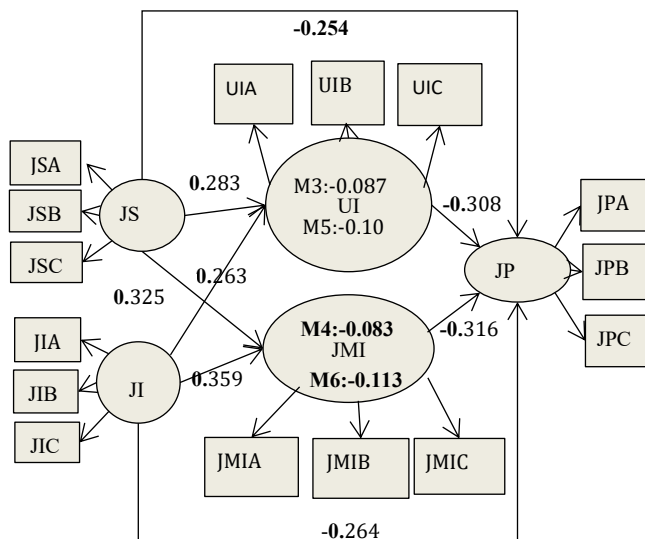


Figure 2. SEM impact effects analysis

4. Conclusion

This study uses Structural Equation Modeling (SEM) for data analysis to explore the relationships among JS, JI, UI, JMI, and JP through six hypotheses. The results show that JS and JI have significant negative impacts on JP, with UI and JMI acting as mediating factors, which verifies relevant theoretical perspectives. The findings provide theoretical support and practical guidance for enterprises to formulate and implement DT strategies to improve employee performance. However, the study has limitations: the sample is limited to seven large furniture manufacturing enterprises, resulting in insufficient industry representativeness; cross-sectional data fail to enable dynamic tracking; important variables are ignored; and insufficient attention is paid to dynamic adaptation strategies at the enterprise level. Future research can conduct cross-industry comparisons, adopt longitudinal designs, introduce more variables for multivariate analysis,

and explore the dynamic adaptation mechanism between enterprises and employees during DT, so as to provide targeted management suggestions for various industries and help enterprises maintain their competitiveness and sustainability.

Acknowledgements

First, extend sincere gratitude to the employees of the seven Chinese furniture manufacturing enterprises who participated in this survey. Their active cooperation and valuable feedback provided the essential data foundation for this research. Special thanks are due to the Research Ethics Committee of Mahachulalongkornrajavidyalaya University for granting ethical approval (certification number R.355/2024), which ensured the scientific and ethical rigor of the study. Finally, to acknowledge the guidance and support from academic experts and industry professionals who contributed to the questionnaire design and content validation. Their insights helped refine the research framework and measurement tools.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

References

- [1] Kraus, S.; Jones, P.; Kailer, N.; Weinmann, A.; Chaparro-Banegas, N.; Roig-Tierno, N. Digital Transformation: An Overview of the Current State of the Art of Research. *Sage Open* 2021, 11, doi:10.1177/21582440211047576.
- [2] Globe Newswire Digital Transformation Market - Growth, Trends, COVID-19 Impact, and Forecasts (2023-2028); 2023;
- [3] Li, Y.; Han, Z.; Qiao, T.; Zhai, K.; Qiu, Z. Changes in National Governance in the Context of Digital Transformation. *Journal of Xi'an Jiaotong University (Social Sciences)* 2022, 42.
- [4] Yao, X.; Qi, H.; Liu, L.; Xiao, T. Enterprise Digital Transformation: Re-Understanding and Re-Starting. *Journal of Xi'an Jiaotong University (Social Sciences)* 2022, 42, 1–9.
- [5] Casalino, N.; Żuchowski, I.; Labrinos, N.; Munoz Nieto, Á.L.; Martín, J.A. Digital Strategies and Organizational Performances of SMEs in the Age of Coronavirus: Balancing Digital Transformation with An Effective Business Resilience. *SSRN Electronic Journal* 2019, doi:10.2139/ssrn.3563426.
- [6] Larjovuori, R.-L.; Bordi, L.; Mäkinen, J.-P.; Heikkilä-Tammi, K. The Role of Leadership and Employee Well Being in Organisational Digitalisation. In *Proceedings*

- of the What's Ahead in Service Research? New Perspectives for Business and Society : Reser 2016 Proceedings; Russo-Spena, T., Mele, C., Eds.; University of Naples Federico II: Napoli, Italia, January 1 2016; pp. 1159–1172.
- [7] Ravishankar, B.; Ponnammam, T.S. Technology Related Anxiety-the Deepest Contributor to Stress. *International Research Journal of Engineering and Technology* 2018, 5, 1840–1847.
- [8] Fan, Q.; Ouppara, N. Surviving Disruption and Uncertainty Through Digital Transformation. In; 2022; pp. 1–22.
- [9] West, D.M. *The Future of Work: Robots, AI, and Automation*; Brookings Institution Press, 2019;
- [10] Peterson, E.; Plowman, G.E. *Business Organization and Management*; Irwin: Chicago, 1953;
- [11] Smith, P.J.; Baumann, E. Human-Automation Teaming: Unintended Consequences of Automation on User Performance. In *Proceedings of the 2020 AIAA/IEEE 39th Digital Avionics Systems Conference (DASC)*; IEEE, October 11 2020; pp. 1–9.
- [12] Burke, R.J.; Singh, P.; Fiksenbaum, L. Work Intensity: Potential Antecedents and Consequences. *Personnel Review* 2010, 39, 347–360, doi:10.1108/00483481011030539.
- [13] Hsu, H.-C. Age Differences in Work Stress, Exhaustion, Well-Being, and Related Factors From an Ecological Perspective. *Int J Environ Res Public Health* 2018, 16, 50, doi:10.3390/ijerph16010050.
- [14] Yerkes, R.M.; Dodson, J.D. The Relation of Strength of Stimulus to Rapidity of Habit-formation. *Journal of Comparative Neurology and Psychology* 1908, 18, 459–482, doi:10.1002/cne.920180503.
- [15] Bartley, M.; Ferrie, J. Glossary: Unemployment, Job Insecurity, and Health. *J Epidemiol Community Health* (1978) 2001, 55, 776–781, doi:10.1136/jech.55.11.776.
- [16] Adekiya, A.A. Perceived Job Insecurity: Its Individual, Organisational and Societal Effects. *Eur Sci J* 2015, 11.
- [17] Tu, Y.; Hao, P.; Long, L. Job Replacement or Job Transformation? Definition, Consequences, and Sources of Technology-Driven Job Insecurity. *Advances in Psychological Science* 2023, 31, 1359, doi:10.3724/SP.J.1042.2023.01359.
- [18] Varshney, D. Digital Transformation and Creation of an Agile Workforce: Exploring Company Initiatives and Employee Attitudes. In *Contemporary Global Issues in Human Resource Management*; Emerald Publishing Limited, 2020; pp. 89–105.
- [19] Dengler, K.; Gundert, S. Digital Transformation and Subjective Job Insecurity in Germany. *Eur Sociol Rev* 2021, 37, 799–817, doi:10.1093/esr/jcaa066.
- [20] Shao, N.; Zhang, Y.; Yang, H.Y.; Duan Y. Y. A Study on the Impact of Clinical Nurses' Work Intensity on Retention Intention from the Perspective of Humanistic Care. *Chinese Medical Ethics* 2021, 34, 1624–1630.
- [21] Chen, J. Investigation on Nurses' Professional Identity, Job Stress, Satisfaction, and Intention to Leave. *Chinese Nursing Management* 2012, 12, 43–46.
- [22] Karamessini, M.; Symeonaki, M.; Stamatopoulou, G.; Parsanoglou, D. Factors Explaining Youth Unemployment and Early Job Insecurity in Europe. In *Youth Unemployment and early job insecurity in Europe: Concepts, consequences and policy approaches*; Edward Elgar, 2019; pp. 45–69.
- [23] Jarda, M.K.; Ben Hamad, S. The Effect of Digital Transformation on Firm Performance: Evidence from Swedish Listed Companies. *The Journal of Risk Finance* 2022, 23, 329–348, doi:10.1108/JRF-12-2021-0199.
- [24] Sverke, M.; Hellgren, J.; Näswall, K. No Security: A Meta-Analysis and Review of Job Insecurity and Its Consequences. *J Occup Health Psychol* 2002, 7, 242–264, doi:10.1037/1076-8998.7.3.242.
- [25] Abolade, D.A. Impact of Employees' Job Insecurity and Employee Turnover on Organisational Performance in Private and Public Sector Organisations. *Studies in Business and Economics* 2018, 13, 5–19, doi:10.2478/sbe-2018-0016.
- [26] Chirumbolo, A.; Callea, A.; Urbini, F. Job Insecurity and Performance in Public and Private Sectors: A Moderated Mediation Model. *Journal of Organizational Effectiveness: People and Performance* 2020, 7, 237–253, doi:10.1108/JOEPP-02-2020-0021.
- [27] Shaikh, S.; Soomro, H.J.; Muqem, M.; Amar, H.; Sarfaraz, A.; Bhutto, S.A. Causal Analysis of Job Insecurity and Job Performance: A Study of Faculty Members Working in Privately Owned Degree Awarding Institutes of ; Sindh. *SALU-Commerce & Economics Review* 2020, 6.
- [28] Kline, R.B. *Principles and Practice of Structural Equation Modeling*; 4th ed.; Guilford Press, 2015;
- [29] Barley, S.R.; Bechky, B.A.; Milliken, F.J. The Changing Nature of Work: Careers, Identities, and Work Lives in the 21 st Century. *Academy of Management Discoveries* 2017, 3, 111–115, doi:10.5465/amd.2017.0034.
- [30] Iranmanesh, M.; Zailani, S.; Moeinzadeh, S.; Nikbin, D. Effect of Green Innovation on Job Satisfaction of Electronic and Electrical Manufacturers' Employees through Job Intensity: Personal Innovativeness as Moderator. *Review of Managerial Science* 2017, 11, 299–313, doi:10.1007/s11846-015-0184-6.
- [31] Na-Nan, K.; Chaiprasit, K.; Pukkeeree, P. Factor Analysis-Validated Comprehensive Employee Job Performance Scale. *International Journal of Quality & Reliability Management* 2018, 35, 2436–2449, doi:10.1108/IJQRM-06-2017-0117.
- [32] De Witte, H. Job Insecurity and Psychological Well-Being: Review of the Literature and Exploration of Some Unresolved Issues. *European Journal of Work and Organizational Psychology* 1999, 8, 155–177, doi:10.1080/135943299398302.
- [33] Tavakol, M.; Dennick, R. Making Sense of Cronbach's Alpha. *Int J Med Educ* 2011, 2, 53–55, doi:10.5116/ijme.4dfb.8dfd.
- [34] Ismail, F.K.M.; Zubairi, A.M.B. Item Objective Congruence Analysis for Multidimensional Items Content Validation of a Reading Test in Sri Lankan

- University. English Language Teaching 2021, 15, 106, doi:10.5539/elt.v15n1p106.
- [35] Hanushek, E.; Jackson, J.E. Statistical Methods for Social Scientists; Academic Press: New York, 1977;
- [36] Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Journal of Marketing Research 1981, 18, 39, doi:10.2307/3151312.
- [37] Anderson, J.C.; Gerbing, D.W. Structural Equation Modeling in Practice: A Review and Recommended Two Step Approach. Psychol Bull 1988, 103, 411–423, doi:10.1037/0033-2909.103.3.411.;
- [38] Byrne, B.M. Structural Equation Modeling with Mplus Basic Concepts, Applications, and Programming; 1st ed.; Routledge, 2011;
- [39] Steyer, R.; Mayer, A.; Fiege, C. Causal Inference on Total, Direct, and Indirect Effects. In Encyclopedia of Quality of Life and Well-Being Research; Springer Netherlands: Dordrecht, 2014; pp. 606–630.



This article is an open-access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).