A Study on the Factor Structure of Digital Skills of Manufacturing Employees in Foshan—Based on Exploratory Factor Analysis

Sheng Xu [1, *], Taorun Xu [2], Chengwei Li [3], Shaohua Li [4], Jiayi Xie [1]

[1] School of Statistics and Data Science, Guangdong University of Finance & Economics, Foshan, China, 528000

[2] BIG DATA AND ARTIFICIAL INTELLIGENCE, Guangdong University of Finance & Economics, Foshan, China, 528000

[3] School of Financial Mathematics and Statistics, Guangdong University of Finance, Guangdong, China, 510520

[4] School of Mechanical and Automotive Engineering, Zhaoqing University, Zhaoqing, China, 526061

* Corresponding Author Email: 3325821523@proton.me

Abstract. In the context of digital transformation in the manufacturing sector, elucidating the internal structure of employees' digital skills is essential for talent development. Drawing on general ability theory, this study utilized 2025 survey data from industrial workers in Guangzhou, selecting a sample of 105 manufacturing workers from Foshan. An exploratory factor analysis was conducted to examine the underlying structure of six skills: equipment manual comprehension, equipment operation, programming problem solving, fault handling, data observation, and data analysis. Initially, the KMO test (0.772) and Bartlett's test of sphericity ($p<0.001$) confirmed the suitability of the data for factor analysis. The findings revealed that all six skills could be attributed to a single underlying factor, termed "digital literacy," which accounted for 69.1% of the total variance. Among these, "data observation" (loading 0.851) and "data analysis" (loading 0.846) emerged as the most critical dimensions constituting this core competency. This study substantiates the existence of a unified underlying structure for digital skills and provides empirical evidence for the development of a comprehensive training and assessment system centered on "digital literacy." This study offers practical guidance for optimizing corporate human resource management and enhancing the efficiency of digital transformation.

Keywords: Digital Literacy, Manufacturing Employees, Exploratory Factor Analysis, Skill Structure.

1. Introduction

The global landscape is currently experiencing a technological revolution characterized by digitalization, networking, and intelligence [1, 2]. As the cornerstone of national economies, the digital transformation of the manufacturing sector is pivotal in enhancing international competitiveness [3,4]. In this context, the digital proficiency of industrial workers is a critical determinant of successful transformation [5,6,7]. In Foshan, a prominent manufacturing center in China, the drive towards intelligent enterprise upgrades has imposed elevated demands on employees' digital competencies, encompassing equipment operation, programming control, data analysis, and troubleshooting [8].

Despite the acknowledged importance of digital skills, the intrinsic connections among these diverse skills, their potential attribution to higher-level latent abilities, and the implications of such a latent structure for talent cultivation and evaluation remain largely unexplored in systematic empirical research. Existing literature predominantly addresses individual skills or their application in specific contexts [9], failing to elucidate the overarching structure of digital skills from a macro perspective. This lack of understanding hinders enterprises from effectively prioritizing training program design, and the absence of standardized criteria for assessing employee skills constrains the efficiency of the digital transformation.

Therefore, this study seeks to address this gap by leveraging general ability theory [5] and employing exploratory factor analysis to empirically investigate the internal relationships and latent structures among six core digital skills of workers in Foshan's manufacturing industry. This research aims to ascertain the existence of a common, underlying capability—termed "digital literacy" [9]—and to elucidate the weight and hierarchy of each skill within this framework. By doing so, this study intends to provide scientific and data-driven decision-making support for manufacturing enterprises in Foshan and beyond, informing digital skills training, talent evaluation, and job matching.

2. Methodology

This study employs a quantitative empirical analysis methodology, with Exploratory Factor Analysis (EFA) serving as the principal technical method [10,11,12], to rigorously elucidate the latent common factors and internal structure underlying the six core digital skills of manufacturing employees in Foshan. The research design adheres to a stringent logical sequence: “data preparation—suitability testing—factor extraction and optimization—model construction.” The data utilized in this study is derived from the authoritative original dataset of the “2025 Guangzhou Industrial Worker Survey.” From this dataset, we meticulously selected 105 manufacturing employees from Sanshui District, Foshan, as valid samples, who met the statistical requirements for factor analysis (sample size > number of variables × 5) [10]. The observed variables in this study were the six core digital skills assessed in the questionnaire: C1—understanding equipment manuals, C2—equipment operation, C3—problem-solving through programming, C4—troubleshooting, C5—data observation, and C6—data analysis, all measured using a 5-point Likert scale.

Prior to the formal analysis, we conducted two essential preliminary tests to ensure that the data structure was appropriate for factor analysis. Initially, the KMO test was used to assess the strength of the partial correlations among the variables [10,13]. Its value (0.772) exceeded the recommended threshold of 0.7, indicating significant common variance among the variables and their suitability for factor extraction. Subsequently, Bartlett’s test of sphericity ($p < 0.001$) rejected the null hypothesis of mutual independence among the variables, confirming that the correlation matrix was not an identity matrix and that there was sufficient correlation among the variables, thereby providing statistical support for the validity of the factor analysis.

After passing these tests, we advanced to the core analysis phase. Principal Component Analysis (PCA) was initially used to extract the initial factors, with the objective of maximizing the explained total variance of the original variables [10]. To determine the number of factors to retain, we applied two mutually reinforcing criteria: the Kaiser criterion (retaining only factors with eigenvalues greater than 1) and scree plot analysis (observing the distinct “elbow” in the slope of the eigenvalue curve) [10,11]. Both methods indicated that extracting one common factor was optimal. Finally, to enhance the interpretability and theoretical significance of the extracted factors, we applied Varimax orthogonal rotation to the initial factor loading matrix [10]. This rotation method aims to maximize the variance of factor loadings, thereby simplifying the factor structure so that each observed variable loads highly on only one factor as much as possible. Consequently, the final latent factor generated (i.e., “digital literacy”) is rendered with a clearer, more distinct, and more convincing structure and definition.

3. Results

3.1. Correlation Analysis of Variables

Initially, a correlation analysis was performed on the six digital skills (C1-C6). The findings indicated moderate to strong positive correlations among all skills, with correlation coefficients ranging from 0.49 to 0.85 and an average coefficient of 0.629. As depicted in the correlation matrix heatmap (Figure 1), the intensity of the color corresponds to the strength of correlation. Notably, "Data Observation Ability" (C5) and "Data Analysis Ability" (C6) exhibited the strongest correlation, whereas "Device Manual Comprehension Ability" (C1) and "Programming Problem-Solving Ability"

(C3) demonstrated the weakest association. This preliminary result suggests that various skills are interdependent and develop synergistically, thereby providing empirical support for the subsequent factor analysis.

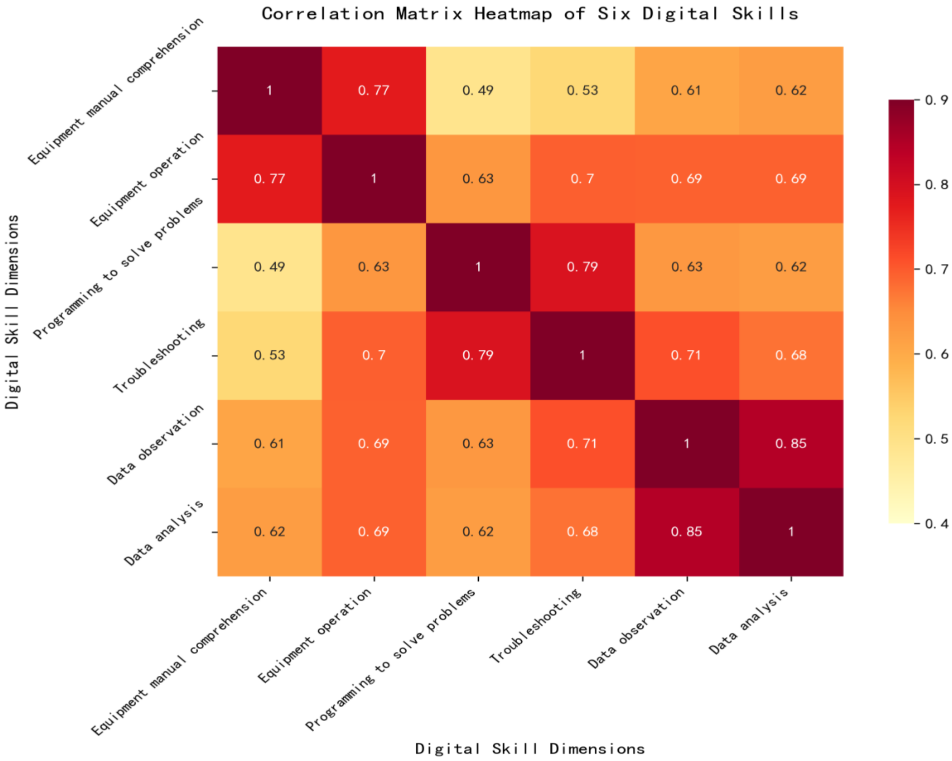

Figure 1. Heatmap of the Correlation Matrix for the Six Digital Skills

3.2. Factor Extraction and Determination of Factor Number

Employing principal component analysis to extract factors, the findings indicate that only the eigenvalue of the first factor (4.149) significantly exceeds 1, accounting for 69.1% of the total variance in the data. The eigenvalues of the subsequent factors were all below 1. As depicted in the scree plot of the factor analysis in Figure 2, the eigenvalue curve levels off rapidly after the first factor, creating a distinct "elbow." Based on the Kaiser criterion and scree plot analysis results, we concluded that a single common factor should be extracted to encapsulate these six digital skills.

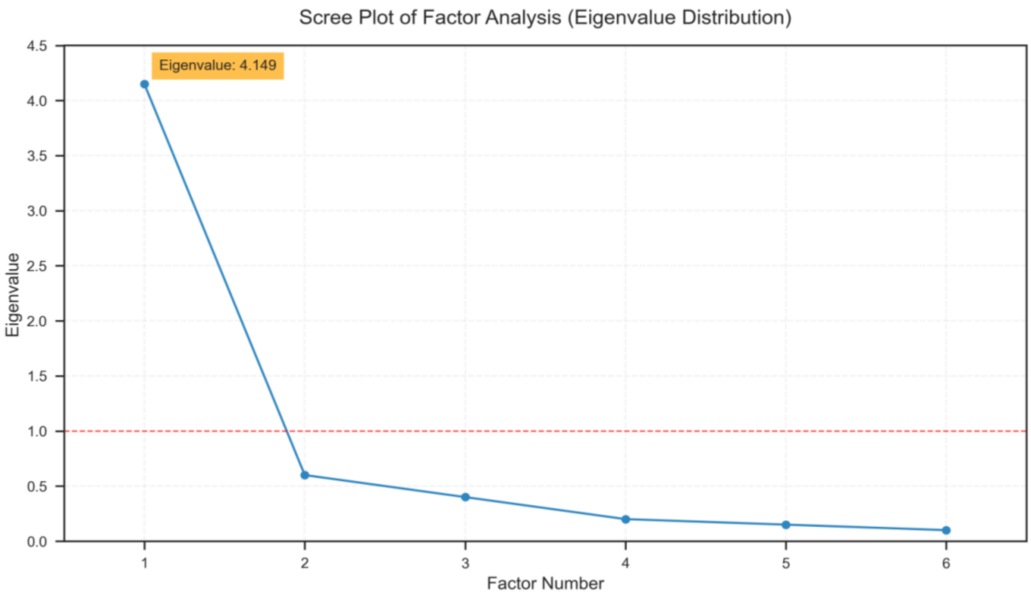

Figure 2. Scree Plot for Factor Analysis

3.3. Factor Rotation, Naming, and Structural Analysis

Following the application of Varimax orthogonal rotation, the single factor was designated as "digital literacy." All six skills exhibited substantial loadings on this factor, each exceeding 0.7, indicating a strong association with this common underlying literacy. As illustrated in Figure 3, which presents a dual-axis chart of factor loadings and skill contributions, the magnitude of the loadings for each skill reveals that "data observation ability" (loading 0.851) and "data analysis ability" (loading 0.846) are the principal components of "digital literacy," collectively accounting for 38.0% of the variance. Subsequently, "fault handling ability" (loading 0.805) contributed 17.1%. "Equipment manual comprehension ability" (loading 0.714) exhibited the lowest loading, serving as the foundational support layer.

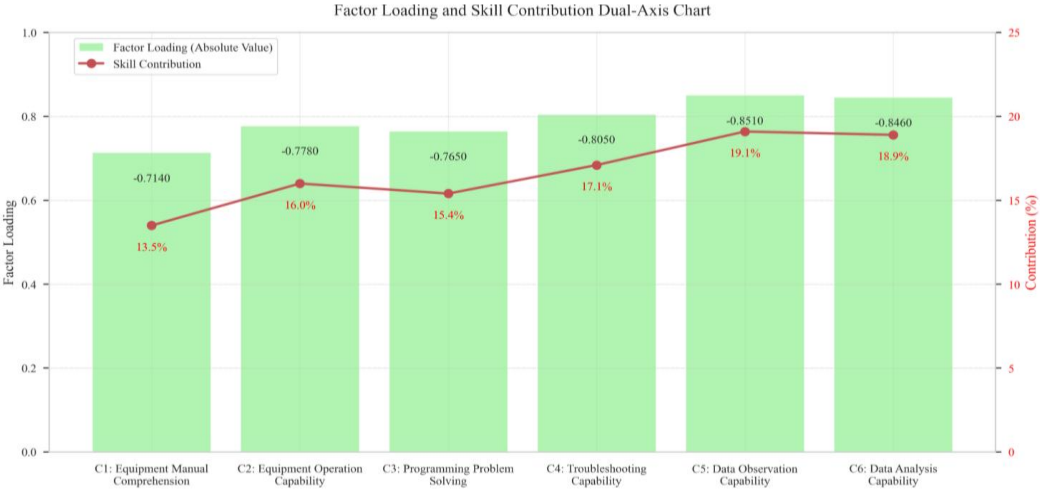

Figure 3. Dual-Axis Chart of Factor Loadings and Skill Contributions for the Digital Literacy Factor

3.4. Descriptive Analysis of Employees' Digital Skills

From the perspective of average skill scores, the average scores and box plot distribution of six digital skills (Figure 4) indicate that employees in Foshan's manufacturing sector demonstrate strong fundamental operational competencies but exhibit weaker proficiency in advanced analytical skills. Notably, "equipment operation ability" received the highest score, whereas "programming and problem-solving ability" and "data observation ability" were identified as the least developed skills.

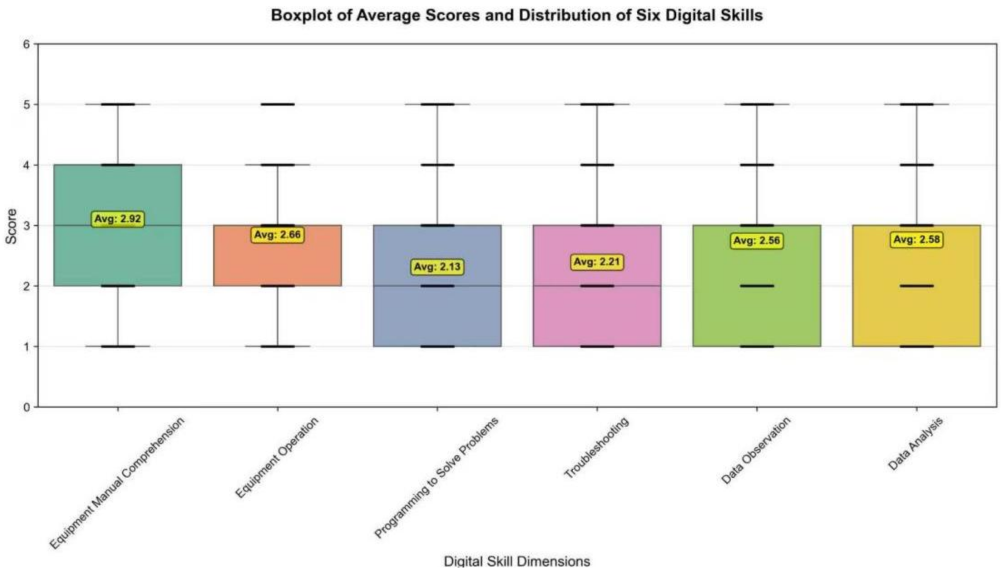

Figure 4. Box Plot of Mean Scores and Distribution of the Six Digital Skills

The radar chart depicting the digital skills of typical workers (Figure 5) further visually demonstrates the disparities in the development of these skills.

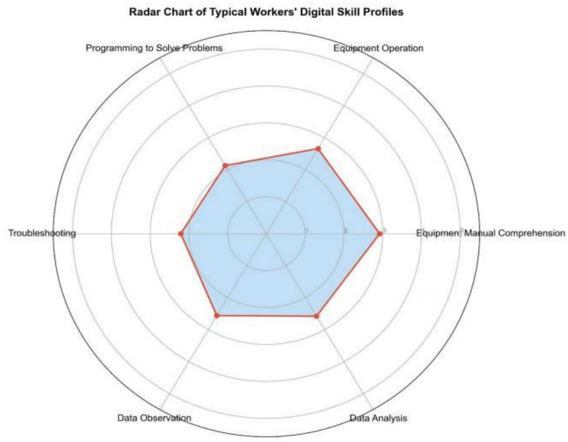

Figure 5. Radar Chart of a Typical Worker's Digital Skill Profile

Figure 6 illustrates the distribution of workers based on their calculated "digital literacy" factor scores. Workers are classified into three distinct categories: those with high digital literacy (score >1, comprising 14.3% of the sample), those with medium digital literacy (score between -1 and 1, comprising 66.7%), and those with low digital literacy (score <-1, comprising 19.0%). This categorization provides empirical support for enterprises to implement stratified and targeted talent management and training programs.

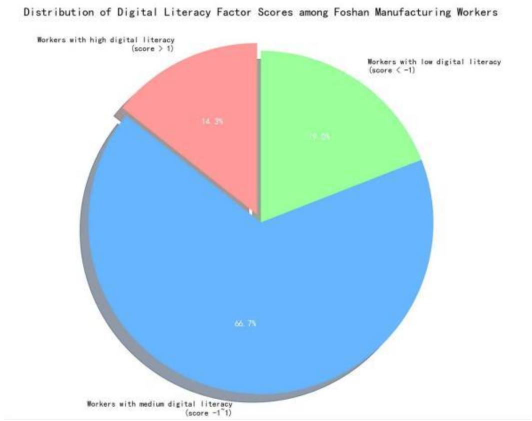

Figure 6. Distribution of Digital Literacy Factor Scores among Foshan Manufacturing Employees

3.5. Model Construction

Following the aforementioned analysis, a single-factor structural model of digital skills for manufacturing employees in Foshan was developed. This model demonstrates that all six observed skills are influenced by a singular "digital literacy" factor. The final model expression is:

$$F = 0.135C1 + 0.160C2 + 0.154C3 + 0.171C4 + 0.191C5 + 0.189C6 \qquad (1)$$

Among them, F represents the "digital literacy" factor score, and the coefficients are weights calculated for each skill based on its contribution.

4. Conclusions

This study undertook an exploratory factor analysis of six fundamental digital skills among 105 manufacturing workers in Foshan and yielded the following principal conclusions:

First, digital skills exhibit a singular underlying structure. The six digital skills of Foshan manufacturing workers are interrelated and can be collectively explained by a single latent factor, termed "digital literacy." This factor demonstrates substantial explanatory power, accounting for 69.1% of the total skill variance, thereby affirming the applicability of the "general ability theory" within the realm of digital skills.

Second, the skill structure reveals a distinct hierarchy. Within this unified framework of "digital literacy," the contributions of each skill vary, forming a four-tiered structure comprising "core layer–important layer–basic layer–supporting layer." Among these, data processing abilities, exemplified by "data observation" and "data analysis," constitute the core with the highest contribution; followed by problem-solving abilities such as "troubleshooting"; then equipment operation skills such as "device control"; and finally, basic comprehension abilities such as "understanding equipment manuals." This structure reflects the data-driven core trend of the digital transformation of the manufacturing industry.

Third, the current status of workers' skills is uneven. Currently, workers perform relatively well at the basic level of equipment operation; however, there are evident deficiencies in core data analysis and advanced problem-solving through programming. Concurrently, differentiation has begun to emerge within the workforce, resulting in three distinct groups of digital literacy: high, medium, and low digital literacy.

In summary, the findings of this study offer significant insights for enterprises and policy makers. Digital skills training should transition from traditional "individualized instruction" to an integrated model that emphasizes enhancing overall "digital literacy," with resource allocation based on skill levels and a primary focus on cultivating data processing abilities. In human resource management, the "digital literacy" factor score can be utilized for precise classification, scientific assessment, and optimized deployment of staff, thereby supporting the digital transformation of the manufacturing industry more effectively.

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