# **Abstract**

This study has investigated the effect of digital transformation on mobility and human resource structure in Chinese firms in focusing on the integration of advanced digital technology such as artificial intelligence, blockchain, cloud computing, and big data via panel regression analysis on long-term data over ten years (2011 to 2022). This study found a correlation between firms' digital transformation and employees' education level and changes of proportion in distribution over the department. The findings show how the maturity of digital transformation increased the need for highly educated and skilled employees, and it indicates the possibility that firms with higher digital adoption rates are more likely to employ highly educated individuals. However, the result showed discrepancies between blockchain technology and current skill needs. Additionally, the findings of this study emphasize the role of the top management team in facilitating digital transformation in the firm. TMTs with diverse and high academic qualifications can effectively use digital technologies to enhance the skills of their workforce. However, the findings also point to potential challenges such as job displacement and the increasing need for continuous professional development to cope with the rapid pace of technological change.

# *Keywords:* digital transformation, workforce mobility, human resource management, advanced technologies, organizational change

**Impact of Digital Transformation on Workforce Mobility and Structure in Chinese Companies**

Organizations increasingly use advanced digital technologies such as artificial intelligence, blockchain, cloud computing, and big data for the same reasons they used to adopt advanced technology and managerial intervention: survival. For example, in the healthcare sector, digital technology, including wearable technology, artificial intelligence, and telehealth, plays crucial roles (Newman, 2023), as reported by Forbes Technology Council. Chinese companies increasingly embrace advanced technologies in the quest for operational efficiency over digital technology, assets, and strategies to integrate into their organizational culture and customer and employee experience (Kim & Song, 2022). Notably, integrating Artificial Intelligence (AI) systems within the healthcare sector emerges as a pivotal contributor to resource optimization, elevating employee satisfaction and enhancing the overall patient experience (Dicuonzo, Donofrio, Fusco, & Shini, 2022). However, the potential impact on employment dynamics remains uncertain. The question arises: How does this transformative trajectory influence its implications for the workforce structure within the sector? What are the ramifications of sustainability in the workplace?

Digital transformation has transcended mere trend-chasing exaggeration to become a globally expected phenomenon of corporate conduct. AI systems, distinguished by their robust predictive and analytical capabilities with automation, are pivotal in mitigating burnout, minimizing operational errors, and curbing resource wastage among workers (CITATION). This positive effect improves a sound workplace environment, attracts highly skilled and educated talent, and enhances the organization's human capital (CITATION). For instance, a technologically advanced and employee-friendly environment may motivate candidates to grow their careers in such organizations, which works as potential talent acquisition within the profession. Nonetheless, the concurrent outcome of this technological assimilation may reduce the workforce, thereby heightening the discernible risk of attrition for existing personnel.

Moreover, adopting these advanced technologies typically necessitates a workforce with enhanced knowledge and skills (CITATION). More talents equipped with a technology-oriented skill set and knowledge of the new technology are required to adopt and integrate advanced new technology with existing strategies and procedures in firms (CITATION). Despite the expected positive benefit of digital transformation, the heavy burden of technology assimilation may cause employee turnover. In the absence of updated skills, particularly in utilizing new systems integrated with cloud technology for data storage, older or less formally educated employees may encounter challenges that could jeopardize their job security (CITATION). This issue may not only diminish employee loyalty but also engender heightened apprehension. Therefore, the importance of ongoing skills development in which firms undergo a digital transformation to ensure workforce resilience and sustained professional engagement has been accentuated in terms of organizational change (CITATION).

Therefore, this study is significant because it is the first attempt to examine the impact of digitization technologies on employee mobility and structure. In addition to investigating the main effect of digital transformation, this study aims to provide a comprehensive explanation of the effect on the workplace by distinguishing the four emerging technologies: artificial intelligence, cloud technologies, big data, and blockchain. This study extends the range of analyses by including how digitalization technology affects employees across diverse departments and educational backgrounds. This study aims to comprehensively explain the intricate interplay between technological advancements and the human resources structure by conducting a multifaceted examination of digital transformation and workforce structure.

**Purpose of the Research and Objectives**

This study proposes to examine the organization's technology maturity or level of integration regarding digital transformation's effect on the structure of employee education levels and distribution across departments in the organization. Using long-term panel data collected in the China Stock Market & Accounting Research Database (CSMAR), specifically, this study aims to provide a proper evaluation and comprehension of how an organization's effort to integrate digital technology that is represented by advancements in technology such as artificial intelligence, blockchain, cloud computing, and big data into the organization's culture, intervention, and strategy influence human capital within the evolving corporate landscape of China.

To fulfill the research objective, this study tests the direct impact of digital technology integration on the educational attainment of the workforce, assuming that more digitally advanced firms are likely to employ a higher number of graduates with advanced degrees due to the complex skills required to manage and implement new technologies, and whether TMTs with higher academic qualifications; diverse experiences are more effective at using digital transformation to improve skill levels within their firms. The study also tests differentiations between types of digital technologies and their specific impacts on educational requirements. It suggests that some technologies may be more conducive to higher educational attainment within the workforce.

Hypothesis 1. Higher degrees of digitalization in Chinese listed companies are associated with an increased proportion of employees holding higher education degrees.

Hypothesis 2. The characteristics of the Top Management Team (TMT), specifically their academic background and experience, moderate the relationship between digitalization and employees' educational structure.

Hypothesis 3: different digital technologies (AI, Big Data, Blockchain, Cloud Technology) have varying impacts on the proportion of higher-educated employees.

**Literature Review**

Emerging digital transformation trends in 2023 indicate a continued focus on enhancing customer experiences and managing data effectively, with the metaverse poised to play a significant role (Casino, Dasaklis, & Patsakis, 2019). However, the adoption of digital technologies also introduces challenges. For example, Gjellebæk et al. (2020) and Palumbo & Cavallone (2022) discuss how digital transformation can lead to job uncertainty and lower job satisfaction, highlighting the need for ongoing learning and adaptation among employees. Also, blockchain technology has emerged to revolutionize business practices across sectors because of its characteristics, which secure transactions through distributed computer networks.

About digital transformation and its positive effect on the organization, Kraus, Schiavone, Pluzhnikova, and Invernizzi (2021) provide a comprehensive review of digital transformation in healthcare, categorizing existing research into operational efficiency, patient-centered approaches, and workforce practices. This systematic categorization aids in understanding how various technology implementations can enhance healthcare operational efficiency. The influence of digital manufacturing technologies (DMTs) on firm performance is also significant. Studies suggest that the organizational and environmental contexts influence the adoption of DMTs, affecting various performance metrics like flexibility, design, delivery, and quality, highlighting the need for organizations to adapt their structures to technological advancements (Gillani et al., 2020).

The investigation into the effects of digital transformation across academia spans from financial impacts to human factors. First, Alarussi and Gao (2021) examined the influence of financial variables on the profitability of non-financial Chinese companies; they found positive correlations between profitability and aspects such as firm size, working capital, and intangible assets while identifying a negative relationship with liquidity. This finding suggests that proficient resource management and efficient utilization of liquid assets are crucial for boosting profitability. However, the effects of leverage present a more complex behavior, indicating a nuanced relationship between debt and profitability. Another industrial sector that is proactively adopting digital transformation is the healthcare sector. To improve efficiency, safety, stability, and accessibility, the healthcare industry has been applying machine learning, natural language processing, and artificial intelligence. It plays an important role in attaining value-centered medication. It also has a high potential to change overall organizational intervention (Chen & Décary, 2019).

On the other hand, studies investigate the relationship between digital transformation and employee competency and skill. Firms that are undergoing digital transformation require advanced technological skills and knowledge. Thus, this highlights the need for workers to adapt and upgrade their skills to succeed in a digitally evolving workforce (Li, Yang, & Yin, 2024). Specifically, it is reported that AI technology increases an organization's financial and operational performance by optimizing HR intervention (Li et al., 2023). The relationship between the digitalization of labor processes and employment changes in Italy underscores that digitally intensive occupations tend to expand, mainly when digital usage is high. However, digitally intensive and routine jobs face growth challenges, supporting the hypothesis of routine-biased technological change (Cirillo et al., 2021).

**Method**

**Sample Selection**

This study focuses on the 3,879 Chinese listed firms from 2011 to 2022 to capture China's digitalization surge and leverage available data while avoiding the immediate post-crisis years. The financial indicators and essential information are collected from the China Stock Market & Accounting Research Database (CSMAR), Wind terminal, and listed firms' annual reports. The official annual reports of those listed firms verify the collected data. This study removes all the firms under financial-related industries and special treatment (ST). After cleaning missing values, this study merges each data section based on the companies’ identifiers and specific years.

**Variables and Measures**

***Dependent Variables: Employees’ Structure***

The study discusses the employees’ structure from three perspectives: education, age, and department. For the department structure, this study focuses on the proportion of employees working within the diverse departments. The education structure in this study refers to the proportion of employees with higher education. For *Degree* and *DegreeP*, the former literature measures higher education as the absolute number of bachelor’s degrees (Chen et al., 2023) or the percentage of employees (Kong et al., 2022). Our result shows that only 5.259% of employees have a master’s degree or higher on average. However, Chen et al. (2023) report that the number of higher-education employees increased by 89% from 19% in 2008 to 36% in 2021 among Chinese domestic non-financial A-share enterprises. The difference in the proportion results from the different definitions of higher education. Chen et al. (2023) utilize the bachelor's degree as the higher education level. The similar traits between bachelor's and master’s degree-holding employees, as well as the possible future trend of masters in the job market, have guided us to define higher education as master’s degree holders or higher. Based on the difference, this study fills the literature gap of research on employees with master's degrees or higher. Furthermore, this study uses text matching to filter the employees holding at least a master’s degree, as shown in Table 1.

***Independent Variables: Digital transformation***

Following the previous literature (Zeng et al., 2022), the study utilizes digitalization keyword frequency directly provided by the CSMAR. In this study, we further discuss digitalization in terms of artificial intelligence technology, blockchain, cloud computing, and big data technology. Li et al. (2024), this study measures the digitalization degree through the natural logarithm of digitalization frequency plus one. Integrating the previous instructions, this study generates the AI, big data, blockchain, and cloud technology degrees to quantify the listed corporations' digitalization degrees.

***Moderate Variables: Top Management Team (TMT) Characteristics***

This study contains three moderate variables: *DegreeM, FinbackM*, and *AcademicM.* The *DegreeM* is quantified as the ratio of top executives holding advanced degrees, specifically master's and doctoral degrees. Moreover, based on the top executives’ resumes in the annual report and the previous study, the financial background (*FinbackM*) and academic experience (*AcademicM*) are captured and counted by specific keywords, shown in Table 1.

***Control Variables***

This study also includes a range of control variables at the firm level. Firms’ profitability is one of the essential factors for employees (Alarussi & Gao, 2023; Li et al., 2022). Regarding the solvency ratio, employees are more willing to stay in a solvent and financially stable working environment. As for the firm’s age, Børing in 2020 proved that employees with higher skills tend to apply for newly established firms. Thus, this study includes the profitability measured by the return on asset (ROA), the firms’ age measured by the natural logarithm of the difference between the listed years and fiscal year, and the solvency measured by the ratio of total non-current liabilities divided by total owners’ equity.

--------------------------------------------

Table1. Variables Definitions

--------------------------------------------

**Model Specification**

This study adopts the multilinear regression model with fixed effects to explore the impact of digitalization on employees’ higher education proportion. Thus, this study proposes the following model:

|  |  |
| --- | --- |
|  | (1) |

Where *i* represents the enterprise, *t* indicates the time periods, εi,t is the error term, *Year* represents the year fixed effect, and Industry represents the industry fixed effect. To control the omitted variable efficiently, this study utilizes the fixed effect in three dimensions, including the intersection between *Year* and *Industry*. Furthermore, this study tests the non-linear relationship and considers the quadric term in representing the digital transformation degree (*Total*) in model 2.

|  |  |
| --- | --- |
|  | (2) |

To test the moderate effect of the TMT characteristics, including the proportion of executives with Academic experience (*AcademicM*) and financial background experience (*FinBackM*), this study builds up the following model (3-4):

|  |  |
| --- | --- |
|  | (3) |

|  |  |
| --- | --- |
|  | (4) |

|  |  |
| --- | --- |
|  | (5) |

To solve the endogeneity issues, this study adopts the instrumental variables. Following the instruction from Cette et al. (2022), this study adopts the leave-one-out mean of digitalization at the sector level. To validate the consistency and accuracy of our results, we conducted robustness tests using two different approaches. First, we introduced a lagged term of digitalization (*LTotal*) to examine if the impact of digitalization remains stable over time (Hao et al., 2023). Following the design of Balsmeier & Woerter (2019), we shifted the measurement of employees with higher education from a relative measure (*Degreep*, the proportion of higher educated employees) to an absolute measure (*Degree*, the total count of higher educated employees).

Furthermore, this study applied K-Nearest Neighbors (KNN) clustering to categorize Chinese companies based on the composition of their workforce across different departments, including production, finance, sales, technology, and other departments. This study identified three clusters representing optimal and classic company personnel distribution structures by analyzing the total within-cluster sum of squares (WSS) and the Silhouette Coefficient. These clusters serve as archetypes for organizational configurations in the Chinese corporate environment. Subsequently, this study examines the impact of digitization on the mobility and distribution of highly educated employees within these identified company structures.

**Findings**

The descriptive statistics and correlation analysis are presented in Table 2 and 3 As shown in Table 2, after handling missing data and merging databases, the dataset comprises 24,942 firm-year observations. The variable of interest, *Degreep*, which represents the proportion of employees with higher education (master’s degree or above), has a mean value of approximately 5.26%, indicating that a relatively small proportion of employees hold higher education degrees. This highlights a potential underutilization of human capital, which could be further explored through the lens of human capital theory (CITATION).

**Descriptive Statistics**

The positive mean of ROA suggests that, on average, listed firms in the sample are profitable. Furthermore, the small standard deviation suggests that the difference in profitability among those listed firms is small. The digital transformation degree, measured by the variable Total, averages around 0.75, indicating that firms are still in the developmental stages of digital transformation, and many firms do not have related keywords in their financial statements. The higher education proportion average is 0.38, with a standard deviation of around 0.3 and a range of 0 to 1. Notably, the large standard deviation suggests that based on the average of 37.9%, organizational differences in TMT education level are apparent. The upper echelon theory can further examine the observation, which suggests that top management characteristics, such as education and career experience, influence strategic decisions relevant to digital transformation. Correspondingly, *FinBackM* and *AcademicM* have similar characteristics to *DegreeM*, showing that they have a relatively small mean and a large variance. These dynamic experiences provided by their combination would potentially position the TMT to drive digital initiatives that leverage the firm's existing resources for sustained competitive advantage.

--------------------------------------------

Table 2. Descriptive Statistics of the Variables

--------------------------------------------

**Correlation Analysis**

Table 3 shows the correlation analysis result revealing several variables' relationships. Most pairs have a p-value lower than 0.1, suggesting they are valid results. The positive correlation between the proportion of employees with higher education (*Degreep*) and the degree of digitization (*Total*) suggests that firms with a more educated workforce are more inclined toward digital transformation. Notably, the relationship between the traditional indicators (*ROA, Solvency*, and *Age*) and their relationship with digital transformation or higher education proposition are all slightly negative, suggesting a need for further research. However, *DegreeP* and *Total* have a positive relation with the dynamic background of TMT, suggesting the TMT’s impact on digital transformation and employee recruitment.

Furthermore, the positive relations with top manager characteristics indicate that top managers would provide a more diversified experience for their working environment and raise proper organizational culture for their enterprises. Naturally, few exceptions exist; higher education proportion and shares per manager’s negative relation also encourage diversity within the TMT team. Meanwhile, *SharesM*’s negative relation with the top manager’s financial background indicates that managers with a comprehensive understanding of corporate finance would be more cautious in approaching the organization's superstructure. The result generally aligns with human capital theory as it highlights the role of skilled employees in adopting new technologies and how human capital tends to herd with similar characteristics (CITATION).

--------------------------------------------

Table 3. Pairwise Correlations

--------------------------------------------

**Regression Analysis Outcomes**

In Table 4, the results of the first six models are displayed; all the models are effective, with only age having a p-value larger than 0.1 in the model. From columns (1)-(2), digital transformation (*Total*) has a highly positive and significant effect on the proportion of employees with higher education degrees, following a non-linear relationship. Within the relevant domain (*Total* ≥ 0), the proportion of employees with advanced degrees continues to rise as firms advance in their digital transformation. This pattern underscores the role of digital transformation in driving demand for highly skilled labor, consistent with human capital theory (CITATION). Furthermore, the regression mainly shows a negative relationship between firms’ age and employees with high education, which fits the results found by Børing (2020).

In columns (3) to (6), this study examines the moderating effects of various characteristics of top managers. Only shares per manager displayed a negative impact directly. However, not only do managers' shares negatively moderate the relationship between digital transformation and employee education level, but the financial experience (*FinBackM*) is also negatively associated with the effect of digital transformation. The negative moderating impact of shares held by managers is possibly due to risk aversion or a shift in priorities toward personal financial security. Additionally, managers with financial backgrounds might prioritize financial conservatism over innovative strategies, potentially limiting the firm's growth opportunities. Generally, the impact of agency cost on the proportion of educated employees is larger than the financial conservatism within the TMT, indicating that financial specialists should be adequately arranged to assist organizations in winning more educated talents and implementing digitization.

Moreover, higher education and academic background showed a positive impact. The positive moderating effect of top managers’ academic backgrounds (*AcademicM*) and higher education (*DegreeM*) suggests that academic expertise contributes to more informed decision-making, positively impacting firm performance. Specifically, the result highlights the positive moderating role of top managers with higher education (*DegreeM*). In general, higher education-related experience would help the development of digital transformation and gain the interest of educated talents. Considering the impact of the four backgrounds, we can conclude that managers and TMT with diverse backgrounds have faith in digital transformation but worry about the cost digital transformation and educated employees would bring. Notably, their faith is stronger than their concerns, so most firms are in the process of digitization and waiting for signs to increase their investments.

--------------------------------------------

Table 4. Impact of Digital Technologies on Workforce Education

--------------------------------------------

Based on the results of Table 4, this study further explores how each four perspectives of digital transformation affect the proportion of educated talents, including artificial intelligence (*AI*), Big data technology (*Big*), Cloud technology (*Cloud*), and Blockchain (*Block*) in Table 5. From columns (1-5), we can conclude that artificial intelligence, big data, and cloud technology positively impact higher education proportion, suggesting that these technologies drive the demand for a more educated workforce. These three factors have already impacted every organization's daily operation and proved their effectiveness in repetitive tasks. According to our former analysis, TMT generally has more interest than concern in educated talents and digital transformation. This tendency would also operate together with the digital transformation indicators to increase the percentage of educated workers. Notably, only age has a p-value larger than 0.1, suggesting that the impact of enterprises’ operating years is not as clear as other control variables.

Only solvency, age, and blockchain negatively affect the higher education employee proportion. Higher solvency suggests a larger long-term liability, while older firms will promote conservatism. These factors would negatively impact TMT’s preference for educated talents due to the changes and costs they might bring. Though blockchain technology brings negative effects, the reason might be opposite to the demographic characteristics of enterprises. Blockchain technology has higher requirements for industry popularity and lower conversion rates in the daily operation of business entities (Casino et al., 2019). However, blockchain would provide a comparative advantage and become a technical barrier for the company (Casino et al., 2019). Thus, when considering investments in digital transformation and talents, resources would either focus only on blockchain development or ignore the blockchain sector. When considering these factors, employees usually negatively perceive changes or try to avoid possible risks. Correspondingly, employees require TMT guidance when considering digital transformation and the proportion of educated talents.

--------------------------------------------

Table 5. Impact of Digital Components on Workforce Education

--------------------------------------------

***Robust Test and Two-stage Least Squares for Potential Endogeneity Issue***

The results presented in Table 6 further confirm the robustness of our initial findings, demonstrating that the relationship between digital transformation and workforce education remains consistent across various measures and time periods. In column (2), digital transformation still has a significant positive effect on the employees with higher education degrees when the calculation turns the relative methods, *Degreep*, to the absolute methods, *Degree*. The result is similar to the findings of Balsmeier & Woerter (2019). With more awareness and adoption of digital transformation, firms tend to attract and hire employees with higher education since those employees can efficiently utilize digital technology and create optimal value (Cirillo et al., 2021). As for column (3), we include the lagged term for digitization, *LTotal*, which also positively affects the employment of highly educated workers. This finding not only underscores the sustained impact of digital transformation but also addresses potential concerns about reverse causality. Positive lagged effects indicate that the benefits of digital transformation on workforce training are not immediate but emerge gradually over time, capturing the lagged impacts as firms implement digital technologies incrementally (Gillani et al., 2020).

--------------------------------------------

Table 6. Robust Test

--------------------------------------------

To control potential endogeneity issues, this study employed the two-stage least squares (2SLS) method with instrumental variables. As Gopalan et al. (2022) suggested, this study used the instrumental variable of the leave-one-out mean as an instrumental variable, calculated by taking the average digitalization level within a sector, excluding the firm being analyzed. This approach helps control endogeneity by using sectoral digitalization trends, excluding the individual firm, as a valid instrument for firm-level digitalization. The Cragg-Donald Wald F statistic (11340.09) is much higher than any of the critical values within the analysis, which shows the strength and reliability of the chosen instrumental variables (Zeng et al., 2022; Gómez-Bengoeche & Jung, 2024). It is also supported by the Anderson-Rubin Wald Test (Guo et al., 2023), shown in Table 7

--------------------------------------------

Table 7. Two stages least square with instrumental variable

--------------------------------------------

***Organizational Clustering and Digital Transformation Effect on Workforce Education Across Organizations***

Additionally, this study employs K-Nearest Neighbors (KNN) clustering to categorize Chinese companies based on the distribution of employees across various departments, including production, finance, sales, technology, and other departments. By analyzing the total within-cluster sum of squares (WSS) and the Silhouette Coefficient (refer to Appendix 2), we identified three distinct organizational structures, shown in Figure 1. This study used principal component analysis (PCA) to reduce the data’s dimensionality for visualization. Group I, Group II, and Group III are the three main types of departments. Group a higher proportion of employees in sales and other departments characterizes me. Group II primarily focuses on production, and Group III is more oriented towards the technology department. The specific proportion for each department is shown in Figure 1 and Appendix 1.

--------------------------------------------

Figure 1. Clusters of listed firm structure

--------------------------------------------

Based on these main types of firm structures, the study further explores the impact of digital transformation on the proportion of employees with higher education. As shown in Table 8, the results indicate that digital transformation has a more pronounced positive effect in Groups II and III, suggesting that firms focusing on production and technology are better positioned to leverage digital transformation to enhance the educational qualifications of their workforce. Surprisingly, digital transformation has more impact on production than the technology sector, indicating the need for further research. Notably, all variables have vital requirements for sectors to become effective predictors. *ROA* has a weak impact on the production sector, which might impact a large percentage of their fixed assets.

Meanwhile, it is hard for the production sector to keep up their plants and equipment with the digital transformation trend. Age is only vital in the production sector because only big companies with years of operating experience must employ more educated employees for continuous development. Correspondingly, solvency’s strong effect in the technology sector suggests that the technology industry focuses on converting debts since most SMEs cannot generate positive income in the beginning stage. This industry difference is significant and differs from each other, requiring further study.

--------------------------------------------

Table 8. Table Title

--------------------------------------------

Table 9 provides a comprehensive summary of the impact of various digital transformation components on the proportion of employees with higher education, which varies across different organizational structures. The findings reveal that Artificial Intelligence consistently positively and significantly influences employee education levels across all types, with stronger effects observed in structures focused on production and technology (Type II and III). Big Data also shows a significant positive impact on production-oriented firms (Type II). However, its negative effect in technology-focused firms (Type III) indicates that different digital strategies prioritize varying skill sets. Big data might become the opportunity cost for more important sectors like Artificial Intelligence and Cloud Technology. Blockchain technology, on the other hand, is associated with a negative effect across all structures. It suggests that the skills required for blockchain may not currently align with higher education, and hiring educated talents may not generate results in the blockchain sector. Cloud technology's impact is mixed, being negative in sales-oriented firms (Type I) but significantly positive in production- and technology-oriented firms (Type II and III), which might be the data storage needed in different sectors. Generally, the sector analysis showed that different skills are preferred in the abovementioned sectors, and the skills might be misplaced with higher education. This reminds the TMT that educated talents do not equal the talent organizational and digital transformation development needs.

--------------------------------------------

Table 9. Type and Digitalization

--------------------------------------------

**Discussion and Conclusion**

The exploration of digital transformation’s impact on the structure and mobility of human resources within Chinese companies underscores a profound shift in these enterprises' operational and strategic frameworks. As they increasingly integrate advanced technologies like artificial intelligence, blockchain, cloud computing, and big data, employee dynamics, and organizational functionality ramifications become significantly pronounced. This study found that digital transformation has significantly increased the proportion of employees with higher education degrees. This means that the more advanced technology required as evidence of undergoing digital transformation a company becomes, the greater the demand for higher education qualifications. This is observed in the healthcare sector, where the integration of AI and cloud technologies is essential in optimizing resources and improving employee satisfaction and patient care (CITATION). However, the shift to more digitalized operations has also brought complex challenges, including the potential for increased unemployment among digitally unfamiliar employees and the need for continuous skills development to keep the workforce adaptable and resilient.

The transformation of Chinese enterprises towards digitalization has significantly redefined the roles and requirements of employees in various sectors. Our findings indicate that the integration of advanced technologies such as artificial intelligence (AI), cloud computing, and big data is driving a shift in the required skill sets, which fundamentally impacts employee mobility within the industry. As companies transition to more digitalized operations, traditional roles are not only being replaced, but new opportunities that require specialized skills are emerging. These changes highlight an important aspect of digital transformation: the need for employees to develop their skills and be adaptable continually.

The impact of digitalization is not uniformly influenced across all departments within organizations. Departments that require advanced technology for the task experience significant changes in jobs, roles, and dynamics overall, which implies the need for a strategic approach to managing these changes. Employees with higher education levels are often expected to adapt to these new demands better because they can better acquire and apply new competencies. This discrepancy in the competency of employees highlights the importance of training programs that improve digital fluency and literacy, enabling the workforce to navigate and adopt new technology adopted in the organization during digital transformation.

The top management team's role and support are critical to successfully exploring the challenges and opportunities presented by digital transformation. In this study, we found that TMT members' education level and experience are pivotal in initiating and directing digital transformation. A more academically accomplished and diverse TMT is better positioned to leverage digital technologies, enhancing the workforce's educational standing and operational efficiency. However, this may reveal the dual-edged nature of digital transoformation, where the potential for job displacement and the necessity for adaptive skills development coexist with opportunities for growth and innovation.

**Challenges and Opportunities**

This study found that the effects of digital transformation extend beyond enhancing operational efficiencies. We found digital transformation influences the educational structure and workforce mobility across the sector. While digital transformation fosters an environment where higher education and advanced skills are increasingly valued, it also necessitates the reevaluation of traditional roles and the development of new competencies. Also, the findings showed a positive correlation between digitalization and the level of employee education, indicating that firms with more educated workforces are more adept at embracing digital transformations. The uneven distribution of required digital skills and competency influences different departments. It represents the varying effects on employee groups that necessitate a tailored approach to digital strategy implementation.

**Limitation and Suggestion**

Like all other research, this study has its limitations, which must be acknowledged better to understand the scope and applicability of its findings. A major limitation of this study is that the focus is on a small number of digital technologies—artificial intelligence, blockchain, cloud computing, and big data. Additionally, the geographical and sectoral confinement limits the generalizability of the findings. These results may not directly translate to other regions or sectors where digital transformation dynamics could differ. In addition, the study's methodological reliance on the frequency of digitization keywords from financial reports as a proxy for digital adoption may not accurately capture the depth and effectiveness of digital technology integration into operational practices.

Future research should broaden the range of technologies and industries studied, incorporate qualitative findings to enrich the understanding of the impact of digital transformation and explore the long-term effects of digitalization on workforce dynamics. To address these limitations, several recommendations for future research can be made. Broadening the range of digital technologies studied could provide a more comprehensive view of the impact of digital transformation. Broadening the geographical and sectoral scope of the research could improve the applicability and relevance of the findings in different contexts. In addition, incorporating qualitative methods, such as interviews and focus groups, could enrich the quantitative data and provide nuanced insights into digitalization's personal and organizational impacts that surveys and financial data cannot capture.

**Conclusion**

In conclusion, as digital technologies continue to permeate the business landscape, their integration must be strategically managed to harness their potential benefits while mitigating risks. This study contributes to the academic discourse on digital transformation and provides practical insights for organizations seeking to navigate these dynamics and complexity. Further research must continue to investigate the multifaceted aspect of digitalization and guide organizations in developing informed, effective strategies that foster an empowered, skilled, and adaptable workforce.

**Reference**

Alarussi, A. S., & Gao, X. (2023). Determinants of profitability in Chinese companies. *International Journal of Emerging Markets*, *18*(10), 4232-4251.

Balsmeier, B., & Woerter, M. (2019). Is this time different? How digital transformation influences job creation and destruction. *Research policy*, *48*(8), 103765.

Børing, P. (2020). Effect of firms’ age on their use of highly skilled workers. *Labour*, *34*(2), 137-153.

Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). A systematic literature review of blockchain-based applications: Current status, classification and open issues. *Telematics and informatics*, *36*, 55-81.

Cette, G., Nevoux, S., & Py, L. (2022). The impact of ICTs and digital transformation on productivity and labor share: evidence from French firms. *Economics of innovation and new technology*, *31*(8), 669-692.

Chen, M., & Decary, M. (2020). Artificial intelligence in healthcare: An essential guide for health leaders. Healthcare management forum,

Chen, T., Zhou, L., & Lv, K. (2023). How Do Higher Educated Employees Affect Firms’ Investment Efficiency in China? *Emerging Markets Finance and Trade*, *59*(11), 3610-3635.

Cirillo, V., Evangelista, R., Guarascio, D., & Sostero, M. (2021). Digital transformation, routineness and employment: An exploration on Italian task-based data. *Research policy*, *50*(7), 104079.

Dicuonzo, G., Donofrio, F., Fusco, A., & Shini, M. (2023). Healthcare system: Moving forward with artificial intelligence. *Technovation*, *120*, 102510.

Gillani, F., Chatha, K. A., Jajja, M. S. S., & Farooq, S. (2020). Implementation of digital manufacturing technologies: Antecedents and consequences. *International Journal of Production Economics*, *229*, 107748.

Gjellebæk, C., Svensson, A., Bjørkquist, C., Fladeby, N., & Grundén, K. (2020). Management challenges for future digital transformation of healthcare services. *Futures*, *124*, 102636.

Gómez-Bengoechea, G., & Jung, J. (2024). The Matthew effect: Evidence on firms’ digital transformation distributional effects. *Technology in Society*, *76*, 102423.

Gopalan, S., Reddy, K., & Sasidharan, S. (2022). Does digital transformation spur global value chain participation? Firm-level evidence from emerging markets. *Information Economics and Policy*, *59*, 100972.

Guo, X., Li, M., Wang, Y., & Mardani, A. (2023). Does digital transformation improve the firm’s performance? From the perspective of digital transformation paradox and managerial myopia. *Journal of Business Research*, *163*, 113868.

Hao, X., Li, Y., Ren, S., Wu, H., & Hao, Y. (2023). The role of digital transformation on green economic growth: Does industrial structure optimization and green innovation matter? *Journal of environmental management*, *325*, 116504.

Kim, S.-H., & Song, H. (2022). How digital transformation can improve hospitals’ operational decisions. *Harvard Business Review [Internet]*.

Kong, D., Zhang, B., & Zhang, J. (2022). Higher education and corporate innovation. *Journal of Corporate Finance*, *72*, 102165.

Kraus, S., Schiavone, F., Pluzhnikova, A., & Invernizzi, A. C. (2021). Digital transformation in healthcare: Analyzing the current state-of-research. *Journal of Business Research*, *123*, 557-567.

Li, P., Bastone, A., Mohamad, T. A., & Schiavone, F. (2023). How does artificial intelligence impact human resources performance. evidence from a healthcare institution in the United Arab Emirates. *Journal of Innovation & Knowledge*, *8*(2), 100340.

Li, Q., Lourie, B., Nekrasov, A., & Shevlin, T. (2022). Employee turnover and firm performance: Large-sample archival evidence. *Management Science*, *68*(8), 5667-5683.

Li, W., Yang, X., & Yin, X. (2024). Digital transformation and labor upgrading. *Pacific-Basin Finance Journal*, *83*, 102280.

Naamati-Schneider, L. (2023). The effect of digital transformation on service orientation and service perception among Israeli healthcare professionals: A qualitative study. *Digital Health*, *9*, 20552076231191892.

Newman , D. (2023 June). *Top 10 Digital Transformation Trends For 2023*. Forbes. Retrieved January 31 from https://www.forbes.com/sites/danielnewman/2022/10/10/top-10-digital-transformation-trends-for-2023/?sh=215299c95a4d

Palumbo, R., & Cavallone, M. (2024). Is work digital transformation without risk? Unveiling the psycho-social hazards of digital transformation in the education and healthcare workplace. *Technology Analysis & Strategic Management*, *36*(6), 1136-1149.

United\_Nations. (2023). *Youth*. https://www.un.org/en/global-issues/youth

Zeng, H., Ran, H., Zhou, Q., Jin, Y., & Cheng, X. (2022). The financial effect of firm digital transformation: Evidence from China. *Technological Forecasting and Social Change*, *183*, 121951.

# **Tables**

**Table 1**

*Variables Definitions*

| **Variables** | **Meaning** | **Measurements** |
| --- | --- | --- |
| *Total* | Total Digitalization Degree | Ln (1+word frequency), the world frequency includes the blockchain, AI, cloud technology, and big data relevant words; if not disclosed, this study denotes the degree as 0. |
| *ROA* | Profitability | (Total Profit + Financial Expenses) / Total Assets |
| *Solvency* | Solvency Ratio | Total Non-current Liabilities / Total Owners’ Equity |
| *Age* | Firm year | Ln(fiscal calendar year- listed year) |
| *DegreeM* | Proportion of Top managers holding a higher education degree | Ratio of top managers with education above or equal to a master’s degree |
| *SharesM* | The shares owned by the top managers |  |
| *Degreep* | The proportion of Employees with higher education | Ratio of employees with education above or equal to master’s degree |
| *Big* | Big Data Degree | ln (1+word frequency), the world frequency includes the big data relevant words; if it is not disclosed, this study denotes the degree as 0. |
| *Cloud* | Cloud Technology Degree | ln (1+word frequency), the world frequency includes the cloud technology relevant words; if it is not disclosed, this study denotes the degree as 0. |
| *Block* | Blockchain Technology Degree | ln (1+word frequency), the world frequency includes the words relevant to Blockchain technology; if it is not disclosed, this study denotes the degree as 0. |
| *AI* | Artificial Intelligence Degree | ln (1+word frequency), the world frequency includes the words relevant to Artificial Intelligence; if it is not disclosed, this study denotes the degree as 0. |
| *FinBackM* | Financial Background of Top Executives | The proportion of top managers with backgrounds in financial experience, including roles in regulatory bodies, commercial banks, insurance companies, securities companies, fund management companies, securities registration and clearing companies, futures companies, investment banks, trust companies, investment management companies, exchanges, and other relevant financial institutions. |
| *AcademicM* | Academic Background of Top Executives | The proportion of top managers possessing an academic background is categorized into distinct areas: teaching experience in higher education, positions held within research institutions, and involvement in research-focused associations. |
| *Degree* | Higher Education degree of employees | The absolute number of employees with higher education |

**Table 2**

*Descriptive Statistics of the Variables*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variables | Obs | Mean | Std. Dev. | Min | Max |
| *Degreep* | 24942 | 5.259 | 7.155 | 0.010 | 81.270 |
| *Total* | 24942 | 0.753 | 1.117 | 0.000 | 6.120 |
| *ROA* | 24942 | 0.048 | 0.184 | -3.324 | 22.003 |
| *Solvency* | 24942 | 0.294 | 1.910 | 0.000 | 232.785 |
| *Age* | 24942 | 2.018 | 0.960 | 0.000 | 3.466 |
| *DegreeM* | 24942 | 0.369 | 0.298 | 0.000 | 1.000 |
| *SharesM* | 24942 | 5.294 | 11.463 | 0.000 | 78.960 |
| *FinBackM* | 24942 | 0.086 | 0.191 | 0.000 | 1.000 |
| *AcademicM* | 24942 | 0.098 | 0.151 | 0.000 | 1.000 |

**Table 3**

*Pairwise Correlations*

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *(1) Degreep* | 1 |  |  |  |  |  |  |  |  |
| *(2) Total* | 0.187\* | 1 |  |  |  |  |  |  |  |
| *(3) ROA* | 0.000 | -0.038\* | 1 |  |  |  |  |  |  |
| *(4) Solvency* | -0.027\* | -0.035\* | -0.034\* | 1 |  |  |  |  |  |
| *(5) Age* | -0.026\* | -0.067\* | -0.043\* | 0.080\* | 1 |  |  |  |  |
| *(6) DegreeM* | 0.228\* | 0.139\* | -0.017\* | -0.018\* | -0.035\* | 1 |  |  |  |
| *(7) SharesM* | -0.028\* | 0.092\* | 0.021\* | -0.045\* | -0.392\* | -0.010 | 1 |  |  |
| *(8) FinBackM* | 0.288\* | 0.015\* | -0.034\* | 0.005 | 0.049\* | 0.175\* | -0.064\* | 1 |  |
| *(9) AcademicM* | 0.166\* | 0.099\* | -0.001 | -0.027\* | -0.134\* | 0.235\* | 0.146\* | 0.045\* | 1 |

*Note. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1*

**Table 4**

*Impact of Digital Technologies on Workforce Education*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| VARIABLES | *Degreep* | *Degreep* | *Degreep* | *Degreep* | *Degreep* | *Degreep* |
| *Total* | 0.7464\*\*\* | 0.2991\*\*\* | 0.3238\*\*\* | 0.8405\*\*\* | 0.9394\*\*\* | 0.5987\*\*\* |
|  | (0.0483) | (0.1083) | (0.0744) | (0.0527) | (0.0519) | (0.0563) |
| *ROA* | 1.9267\*\*\* | 1.9367\*\*\* | 1.9879\*\*\* | 1.9781\*\*\* | 1.8810\*\*\* | 1.8899\*\*\* |
|  | (0.3733) | (0.3731) | (0.3692) | (0.3728) | (0.3725) | (0.3706) |
| *Solvency* | -0.1157\*\* | -0.1160\*\* | -0.1102\*\* | -0.1192\*\* | -0.1108\*\* | -0.1113\*\* |
|  | (0.0507) | (0.0506) | (0.0501) | (0.0506) | (0.0505) | (0.0503) |
| *Age* | -0.0934\* | -0.0949\* | -0.0846\* | -0.1931\*\*\* | -0.0954\* | -0.0295 |
|  | (0.0498) | (0.0498) | (0.0493) | (0.0530) | (0.0497) | (0.0497) |
| *DegreeM* |  |  | 2.3393\*\*\* |  |  |  |
|  |  |  | (0.1757) |  |  |  |
| *DegreeM ´ Total* |  |  | 0.7886\*\*\* |  |  |  |
|  |  |  | (0.1315) |  |  |  |
| *Total´ Total* |  | 0.1347\*\*\* |  |  |  |  |
|  |  | (0.0292) |  |  |  |  |
| *SharesM* |  |  |  | -0.0127\*\* |  |  |
|  |  |  |  | (0.0050) |  |  |
| *SharesM ´ Total* |  |  |  | -0.0133\*\*\* |  |  |
|  |  |  |  | (0.0031) |  |  |
| *FinBackM* |  |  |  |  | 1.2502\*\*\* |  |
|  |  |  |  |  | (0.3903) |  |
| *FinBackM ´ Total* |  |  |  |  | -2.2644\*\*\* |  |
|  |  |  |  |  | (0.2274) |  |
| *AcademicM* |  |  |  |  |  | 3.9561\*\*\* |
|  |  |  |  |  |  | (0.3586) |
| *AcademicM ´ Total* |  |  |  |  |  | 0.8179\*\*\* |
|  |  |  |  |  |  | (0.2349) |
| *Constant* | 4.8288\*\*\* | 4.9184\*\*\* | 4.0121\*\*\* | 5.0943\*\*\* | 4.7362\*\*\* | 4.3449\*\*\* |
|  | (0.1167) | (0.1183) | (0.1320) | (0.1316) | (0.1207) | (0.1241) |
|  |  |  |  |  |  |  |
| *Year* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Industry* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Year ´ Industry* | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 20069 | 20069 | 20069 | 20069 | 20069 | 20069 |
| R-squared | 0.327 | 0.328 | 0.342 | 0.329 | 0.33 | 0.336 |
| Adjusted R-squared | 0.297 | 0.298 | 0.313 | 0.299 | 0.301 | 0.307 |

*Note.* Standard errors in parentheses.   
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 5**

*Impact of Digital Components on Workforce Education*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| VARIABLES | *Degreep* | *Degreep* | *Degreep* | *Degreep* | *Degreep* |
| *Total* | 0.7464\*\*\* |  |  |  |  |
|  | (0.0483) |  |  |  |  |
| *AI* |  | 0.8393\*\*\* |  |  |  |
|  |  | (0.0619) |  |  |  |
| *Big* |  |  | 0.5533\*\*\* |  |  |
|  |  |  | (0.0727) |  |  |
| *Cloud* |  |  |  | 0.9159\*\*\* |  |
|  |  |  |  | (0.0665) |  |
| *Block* |  |  |  |  | -0.7260\* |
|  |  |  |  |  | (0.4398) |
| *ROA* | 1.9267\*\*\* | 1.9005\*\*\* | 1.9439\*\*\* | 1.9334\*\*\* | 1.9352\*\*\* |
|  | (0.3733) | (0.3738) | (0.3750) | (0.3737) | (0.3755) |
| *Solvency* | -0.1157\*\* | -0.1153\*\* | -0.1237\*\* | -0.1182\*\* | -0.1240\*\* |
|  | (0.0507) | (0.0507) | (0.0509) | (0.0507) | (0.0510) |
| *Age* | -0.0934\* | -0.0709 | -0.0960\* | -0.1007\*\* | -0.0794 |
|  | (0.0498) | (0.0499) | (0.0501) | (0.0499) | (0.0501) |
| *Constant* | 4.8288\*\*\* | 5.0480\*\*\* | 5.2120\*\*\* | 5.0721\*\*\* | 5.3712\*\*\* |
|  | (0.1167) | (0.1140) | (0.1137) | (0.1136) | (0.1123) |
|  |  |  |  |  |  |
| *Year* | Yes | Yes | Yes | Yes | Yes |
| *Industry* | Yes | Yes | Yes | Yes | Yes |
| *Year ´ Industry* | Yes | Yes | Yes | Yes | Yes |
| Observations | 20069 | 20069 | 20069 | 20069 | 20069 |
| R-squared | 0.327 | 0.325 | 0.321 | 0.325 | 0.319 |
| Adjusted R-squared | 0.289 | 0.289 | 0.289 | 0.289 | 0.289 |

*Note.* Standard errors in parentheses.   
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 6**

*Robust Test*

|  |  |  |  |
| --- | --- | --- | --- |
|  | (1) | (2) | (3) |
| VARIABLES | *Degreep* | *Degree* | *Degree* |
| *Total* | 0.7464\*\*\* | 81.5616\*\*\* |  |
|  | (0.0483) | (10.7431) |  |
| *LTotal* |  |  | 0.7515\*\*\* |
|  |  |  | (0.0526) |
| *ROAA* | 1.9267\*\*\* | 126.6120\*\* | 4.3274\*\*\* |
|  | (0.3733) | (53.0379) | (0.5377) |
| *Solvency* | -0.1157\*\* | -0.4665 | -0.0836 |
|  | (0.0507) | (5.1229) | (0.0552) |
| *AgeF* | -0.0934\* | 162.0389\*\*\* | 0.0921 |
|  | (0.0498) | (10.7670) | (0.0665) |
| *Constant* | 4.8288\*\*\* | -62.6662\*\* | 4.3285\*\*\* |
|  | (0.1167) | (25.0094) | (0.1608) |
|  |  |  |  |
| *Year* | Yes | Yes | Yes |
| *Industry* | Yes | Yes | Yes |
| *Year ´ Industry* | Yes | Yes | Yes |
| Observations | 20069 | 24803 | 16274 |
| R-squared | 0.327 | 0.294 | 0.338 |
| Adjusted R-squared | 0.309 | 0.266 | 0.309 |

*Note.* Standard errors in parentheses.   
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 7**

*Two Stages Least Square with Instrumental Variable*

|  |  |  |
| --- | --- | --- |
|  | (1) | (2) |
| VARIABLES | *Total* | *Degreep* |
| *IVTotal* | 0.9777\*\*\* |  |
|  | (0.0092) |  |
| *Total* |  | 2.1289\*\*\* |
|  |  | (0.0744) |
| *ROAA* | -0.029 | 1.0924\*\*\* |
|  | (0.0306) | (0.2423) |
| *Solvency* | -0.0054\* | -0.0165 |
|  | (0.0029) | (0.0233) |
| *AgeF* | 0.0313\*\*\* | -0.0788\* |
|  | (0.0060) | (0.0470) |
| Constant | -0.0848\*\*\* | 3.8714\*\*\* |
|  | (0.0300) | (0.2372) |
|  |  |  |
| Cragg-Donald Wald F statistic | 11340.09 | |
| Anderson-Rubin Wald Test (*F, Chi*) | (818.44, 819.00)\*\*\* | |
| Observations | 24942 | 24942 |
| R-squared | 0.377 | 0.046 |
| Adjusted R-squared | 0.376 | 0.045 |

*Note.* Standard errors in parentheses.   
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 8**

*Additional Results from Firms’ Structure*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
| *Type* | *Whole* | *I* | *II* | *III* |
| VARIABLES | *Degreep* | *Degreep* | *Degreep* | *Degreep* |
| *Total* | 0.7464\*\*\* | 0.1573 | 0.2308\*\*\* | 0.2259\* |
|  | (0.0483) | (0.1132) | (0.0433) | (0.1283) |
| *ROA* | 1.9267\*\*\* | 4.2274\*\*\* | 0.2174 | 11.0484\*\*\* |
|  | (0.3733) | (0.9464) | (0.2528) | (1.7235) |
| *Solvency* | -0.1157\*\* | -0.186 | -0.0319 | -1.0528\*\* |
|  | (0.0507) | (0.1279) | (0.0328) | (0.4669) |
| *Age* | -0.0934\* | -0.1729\* | 0.1645\*\*\* | -0.1687 |
|  | (0.0498) | (0.1039) | (0.0388) | (0.1680) |
| *Constant* | 4.8288\*\*\* | 6.8688\*\*\* | 2.3994\*\*\* | 9.5143\*\*\* |
|  | (0.1167) | (0.2564) | (0.0893) | (0.3988) |
|  |  |  |  |  |
| *Year* | Yes | Yes | Yes | Yes |
| *Industry* | Yes | Yes | Yes | Yes |
| *Year ´ Industry* | Yes | Yes | Yes | Yes |
| Observations | 20,069 | 5,094 | 10,681 | 3,899 |
| R-squared | 0.327 | 0.55 | 0.188 | 0.162 |
| Adjusted R-squared | 0.297 | 0.498 | 0.137 | 0.1 |

*Note.* Standard errors in parentheses.   
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table 9**

*Type and Digitalization*

|  |  |  |  |
| --- | --- | --- | --- |
| *Type  Digitalization* | **I** | **II** | **III** |
| *Artificial Intelligence* | **+\*\*** | **+\*\*\*** | **+\*\*\*** |
| *Big Data* | **+** | **+\*\*\*** | **-\*\*\*** |
| *Blockchain* | **-** | **-** | **-\*** |
| *Cloud Technology* | **-** | **+\*\*\*** | **+\*\*** |

*Note.* + /- represents the Positive/Negative effect.   
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Figures**

Figure 1

*Clusters of Listed -Firm Structure*

A blue and red dot

Description automatically generated with medium confidence

**Appendix**

Appendix 1

*Cluster Profile*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| ***Cluster*** | ***Prodp*** | ***Finp*** | ***Salesp*** | ***Techp*** | ***Otherdp*** |
| 1 | 24.06% | 4.90% | 27.89% | 13.26% | 29.89% |
| 2 | 62.91% | 2.27% | 6.53% | 15.38% | 12.91% |
| 3 | 21.18% | 2.88% | 11.71% | 50.62% | 13.60% |

Appendix 2

*Elbow method for Determining Optimal Number of Clusters*

**A graph of a graph

Description automatically generated**