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How Does Enterprises' Digital Transformation Impact the Educational Structure of Employees? Evidence from China

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Abstract: Digital transformation has had extensive impacts on enterprises and increased the concern that employees will be replaced by digital technologies. Achieving sustainability at the human resource level is a problem for enterprises. In this case, improving academic qualifications is regarded by most Chinese employees as an approach to improving their competitive advantages. Based on the panel data of China's listed enterprises from 2014 to 2020, the twice fixed effects (TWFE) and continuous difference-in-differences (DID) methods are used to study the impact of enterprises' digital transformation on employees' educational structure (EES). The results show that enterprises' digital transformation has a significantly positive impact on EES. For enterprises, specifically, the digital transformation increases the demand for employees with undergraduate degrees and reduces the demand for employees with high school degrees and below. The above results remain significant after controlling for endogeneity. However, the impact of digital transformation on employees with graduate degrees and above and associate degrees is not significant. We explain the above phenomena from the technological change assumption, the concept of human capital specificity, and the resource-based view. Results in this study provide references for employees to balance study or find a job and are beneficial for enterprises seeking to take advantage of digital transformation. Furthermore, the results can provide suggestions for achieving sustainability at the human resource level for enterprise development.

Keywords: digital transformation; educational structure; sustainable human resource management; resource-based view; continuous difference-in-differences

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1. Introduction

In recent years, the word "involution" has attracted widespread attention in China. This word refers to vicious competition in a context, which is reflected in the use of unconventional means of competition to blindly pursue honor, education degree, status, and so on. More often, Chinese people use the word to describe the current increasingly fierce competition situation. Especially in the education field, the impact of the COVID-19 pandemic has made the employment situation in China extremely severe, causing many graduates to give up the idea of direct employment and turn to taking the Graduate Entrance Examination to improve their academic qualifications. In their opinions, higher qualifications mean easier access to find a satisfying job. Of course, their opinions are reasonable, but what would happen if everyone thought so? The answer is apparent: tougher competition, like the bad results of Prisoner's Dilemma.

At the same time, the pandemic has exacerbated the crisis for the survival of Chinese enterprises. While the development of offline channels is hindered, many Chinese enterprises have shifted their operations to online channels. In this case, major enterprises have carried out measures such as layoffs to reduce costs. Not completely replacing human labor, most enterprises are just processing digital transformation to replace some kinds of human jobs with digital technology [1,2]. Autor et al. [3] and Acemoglu and Restrepo [4] show that automation technology can replace low-skilled jobs while increasing high-skilled jobs in enterprises. In this perspective, enterprises after digital transformation need more highly educated talents to operate and set up these digital technologies. Hence, the pursuit of high academic qualifications seems to be commendable. For low-educated employees, concerns about "digital substitution" (i.e., the concept that human-operated jobs may be replaced by digital technologies) arise.

For enterprises, furthermore, the "digital substitution" is closely related to recruitment in human resource management (HRM). The importance of the impact of HRM on people doing the work of organizations, such as employees, contractors, and consultants, is central to sustainable HRM [5,6]. The importance of an organization's contribution to sustainability arises great attention, which motivates enterprises to report on their sustainability activities [7]. The impact of system-wide ecological approaches on the design and implementation of human resource systems has been explored. Ehnert et al. [8] have summarized some best human resource practices supporting environmental sustainability. In the past decade, a new approach named sustainable HRM has been developed. The term sustainability is fraught with semantic difficulties, as is conceptualizing its relationship to HRM. Sustainable HRM is therefore viewed in many ways [9]. The structure of employees is an important part of achieving sustainable HRM. In this case, enterprises should at least ensure that their employee structure is stable. If employees change frequently, it is hard for enterprises to achieve sustainable and competitive advantages. Currently, "digital substitution" has brought opportunities and threats to achieving sustainable HRM. How to combine digital technologies and human employees reasonably, that is, how to suitably substitute jobs with digital technologies, deserves attention for enterprises.

However, the current situation in China shows that the digital transformation of enterprises does not completely exhibit the above effect on employees. Indeed, digital technologies have replaced some low-skilled jobs. For example, many doorman jobs have been replaced by intelligent control devices. For high-skilled jobs, however, there is no clear sign that the digital transformation of enterprises has significantly increased the demand for highly educated talents. Generally, high-skilled jobs in enterprises are rare, and these jobs are usually related to the core competitiveness of the enterprise. Therefore, such high-skilled jobs may not be easy to be substituted by digital technologies. If that is true, the activity that many graduates blindly engage in, involution, may not be recommended. For convenience, we use the concept of employees' educational structure (EES) to measure the overall talent composition degree of employees in an enterprise. In addition, the main educational stages in China are represented in Figure 1, which may facilitate the understanding of the position of each degree in the Chinese education stage.

As mentioned, the employment situation in China may exacerbate the phenomenon that many employees or graduates may choose to engage in improving degrees. Meanwhile, many enterprises are processing digital transformation to improve operational efficiency and reduce employment costs. However, even though digital technologies have exhibited astounding productivity, human capital (i.e., the knowledge and skills of employees) has gradually become the core competitiveness of enterprises [10]. In this case, to analyze the phenomenon of digital substitution, to some extent, is to analyze the impact of digital transformation on employees of different education levels. Hence, based on the panel data of Chinese listed companies from 2014 to 2020, we divide the educational background of employees into four categories. First, we use the twice fixed effects (TWFE) method to analyze the significance of the impact of digital transformation on employees with each educational attainment. Second, the continuous difference-in-differences (DID) and propensity score matching (PSM) methods are used to obtain the causal relationship between the digital transformation of EES. The specific research process is shown in Section 3.

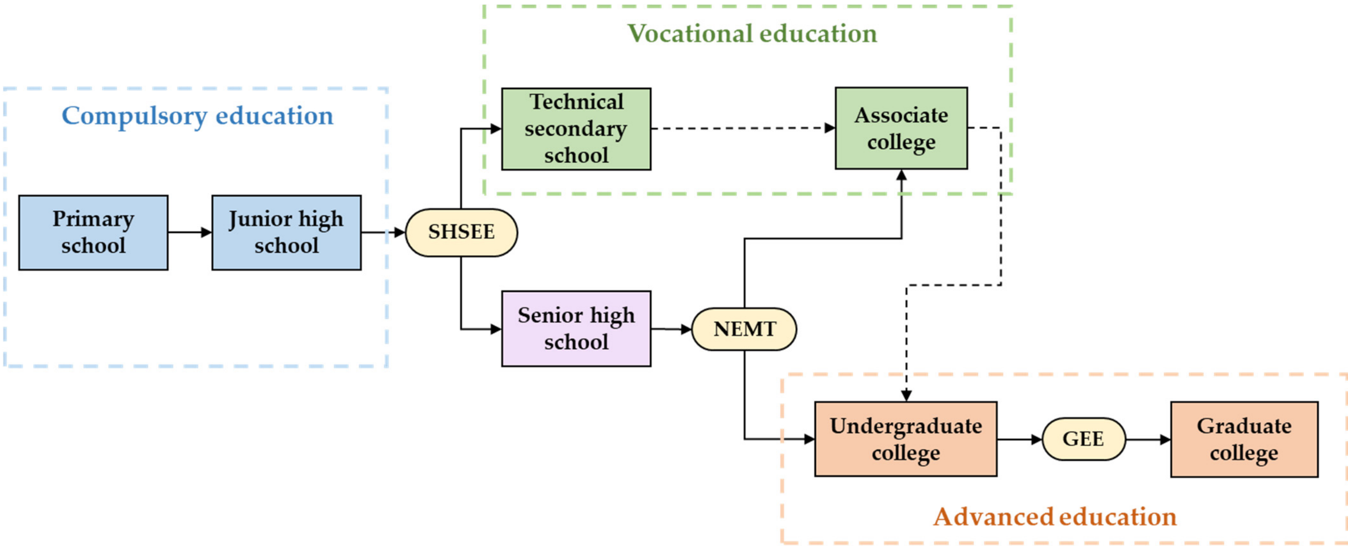


Figure 1. Main educational stages and systems in China. Note: SHSEE: the Senior High School Entrance Examination; NEMT: the National College Entrance Examination; GEE: the Graduate Entrance Examination in China. Graduate college includes both master's and doctoral stages.

Our study refines the existing field on the enterprises' digital transformation, combing with classic research about the impact of automation (or technology advancement) on the employees and standing the viewpoint of human capital. The major novelty in this study is the combination of transaction cost theory and digital transformation via refined research methodology so that we can obtain many specific suggestions for enterprises and employees (or graduates) with different degrees. Other contributions are as follows: first, we analyze the impact of digital transformation on the talent composition of enterprises, providing a reference for the human resources management and employees recruitment of enterprises; second, we use the continuous DID and PSM methods to enrich the related research in the field of DID; third, we explain the impact of digital transformation on highly educated and skilled employees from the perspective of specificity of transaction cost theory and resource-based view, expanding the theoretical perspective of digital transformation; fourth, our conclusions may provide a reference for students in the choice and balance between continuing education and looking for a job.

The rest of this paper is presented as follows. Section 2 reviews the relevant literature and proposes hypotheses. Section 3 introduces the data sources, variable measurement, and econometric model. Section 4 conducts empirical analyses and robustness tests. Section 5 makes conclusions and discussions.

2. Literature Review and Theoretical Background

2.1. The Impact of Digital Transformation on Organizations and Labor

Digital technologies have injected new impetus into traditional developments [11]. Traditionally, digitalization refers to the application of digital technology in a process [10]. For enterprises, the prominent feature of digital transformation is the application of advanced information technologies such as big data, artificial intelligence, the Internet of Things, cloud computing, etc. [12]. By using these digital technologies, enterprises can optimize production and operation activities and solve problems in management, and ultimately improve production efficiency. Therefore, digital transformation has a great impact on enterprises [13], and almost every enterprise can expand their organization's potential success via digital technologies [14]. Meanwhile, the digital transformation of enterprises is accompanied by the widespread application of automation and information technology in enterprises. In this case, we can treat digital technologies and automation technologies as equivalent.

Most research focuses on the direct effect of digital transformation on employment. Owing to different economic backgrounds and digitization degrees, the conclusions on the impact of enterprise digital transformation on employment remain divergent [15]. In general, the application of digital technologies will reduce the proportion of the manufacturing labor force. However, there may be exceptions for employees in some skilled jobs. The transformation brought about by the application of AI and digital technologies may lead to "job polarization" [16]. That is, technological advancement exerts a complementary effect on the employment of high- and low-skilled workers and a substitution effect on the employment of middle-skilled workers [17].

In this case, most studies conclude the representative reasons as the productivity effects and technological effects generated by the digital technologies [16]. It is undeniable that in terms of human flexibility, digital technologies have their inherent disadvantages [18]. Increased digital investment has been associated with increased employment of high-skilled workers and decreased employment of low-skilled workers [19]. Meanwhile, digital transformation may facilitate the creation of some new jobs as well. This impact is called the recovery effect [20].

Conventional perspectives tend to exaggerate the extent to which automation technologies can replace human labor, ignoring the strong complementarities between automation and labor. These changes have really stroked the types of jobs. In recent years, the influence of technological advancement on employment structure has been paid attention by many scholars. From the experience of the US labor market, the demand structure of labor changed dramatically since the early 20th century, which caused income inequality to violate the classical Kuznets theory. Acemoglu [21] believes that technological advancement can be divided into the skill-complementary type and the skill substitution type. If it is a skill substitution type, the demand for a simple low-skilled labor force will increase, while the demand for a high-skilled labor force will be insufficient, and vice versa.

2.2. Human Capital Theory

2.2.1. Transaction Cost Theory and Specificity

The concept of human capital is wide, and the part relevant to this study is the human capital specificity in transaction cost theory. Specificity is one of the core concepts of transaction cost economics. Williamson [22] primarily defined specificity as the nature of capitals, and these capitals are hard to use for other purposes or by other subjects without sacrificing their productive value. That is, the value of capitals with specificity will drop significantly after its formation for other uses. In this case, the specificity capital can be regarded as an enduring investment made to produce a particular team [23]. In other words, the value of specific capital depends heavily on the existence of the team and the behavior of other team members. Therefore, specific resources and capitals are the basis for the existence and development of enterprises. Specific capitals directly affect the size of the rent of enterprises and the value of other team members [24].

Human capital or human resource is an important part of enterprises [25]. The concept of human capital was first introduced as the opposite of physical capital in enterprises [26]. Dedicated human capital is generally considered to be the special knowledge and abilities that employees have developed through learning and experience while working in an enterprise. Hence, these employees have developed unique or specific knowledge through means such as "learning by doing". However, when studying human capital from the perspective of market contracts, we must pay attention to the important characteristics of the form of human capital property rights [27]. Other economic resources, including various non-human capital, may belong to individuals, families, communities, and states. Additionally, they may not belong to any person or group of persons [28].

Transaction cost theory argues that employees move freely in the external market because their human capital is less specialized [22]. The essence of enterprise is to create and distribute organizational rent. The source of organizational rent comes from team production; that is, team production can create greater productivity than dispersed production [24]. Since then, some economists have come to further believe that organizational rent is the product of the joint production of specific human and non-human capital [23,29,30].

2.2.2. Resource-Based View

The resource-based view (RBV) of the firm has influenced the field of strategic human resource management [31–33]. In an RBV, the resources which can bring sustainable competitive advantages usually are valuable, rare, costly to imitate, and non-substitutable [34]. For enterprises, human capital becomes an increasing resource to improve core competencies [35]. In order to analyze the characteristic of human resources, we categorized the competitiveness of employees as knowledge and skills. In this case, because of their high education background, the core competitive advantage of employees with graduate degrees and above is knowledge. Compared with this, the competitiveness of technical employees may come from long-term professional and technical training. In China's current education system, undergraduates emphasize general education, while associate college students emphasize vocational education. Because of its shorter educational term and stronger practicality, associate college graduates can quickly adapt to their corresponding industries and are generally engaged in technical practical positions, which are significantly different from the management positions most undergraduates are engaged in.

2.3. Hypotheses Development

From the impact of digital transformation on organizations, the results from Acemoglu and Autor [17], Acemoglu [16], and Autor et al. [36] show that a complementary effect is generated by technological advancement on high-skilled jobs and a substitution effect on low- and medium-skilled jobs. The impact of technological advancement on the skill structure of the workforce may be linear. However, the relationship between digital transformation and the employment scale is hotly debated [18]. Digital technology cannot temporarily replace entire human activities. With the popularization of digital technology, a relative increase in low-skilled and high-skilled jobs may exist. After manufacturing enterprises apply digital technologies, the proportion of low-skilled employees decreases significantly, and these substitution effects generated by digital technologies are strengthened with time [37]. Therefore, digital transformation will inevitably impact the existing structure of employees, so we develop Hypothesis 1 as follows:

Hypothesis 1 (H1). *Enterprises' digital transformation may decrease and increase the number of employees with lower and higher educational degrees, respectively, therefore having a positive and direct impact on EES.*

Meanwhile, we decompose the EES into four types to refine the research: graduate degree and above (GDR), undergraduate degree (UDR), associate degree (ADR), and senior high school degree and below (SDR). As Figure 2 shows, UDR and SDR account for the largest proportion of employees, and the changes are relatively stable. Combined with the analysis of the impact of technological advancement and skill structure in Figure 2, we speculate that the most direct impact of digital transformation or technological advances on EES is reflected in the impact on employees with UDR and SDR. It is noted that UDR is the higher degree among all degrees, while SDR is the lower degree, and both correspond to a higher complexity technology and a lower complexity technology structure, respectively.

From RBV, besides, employees with UDR are usually valuable and relatively not rare, which indicates that they may be better to adjust to the digital technologies; employees with SDR are not rare and substitutable, indicating that their work may be easier to be substituted by digital technologies. From the transaction cost theory, as mentioned, employees with UDR and SDR are both with weak specificity due to the fact all of them cannot possess the characteristics of being valuable, rare, costly-to-imitate, and non-substitutable simultaneously. Therefore, we propose the following hypotheses:

Hypothesis 2 (H2). *Enterprises' digital transformation has a positive and direct impact on the proportion of employees with UDR.*

Hypothesis 3 (H3). *Enterprises' digital transformation has a negative and direct impact on the proportion of employees with SDR.*

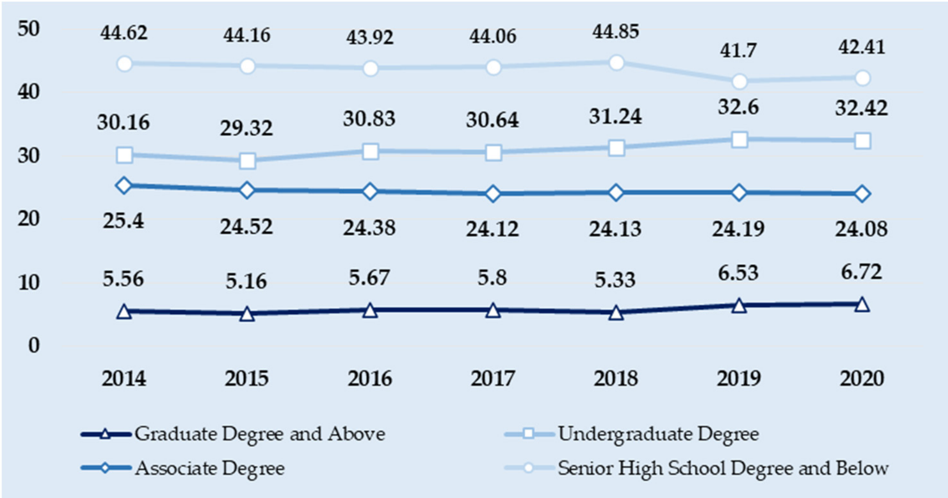


Figure 2. The average proportion of employees with each degree in China's listed enterprises from 2014 to 2020 (vertical axis unit: percentage, %).

Based on the technology change theory, employees with different educational levels often engage in different skill-based jobs in the enterprise, and these jobs are generally in different departments. Among them, most employees with UDR are usually in the technical department, and employees with SDR are usually in the production department. In this case, we speculate that digital technologies can replace some manual jobs in the production department and create some jobs for maintaining and operating these digital devices. Therefore, we propose the following hypotheses:

Hypothesis 4 (H4). *The impact of enterprises' digital transformation on employees with UDR can be achieved by complementing employees in the technical department.*

Hypothesis 5 (H5). *The impact of enterprises' digital transformation on employees with SDR can be achieved by substituting employees in the production department.*

To analyze the impact of digital transformation on employees with GDR and SDR, we need to further study the characteristics of specificity. Combing China's educational system, we divide the specificity into two types: knowledge specificity and skill specificity. From the perspective of the demand side of employment for enterprises, employees with GDR have a strong professional, technical, and academic threshold. Such highly educated employees are often directly engaged in positions related to the core competitiveness of the enterprise. Therefore, these employees have strong specificity for enterprises. This specificity is mainly reflected at the knowledge level because these employees are highly educated in the academic field. As the transaction cost theory represents, the specificity of human capital can lead to a lock-in effect between enterprises and employees. In this case, the lock-in effect is mainly reflected in the long-term contracts signed by enterprises with these employees. Hence, the digital transformation of enterprises will not significantly influence highly educated employees in the short term.

Unlike employees with graduate degrees or above, employees with ADR do not have the characteristics of high education. However, it should be noted that in China's existing associate college education and training system, many students enter the technical secondary school for vocational education after the completion of their nine-year compulsory education, while most students who do not enter undergraduate colleges and universities after the college entrance examination enter associate college. There are essential differences between the training systems of undergraduate and junior colleges. The former focuses on general education, that is, cultivating people's knowledge and quality, which has been increasingly emphasized by the state in recent years, while the latter focuses on vocational training, that is, learning specific techniques and skills to be able to find a suitable employer for the corresponding professional job after graduation. From the analysis of training time, by the time undergraduate students graduate, those who enter secondary school have already undergone up to seven years of vocational training, while those who enter junior college have also undergone up to four years of vocational training. Although the undergraduate education of science and technology majors is equally specialized and vocational, the purpose of training is quite different from that of junior college. Therefore, unlike highly educated graduates, associate college graduates often engage in specific skilled positions after entering an enterprise. For manufacturing enterprises, it is still difficult to replace many technical operation processes existing in the production process with digital technology, and employees engaged in such work are mostly with junior college degrees. Therefore, to a certain extent, employees with ADR also have certain special characteristics, but this special characteristic is more reflected in their skill level. It should be emphasized that the lock-in effect of junior college employees is not as good as that of highly educated employees, but unless digital technology can completely replace the production process they are engaged in, enterprises will not easily dismiss many existing junior employees or hire new employees to engage in similar production work.

Furthermore, due to the skill-based characteristics and higher familiarity with enterprises after a longer period in an enterprise, employees with associate degrees may possess the characteristics of specificity. In addition, the knowledge-based characteristics of employees with graduate degrees make them easily engage in activities that are related to the core competencies of enterprises. From the RBV, employees who cannot be easily substituted usually have something valuable and rare for enterprises. For employees with graduate degrees, their core competencies usually are knowledge, which can help enterprises to optimize the operation process and gain more profits. For employees with associate degrees, their core competencies are proficiency in skill-based jobs. All the competencies mean they are not easy to be replaced by digital technologies. Thus, we speculate that the impact of digital transformation on GDR and ADR may be small. Based on the above analysis, Hypothesis 6 and Hypothesis 7 are developed.

Hypothesis 6 (H6). *The impact of digital transformation on the proportion of employees with GDR is not significant.*

Hypothesis 7 (H7). *The impact of digital transformation on the proportion of employees with ADR is not significant.*

3. Data, Variables and Methodology

The methodology in this study is described as follows. First, we conduct a baseline regression using the TWFE model to test whether the impact of digital transformation on EES is significant. Meanwhile, we conduct the component analysis, namely, segment the talent composition of EES (into GDR, UDR, ADR, and SDR) and conduct group regressions. Second, owing to the potential reverse causal relationship, we control the endogeneity by using the instrumental variable and two-stage least square regression (IV-2SLS) method. Third, we conduct robustness tests of the estimated results, including the placebo test, and further refine EES to make a more specific component analysis (i.e., from Ph.D. to JHS). Fourth, to study the causal relationship rather than the related relationship, we construct the treatment and control group and then use the continuous DID method to re-estimate the model. Of course, we conduct the parallel trend test (see Section 4.4.2) to ensure the validity of the DID method. In addition, the PSM method is used to alleviate the self-selection problem. Finally, through the mechanism analysis, we explain why digital transformation could affect EES from the perspective of the technology change theory, human capital theory, and RBV. Our framework and steps are shown in Figure 3.

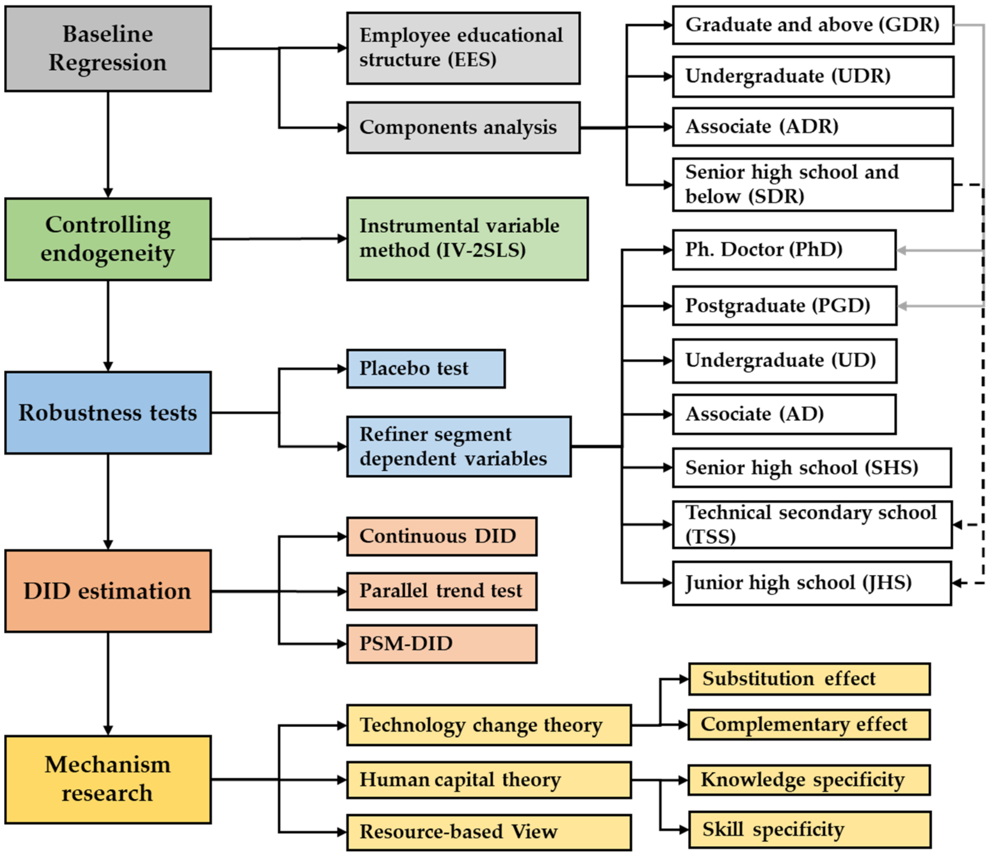


Figure 3. Research process and framework.

3.1. Data Source

We choose 2014–2020 as the research period to make the research results reflect the latest trends. Our data consist of two parts. The first part is the China Stock Market & Accounting Research Database (CSMAR). Specifically, the enterprises' digital transformation data are from the digital economy database of the CSMAR database, and other enterprise-level data are from the Governance Structure Library, R&D Innovation Library, and Family Enterprise Library of the CSMAR database. The second part is the Wind database, which provides the number of employees' degrees for each listed enterprise in China. The links to the databases are given in the Data Availability Statement at the end of the article.

3.2. Variables Description

3.2.1. Enterprises' Digital Transformation

The independent variable in this study is the level of enterprises' digital transformation (*lnDigitalTrs*). Combining the measurement ideas of Li et al. [38], Zhao et al. [39], and Hu et al. [40], we obtain the frequency of the digital-related word in annual reports of enterprises using principal component analysis (PCA) based on the frequency to obtain an indictor (i.e., *DigitalTrs*) to reflect the level of digital transformation for each enterprise. Finally, the logarithm of that indictor (i.e., *lnDigitalTrs*) is the independent variable in this study. The frequency of digital-related words was obtained from the digital economy library in the CSMAR database, and the PCA method is processed to the main digital-related words: the Internet, cloud computing, big data, artificial intelligence, and so on.

3.2.2. Educational Structure of Employees

The dependent variable is employee educational structure (*EES*). Referring to the ideas of Ojstersek et al. [41], Leider et al. [42], and Habibi and Kamis [43], the proportion of employees with undergraduate degrees and above is used to represent the education structure. This indicator reflects the proportion of highly educated employees of an enterprise to a certain extent. To make the economic implications of the estimated coefficients elasticity, we take the logarithm of that proportion and obtain the *EES*. The specific calculation method is shown in Formula (1).

$$EES = ln\frac{\text{Number of employees with undergraduate degrees and above}}{\text{Total number of employees}} \tag{1}$$

We should point out that *EES* is an aggregate indicator, meaning that it is difficult to reflect the specific impact on employees with different degrees. Therefore, we further use the proportion of employees with different degrees as the density of employees in each degree. Considering the education system in China, we divide the educational degree into four levels: graduate degree and above (*GDR*), undergraduate degree (*UDR*), associate degree (*ADR*), and senior high school degree and below (*SDR*).

3.2.3. Control Variables

We refer to Balsmeier and Woerter [19], Biagi and Falk [44], and Bloom et al. [45] to select enterprise-level control variables. Specifically, we control the enterprise size (*Size*), measured by the logarithm of the enterprise's total assets; enterprise profit capability (*ROA*), measured by the enterprise's return on assets; enterprise risk indictor (*DAR*), measured by the enterprise's debt-to-assets ratio; enterprise value (*TobinQ*), measured by Tobin's Q value; enterprise ownership (*SOE*), measured by a dummy variable, which equals 1 if the enterprise is a state-owned enterprise; and enterprise innovation level (*Innovation*), measured by the proportion of the enterprises' research and development (R&D) expenditure each year. The data of the above variables were obtained from the CSMAR database, and all variables were subjected to the upper and lower 1% tail-shrinking process to eliminate outliers. The description of the variables is shown in Table 1, and the descriptive statistics are shown in Table 2.

Table 1. Primary variables and explanations.

Variable Type	Symbol	Variable Name	Processing Methods or Explanations
Dependent variable	*lnDigitalTrs*	Digital transformation level of enterprises	Indictor of digital-related word frequency of enterprises, obtained by using the PCA method. Logarithmic value.
Independent variable	*EES*	Educational structure of employees	(Number of employees with undergraduate degrees and above/number of employees) × 100
	GDR	Proportion of employees with graduate degrees and above	(Number of employees with graduate degrees and above/number of employees) × 100
	UDR	Proportion of employees with undergraduate degrees	(Number of employees with undergraduate degrees/number of employees) × 100
	ADR	Proportion of employees with associate degrees	(Number of employees with associate degrees/number of employees) × 100
	SDR	Proportion of employees with senior high school education degrees and below	(Number of employees with senior high school degrees and below/number of employees) × 100

Table 1. *Cont.*

Variable Type	Symbol	Variable Name	Processing Methods or Explanations
Control variable	*ROA*	Return on assets	Net profit/total assets of the enterprise
	DAR	Debt-to-asset ratio	Total liabilities/total assets of the enterprise
	Size	Enterprise size	Logarithmic value of enterprises' total assets.
	SOE	Enterprise ownership	Dummy variable
	TobinQ	Tobin's Q value	Measure the value of enterprises
	Innovation	Enterprise innovation level	R&D expenditure/total expenditure of the enterprise
Mediation variable	*RDPR*	The R&D personnel ratio	See Section 5.1
	RrodR	The production personnel ratio	See Section 5.1

Table 2. Descriptive statistics.

Variable Type	Symbol	Simple Size	Mean	Standard Deviation	Min.	Max.
Independent variable	*lnDigitalTrs*	10,538	2.200	1.170	0.690	6.180
Dependent variable	*EES*	10,538	3.420	0.720	0.450	4.620
	GDR	10,538	6.010	7.690	0.020	72.87
	UDR	10,538	31.36	19.26	0.160	96.77
	ADR	8815	24.30	10.17	0.020	96.63
	SDR	5102	43.36	24.17	0.020	97.47
Control variable	*ROA*	10,538	0.030	0.140	−4.780	7.450
	DAR	10,538	0.430	0.230	0.000	5.000
	Size	10,538	22.36	1.350	18.98	26.85
	SOE	10,538	0.230	0.420	0.000	1.000
	TobinQ	10,538	3.800	2.770	0.050	126.50
	Innovation	10,538	4.720	4.400	0.000	58.850
Mediation variable	*RDPR*	4994	19.431	16.923	0.000	92.120
	ProdR	7091	40.597	25.796	0.000	100.00

As shown in Table 2, the sample size for our main variables is 10,538, which is sufficient to ensure the validity of our results. For the main variables, the standard deviations of *lnDigitalTrs* and *EES* are comparatively low, which means they have fewer extreme values. Other variables have similar features. Therefore, the data we use are comparatively suitable, and our later research results are credible.

4. Results and Analysis

4.1. Baseline Regression

4.1.1. Regression of EES

To estimate the impact of the digital transformation of enterprises on the educational structure of employees, the econometric model is designed in Formula (2), using the TWFE model and clustering into enterprises.

$$EES_{i,t} = \alpha_0 + \alpha_1 lnDigitalTrs_{i,t} + \sum_j \alpha_i X_j + \lambda_t + \gamma_i + \varepsilon_{i,t} \quad (2)$$

where $EES_{i,t}$ is the educational structure of employees, $lnDigitalTrs_{i,t}$ denotes the enterprises' digital transformation level, and X is a series of control variables. λ_t and γ_i are the year and enterprises fixed effects, respectively; α_0 is the constant term; and $\varepsilon_{i,t}$ is the random disturbance term. The core coefficient in this model is α_1, whose economic implication is the substitution elasticity of the digital transformation of enterprises to the EES.

The estimated results are shown in Table 3, where control variables are gradually added from column (1) to column (7). The results show that the primary estimated coefficient of digital transformation of enterprises on EES is 0.025 and is significant at the level of 1%. After gradually adding control variables, the estimated coefficient becomes 0.023 and is still significant at the level of 1%. Hence, the digital transformation of enterprises improves EES, so we accept hypothesis H1.

Table 3. Regression results of the digital transformation of enterprises on EES.

Variable	***EES***						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
lnDigitalTrs	0.025 ***	0.025 ***	0.026 ***	0.023 ***	0.023 ***	0.023 ***	0.023 ***
	(3.39)	(3.40)	(3.45)	(3.12)	(3.14)	(3.20)	(3.19)
ROA		−0.019	−0.058 **	−0.070 ***	−0.068 ***	−0.070 ***	−0.065 ***
		(−0.92)	(−2.23)	(−3.28)	(−3.23)	(−3.39)	(−3.06)
DAR			−0.113 **	−0.130 ***	−0.118 ***	−0.114 **	−0.108 **
			(−2.31)	(−2.89)	(−2.64)	(−2.52)	(−2.38)
Size				0.040 **	0.042 **	0.044 **	0.046 **
				(2.18)	(2.28)	(2.37)	(2.46)
SOE					−0.067 ***	−0.067 ***	−0.060 ***
					(−5.59)	(−5.57)	(−4.91)
TobinQ						0.003	0.003
						(1.15)	(1.26)
Innovation							0.005 ***
							(7.05)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.243 ***	3.244 ***	3.290 ***	2.421 ***	2.401 ***	2.339 ***	2.268 ***
	(179.73)	(179.85)	(118.84)	(5.91)	(5.88)	(5.62)	(5.41)
Observations	10,538	10,538	10,538	10,538	10,538	10,538	10,538
Within R-squared	0.094	0.094	0.096	0.100	0.104	0.105	0.108
F Statistics	39.995	35.057	32.279	29.062	29.445	27.260	25.629

Note: *t*-values are reported in parentheses. The robust standard errors are clustered at the enterprise level. *** and ** represent significance at the levels of 1% and 5%, respectively. *EES*: employees' educational structure; *lnDigitalTrs*: enterprises' digital transformation level. *ROA*: return on assets; *DAR*: debt-to-assets ratio; *Size*: enterprise scale; *SOE*: enterprise ownership. *TobinQ*: Tobin's Q value. *Innovation*: enterprises' innovation level.

4.1.2. Component Analysis

As we mentioned, EES is an aggregated indicator, which is difficult to reflect the specific impact. Therefore, we process the component analysis, that is, study the influence of digital transformation on each proportion of degree. The estimation models are designed as Formulas (3)–(6).

$$GDR_{i,t} = \beta_0 + \beta_1 lnDigitalTrs_{i,t} + \sum_i \beta_i X_i + \lambda_t + \gamma_i + \varepsilon_{i,t} \quad (3)$$

$$UDR_{i,t} = \delta_0 + \delta_1 lnDigitalTrs_{i,t} + \sum_i \delta_i X_i + \lambda_t + \gamma_i + \varepsilon_{i,t} \quad (4)$$

$$ADR_{i,t} = \theta_0 + \theta_1 lnDigitalTrs_{i,t} + \sum_i \theta_i X_i + \lambda_t + \gamma_i + \varepsilon_{i,t} \quad (5)$$

$$SDR_{i,t} = \zeta_0 + \zeta_1 lnDigitalTrs_{i,t} + \sum_i \zeta_i X_i + \lambda_t + \gamma_i + \varepsilon_{i,t} \quad (6)$$

where $GDR_{i,t}$, $UDR_{i,t}$, $ADR_{i,t}$, and $SDR_{i,t}$ denote the proportion of employees with graduate degrees and above, undergraduate degrees, associate degrees, and senior high school degrees and below, respectively. β_0, δ_0, θ_0, and ζ_0 are the constant terms of each model, and the other variables are the same as model (2).

The estimation results are shown in Table 4. After adding control variables and fixed effects, the estimated coefficient of digital transformation on *UDR* and SDR is 0.787 and −0.987, respectively. These coefficients are all significant at the level of 1%, indicating that the digital transformation of enterprises increases the employees with undergraduate degrees and decreases the employees with senior high school degrees, respectively. Hence, we accept H2 and H3.

Table 4. Regression results of the digital transformation of enterprises on each degree.

Variable	*GDR*		*UDR*		*ADR*		*SDR*	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
lnDigitalTrs	−0.019	−0.044	0.882 ***	0.787 ***	0.082	0.130	−1.012***	−0.987 ***
	(−0.31)	(−0.73)	(5.05)	(4.65)	(0.50)	(0.79)	(−3.37)	(−3.20)
ROA		−0.470 **		−1.392 **		0.807 *		0.865
		(−2.13)		(−2.37)		(1.66)		(0.98)
DAR		−1.005 **		−2.077 **		2.588 **		−0.409
		(−2.11)		(−2.09)		(2.29)		(−0.21)
Size		0.596 ***		1.415 ***		−0.571 *		−0.394
		(2.66)		(3.17)		(−1.68)		(−0.54)
SOE		−0.836 ***		−1.117 ***		−0.040		1.636 ***
		(−5.22)		(−3.68)		(−0.14)		(3.37)
TobinQ		0.053 *		0.068		0.008		−0.017
		(1.91)		(1.11)		(0.12)		(−0.21)
Innovation		0.040 ***		0.141 ***		−0.034		−0.171***
		(3.48)		(5.86)		(−1.00)		(−2.66)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.056 ***	−7.667	24.755 ***	−5.724	25.862 ***	37.315 ***	51.595 ***	60.503 ***
	(31.67)	(−1.54)	(56.47)	(−0.58)	(63.93)	(5.06)	(84.14)	(3.78)
Observations	10993	10993	13259	13259	12115	12115	7430	7430
Within R-squared	0.046	0.065	0.086	0.098	0.001	0.004	0.077	0.081
F Statistics	20.780	13.868	43.837	29.380	1.821	1.648	28.895	18.707

Note: *t*-values are reported in parentheses. The robust standard errors are clustered at the enterprise level. ***, **, and * represent significance at the levels of 1%, 5%, and 10%, respectively. *GDR*: employees with graduate degrees; *UDR*: employees with graduate degrees; *ADR*: employees with associate degrees; *SDR*: employees with senior high school degree and below; *lnDigitalTrs*: enterprises' digital transformation level; *ROA*: return on assets; *DAR*: debt-to-assets ratio; *Size*: enterprise scale; *SOE*: enterprise ownership; *TobinQ*: Tobin's Q value; Innovation: enterprise innovation level.

Table 4 also shows that the estimated coefficients of digital transformation on *GDR* and *ADR* are not significant, indicating that we accept H6 and H7. That is, employees who are most affected by the impact of digital transformation are employees with undergraduate degrees and senior high school degrees (and below). These impacts lead to the overall increase in EES.

4.2. Controlling Endogeneity

The estimated results of the baseline regression may be biased due to the reverse causality problem; that is, enterprises with higher EES may be more inclined to carry out digital transformation. In order to alleviate the bias of estimation results caused by the endogeneity, we selected the lag period of the digital transformation of enterprises (*l.lnDigitalTrs*) as an instrumental variable (IV). The intrinsic logic is that the degree of digital transformation of an enterprise that lags one period will significantly affect the current level of digital transformation, while the current level of digital transformation cannot affect the previous level of digital transformation. In addition, for disturbance terms, the digital transformation with a lag period satisfies the exogenous requirement. Hence, we selected the digital transformation with a lag of one period as an IV and then used two-stage least squares (2SLS) regression to control endogeneity. The estimated results are shown in Table 5.

Table 5. Regression results of enterprise digital transformation on EES (IV-2SLS).

Variable	Stage 1	Stage 2
	lnDigitalTrs	***EES***
	(1)	**(2)**
lnDigitalTrs		0.050 **
		(2.16)
l.lnDigitalTrs	0.299 ***	
	(18.79)	
Control	Yes	Yes
Year fixed effect	Yes	Yes
Enterprise fixed effect	Yes	Yes
Observations	6768	6768
Kleibergen–Paap rk LM statistics	172.756 ***	
Cragg–Donald Wald F statistics	630.764	
Kleibergen–Paap rk Wald F statistics	352.880	

Note: *t*-values are reported in parentheses. The robust standard errors are clustered at the enterprise level. *** and ** represent significance at the levels of 1%, 5%, respectively. The 10%, 15%, and 20% biases critical values of the Stock–Yogo weak ID test are 16.38, 8.96, and 6.66, respectively.

Table 5 represents that the Kleibergen–Paap rk LM statistic is 172.756 and is significant at the 1% level, rejecting the hypothesis that "instrumental variables are unidentifiable"; the Cragg–Donald Wald F statistic is 630.764, and th Kleibergen–Paap rk Wald F statistic is 352.880, all of which are significantly greater than the critical value of 16.38 for the Stock–Yogo weak ID test under 10% biases, excluding the problem of a "weak instrumental variable." Therefore, the IV is valid. After controlling endogeneity, the estimated results of baseline regression remain significant.

Similarly, we use the IV to perform 2SLS regression on *GDR*, *UDR*, *ADR*, and *SDR*. The results are shown in Table 6. While excluding endogeneity, the obtained estimated coefficients are still consistent with the estimated results of the benchmark regression in terms of significance level and direction of influence, indicating that the estimated results of this study remain significant after controlling endogeneity.

Table 6. Regression results of enterprises' digital transformation on each educational degree (IV-2SLS).

Variable	***lnDigitalTrs***							
	Stage 1	***GDR***	**Stage 1**	***UDR***	**Stage 1**	***ADR***	**Stage 1**	***SDR***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
lnDigitalTrs		−0.209		1.340 **		0.561		−3.370 ***
		(−0.86)		(2.28)		(1.04)		(−2.87)
l.lnDigitalTrs	0.274 ***		0.274 ***		0.260 ***		0.240 ***	
	(15.66)		(15.66)		(13.52)		(9.07)	
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6016	6016	6016	6016	4989	4989	2833	2833
KP LM Statistics	133.177 ***		133.177 ***		105.885 ***		51.840 ***	
CDW Statistics	441.441		441.441		324.683		155.057	
KP WF Statistics	245.338		245.338		182.811		82.243	

Note: *t*-values are reported in parentheses. The robust standard errors are clustered at the enterprise level. *** and ** represent significance at the levels of 1%, 5%, respectively. The variable represented by Stage 1 in the second row of the table is *lnDigitalTrs*. KP LM Statistics: Kleibergen–Paap rk LM Statistics; CDW Statistics: Cragg–Donald Wald F Statistics; KP WF Statistics: Kleibergen–Paap rk Wald F Statistics. The 10%, 15%, and 20% biases critical values of the Stock–Yogo weak ID test are 16.38, 8.96, and 6.66, respectively.

4.3. Robustness Test

4.3.1. Placebo Test

To verify the robustness of the baseline regression results, we refer to Wang et al. [46] to carry out the placebo test, which is a random matching of the degree of digital transformation of all enterprise samples within the study interval and a random sampling of 500 times, and the kernel density of the coefficient distribution of the explanatory variables is obtained as shown in Figure 4. The estimated coefficient obtained by the benchmark regression in this study is 0.023 (marked with a dashed line in Figure 4), which is significantly different from the kernel density map of the coefficient estimated by the placebo, so the robustness of the estimation results of the baseline regression is enhanced.

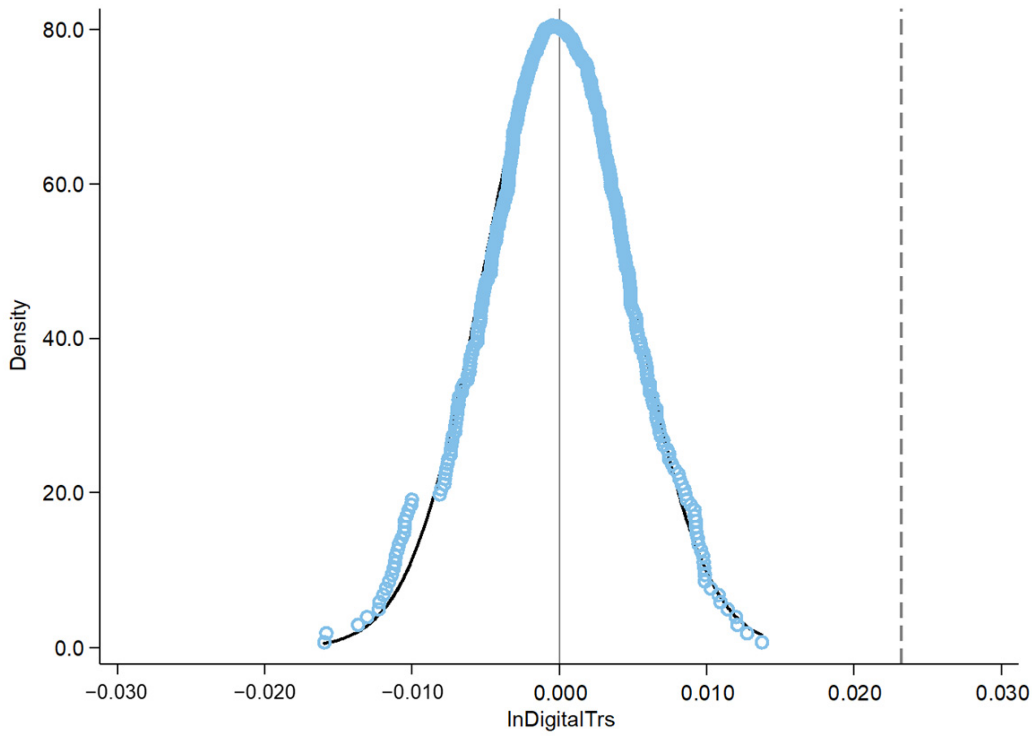


Figure 4. Result of the placebo test. The dashed line marks the estimated coefficient in baseline regression (i.e., 0.023). The hollow blue circles describe every 'pseudo' coefficient. Due to space limitations, we only report the placebo test result of digital transformation to EES.

4.3.2. Refiner Segment Dependent Variables

Furthermore, we divide the employees of the enterprises according to more refined educational degrees (the specific variables after dividing are explained in the note below Table 7). In this section, we use the number of employees with different degrees rather than the proportion. To avoid ambiguity, we will use different denotations from the baseline regression to represent these variables. Table 7 describes that the estimated coefficient of digital transformation on the number of employees with undergraduate degrees (i.e., UD) is 0.04 and remains significant. The estimated coefficient of digital transformation on the number of employees with senior high school degrees (i.e., SHS) is −0.013 and remains significantly negative. Meanwhile, the impact on the number of employees with graduate degrees and above (i.e., Ph.D. and PGD) and the number of employees with associate degrees (i.e., AD) are not significant. All the above-estimated results correspond with the baseline regression, so the robustness of the results from baseline regression is enhanced.

Table 7. Regression results of enterprise digital transformation on each education degree.

Variable	Number of Employees with Different Educational Degrees						
	PhD	**PGD**	**UD**	**AD**	**SHS**	**TSS**	**JHS**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
lnDigitalTrs	0.004	−0.047	0.040 **	−0.007	−0.013 **	0.060	0.057
	(0.13)	(−1.16)	(2.54)	(−0.84)	(−2.32)	(1.12)	(1.13)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−5.238 ***	−12.035 ***	−8.793 ***	−0.208	0.378	−4.649	5.861 ***
	(−3.51)	(−7.61)	(−12.28)	(−0.76)	(1.25)	(−1.64)	(2.64)
Observations	4657	6656	8018	7954	4329	6342	3506
Within R-squared	0.103	0.405	0.238	0.005	0.080	0.133	0.315
F Statistics	15.933	93.130	91.949	0.79	11.911	33.134	12.644

Note: *t*-values are reported in parentheses. The robust standard errors are clustered at the enterprise level. *** and ** represent significance at the levels of 1% and 5%, respectively. Ph.D.: Ph. Doctor degree; PGD: postgraduate degree; UD: undergraduate degree; AD: associate degree (i.e., college degree); SHS: senior high school degree; TSS: technical secondary school degree; JHS: junior high school degree.

4.4. Continuous Difference-in-Differences Estimation

The baseline regression results only verify the correlation between the digital transformation of enterprises and EES rather than the causation relationship. To infer the causal relationship, we further use the DID method to re-estimate the model. It is worth noting that the traditional DID method is suitable for cases where the independent variable is a dummy variable. In this study, however, all enterprises are affected by digital transformation, so there is no control group (i.e., enterprises that are not digitally transformed) in the traditional DID method. In this case, referring to Nunn and Qian [47] and Moser and Voena [48], we use the staggered and continuous DID method to re-estimate the model. The 'staggered' means that the year of the policy (i.e., digital transformation) across enterprises is different, and 'continuous' means that the policy variable (i.e., *lnDigitalTrs*) is a continuous variable rather than a dummy variable. Therefore, after some enterprises processing digital transformation (i.e., *lnDigitalTrs* > 0), enterprises that have not processed digital transformation (i.e., *lnDigitalTrs* = 0) can be divided into the control groups. As we mentioned, however, no strict control groups exist in this study, indicating that we need to construct the control groups, namely, identify whether an enterprise processes digital transformation.

The illustration of the construction process is shown in Figure 5. First is the case that the digital-related word frequency cannot truly reflect whether the enterprise processes digital transformation. In this case, however, we believe that if the frequency is substantial or rare, the enterprise is likely to process or not process digital transformation. Second, we set a dummy variable *dum_t* to identify whether an enterprise is treated, namely, has processed digital transformation. The treatment group includes enterprises whose digital-related word frequency is higher than the upper quartile level (i.e., *lnDigitalTrs* $\geq$ upper quartile of *lnDigitalTrs*) in a certain year. Additionally, the control group includes enterprises whose frequency is lower than the lower quartile (i.e., *lnDigitalTrs* $\leq$ lower quartile of *lnDigitalTrs*) in a certain year. Meanwhile, the remaining samples (i.e., lower quartile of *lnDigitalTrs* < *lnDigitalTrs* < upper quartile of *lnDigitalTrs*) are eliminated because it is hard to judge whether they process digital transformation. Third, the DID estimator *Intensity* is constructed as in Equation (7):

$$Intensity_{i,t} = dum\_t * lnDigitalTrs_{i,t} \tag{7}$$

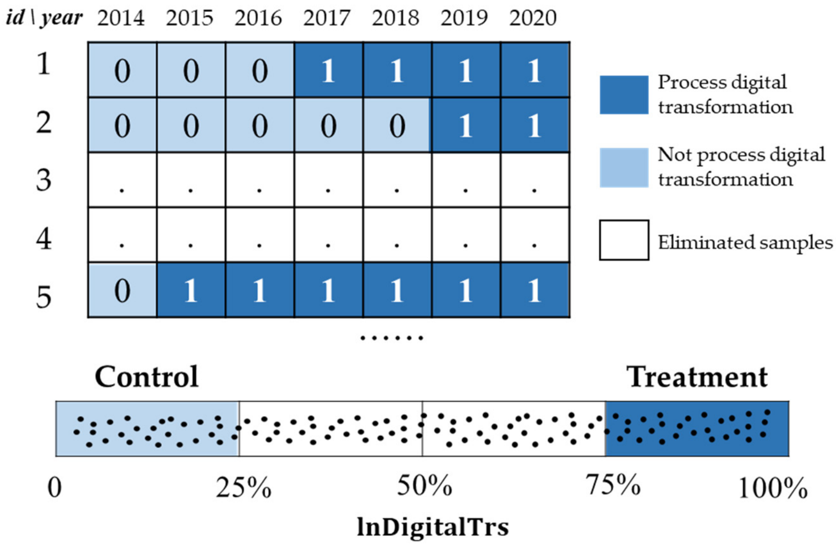


Figure 5. Illustration of the staggered and continuous DID model. Note: The solid black circles denote the sum of the digital-related word frequency of each enterprise. The numbers 0 and 1 in the blank are values of *dum_t*. The DID estimator *Intensity* is the product of *dum_t* and *lnDigitalTrs* (i.e., $Intensity = dum\_t * lnDigitalTrs$), which means that *Intensity* is a continuous (or semi-continuous) variable.

The feasibility of the method can be described in two parts. First, before the enterprise is processing digital transformation, the development trend of EES is generally stable with time changing, meeting the requirements of the parallel trend (see Section 4.4.2). Second, after some enterprises have processed digital transformation, EES still maintains a stable development trend for enterprises that have not processed digital transformation, namely, the counterfactual situation is stable.

4.4.1. Estimated Results

The estimated results shown in Table 8 describe that the impact of *Intensity* on EES is still significantly positive. Meanwhile, the significance and direction of estimated results of *Intensity* on *GDR*, *UDR*, *ADR*, and *SDR* are the same as the baseline regression. Hence, the robustness of the estimated results is enhanced, and the results by the continuous DID method reveal a certain causal relationship between digital transformation and EES. That is, the digital transformation of enterprises is indeed one of the reasons for the changes in EES.

Table 8. Estimated results of the staggered and continuous DID method.

Variable	*EES*	*GDR*	*UDR*	*ADR*	*SDR*
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Intensity	0.021 ***	0.004	0.505 **	0.148	−0.989 **
	(2.62)	(0.07)	(2.44)	(1.05)	(−2.17)
Control	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes
Constant	2.491 ***	−6.672	10.377	48.221 ***	20.341
	(4.06)	(−1.14)	(0.60)	(4.03)	(0.75)
Observations	5443	5443	5443	4472	2360
Within R-squared	0.112	0.071	0.097	0.016	0.102
F Statistics	13.971	7.406	11.864	2.264	6.827

Note: *t*-values are reported in parentheses. The robust standard errors are clustered at the enterprise level. *** and ** represent significance at the levels of 1% and 5%, respectively.

4.4.2. Parallel Trend Test

To verify the validity of the above DID method, we refer to Zhao and Wang [49] to carry out a parallel trend test. Specifically, we need to verify whether the EES of the treatment and control groups maintains a parallel development trend over time before the digital transformation occurs. The results of the parallel trend tests are shown in Figure 6, which shows that before the digital transformation occurs, the 95% confidence interval of the estimated coefficients of *EES*, *UDR*, and *SDR* in the treatment and control group includes the 0-axis. Therefore, the difference between the treatment and control groups is not significant. In addition, the confidence interval is significantly different from the 0 axis, which means that a significant difference exists between the treatment and control groups after the treatment group processing digital transformation. Therefore, the parallel trend tests are passed, and the above DID method is valid.

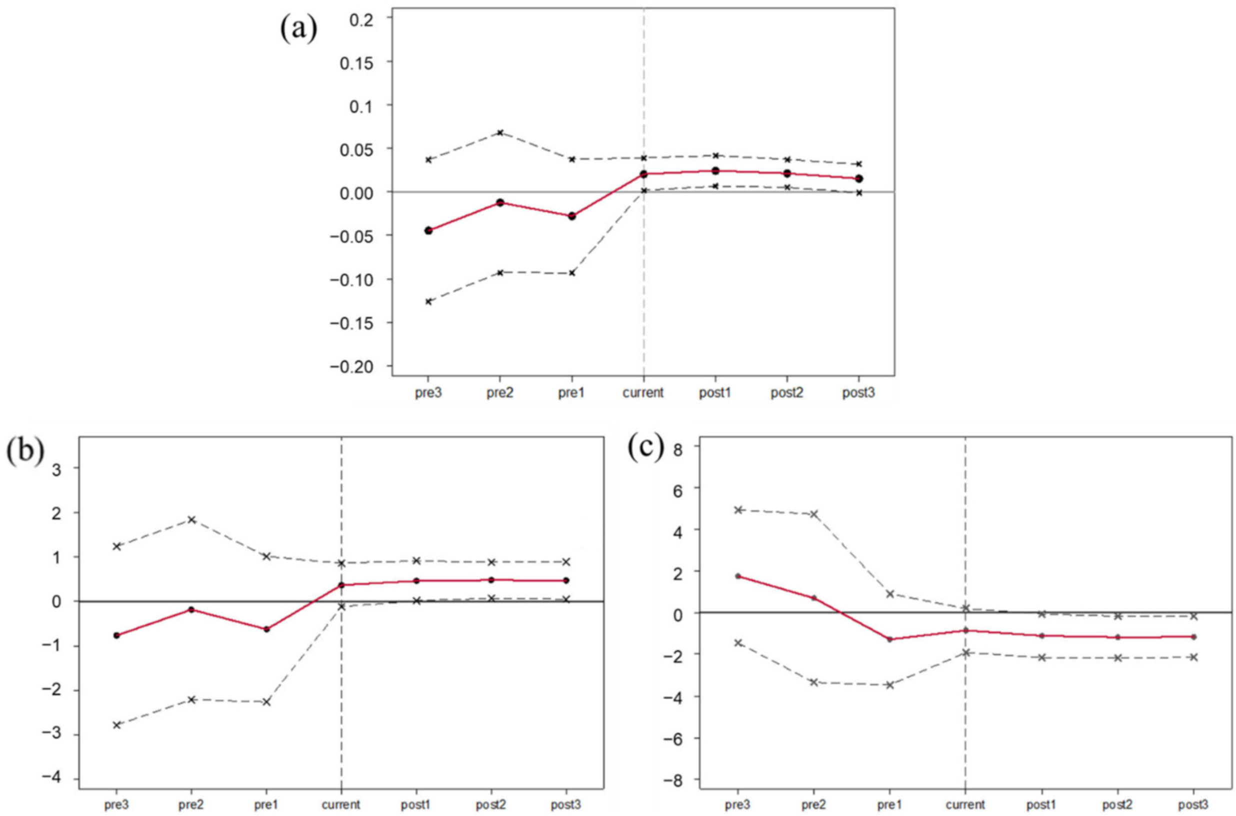
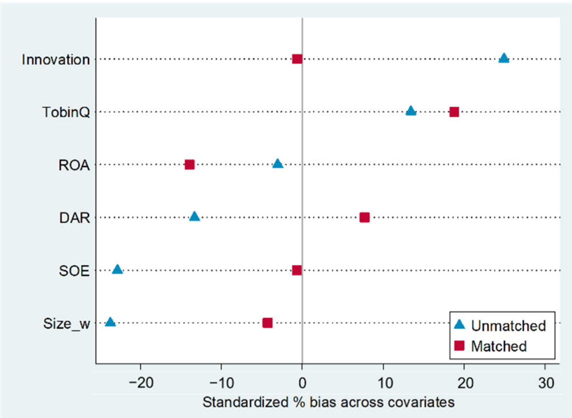


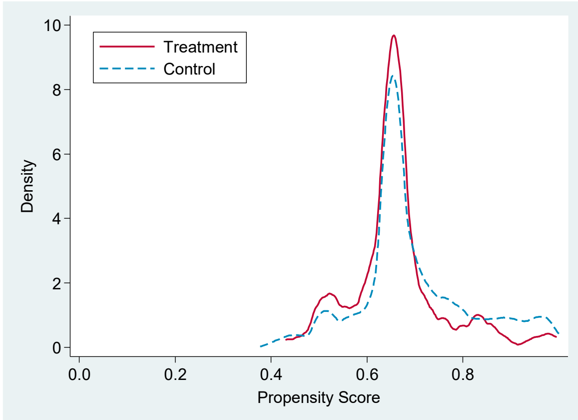
Figure 6. Parallel trend test results. (**a**–**c**) are the parallel trend test results of digital transformation on *EES*, *UDR*, and *SDR*, respectively. The horizontal axis indicates the years before and after the digital transformation occurrence. The vertical axis represents the percentage change in each variable of the treatment and control groups. The solid red line represents the point estimators of the difference between the treatment and control groups. The grey dashed line represents the 95% confidence intervals of the point estimator.

4.4.3. Propensity Score Matching

The DID estimation can solve the problem of endogeneity to a certain extent, but the self-selection problem may still exist. To eliminate the problem, we select covariates to perform PSM and then perform a DID estimate on the matched sample (i.e., the PSM-DID method). This method can alleviate the self-selection problem brought by education and digital transformation and better reflect the true causal effect.

All control variables are selected as covariates, and the 1:3 nearest neighbor matching method is used to carry out PSM for all enterprises. The changes in the standard deviation of covariates before and after matching are shown in Figure 7a. The propensity score density of the matched treatment and control group is shown Figure 7b. From Figure 7, the standard deviation of most covariates is significantly reduced by 10%, indicating that the match is sufficient. Meanwhile, the propensity score of the treatment and control group is gathered in (0.6, 0.8), and the density of the score for the treatment and control group almost overlaps, indicating the number of matched samples is enough.





(**a**) (**b**)

Figure 7. Propensity score matching results. (**a**,**b**) describe the standardized bias across matched and unmatched covariates and propensity score density of the treatment and control groups after matching, respectively.

The matched samples were estimated using the DID method, and the obtained estimation results are shown in column (3) of Table 9. For the convenience of comparison, the estimated results of baseline regression, the DID method before PSM, and the PSM-DID method are reported in columns (1) and (2) of Table 9 as well. Table 9 shows that all the estimated coefficients of the three estimation methods (i.e., 0.023, 0.021, and 0.027) remain significantly positive. Therefore, the robustness of our results is enhanced.

Table 9. Comparison of the estimation results of the three models.

Variable	*EES*		
	(1)	**(2)**	**(3)**
	Baseline Regression	**Continuous DID Estimation**	**PSM-DID Estimation**
lnDigitalTrs	0.023 ***		
	(3.19)		
Intensity		0.021 ***	0.027 **
		(2.62)	(2.13)
Control	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes
Constant	2.268 ***	2.494 ***	1.853 ***
	(5.41)	(4.06)	(3.51)
Observations	10538	5443	3912
Within R-squared	0.108	0.112	0.124
F Statistics	25.629	14.043	11.457

Note: *t*-values are reported in parentheses. The robust standard errors are clustered at the enterprise level. ***, **, represent significance at the levels of 1%, 5%, respectively. The baseline regression results show that the digital transformation of enterprises has significantly promoted the improvement of EES. The DID estimation results show that the baseline regression results can be explained by a certain causal relationship. The PSM-DID method further reduces the bias caused by the self-selection problem.

4.5. Mediation Analysis: Technological Change Theory

We analyze the impact mechanism of enterprises' digital transformation on EES from the perspective of the technology change theory on enterprise departments. Using the mediation effects to verify the complementary effects and substitution effects, we analyze the promotion of digital transformation on EES, UDR and SDR.

The essence of the digital transformation of enterprises is to use information and digital technology to improve production and management processes. At the production level, this improvement is reflected in the use of technologies such as the Internet, cloud computing and big data to intelligently monitor and adjust the production process. From this perspective, a digitally transformed enterprise may have some employee positions replaced by digital technology. The baseline regression has shown that digital transformation will significantly promote the proportion of employees with graduate degrees and suppress the proportion of employees with senior high school degrees and below. This can be explained by the substitution effect and complementary effect of the technological theory.

The complementary effect is considered first. For enterprises, in general, the department most affected by the complementary effect is the R&D department. Therefore, we use the R&D personnel ratio (*RDPR*) as a proxy variable for the indicator. The results of the mediation effect estimation are shown in Table 10. The estimated results in Table 10 show that *lnDigitalTrs* significantly increases *RDPR* and decreases *ProdR* with the estimated coefficients of 0.604 and −0.009, respectively. After controlling *RDPR*, furthermore, the estimated coefficient of *lnDigitalTrs* on *GDR* is −0.015; this becomes insignificant, which means there is a complete mediation effect from *lnDigitalTrs* to *GDR* through *RDPR*. Meanwhile, the estimated coefficients of *lnDigitalTrs* on *EES* and *SDR* are 0.03 and −0.686, respectively, and these remain significant, indicating that the mediation effects from *lnDigitalTrs* to *EES* and *SDR* through *RDPR* are partial. Similarly, there are complete mediation effects from *lnDigitalTrs* to *EES* through *ProdR* and partial mediation effects from *lnDigitalTrs* to *EES* and *UDR* through *ProdR*. To confirm these partial mediation effects are valid, we need to conduct bootstrap tests on these effects, and the bootstrap test results are presented in the Supplementary Materials in the attachment.

Table 10. Regression results of the mediation effects.

Variable	*RDPR*	*EES*	*UDR*	*SDR*	*ProdR*	*EES*	*UDR*	*SDR*
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
lnDigitalTrs	0.604 **	0.030 ***	−0.015	−0.686 *	−0.009***	0.015 **	0.297 *	−0.329
	(2.50)	(3.39)	(−0.19)	(−1.83)	(−2.88)	(2.04)	(1.74)	(−0.88)
RDPR		0.010 ***	0.073 ***	−0.234 ***				
		(6.97)	(3.28)	(−3.77)				
ProdR						−0.916 ***	−22.654 ***	36.380 ***
						(−5.24)	(−5.15)	(8.47)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Enterprise fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	5.568	1.983 ***	−15.736 ***	59.687 *	0.389 *	1.940 ***	−7.249	32.938
	(0.40)	(3.60)	(−2.67)	(1.72)	(1.73)	(3.65)	(−0.52)	(1.39)
Observations	4994	4994	4994	2514	7091	7091	7091	3622
Within R-squared	0.044	0.169	0.106	0.077	0.022	0.264	0.260	0.218

Note: *t*-values are reported in parentheses. The robust standard errors are clustered at the enterprise level. ***, **, and * represent significance at the levels of 1%, 5%, and 10%, respectively. EES: employees' educational structure; *lnDigitalTrs*: enterprises' digital transformation level; *PDPR*: the R&D personnel ratio; *ProdR*: the production personnel ratio; SDR: employees with senior high school degree and below; UDR: employees with undergraduate degrees.

For the complementary effect, new digital technologies have brought great changes to the production and manufacturing of the traditional manufacturing industry. For manufacturing enterprises, the direct impact of digital transformation is the production sector. Employees with lower education are mostly engaged in medium and low-skill positions, and the main body of such positions is the production department. Therefore, if the proportion of employees in the production department of enterprises after digital transformation is significantly reduced, the substitution effect of digital transformation on employees with senior high school degrees and below can be explained. Considering the characteristics of the transmission path of this influence mechanism, it is more appropriate to use the mediation effect analysis. Let *ProdR* be the proportion of employees in the production sector (or operational sector) of the enterprise; then the estimated results of the mediation effect are shown in Table 10.

Hence, the positive impact of digital transformation on EES is achieved through two mechanisms. The first mechanism is that digital transformation reduces the proportion of employees in the technical departments through the substitution effect. The second mechanism is that digital transformation exerts a substitution effect on employees with SDR and lower by reducing the proportion of employees in the production department of enterprises.

5. Conclusions and Discussions

5.1. Conclusions

The main objective of this study is to find the relationship between the digital transformation of enterprises and EES using the TWFE, continuous DID, and PSM methods. The results show that enterprises' digital transformation has a significantly positive impact on EES, specifically, a significantly positive impact on employees with UDR and a significantly negative impact on employees with SDR. The impact on employees with GDR and ADR is not significant. All the above results verify the hypotheses H1 to H5. Furthermore, we show that enterprises' digital transformation increases the number of employees in the technological department and decreases the number of employees in the production department. These indicate that digital transformation has a complementary effect on employees with UDR and has a substitution effect on employees with SDR, which verifies the technology change theory. From the theory of specificity and RBV, however, we show that both employees with GDR and ADR possess some characteristics of sustainable human resources: they are rare, valuable, costly to imitate, and non-substitutable. These characteristics determine that employees with GDR and ADR are human capital with specificity, which means that digital transformation makes little impact on their jobs. Our main results are presented in Figure 8.

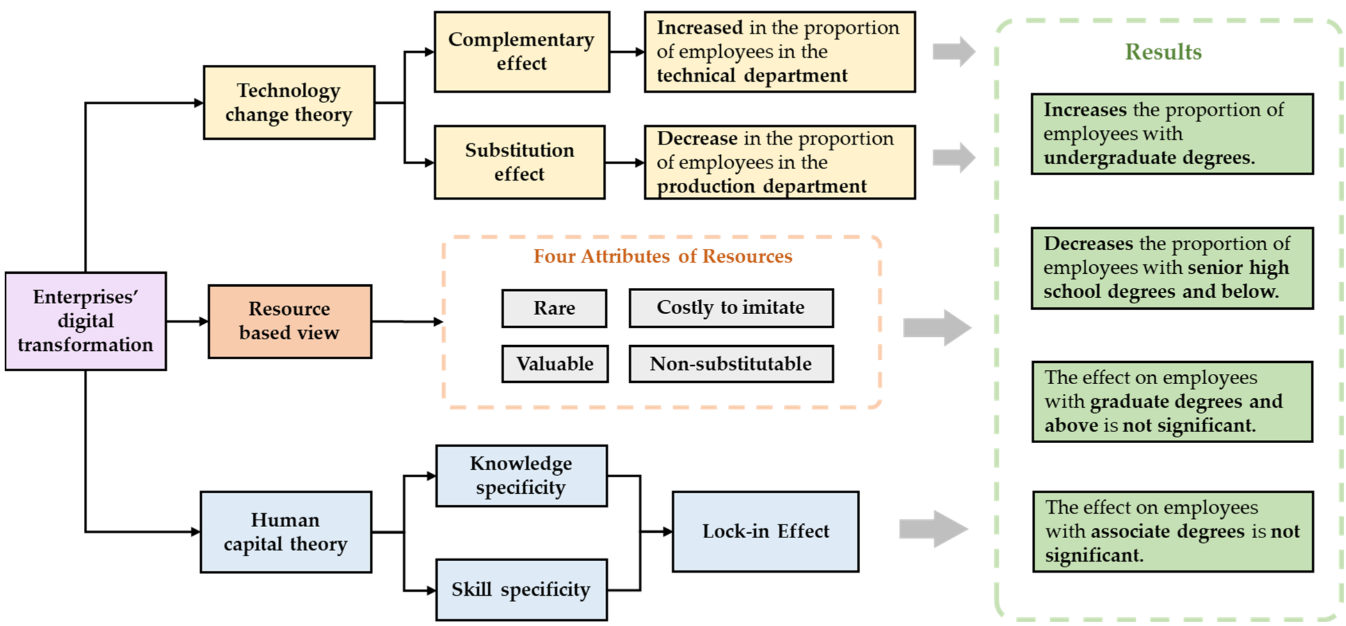


Figure 8. Main impacts of digital transformation on EES.

An important objective of this research is to study whether the pursuit of higher education degrees for employees and graduates is always beneficial. From the digital transformation perspective, we show that the core competency of employees is the value of their resources, that is, whether their jobs are valuable, rare, costly-to-imitate, and non-substitutable. In general, employees who simultaneously possess the above four characteristics have relatively strong specificity. From the transaction cost theory, resources with strong specificity will bring a lock-in effect to enterprises, indicating that the loss of replacing them is huge for enterprises. To sum up, all the above results show that the relationship between the degree of digital transformation and the demand for employees in different educational degrees is not linear. For employees and graduates, that is, higher degrees may not always bring more satisfying jobs, so they are not supposed to blindly engage in the "involution".

5.2. Marginal Contributions and Limitations

We believe that our research can make the following marginal contributions to existing literature. First, we verify the relationship between digital transformation and talent composition, which may provide a reference for research to make deeper studies. Second, we investigate the perspective of the transaction cost theory and resource-based view to analyze the intrinsic characteristic of human capital, enriching the relevant research and filling the gap in research on the impact of digital transformation on human capital. Third, the approach of constructing treatment and control groups in continuous DID may help to use DID to analyze cases in which dependent variables are not dummy variables. Fourth, the research results may provide a reference for employees and graduates to balance the selection between finding a job and further study. Meanwhile, our research results may provide the following implications for theories. First, we show that employees with high educational degrees or skilled technologies may possess the specificity characteristic, which extends the original concept of specificity. Williamson [23] suggests that enterprises can alleviate negative impacts generated by the specificity of capital by signing long-term contracts or processing vertical integration. In this case, similar approaches may work for enterprises to keep their employees with specific characteristics. Second, based on the RBV, our research results can provide evidence that human capital is a vital part of enterprises to achieve core competencies and sustainable competitive advantages. Third, our results represent that the impact of technology advancement or digital transformation on employees with different skills is not linear, which provides evidence for the technology change assumptions of Acemoglu [21] and verifies the "job polarization" of Acemoglu [16]. Of course, this study has a few limitations that should be mentioned. First, the research period in this paper is 2014–2020, indicating that our results only can reflect the latest trend and have difficulty representing the long-term trend. Additionally, we only study the case in China due to the prominent "involution" problem. Second, we use digital word frequency in the annual reports of listed companies to measure the digital transformation of enterprises. The measuring method cannot truly reflect the digital transformation level of enterprises, which is why we conduct multiple econometric methods. Third, we use the theory of human capital specificity to explain how the impact of digital transformation on highly educated and associate employees is not significant. Our explanation is only from a limited perspective and may not include some potential reasons. Fourth, the continuous DID method is used only for testing the causal relationship between enterprises' digital transformation and EES. We should point out that research that used continuous DID is rare, which means that we may neglect some important references to make a robustness test for the method. Therefore, further research can be conducted based on the above limitations.

Finally, we should point out that our research is based on the current employment situation in China, which means we should remain cautious when extending these results to other countries. As mentioned, the employment market and education system in China are quite different from that in Western countries. The prominent feature of the Chinese labor market can be concluded as excess supply and less demand. Additionally, the COVID-19 pandemic has made the phenomena more severe. Therefore, we believe that one of the main motivations for Chinese enterprises to process digital transformation is to reduce costs and achieve sustainable production. Meanwhile, facing the situation that enterprise needs fewer human employees, many Chinese people are forced to engage in "involution", and one of the available pathways is to improve their educational degrees. Owing to the huge population, the competition in the Chinese employment market and stress in the Chinese education system is extremely severe. Therefore, we believe that our results may provide a reliable reference for countries with a similar situation.

5.3. Recommendations

Our conclusions have certain implications for employees, organizations, and education systems. The digital transformation of enterprises is regarded as a high-tech value-added technological transformation, which often requires more highly educated talents. That is, the digital transformation of enterprises implies the intuition of improving the knowledge structure of employees. However, our results show that the digital transformation can indeed improve the EES of the enterprise, but the main promotion derives from employees with undergraduate degrees and not from employees with higher education (i.e., graduate degrees and above), who are not significant. Hence, this result can provide a reference for undergraduates to balance their future studies and employment. At the least, they should not blindly participate in the Graduate Entrance Examinations just to improve their academic qualifications.

Enterprises need talents with certain knowledge and skills in digital transformation. Although there has been a lot of speculation in the domestic media in recent years about one-sided news such as "Peking University doctor working as a security guard," which devalues the value of education, in general, there is still an oversupply of highly educated employees for enterprises because job seekers with graduate degrees and above are relatively few in general. Moreover, such highly educated employees often have certain characteristics of human capital specificity, which is embodied in their specificity of knowledge. The reasonable measure of enterprises is to sign long-term contracts to retain them. Hence, the impact of digital transformation generally does not affect the number of such highly educated employees of enterprises. In addition, the professional threshold of highly educated employees and the academic orientation of the training process are making this type of group less and less likely to directly enter an enterprise to work. Even if they do, it often requires higher costs (i.e., wages) for enterprises to retain them, which makes it difficult for most enterprises to employ highly educated people on a large scale.

From the perspective of employment preference of highly educated talents, that is, the employment supply-side analysis, although China's employment situation has become increasingly severe in recent years, in general, the training goal of graduate students should adhere to an academic orientation rather than an employment orientation. In the process of cultivating graduate students, academic-oriented instructors attach great importance to the training of their scientific research capabilities to cultivate them as researchers in a certain discipline or field. This orientation emphasizes the scientific research of postgraduates in their work and does not mean that postgraduates can only engage in scientific research. For example, many engineering graduates often make suggestions for project construction of enterprises, while business graduates mostly serve as independent directors in listed companies, providing advice and suggestions for operations and decision-making of enterprises. Hence, although enterprises may consult highly educated researchers or experts in related fields on professional issues, in general, directly entering enterprises after graduation may not be the main employment preference of highly educated groups.

For the education system, our results indicate that the government ought to clarify the directions in different educational stages. For example, vocational education should emphasize cultivating talents with strong applicable skills, and advanced education should pay more attention to cultivating talents with profound knowledge in different subjects. In addition, the government should also governance the excess "involution" in competition.

At the least, blindly pursuing higher education degrees is not recommended for graduates. This may be the most significant implication of this research.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su14159432/s1, Figure S1: Illustration of the mediation effects; Table S1: Results of the Bootstrap test in the mediation effects.

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