WISVORA

International Theory and Practice in Humanities and Social Sciences
2025 Volume2,Issue4 ISSN 3078-4387

Beyond Turnover: How Skill-Level Employee Dynamics Shape Corporate Digital Transformation

Shi Shuyi [1] **Liu Zixu**[1] **Xue Yiwei**[2] **Zhang Xinyue**[2]
[1]*Department of Finance, Wenzhou-Kean University*
[2]*Department of Accounting, Wenzhou-Kean University*

Accepted

29 March 2025

Keywords

Digital transformation,labor turnover rate,low-skillde employees,high-skilled employees

Corresponding Author

Shi Shuyi

https://doi.org/10.70693/itphss.v2i4.338

Abstract
We investigated the impact of employee turnover rates at different levels on the degree of digital transformation of non-financial A-share listed companies in China. Using the employment rates of different educational backgrounds and non-financial A-share listed companies in China from 2009 to 2016, we applied panel data and conducted regression analysis on the data to test their relationship. The baseline testing shows that companies can address the turnover of low skilled employees by adopting labor-saving technologies, which significantly improves the sustainability of digital transformation. The robustness test further validated these findings, emphasizing that the departure of highly skilled employees will have a negative impact on the sustainability of digital transformation initiatives, highlighting the necessity for companies to retain talent. Our research findings emphasize the importance of using advanced technology to replace low skilled tasks, workforce, and prioritizing the retention of high skilled talent to ensure a sustainable and competitive digital transformation trajectory for companies.

1. Introduction

With the increasingly fierce market competition, sustainable development has become the goal pursued by many enterprises and has become one of their most fundamental challenges (Wolf, 2013). How to achieve sustainable development and maintain sustainable competitive advantage is the problem that enterprises try to solve. In addition, the rapid development and continuous updating of digital technology also bring new challenges for organizations. Recent studies have shown that digitalization can improve corporate performance, enabling organizations to achieve higher levels of operational efficiency, market responsiveness, and customer satisfaction (Lee et al., 2022). Therefore, companies undergoing digital transformation to improve efficiency and customer satisfaction in order to better cope with market competition. However, while digital transformation is often driven by strategic decisions from management, its success depends largely on employees' digital literacy, that is, their knowledge, skills, and ability to effectively adopt and apply digital technologies (Cetindamar & Abedin, 2021). Employees play a key role in bridging the gap between technology theory and actual implementation, as their adaptability, creativity, and engagement determine the extent to which digital systems are successfully integrated into organizational workflows. At the same time, according to the Resource-Based View (RBV) proposed by Wernerfelt in 1984**,** the internal factors of an enterprise are much more important than the external factors in maintaining a sustainable competitive advantage. As one of the internal factors of the enterprise, employees can actively regulate the structural implementation of sustainability to a certain extent (Wolf, 2013). Therefore, it is necessary to study how employees' skills and educational background affect an enterprise's digitization degree.

Many existing studies have highlighted how digital transformation drives improved performance by enabling organizations to operate more efficiently. For example, according to Zhai et al. (2022), digital transformation provides companies with the tools and processes needed to streamline operations, optimize resource allocation, and increase productivity, ultimately contributing to improved organizational performance. A growing number of scholars have also studied the impact of digital transformation on the labor market, especially its role in reshaping the labor structure. Bertani et al. (2020) discussed how technological advances associated with digital transformation have caused significant disruptions to the labor market, and they concluded that this often leads to "technological unemployment" for both blue-collar and white-collar workers.

While these studies provide valuable insights into the economic and operational impacts of digital transformation, there is limited research on the subtle interactions between a differently skilled workforce, employee turnover, and organizational digitization. Most existing studies focus on either the performance benefits of digital transformation or its negative impact on the labor, without delving into how specific factors such as employees affect the adoption and success of digital technologies within an organization. Therefore, our research aims to fill this gap and investigate how changes in education levels and employee turnover affect the speed and success of digital transformation in enterprises. By examining these, this study provides a deeper understanding of the labor-related factors that promote or hinder organizational digitalization. By doing so, we hope to provide practitioners and policymakers with actionable recommendations for optimizing the workforce.

We use data from the Ministry of Human Resources and Social Security of the People's Republic of China and public information from China's non-financial A-share listed companies to gain insight into the relationship between labor characteristics and digital transformation outcomes. In this study, high-skilled employees are operationalized as individuals with advanced educational qualifications, whereas low-skilled employees are operationalized as individuals with basic or limited educational qualifications. Anduse regression analysis to quantitatively assess how changes in employee education levels and turnover rates affect the speed and success of an organization's digital adoption. This approach allows us to uncover correlations that have not been fully explored in previous research. By examining these relationships, this study makes important contributions to the academic and practical fields. From a theoretical perspective, it enriches the ongoing discussion on the role of differently skilled employees in the digital transformation of organizations, especially in rapidly developing economies like China. It also improves understanding of how the labor interacts with digital technology innovation, shedding new light on the complex reasons behind successful digital transformation.

From a practical perspective, the findings provide practical guidance for companies preparing to strengthen their digital transformation strategies. By identifying the specific impacts of employee skills and turnover on the adoption of digital technologies, this study provides organizations with the knowledge they need to allocate resources more effectively. The findings also have broader implications for policymakers and industry leaders as they highlight the huge role that a workforce with different education levels plays in digital transformation. By bridging the gap between differently skilled labors and organizational digitalization, this research lays the foundation for sustainable growth in the era of digital innovation.

2. Literature Review

With the advancement of technology, digitalization has spread across various industries, deeply influencing corporate governance and organizational structure. Many existing studies focused on the relationship between organizational structure and digitization and how they affect companies' sustainable development. They indicate that digitalization can enhance a company's efficiency and lead to a balance of sustainable development and profitability.

Digitalization has brought many cost benefits to the company. According to Goldfarb and Tucker (2019), the digitalization of enterprises will improve the cost-effectiveness of enterprises by lowering the search cost, replication cost, transportation cost, tracking cost, and verification cost, which will benefit the countries, enterprises, and consumers. Babina et al. (2021) stated that the emergence of digital technologies such as artificial intelligence can enable companies to learn better and faster, which can expand business investment opportunities by reducing the cost of development and production. According to Zhang et al. (2023), through research on Chinese SMEs, they found that the digital transformation of financial services has an impact on the financing of SMEs, and more digitalization of finance-related technologies will reduce the financing restrictions of SMEs. Besides, According to Gileva, Tatyana, and Elena (2022), digital companies have greater flexibility in managing their workforce structure and are particularly effective in remote work. Most of the current research focuses on the impact of supply chain digitization on firm performance, and they believe that supply chain digitization can bring business activities sustainable competitive advantage. For example, Bahjat (2024) studied the mediating effect of industrial chain digitization on the relationship between supply chain agility and operational performance, and the results showed that supply chain digitization has a positive impact on operational performance, which can increase the company's profit.

Besides, R and Lakshmi (2023) investigated the impact of supply chain digitization on corporate performance and resilience, as well as the moderating effect of technological turbulence and executive commitment. The results showed that supply chain digitization has a significant impact on corporate performance, which in turn has a positive effect on the company's operational performance. The moderating effect of technological turbulence and executive commitment proves the important role of technology and digitization in corporate performance. Most articles indicate that digitization has a positive impact on business performance and has become a necessity for enterprise transformation. This also implies that if a company aims to maintain a sustainable competitive advantage in the market and achieve higher profits, it must undergo digital transformation to make sure companies develop digital capabilities.

For companies, organizational structure plays the same crucial role as digitalization in shaping a company's efficiency, decision-making processes, and overall strategic execution. An efficient organizational structure fundamentally depends on the strategic allocation and utilization of human resources. As mentioned by Kucharcikova et al. (2024), human capital refers to the knowledge, skills, and abilities that individuals possess, which can contribute to the competitiveness of a company. Employees serve as the cornerstone of organizational effectiveness, and their proper deployment is critical to achieving operational coherence and sustaining competitive advantage. That's why some experts have extensively explored workforce allocation and employment in digital enterprises. They found that low-skilled employees, typically those with lower education levels, are often associated with routine and manual tasks that are more susceptible to automation and digital replacement (Autor et al., 2003). When low-skilled employees leave, organizations are incentivized to invest in digital technologies to replace labor-intensive processes, thereby accelerating digitization. This aligns with the concept of creative destruction (Schumpeter, 1942), where the departure of low-skilled labor forces firms to innovate and adopt new technologies to maintain efficiency. Additionally, the turnover of low-skilled employees reduces resistance to change, as these employees may be less adaptable to new technologies (Brynjolfsson & McAfee, 2014). When they talk about high-skilled employees who possess the technical expertise and digital literacy necessary(Cetindamar & Abedin, 2021). They found the loss of highly skilled employees creates a knowledge gap, hindering the adoption and integration of digital technologies.This is consistent with the knowledge-based view (Grant, 1996), which highlights the importance of retaining skilled employees to sustain innovation and technological advancement.

Based on that, there is a close relationship between workers' skill levels and the creation of digital technologies. Then existing studies also found digitalization have two side effects on employees. For example, some research found that digitalization has a positive impact on the redistribution of labor and the sustainable development of companies. Hjort and Poulsen's (2019) study explored how digital infrastructure improvements will affect employment and company operations. The result shows that the introduction of high-speed Internet has had a positive effect on the employment rate of African workers, especially the demand for highly skilled workers. It also has a positive impact on the productivity and profitability of enterprises.

However, it is difficult to conclude whether digitization will increase employment. For example, Acemoglu and Restrepo (2019) pointed out the problem of digitalization and task distribution, that is, digitalization can replace labor to complete tasks, improving productivity and leading to the rise of labor unemployment. On the other hand, digitalization can create new tasks, and new tasks can help create jobs that are more suitable for labor. However, their result shows that while digitalization has increased productivity, it has failed to fully create new jobs, leading to an overall downward trend in labor demand. The study of Cirillo et al. (2021b) showed that digitalization can mediate employment by varying the level of routineness in each field. As a result, the local economic structure focusing on manufacturing faces a risk under digitalization. According to Acemoglu &Autor (2011), with the development of computer arithmetic and the reduction of automation costs, the market labor force has become polarized, low-income workers are much more affected than high-income workers, which may cause the market to shed low-income workers to recruit more high-income workers. Therefore, in the United States, some studies have predicted that about half of the population will be at risk from digitization, sparking fears of mass unemployment.

As stated by Arntz et al. (2019), there is a discrepancy between people's actual jobs and their occupational definitions. Some employees in what are considered replaceable occupations have shifted their focus to non-automatable tasks to reduce the impact of digitalization on them. Balsmeier and Woerter (2019), who also discuss the impact of digitalization on jobs, show that digitalization can promote job creation for high-skilled workers but curb jobs for low-skilled workers. In addition, digital developments require employees to be digitally literate and use digital knowledge, and many companies are selecting talent on this basis (Foroughi, 2021). Research like this explains the relationship between the digitalization level and employment in the job market, or it just discusses the relationship between digitalization and work efficiency. However, they have not discussed from another perspective: how labor turnover affects a company's digitalization. Therefore, this study will analyze the relationship between the different labor turnover rates for high-skilled employees and low-skilled employees in China’s province and the digitalization degree in the company.

3. Research Question

In this section, we propose research questions that will be explored through empirical analysis. Our research focuses on the impact of employee turnover at different skill levels on the level of digitalization in companies, and verifies these relationships through descriptive statistics and regression analysis (including baseline models and robustness tests). To construct the research question, we integrated insights from multiple relevant literature, with a focus on the interaction between digitization and labor dynamics.

In terms of digitization, we first explored the multidimensional definition of digital transformation. Some studies define digitization as the degree of automation of repetitive and programmable tasks in workflows (Cirillo et al., 2021b), while others emphasize investment in advanced digital technologies such as computerized automatic control systems and 3D printing (Balsmeier and Woeter, 2019). In terms of labor dynamics, we studied the heterogeneous impact of digitization on labor demand. For example, the manufacturing industry faces higher unemployment risks under high-level digitization, while the high-tech industry may benefit from it. In addition, the impact of digitization varies depending on the skill level of employees: high skilled employees typically benefit from technological advancements, while low skilled employees may face greater unemployment risks.

Based on the above background, we propose the following research questions:

RQ1： How does the turnover rate of low skilled employees affect the digitalization level of a company?

We assume that there is a positive correlation between the turnover rate of low skilled employees and the degree of digitalization in the company. Specifically, the high turnover rate of low skilled employees may reflect that the company is replacing low skilled positions with automation technology, thereby driving digital transformation. Furthermore, we explore whether this relationship varies depending on industry type (such as manufacturing vs. services) or company size (such as small and medium-sized enterprises vs. large enterprises).

RQ2： How does the turnover rate of high skilled employees affect the digitalization level of a company?

We assume that there is a negative correlation between the turnover rate of high skilled employees and the degree of digitalization in the company. The loss of highly skilled employees may lead to a decline in the company's ability to implement digital technology, thereby delaying the process of digital transformation. We also explore whether the turnover rate of high skilled employees is related to the level of investment in digital infrastructure by companies.

Through these questions, we aim to reveal the complex relationship between employee turnover and digital transformation of companies, and provide theoretical support and practical guidance for the digital strategy of enterprises.

4. Data, variables and Methodology

4.1 Data source

This study aims to explore the achievements of China's digital transformation after 2010, focusing on A-share non-financial listed companies in China during the period from 2010 to 2016. It follows two necessary criteria: first, China is a relatively developed country, having complex economies; and second, digital transformation is developing rapidly in China.The rapid development of China's digital transformation has been driven by the continuous advancement of digital technologies. And the widespread adoption of digital tools in China began after 2009 (Zhao & Ren, 2023). For the time, this period is the year when the rapid digital development in China.

Our data consist of two parts. For the data about digital transformation， We obtained observational data from Zhao and Ren (2023), who studied the impact of enterprise digital transformation on firms' capacity utilization. Their research focused on 15,942 observations from Chinese companies between 2010 and 2018. We further processed and filtered this dataset for our analysis. The original data were derived through Python-based textual analysis of annual reports from A-share non-financial listed companies, focusing on keywords related to digital transformation. Additionally, financial information in their article, which we used for control variables in our study, was initially sourced from the CSMAR database, which relies on data from the China City Statistical Yearbook of previous years.

For the labor turnover data, we draw on comprehensive data from China's principal labor market survey, covering educational attainment and employment figures across 31 provinces from 2009 to 2016. The primary data source is the China Labor Force Survey (CLFS), conducted by the People's Republic of China (PRC). As the largest labor market monitoring initiative in China, the CLFS offers robust annual insights into key employment indicators, including wages, education levels, gender distribution, enterprise types, and access to social benefits.

The survey's extensive sample, encompassing approximately 135 million individuals across all 31 inland provinces, ensures the data's statistical reliability and representativeness. Notably, the survey operates within the Three-in-One Statistical System, comprising three interconnected components. The first component, urban unit labor statistics, is managed by the Ministry of Human Resources and Social Security (MOHRSS) and focuses on formal employment within state-owned enterprises and institutional sectors. The second component, covering private and self-employed sector statistics, is overseen by the State Administration for Market Regulation (SAMR). This segment captures employment dynamics within urban private enterprises and among self-employed individuals, effectively addressing coverage gaps in the formal urban labor market. The third component, rural employment statistics, is conducted by the Rural Social and Economic Survey Team, commonly known as the Agricultural Survey Team, which monitors employment trends in rural areas. The integration of these three datasets is pivotal due to their complementary nature. The urban unit labor statistics provide critical insights into formal employment, while private sector data capture informal urban employment trends. Rural employment statistics complete the picture by accounting for labor market dynamics in non-urban areas. This holistic approach ensures comprehensive coverage of China's diverse labor market, bridging the urban-rural divide. Accordingly, this integrated dataset forms the foundation of our analysis, enabling us to examine employment status across provinces and educational levels with precision and depth (Cai et al., 2013).

To ensure the quality of the research findings, we performed a secondary screening of the sample based on the original data. The specific methods are as follows.

First, to operationalize the variables, binary coding was employed in this paper. Since our paper's independent variable is the turnover rate of high-level and low-level employees, and our research focuses on its positive and negative values rather than its size, we used binary indicators to replace the turnover rate of high-level and low-level employees. We use "1" instead of positive turnover rate and "0" instead of negative turnover rate. Binary indicators help clarify the directionality of independent variables and shift the focus of research from the size of the independent variable to its positive or negative sign. Moreover, binary simplifies the model and studies the degree of digital transformation of the dependent variable, which allows us to more intuitively see the positive and negative group ratios and helps us have more stable analysis.

Second, we also use Winsorization techniques to limit extreme values or outliers to a specified range (usually based on percentiles) to handle them - replacing them with the closest values within the specified percentile range.

For overall data analysis we used panel data, we used the turnover rates of high and low educated employees from 2010 to 2016, as well as company related data.

Since we used high-dimensional fixed effects, we use the Reghfe test as our regression test. It refers to categorical variables with multiple levels or categories (such as fixed effects at the individual level, company level, or time level) when used as fixed effects in the regression model.

During the data collection process, Excel was used for the collection, summarization, and screening of primary labor data, while Stata 18 was employed for data integration, processing, and presenting the final results.

4.2 Variable Description

4.2.1 Enterprises' Digital Transformation（DT）

Because of the absence of standardized metrics for measuring the level of corporate digital transformation, and considering that existing studies primarily rely on textual analysis to capture firms' adoption of information technologies such as the internet (Yang & Liu, 2018), we opted to reference and further process data from related studies. Specifically, we obtained the digital transformation data provided by Zhao and Ren (2023) using Python from the annual reports of listed companies.

Compared to previous research, they introduced a new semantic approach to textual analysis digital transformation by incorporating the concept of 'national digital economy policies', resulting in a more comprehensive measurement. In addition, they employed machine learning-driven textual analysis techniques to create a more reliable indicator that captures the level of digitalization among Chinese publicly listed companies.

Based on their methodology, higher DT index values correspond to a greater degree of digital transformation.

4.2.2 Employee Education Levels on Turnover

The independent variable in our study is the labor turnover rate among individuals with varying educational attainment across 31 inland Chinese provinces from 2009 to 2016. It is important to note that data from Taiwan, Hong Kong, and Macao are excluded due to their geographical separation and potential discrepancies in labor market conditions compared to mainland provinces.

In order to further explore the impact of employee turnover rates with different educational levels on corporate digitization, we divided the independent variable into two categories. According to Lv, Zhao, Zhu, and Zhu's (2024) study of '*Enterprise Digital Transformation and Labor Structure Evolution'*, as well as the categorization framework proposed by Habibi and Kamis (2021), we segmented the labor into high education workers and low education workers. This classification consist with established economic theories, which posit that highly educated individuals are typically employed in high-skilled occupations, whereas those with lower educational attainment are more likely to occupy low-skilled positions (Acemoglu & Restrepo, 2018; Katz & Margo, 2014).

Based on this classification, we calculated the high education turnover and low education turnover. The specific calculation formula is as follows:

Low-education turnover =No. Low education employee $_{current\ year}$ – No. Low education employee $_{previous\ year}$---(3)

High-education turnover =No. High education employee $_{current\ year}$ – No. High education employee $_{previous\ year}$---(4)

4.2.3 Control variables

As for the control variable, we referred to Balsmeier and Woerter (2019), Biagi and Falk (2017), Liu, Bian, and Zhang(2022), and Zhao and Ren (2023) choosing our control variables. Specifically, in order to get more accurate result, we control the firm scale(size), which measured by the logarithm of the total number of employees; enterprise's profitability(ROA), which measured by the firm's return on assets; the financial leverage(lev), which measured as the total liability divided by the total assets; and the institutional ownership ratio(Inst_share),which measured as the proportion of shares held by institutions to the total shares outstanding. The financial data referenced above is also obtained from the study by Zhao and Ren(2023). The original data were sourced from the CSMAR database and the *China City Statistical Yearbook*. The descriptions of the variables are presented in Table 1, while the descriptive statistics are provided in *Table 1*.

Tale 1. Primary variables and explanations

Variable Type	**Symbol**	**Variable Name**	**Measurement**
Dependent Variable	DT	Digitalization of enterprises	Text analysis of the annual reports of listed companies using Python to estimate the degree of digital transformation

Independent Variable	High-education turnover	Employees' turnover with undergraduate college degrees and above	The number of High education employees in the current year - the number of High education employee in the previous year
	Low-education turnover	Employees' turnover with less than a college degree	The number of Low education employees in the current year - the number of Low education employees in the previous year
Control Variable	Size	Enterprise size	Logarithmic value of enterprises' total number of employees
	Roa	Return on assets	Net profit/total assets of the enterprise
	Lev	Leverage ratio	(Total liabilities at the end of period / total assets) x 100%
	Inst_share	Institutional shareholding ratio	（Total Outstanding Shares of the CompanyTotal Shares Held by Institutions） ×100%

4.3 Descriptive Analysis

4.3.1 Summary Statistics

In the paper, we used binary ("1", "0") to represent the positive or negative sign of high and low-educated employees resigning: "1" is positive, and "0" is negative. In the descriptive analysis, we analyzed the turnover rates of employees at different levels before binary, as well as the turnover rate data after binary.

The data before binary can be used to calculate the average, median, standard deviation, and

range of turnover rates in each province. Pre-binary data is beneficial for determining patterns or trends in the magnitude of changes, facilitating a deeper understanding of the distribution of turnover rates (such as skewness, and kurtosis), and is useful for comparison.
Using binary data allows for a clear observation of the percentage of positive turnover and the differences in the proportion of positive turnover among different provinces.

Table 2-Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
province	0			2010	2016
year	11647	2013.377	1.924032	2010	2016
Lowedu-turnover	11647	-0.9954863	12.79211	-31.91176	46.44249
Highedu-turnover	11647	-1.676132	12.18241	-17.51612	15.88791
turnover_d	11647	0.3105221	0.46	0	1
turnover_g	11647	0.4487851	0.493915	0	1
digital	11647	0.1981517	0.32526	0	3.637175
size	11647	22.07029	1.1385169	17.81321	28.50873
lev	11647	0.4260593	0.546421	0.0079799	0.9946557
roa	11647	0.041885	0.368681	-0.6906772	4.836601
Inst_Share	11017	0.3945964	0.238085	1.4e-05	0.890143

Table 2-Summary Statistics

Summary Statistics for Turnover Variables

Next, we will conduct a more detailed summary and statistical analysis of the variables turnover-d and turnover_g to observe the binary data of the turnover rate of employees with high and low education levels. The summary and statistical data provide insights into the distribution and variability of the data.

1. Mean value:

The mean value of turnover rate d_ is 0.3106, indicating that approximately 31% of low educated employees in the data have a positive turnover rate. The turnover rate_g has an average of 0.4488, indicating that 44.88% of highly educated employees have a positive turnover rate.

2. Variability:

The standard deviation of turnover rate_d (0.4627) and turnover rate _g (0.4974) reflects the changes in these binary variables, and it can be observed that the turnover of highly educated employees is slightly higher than that of low educated employees.

3. Distribution:

Flipping the tilt angle (0.8188) shows that the turnover rate of low educated employees has a certain right bias, indicating that 0 is more frequent than 1. The skewness of revenue g is relatively low (0.2059), which means that the distribution of highly educated employees' mobility is more balanced.

4. Percentile:

For these two variables, the 25th percentile, median, and 75th percentile values are consistent with their binary properties, with a median of 0 indicating that more than half of the observations belong to the 0 category.

Summary:

From the overall data, the relatively low mean highlights the low frequency of positive mobility in the data, with low educated employees generally more likely to resign and higher educated employees having a lower turnover rate.

Table 3: Summary Statistics for Turnover Variables

Statistic	Turnover_d	Turnover_g
Observations	11,647	11,647
Mean	0.3106	0.4488
Standard Deviation	0.4627	0.4974
Variance	0.2141	0.2474
Skewness	0.8188	0.2059
Kurtosis	1.6705	1.0424
Minimum	0	0
25th Percentile	0	0
Median (50th Pctl)	0	0
75th Percentile	1	1
Maximum	1	1

4.3.2 Correlation Analysis

The correlation matrix in *Table 4* represents the pairwise correlations between our independent variables and the characteristics of the enterprise. It provides significant values for individual variables and expands the sample.

Table 4 Correlation Matrix

	turnover_d	turnover_g	digital	size	lev	roa	Inst_Share
turnover_d	1.0						
turnover_g	-0.0187**	1.0					
digital	0.0647***	-0.0096	1.0				
size	0.0147	-0.0126	-0.1348***	1.0			
lev	-0.0292***	-0.0111	-0.1828***	0.5459***	1.0		
roa	0.018*	0.0174*	0.062***	-0.0641***	-0.2831***	1.0	
Inst_Share	0.0035	-0.036***	-0.1233***	0.4458***	0.2884***	0.0239**	1.0

****, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

4.4 Methodology

The methodology of this study is described as follows. Inspired by Liu, Bian, and Zhang (2022), who studied how digital transformation affects the educational structure of employees. We conducted a baseline regression to test whether the effect of low-educated employee turnover on company digitization is significant. Second, we used the turnover of high education employees as a robustness test. By treating the turnover of high education employees as a comparison group, we can further confirm the robustness of the regression results for the turnover of low education employees. If the robustness regression results differ from the baseline regression, this can provide additional support for our findings. Our regression equation is shown below:

$$\boldsymbol{DT_{i,t} = \beta_0 + \beta_1\, turnover\_d_{i,t} + \sum \beta_j \cdot Control\ Variables_{i,t} + \epsilon_{i,t}} \text{ --- (3)}$$

$DT_{i,\ t} = \delta_0 + \delta_1 \cdot turnover\_g_{i,\ t} + \sum \delta_j \cdot Control\ Variables_{i,t} + \epsilon_{i,\ t}$--- (4)

Where $DT_{i,\ t}$ is the digital transformation level; $\beta_0,\ \delta_0$ is the constant term; $\beta_1,\ \delta_1$ are the core coefficient in this model; $turnover\_d_{i,t}$ is the low education employees' turnover, while the $turnover\_g_{i,\ t}$ is the high education employees' turnover. Control Variables $_{i,t}$ means a series of control variables: roa, inst_share, lev and size; $\epsilon_{i,\ t}$ is the error correct term.

5. Findings

Baseline test:

H1: The turnover rate of employees with low education has an increasing effect on the digitalization degree of the company

Table 5 baseline test for low-skilled employees

digital	Coefficient	Std.err.	t	P>|t|	[95% conf. interval]	
turnover_d	0.0068258**	0.0032569	2.10	0.0360	0.0004415	0.0132101
size_w	0.1188209***	0.0038995	30.47	0.0000	0.111177	0.1264647
lev_w	-0.0094018	0.0192055	-0.49	0.6240	-0.0470491	0.0282455
roa_w	-0.0255787	0.0509797	-0.50	0.6160	-0.1255109	0.0743534
Inst_Share_w	0.0191376	0.0110975	1.72	0.0850	-0.0026161	0.0408912
_cons	-2.4263750***	0.0838946	-28.92	0.0000	-2.590828	-2.261922

****, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Table 5 presents the main findings of our study, focusing on the relationship between low-skilled employee turnover rates and digitalization, along with key control variables.

Low-Skilled Employee Turnover Rate

The results indicate that the turnover rate for low-skilled employees has a positive impact on digitalization. The coefficient is small but statistically significant at the 5% level, with a p-value of 0.036. This suggests that higher digitalization levels are associated with increased turnover rates for low-skilled workers. One possible explanation is the enterprise has reduced its investment in human capital and instead invested in researching and developing digital technologies to replace low skilled labor, and the use of high technology can to some extent improve production efficiency.

Control Variables:

1. Company Size

   Company size is highly significant in relation to digitalization, with a p-value of 0.000. The positive coefficient suggests that larger firms tend to experience higher turnover rates among low-skilled workers. This could be attributed to several factors, such as larger firms' greater capacity for technological adoption and restructuring initiatives, which may render some low-skilled roles redundant. Additionally, larger companies may have more resources to invest in automation, contributing further to workforce turnover. The 95% confidence interval (CI) for company size, ranging from 0.111177 to 0.126464, does not cross zero, reinforcing the robustness of this finding.

2. Leverage

The relationship between leverage and low-skilled employee turnover is negative, with a coefficient of -0.0094018. However, the p-value of 0.624 indicates that this relationship is just weakly significant. This suggests that a company's financial leverage does not have a meaningful impact on the turnover rate for low-skilled workers. Financial constraints or debt levels may not directly influence decisions related to low-skilled workforce retention or turnover.

3. Return on Assets (ROA)

The coefficient for return on assets is -0.0255787, indicating a negative relationship with low-skilled employee turnover. However, the p-value of 0.616 suggests that this relationship is also not statistically significant. ROA reflects a company's profitability, and the lack of significance implies that profitability does not play a crucial role in influencing turnover rates among low-skilled employees. This finding suggests that other factors, such as organizational culture, management practices, or external economic conditions, might have a more substantial impact on turnover than profitability alone.

4. Institutional Shareholding

Institutional Shareholding shows a positive relationship with low-skilled employee turnover, with a coefficient indicating a marginally significant p-value of 0.085. This suggests a weak but positive relationship between institutional ownership and turnover rates. One possible interpretation is that higher institutional ownership may influence corporate governance and strategic decisions related to labor management. Institutional investors may prioritize efficiency and profitability, potentially leading to policies that contribute to higher turnover, such as cost-cutting measures or restructuring initiatives. The confidence interval for institutional shareholding also supports this finding, albeit marginally.

Robustness and Confidence Intervals

To ensure the robustness of our significant findings, we examined the 95% confidence intervals (CIs). For the turnover rate of low-skilled employees, the CI ranges from 0.0004415 to 0.0132101, which does not cross zero, reinforcing the significance of this variable. Similarly, the CI for company size, ranging from 0.111177 to 0.126464, further validates its strong significance.

In summary, our baseline analysis reveals a positive relationship between low-skilled employee turnover rates and digitalization. Among the control variables, company size and institutional shareholding positively influence turnover rates, while leverage and return on assets do not show significant impacts. These findings highlight the complex dynamics at play in the digital transformation process, particularly for low-skilled workers. Larger firms and those with higher institutional ownership appear more likely to experience increased turnover, potentially due to restructuring and automation. Future research could broaden this analysis by including variables such as workforce development initiatives and investments in technology. This would offer a more holistic perspective on the factors affecting labor turnover in the area of digital transformation.

Robustness Test

Table 6 Robustness test for high-skilled employees

digital	Coefficient	Std.err.	t	P>|t|	[95% conf. interval]	
turnover_g	-0.0066161**	0.0029226	-2.26	0.024	-0.012345	-0.0008872
size_w	0.1199379***	0.0038903	36.83	0.0000	0.1123121	0.1275637
lev_w	-0.0123341	0.019193	-0.64	0.520	-0.0499569	0.0252886
roa_w	-0.0242929	0.0509938	-0.48	0.634	-0.1242527	0.075667
Inst_Share_w	0.0189798*	0.0110982	1.71	0.087	-0.0027756	0.0407345
_cons	-2.444746***	0.0837289	-29.20	0.0000	-2.608874	-2.280618

****, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.*

Table 6 presents the main findings of our study, focusing on the relationship between high-skilled employee turnover rates and digitalization, along with key control variables.

High-Skilled Employee Turnover Rate

In order to study the relationship between the turnover rate of highly skilled employees and the digital transformation of enterprises, we conducted a robust regression analysis. This section focuses on the impact of the turnover of high-skilled labor on the digital transformation of enterprises to gain a deeper understanding of its meaning and mechanism.

The findings highlight a statistically significant negative relationship between high-skilled labor turnover and corporate digitalization, revealing the critical role played by this specific labor segment.

The coefficient of high-skilled employee turnover is -0.0066161, which is significant at the 5% level, indicating that an increase in the high-skilled employee turnover rate will significantly inhibit the digitalization process of enterprises.

Control Variables:

The inclusion of control variables in the regression model provides additional insights into the factors influencing corporate digitalization:

1. Company Size (Size): The coefficient on company size is 0.1199379, which is significant at the 1% level, indicating that larger companies are more capable of advancing digitalization efforts. This advantage may stem from their greater financial resources, access to advanced technologies, and ability to attract and retain skilled talent. Larger companies may also benefit from economies of scale when applying digital systems.

2.Leverage Ratio (Lev): The coefficient of leverage is -0.0123341, but it is not statistically significant. This shows that a company's financial leverage does not have a decisive impact on its level of digitalization. This result may suggest that when considering high-skilled labor mobility, digital transformation will not be severely constrained by short-term debt levels, but is more likely to be driven by long-term planning and other priorities.

3.Return on Assets (ROA): The coefficient on ROA is -0.0242929, which is also not statistically significant. This means that the company's current profitability will not significantly affect its digitalization. Digital transformation may be influenced by broader strategic goals rather than direct financial performance.

Institutional Holdings (Inst_Share): Although the coefficient is positive (0.0189794), it is not statistically significant. This finding suggests that while institutional investors are influential in corporate governance, they may not directly impact digital transformation when labor turnover disrupts operations. This may be because they focus on broader financial performance metrics rather than operational details such as labor stability.

Model Performance

The robustness regression model has strong explanatory power, with an adjusted R-squared value of 0.8040, indicating that the model explains 80.4% of the variance in the level of corporate digitalization. Furthermore, the F statistic is highly significant ($p < 0.0001$), confirming the overall reliability and validity of the regression results. This high explanatory power emphasizes the robustness of the model and highlights the strong interaction between labor mobility and digitalization.

Robust regression analysis confirmed that there is a significant negative relationship between the turnover of high-skilled employees and corporate digitalization. This finding highlights the integral role of highly educated employees in driving digital transformation and highlights the potential risks associated with their departure. The analysis also highlights the positive contribution of company size to digitalization, while leverage, profitability and institutional ownership have a limited impact in this context.

These results provide a solid foundation for understanding how employees with different education levels affect firm digitalization. Future research should explore potential mediating mechanisms, such as knowledge loss and resource reallocation, to better understand how labor turnover affects digitalization.

6. Conclusion and policy implications

This study explores the impact of high-skilled and low-skilled employee turnover on the digitalization level of companies, controlling for variables such as return on assets (ROA), institutional share, size, and leverage. Our analysis aims to establish baseline testing by examining the impact of low-skilled employee turnover and robustness testing using high-skilled employee turnover.

The research results indicate that the departure of low-skilled employees has a positive impact on the digital transformation of companies. This result suggests that this may be due to the organization's motivation to compensate for the loss of low-skilled labor by utilizing digital transformation solutions to maintain productivity and competitiveness. On the contrary, the departure of highly skilled employees has had a negative impact on the digitalization of the company. This result implies that the loss of highly skilled talent may hinder the company's adaptation and implementation. High-skilled talents can often drive innovation in companies and contribute to digital transformation strategies. Their departure can damage the company's professional strategic capabilities, which may lead to the loss of strategic advantages in digital transformation.

In line with previous research on the replacement of manual jobs by digital transformation, this study found that digital transformation poses a challenge for low-skilled employees but offers opportunities for highly skilled workers. However, most existing research primarily focuses on the impacts of digital transformation on employees, with few studies examining how companies should manage employees with different skill levels to adapt to the digital age. This study fills that gap by investigating the reverse impact—how turnover among high-skilled and low-skilled employees affects the company’s digital transformation.

While prior studies mainly emphasize the difficulty of replacing low-skilled workers with technology, this paper presents a different perspective: the departure of low-skilled employees can encourage companies to utilize digital solutions to maintain productivity and competitiveness. In contrast, the loss of highly skilled employees, who often drive innovation and contribute to the digital transformation strategy, can harm a company’s ability to adapt and implement digital strategies. This finding diverges from the general assumption that digital transformation is primarily driven by highly educated employees. Overall, the study emphasizes the complex relationship between labor force composition and digital strategy. It emphasizes that the company's human resource management goals should be aligned with the company's development goals, indicating that if the company has the ability to reasonably replace low skilled employees with machines, it is beneficial for its digital transformation, but strategically retaining or replacing high skilled employees is crucial for maintaining and advancing digital plans.

Overall, the study emphasizes the complex relationship between labor force composition and digital strategy. It emphasizes that the company's human resource management goals should be aligned with the company's development goals, indicating that if the company has the ability to reasonably replace low skilled employees with machines, it is beneficial for its digital transformation, but strategically retaining or replacing high skilled employees is crucial for maintaining and advancing digital plans.

Suggestions:

Based on the results of this study, employee composition plays a crucial role in the success or failure of a company's strategic transformation. In order to promote the digital transformation of the company to keep up with the times and maintain its strategic advantages from being eliminated by the market, company managers and policy makers should understand the company's talent composition and use appropriate policies to retain and optimize talent.

The company should consider the following suggestions:

1. Appropriate conditions to retain highly skilled talents: Optimizing the company's working environment, providing attractive and suitable compensation, bonuses, etc., and offering opportunities for career growth are the core competitiveness of the company in recruiting talents.
2. Balancing employee turnover: The departure of low skilled employees is indeed beneficial to the company's digital transformation to some extent, but layoffs may lead to negative effects, such as decreased employee loyalty. Managers need to balance the two.
3. Improving employee skills: The company should arrange appropriate training for existing

employees to enhance their abilities, which will increase their loyalty to the company and improve their skills.
4. Reasonably utilizing technology to enhance productivity: The advantage of digital transformation is that it improves productivity and reduces error rates compared to manual labor.
5. Integrating digital concepts into corporate strategy: Enterprises should ensure that their digital transformation efforts are aligned with their core business objectives. This includes prioritizing projects that can bring practical benefits, such as improving operational efficiency and customer engagement, while maintaining the company's competitive advantage.
6. Integration of employees and technology: Enterprises should fully utilize their manpower and technology to effectively enhance productivity. Only company employees can effectively utilize technology and achieve effective integration of people and technology. The company should train employees to understand technology and effectively manage it.

7. Discussions and limitations:

A potential way to enhance this research is by incorporating more control variables. For data collection, we only considered variables such as firm size, leverage (LEV), return on assets (ROA), and institutional shareholding (inst-share). While these factors provide valuable insights, they do not fully control for all inter-provincial differences. Variables such as regional innovation capacity, government incentives for digital transformation, and local economic policies were not included, which may limit the scope of our analysis. Another interesting area for future research could focus on the contribution of different digital technologies to employment redistribution and sustainable development. Our dependent variable measures the degree of digitization within firms, but the demand for labor and the extent of digitalization vary considerably across regions and industries. As discussed in this essay, digitalization investments may include technologies such as computerized automated control systems, robotics, and 3D printing (Balsmeier and Woerter, 2019). However, traditional manufacturing industries may have lower digitalization investment needs compared to high-tech sectors, which are inherently more reliant on advanced technologies. This variation could introduce industry-specific biases, making it difficult to draw broad conclusions. Future research could therefore focus on the High-tech industry， and contribution of different technologies to sustainable development. For example, 3D printing may reduce material waste, while automated systems may increase resource efficiency. Such research will compare the application of these technologies in different regions and industries to identify which digital investments most effectively promote resource efficiency, green production, and social fairness through the redistribution of employment, thereby supporting the long-term goals of sustainable development.

In addition, the criteria for classifying labor turnover need to be significantly improved and perfected. In this study, we classified labor turnover rates from different provinces into high-skilled and low-skilled categories. High-skilled workers are those holding a university degree or higher, while low-skilled workers have a high school diploma or lower. However, this classification may introduce discrepancies, especially in underdeveloped regions where data collection is more challenging due to limited infrastructure (Elahi, 2008). For instance, data for Tibet in 2009 was unavailable, highlighting regional disparities in education and infrastructure, which affect sustainable development goals. Additionally, focusing solely on educational background overlooks other influential factors such as cultural context, talent policies, and cost of living, which significantly impact labor turnover rates (Ayodele et al., 2020). This study considers educational attainment as the primary indicator of labor turnover, but it does not account for the quality of education or technical training like VEDT, which are essential for workforce preparedness (Anane, n.d.). Moreover, different job roles and industries have varying requirements for digitalization, so higher education does not always correlate with the skills needed for specific digital tasks. Incorporating skill proficiency, vocational training, and continuous professional development would provide a more comprehensive view of the education-digitalization relationship. Finally, regional disparities in economic foundations, policy environments, and industrial structures (Heilig, 2006) may impact labor turnover rates. Developed regions typically have better infrastructure and more robust labor markets, which can create biases and affect the generalizability of our findings. This refined standard will contribute to a more comprehensive understanding of the actual impact of employee turnover on a company's digitalization, thereby helping companies make smarter and more strategic decisions about labor allocation.

References

Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Aljawazneh, B. (1970, January 1). The mediating role of supply chain digitization in the relationship between supply chain agility and operational performance. Uncertain Supply Chain Management. https://m.growingscience.com/beta/uscm/6718-the-mediating-role-of-supply-chain-digitization-in-the-relationship-between-supply-chain-agility-and-operational-performance.html

Ammar, A., Nassereddine, H., AbdulBaky, N., AbouKansour, A., Tannoury, J., Urban, H., & Schranz, C. (2022, May 17). Digital Twins in the construction industry: A perspective of practitioners and Building Authority. Frontiers. https://www.frontiersin.org/journals/builtenvironment/articles/10.3389/fbuil.2022.834671/full n ment/articles/10.3389/fbuil.2022.834671/full

Anane, C. (n.d.).) Electronics at National Vocational Training Institute; Level 4 (Certificate 2) Welding at Accra Technical Training Centre, and Level 6 (Higher National Diploma (HND) Plant Engineering at Accra Polytechnic. 2(2). http://erint.savap.org.pk/PDF/Vol.2(2)/ERInt.2013(2.2-14).pdf

Arntz, M., Gregory, T., & Zierahn, U. (2019). Digitization and the future of work: macroeconomic consequences. In Handbook of labor, human resources and population economics (pp. 1-29). Cham: Springer International Publishing. (n.d.).

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. The Quarterly Journal of Economics, 118(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Ayodele, O. A., Chang-Richards, A., & González, V. (2020). Factors Affecting Workforce Turnover in the Construction Sector: A Systematic Review. Journal of Construction Engineering and Management, 146(2), 03119010.

Babina, T., Fedyk, A., He, A. X., & Hodson, J. (2021, May 7). Artificial Intelligence, Firm Growth, and Industry Concentration. Papers.ssrn.com. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3651052

Bai, H., Gao, M., Goodell, J. W., He, F., Hu, J., Kong, D., Li, C., Lian, Y., & Wang, J. (2024, July 10). Supply chain digitalization and corporate ESG performance: Evidence from Supply Chain Innovation and Application Pilot policy. Finance Research Letters.

https://www.sciencedirect.com/science/article/abs/pii/S1544612324008481

Balsmeier, B., & Woerter, M. (2019). Is this time different? How digitalization influences job creation and destruction. Research Policy, 48(8). https://doi.org/10.1016/j.respol.2019.03.010

Bertani, F., Raberto, M., & Teglio, A. (2020). The productivity and unemployment effects of the digital transformation: an empirical and modeling assessment. Review of Evolutionary Political Economy, 1(3), 329-355

Biagi, F., & Falk, M. (2017). The impact of ICT and e-commerce on employment in Europe. Journal of Policy Modeling, 39(1), 1-18.https://www.sciencedirect.com/science/article/abs/pii/S0161893817300029?via%3Dihub

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W.W. Norton & Company.

Cai, F., Du, Y., & Wang, M. (2013). Demystify the labor statistics in China. China Economic Journal, 6(2-3), 123–133. https://doi.org/10.1080/17538963.2013.861116

Cetindamar, D., & Abedin, B. (2021). Understanding the role of employees in digital transformation: Conceptualization of digital literacy of employees as a multi-dimensional organizational affordance. *Journal of Enterprise Information Management*, 34(6), 1649–1672

Cirillo, V., Evangelista, R., Guarascio, D., & Sostero, M. (2021). Digitalization, routineness and employment: An exploration on Italian task-based data. Research Policy, 50(7), 104079. https://doi.org/10.1016/j.respol.2020.104079

Deadrick, D. L., & Stone, D. L. (2014). Human resource management: Past, present, and future. Human Resource Management Review, 24(3), 193–195. https://doi.org/10.1016/j.hrmr.2014.03.002

Elahi, A. (2008). Challenges of data collection in developing countries – the Pakistani experience as a way forward. Statistical Journal of the IAOS, 25(1-2), 11–17. https://content.iospress.com/articles/statistical-journal-of-the-iaos/sji00681

Gileva Tatyana, & Elena, S. (2022). Reframing strategic management of enterprise development in the digital environment: stages and tools. https://doi.org/10.18721/je.15502

Goldfarb, A., & Tucker, C. (2019). Digital Economics. Journal of Economic Literature, 57(1), 3–43. https://doi.org/10.1257/jel.20171452

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, 17(S2), 109–122

Habibi, N., & Kamis, A. (2021). Reaching for the stars and settling for the moon: recent trends in overeducation of US workers 2002-2016. Journal of education and work, 34(2), 143-157.https://www.tandfonline.com/doi/abs/10.1080/13639080.2021.1897551

Heilig, G. K. (2006). Many Chinas? The Economic Diversity of China 抯 Provinces. Population and Development Review, 32(1), 147?61. https://doi.org/10.1111/j.1728-4457.2006.00109.x

Hjort, J., & Poulsen, J. (2019). The Arrival of Fast Internet and Employment in Africa. American Economic Review, 109(3), 1032–1079. https://doi.org/10.1257/aer.20161385

Katz, L. F., & Margo, R. A. (2013). Technical Change and the Relative Demand for Skilled Labor: The United States in Historical Perspective. RePEc: Research Papers in Economics, 15–57.

Klaus Bruhn Jensen, Craig, R. T., Pooley, J., & Rothenbuhler, E. W. (2016). The international encyclopedia of communication theory and philosophy. John Wiley & Sons.

Lee, K., Azmi, N., Hanaysha, J., Alzoubi, H., & Alshurideh, M. (2022). The effect of the digital supply chain on organizational performance: An empirical study in Malaysia manufacturing industry. Uncertain Supply Chain Management, 10(2), 495-510.

Liu, Y., Bian, Y., & Zhang, W. (2022). How does enterprises?digital transformation impact the educational structure of employees? Evidence from China. Sustainability, 14(15), 9432.https://pdfs.semanticscholar.org/f9d2/920e33d912bd53eb6252b02f0c5d826ff484.pdf

Lv, K., Zhao, Y., Zhu, S., & Zhu, L. (2024). Enterprise digital transformation and labor structure evolution: evidence from China. Chinese Management Studies.https://www.emerald.com/insight/content/doi/10.1108/cms-09-2023-0485/full/html

Madariaga, R. (2018). Factors driving sectoral and occupational employment changes during the Spanish boom (1995–2005). Economic Systems Research, 30(3), 400–421. https://doi.org/10.1080/09535314.2018.1474182

R, S. K., & Lakshmi, J. (2023). Hybrid Serverless Platform for Service Function Chains. 2023 IEEE 16th International Conference on Cloud Computing (CLOUD), 493–504. https://doi.org/10.1109/cloud60044.2023.00066

Martez-Caro, E., Cegarra-Navarro, J. G., & Alfonso-Ruiz, F. J. (2020). Digital technologies and firm performance: The role of digital organisational culture. Technological Forecasting and Social Change, 154, 119962.

Matsumoto, I. T., Stapleton, J., Glass, J., & Thorpe, T. (2005). Developing a framework to measure organizational and employee skills development in a professional engineering design consultancy. Construction Innovation, 5(1), 53–66. https://doi.org/10.1108/14714170510815177

Schumpeter, J. A. (1942). *Capitalism, socialism and democracy*. Harper & Brothers

S Sofaer. (1999). Qualitative methods: what are they and why use them? Health Services Research, 34(5 Pt 2), 1101. https://pmc.ncbi.nlm.nih.gov/articles/PMC1089055/

Wolf, J. (2012). Improving the sustainable development of firms: The role of employees. *Business Strategy and the Environment, 21*(3), 205–216. https://doi.org/10.1002/bse.1731

Yang, D., & Liu, Y. (2018). "Internet Plus": Why has it improved performance? China Industrial Economics, (05), 80?8. https://doi.org/10.19581/j.cnki.ciejournal.2018.05.005

Zhai, H., Yang, M., & Chan, K. C. (2022). Does digital transformation enhance a firm's performance? Evidence from China. Technology in Society, 68, 101841.

Zhang, X., Li, J., Xiang, D., & Worthington, A. C. (2023). Digitalization, financial inclusion, and small and medium-sized enterprise financing: Evidence from China. 126, 106410–106410. https://doi.org/10.1016/j.econmod.2023.106410

Zhao, N., & Ren, J. (2023). Impact of enterprise digital transformation on capacity utilization: Evidence from China. Plos one, 18(3), e0283249.https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0283249#pone.0283249.ref026