The Digital Transformation Factors Affected the Operation With Digital System in the Garment Manufacturing Industry in China

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Abstract

Digitalization is boosting the economy and society, but there's a lack of empirical research on the digital transformation of China's garment manufacturing industry. As a result, the purpose of this study aimed to determine the factors driving the digital transformation of China's garment manufacturing industry. In this study digital transformation was proposed to be affected by external factors, operation with digital system, organizational and management factors, and digital transformation of organization. The participants consisted of 260 executives and employees who were analyzed for valid and qualified respondents. The research instrument was a questionnaire. A second order confirmatory factor analysis was conducted to examine the proposed model. The findings revealed that there were seventeen factors which were significant at the 0.01 level. On the other hand, four factors were significant at the 0.05 level. Additionally, the correlation matrix analysis of 21 observed variables on Chinese garment manufacturing' digital transformation revealed a level of statistical significance of .05, and KMO was 0.697. The regression from diagram is analyzed in Null Plot. Thus, it can be summarized that the variance of each latent variables in the correlation matrix is acceptable to conduct a second order confirmatory factor analysis. Furthermore, the findings revealed that a set of statistics indicated that the proposed model showed a good fit of empirical date when chi-square = 421.676, degree of freedom = 174, $\square^2$ / df = 2.42, GFI = 0.90, AGFI = 0.86, NFI = 0.92, CFI = 0.97, RMR = 0.46, RMSEA = 0.068. Therefore, the proposed model is fitted to empirical data according to aforementioned goodness of fit indices. It can be summarized that there are four measurements that significantly affect the digital transformation of China's garment manufacturing industry including external factors, operation with digital system, organizational and management factors, and digital transformation of organization.

Keywords: Digital Transformation; Factors; China's Garment Manufacturing Industry; The operation with digital system

Introduction

Digitalization is increasingly driving economic and societal prosperity in today's era. As economic globalization continues, competition among garment companies has intensified, making technological innovation essential for sustainable growth (Mai and Yao, 2023). Research on digital transformation can be categorized into three areas. Some scholars focus on the background and current state of digital transformation. For example, Guxian (2019) highlighted that digital technology in clothing production can enhance efficiency by gathering consumer demand information, promoting industry chain development, and proposing

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a digital enterprise model based on the industrial Internet. Gonzalo et al. (2020) analyzed fashion industry sales before and after the pandemic, finding that highly digitalized companies better withstand its impact, making digital transformation a core strategy. In the post-pandemic era, a contactless economy will become the new norm.

Some researchers blend models in their research. For example, Jian et al. (2021) applied the C2M model to evaluate digital structure stability in the clothing industry, illustrating how digital transformation benefits top-notch garment companies. Sabrina et al. (2019) examined electronic supply chain management's role in Indonesia's apparel sector, underscoring its significant impact on the apparel value chain. Moreover, certain scholars concentrate on specific case studies. Songyuan and Genqin (2021) utilized the Y Group to advocate for a digital platform and bolster digitalization, stressing the need for management mechanisms and nurturing digital expertise in traditional clothing firms. The digital economy has emerged as a primary catalyst for global expansion, urging conventional manufacturing to embrace digital transformation for industrial advancement and stability. Shaoxing Keqiao, a key Chinese textile industry center, aspires to be "The World's Fashion Textile Capital" by prioritizing intelligence, upscale production, and globalization. It's imperative to tackle the challenges facing Shaoxing's textile manufacturing in digital transformation, propose remedies, and drive comprehensive enhancements to enhance China's standing in the global value chain (Yuxin et al., 2021).

Yuxin et al. (2021) highlighted issues within the Chinese textile manufacturing sector. Despite the industry's significant contribution, particularly in Shaoxing where it makes up 28% of the local economy and a third of Zhejiang's textile industry, the majority of textile enterprises are small or medium-sized, with only 1,862 meeting designated size criteria out of nearly 70,000 citywide. These smaller enterprises often grapple with outdated technology, limited innovation awareness, reliance on cheap labor for minimal profits, and a lack of digitalization. While many recognize the potential of digital transformation, constraints like capital and resources hinder progress, leaving intelligent manufacturing out of reach. The COVID-19 pandemic further exacerbated these challenges, especially for export-dependent businesses reliant on processing trade, with limited funds severely impeding comprehensive digital transformation efforts.

In 2020, Shaoxing's textile industry led China in innovation and digital intelligence, yet significant technological hurdles persist. Dependence on imported components and outdated equipment hinders data collection, integration, and intelligent operations. Traditional mindsets pose a major barrier to digital transformation, compounded by limited academic qualifications and resources, fostering reliance on imitative innovation. As industries evolve digitally, there's a growing need for professionals adept in both digital and industry knowledge. However, varying levels of informatization and transformation approaches among Chinese enterprises make replication of success impractical. Tailored transformation plans are essential. Despite this, garment enterprises face talent shortages in advanced design, technical management, and research. Geographical constraints in Shaoxing deter high-level digital talent, exacerbating a long-term structural shortage (Yuxin et al., 2021).

According to a report by management consultants McKinsey, for example, in 2018, the proportion of Chinese companies that were active in the Cloud was only 40%, compared to 85% in the US and 70% in the EU (Dong et al., 2018). Only 46% of Chinese manufacturing companies surveyed in 2016 had dedicated Industrial Internet of Things (IIoT) strategies. The most significant barriers cited were a lack of interoperability and common standards, data ownership and security concerns, and under-qualified operators (Deloitte, 2017). Furthermore, more than half of the surveyed Chinese manufacturing companies did not have industrial clouds in place in 2017 (Deloitte, 2019). However, there has been very little digital research with the garment manufacturing industry as the primary research object. There is insufficient empirical evidence to conduct research on performance evaluation and driving factors in the Chinese garment manufacturing industry's digital transformation. As a result, the purpose of this research is to assess the digitalization performance of China's garment manufacturing industry. It also aims to survey driving factors in the Chinese garment manufacturing industry's digital transformation in order to provide key findings for the Chinese garment manufacturing industry to find new developments in digital industrial platforms.

Research Objective

The purpose of this study aims to determine the factors driving the digital transformation of China's garment manufacturing industry.

Literature Review

Digitalization is increasingly driving economic and societal prosperity in today's era. With ongoing economic globalization, competition among garment companies has intensified, making technological innovation essential for sustainable development (Mai and Yao, 2023). Research on digital transformation is categorized into three areas. Some scholars focus on the background and current state of digital transformation. For instance, Guxian (2019) found that digital technology can enhance clothing production by gathering consumer demand information, promoting efficient industry chain development, and proposing a digital enterprise model based on the industrial Internet. Gonzalo et al. (2020) analyzed fashion industry sales before and after the pandemic, concluding that highly digitalized companies better withstand the pandemic's impact, making digital transformation a core strategy. In the post-pandemic era, the contactless economy will become the norm.

Research by Yuxin et al. (2021) identified several issues in the Chinese textile manufacturing industry. As of 2019, Shaoxing's textile industry comprised 28% of its industrial economy and about one-third of Zhejiang's total, making it the largest in China by scale. However, only 1,862 of Shaoxing's nearly 70,000 textile enterprises are large, with small and medium-sized businesses (SMEs) dominating. These SMEs often struggle with outdated production technology, a lack of innovation, reliance on low-cost labor, and insufficient digitalization. Despite recognizing the potential of digital transformation, many cannot afford intelligent production line upgrades due to limited capital and resources. The COVID-19 pandemic has worsened the situation, particularly for export-dependent businesses, severely hindering their digital transformation efforts.

A McKinsey report in 2018 highlighted that only 40% of Chinese companies were using cloud technology, compared to 85% in the US and 70% in the EU (Dong et al., 2018). In 2016, only 46% of Chinese manufacturing companies had Industrial Internet of Things (IIoT) strategies, with major barriers including lack of interoperability and common standards, data ownership and security concerns, and under-qualified operators (Deloitte, 2017). By 2017, more than half of these companies still lacked industrial clouds (Deloitte, 2019). Despite this, there is limited research focusing on digital transformation in the garment manufacturing industry, with insufficient empirical evidence on performance evaluation and driving factors. Therefore, this research aims to assess the digitalization performance of China's garment manufacturing industry and identify key factors driving its digital transformation to support new developments in digital industrial platforms.

Research Methodology

This research was conducted using the steps involved in quantitative research as follows.

Population

The purpose sampling rule is commonly employed in multi-case studies to effectively control external influences and limit the scope of research results. In this study, the population was drawn from three garment manufacturing industries that have adopted AI technology. These industries were selected based on research design, data availability and quality, theoretical requirements, and the marginal utility of including additional industries. The selected industries are leading players in the Chinese garment manufacturing sector, with abundant public data and online information, and AI technology plays a significant role in transforming traditional manufacturing and creating value for enterprises (Wang and Su, 2021).

This study selects three industries that represent different approaches to AI adoption. Industry A has established a wholly owned IT subsidiary early on, Industry B utilizes its industrial internet platform to form a cooperative holding company and leverage external resources alongside its own technology, while Industry C adopts a completely outsourced development model. The background and implementation of the 'AI+' mode in each industry are introduced in this section (Wang and Su, 2021). Table 1 provides detailed information on these industries.

Table 1 Basic information and features of industries

Basic features	Industry A	Industry B	Industry C
Ownership type	Listed industry (state-owned)	Private (shareholding)	Local state-owned (shareholding)
Main products	Garment manufacturing industry		
Annual sales turnover	¥45 million	¥38 million	¥23 million

Basic features	Industry A	Industry B	Industry C
AI adoption model	Wholly-owned subsidiary (established in 2016)	Holding company (established in 2015)	Outsourcing
Intelligent manufacturing method	Digitalize the entire value chain and process equipment with intelligent manufacturing technologies.	Adopt a product lifecycle management platform and build a cloud intelligent system.	Use information system to connect equipment terminals.
Intelligent manufacturing features	Integration of the informatization and industrialization.	From selling products to selling services; intelligent synchronization of internal and external.	Digital factory technology
Progress in intelligent manufacturing	Leading the industry in both the number and the application of intelligent devices.	Transform from a Traditional manufacturing enterprise to a high-end intelligent service enterprise.	Smart factory with large-scale computing systems and production equipment.
Interviewee	The executives and employees including technician, product manager, product director, technology department leader, AI team members, etc.		
Supplementary data sources	Official Website; News Report; Public Annual Report	Official Website; News Report; Public Annual Report	Official Website; News Report; Public Annual Report

Source: Adapted from Wang and Su (2021)

Sample Size

Determining the sample size was crucial for statistical analysis in this study. A total of 260 executives and employees were selected through convenience sampling, all of whom were knowledgeable about digital transformation in garment manufacturing. According to

Hair et al. (2010), sample size guidelines for Structural Equation Model (SEM) analysis recommend a minimum of 100 for models with up to five constructs, 150 for seven constructs with moderate communalities, 300 for seven constructs with low communalities, and 500 for complex models. Kline (2011) suggests having 10-20 respondents per parameter. Thus, the sample size of 260 is sufficient for the SEM analysis in this study, which involves 21 measurements and 5 hypotheses.

Data Collection

According to study driving factors about digital transformation in the Chinese garment manufacturing industry as aforementioned in chapter 1, several studies have collected data from the other companies or enterprises, therefore the results could not single out driving factors relative influence on digital transformation of the Chinese garment manufacturing industry (Hsu and Lam, 2003). The qualified respondents needed to be the executives and employees, who have some awareness about digital transformation of the Chinese garment manufacturing industry. Additionally, this study employed an online questionnaire survey for data collection. The questionnaire will be launched on Wjx.cn, a popular Chinese survey platform, allowing respondents to complete the survey via the website. The data collection period is scheduled from May 1st to May 30th, 2024.

Survey Instrument

The questionnaire was designed as a research instrument based on the comprehensive review of relevant literature focusing on driving factors about digital transformation in the Chinese garment manufacturing industry. The draft questionnaire was also viewed by the executives, employees, and academic scholars who provided helpful comments and feedback to revise and develop appropriate instruments for this research. The questionnaire was originally developed in English and then translated into Chinese. A back-translation was carefully translated and checked the correspondent of meaning between the two versions by an academic scholar to ensure that both English and Chinese versions were comparable. The equivalence of the translation must be verified. According to Beaton et al. (2000), a Back-translation is a very helpful tool for a cross cultural study, the items of the original instrument must be translated into the language of the target and adjusted for cultural differences to maintain content validity. The electronic survey is utilized to collect data of this study and the result is reported in English. The data collected from electronic survey. The questionnaire consists of 5 sections as shown in Table 2.

Table 2 Structure of the survey instrument

Section	Questionnaire Included
1	Demographic Characteristics; gender, age, marital status, educational background, ownership type, annual sales turnover, AI adoption model, intelligent manufacturing method, intelligent manufacturing features, progress in intelligent manufacturing, and supplementary data sources.
2	External factors - Customer behaviours and expectations - Digital shifts in the industry - Changing competitive landscape - Regulative changes

Section	Questionnaire Included
3	Operation with digital system - Ensuring digital readiness - Digitally enhancing products and services - Embracing product innovation - Developing new business models - Improving digital channels - Increasing customer satisfaction
4	Organizational and management factors - A supportive organizational culture - Well-managed transformation activities - Leveraging external and internal knowledge - Engaging managers and employees - Growing information system capabilities - Developing dynamic capabilities - Developing a digital business strategy - Aligning business and information systems
5	Digital transformation of organization - Reforming an organization's information system - New business models - Affecting outcomes and performance

Source: Adapted from Osmundsen et al. (2018)

The five academic scholars and experts in the department of Business Administration, Rangsit University were requested to review the content reliability and validity of the indicators and evaluated indicators of each construct and gave the useful suggestion to organize the appropriate instrument for this research. The research instrument was corrected and adjusted in accordance with the recommendations and comments. The Index of Item Objective Congruence (IOC) was applied to find the content validity. The Item Objective Congruence (IOC) was used to evaluate the items of the questionnaire based on the score range from -1 to +1. Congruent = + 1 Questionable = 0 Incongruent = -1. The items that had scores lower than 0.5 were revised. On the other hand, the items that had scores higher than or equal to 0.5 were reserved. After the items of the measurement scales were adjusted and developed, the pre-testing of the scales was conducted in order to evaluate the reliability and validity of this research before gathering data (Hinkin et al., 1997). According to the determine pilot sample size using the confidence interval approach, a sample with 80% accuracy at the 95% confidence level was calculated as n = 1.962 (0.5*0.5)/ 0.22, The result based on this formula is 25 (Chi, 2005). Thus, the first version of questionnaire was conducted and distributed in a small-scale preliminary testing to 30 Chinese executives and employees in the garment manufacturing industry in order to ensure the reliability and validity of the construct before the main research.

The scale in this study was adapted from established existing measures that have been applied and validated in several of the garment manufacturing industry research. In order to ensure that the measurement scale was reliable, the reliability of measurement is examined by Cronbach’s alpha test which is frequently used in various research. The reliability coefficients score is generally agreed upon limit for Cronbach’s Alpha is 0.70 which is defined as adequate, while 0.80 and 0.90 are defined as good and excellent respectively (Chang, 2013; Kim, 2015). The discrimination indices of the research instrument are analyzed to measure how well an item was able to distinguish by using Pearson product moment coefficient between the item's scores and the total test scores with the pilot survey data, the total test scores are derived partly from that item's scores. The correlational indices, so values can range from -1.00 to 1.00 and more than 0.20 is defined as acceptable (Ebel and Frisbie, 1986).

According to the survey from pilot study of 30 respondents, the reliability of research instrument was examined by Cronbach's alpha test together with the discrimination indices of each research construct from analyzing the result from the survey in section 2 to section 5. Table 3 presents Cronbach's alpha coefficient and item discrimination index from the reliability testing.

Table 3 Reliability testing and Discrimination Index

Item	Cronbach's Alpha Coefficient	Item Discrimination Indices
External factors - Customer behaviors and expectations - Digital shifts in the industry - Changing competitive landscape - Regulative changes	0.704	0.612-0.706
Operation with digital system - Ensuring digital readiness - Digitally enhancing products and services - Embracing product innovation - Developing new business models - Improving digital channels - Increasing customer satisfaction	0.862	0.532-0.773
Organizational and management factors - A supportive organizational culture - Well-managed transformation activities - Leveraging external and internal knowledge - Engaging managers and employees - Growing information system capabilities - Developing dynamic capabilities - Developing a digital business strategy - Aligning business and information systems	0.935	0.584-0.784
Digital transformation of organization - Reforming an organization's information system - New business models - Affecting outcomes and performance	0.857	0.614-0.799

Statistical Methods

The Structural Equation Model (SEM) was utilized to estimate the causal relationship model and confirm the relationship between observed variables and corresponding latent variables. To assess the overall fit of the proposed model, multiple goodness-of-fit indices were employed. According to Kline (2011), various fit indices, including the goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), normed fit index (NFI), comparative fit index (CFI), root mean square residual (RMR), and root mean square error of approximation (RMSEA), should be used to evaluate model fit comprehensively. Additionally, Kline (2004) suggested that the relative chi-square statistic (χ^2/df) should be considered satisfactory when its value is less than 3 in large samples (N > 200), less than 2.5 in medium-sized samples (100 < N < 200), and less than 2 in small samples (N < 100). Since the sample size in this study exceeds 200, a χ^2/df value less than 3 indicates a reasonable model fit. Table 4 displays acceptable thresholds for these goodness-of-fit indices used in SEM (Kline, 2011).

Table 4 Goodness-of-fit indices Criteria

Fit Index	Criteria
Goodness-of-fit Index (GFI)	> .90
Adjusted Goodness-of-fit Index (AGFI)	> .90
Normed Fit Index (NFI)	> .90
Comparative Fit Index (CFI)	> .90
Root Mean Square Residual (RMR)	< .50
Root Mean Square Error of Approximation (RMSEA)	< .08
Relative Chi Square (χ^2 / df)	< 3.0

Source: Applied from Kline (2011)

Research Conceptual Framework

In association with the research objectives, 4 latent variables and 21 observed variables were proposed based on the extensive literature review. In the proposed model, the research hypotheses and proposition derived from the literature based on the theories of related constructs of digital transformation in manufacturing industry. The conceptual framework is shown in figure 1

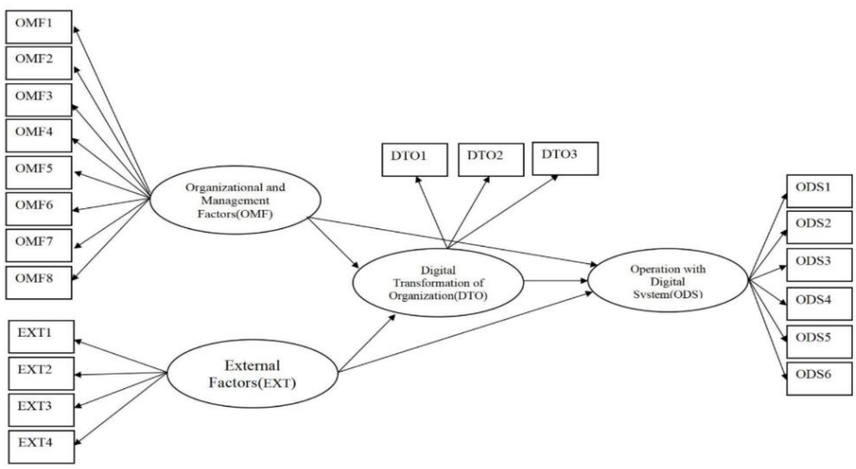

Figure 1 Research Conceptual Framework

Note*: OMF = Organizational and management factors, OMF1 = A supportive organizational culture, OMF2 = Well-managed transformation activities, OMF3 = Leveraging external and internal knowledge, OMF4 = Engaging managers and employees, OMF5 = Growing information system capabilities, OMF6 = Developing dynamic capabilities, OMF7 = Developing a digital business strategy, OMF8 = Aligning business and information systems, EXT = External factors, EXT1 = Customer behaviors and expectations , EXT2 = Digital shifts in the industry, EXT3 = Changing competitive landscape , EXT4 = Regulative changes , DTO = Digital transformation of organization , DTO1 = Reforming an organization's information system , DTO2 = New business models , DTO3 = Affecting outcomes and performance, ODS = Operation with digital system , ODS1 = Ensuring digital readiness , ODS2 = Digitally enhancing products and services, ODS3 = Embracing product innovation , ODS4 = Developing new business models , ODS5 = Improving digital channels , ODS6 = Increasing customer satisfaction

Research Results

The findings of correlation matrix of latent variables in the overall measurement model revealed that all variables in correlation matrix had a value of correlation between 0.073 – 0.897. The correlation matrix analysis of 21 observed variables on Chinese garment manufacturing' digital transformation revealed a level of statistical significance of .05, and KMO was 0.697. The regression from diagram is analyzed in Null Plot. Thus, it can be summarized that the variance of each latent variables in the correlation matrix is acceptable to conduct a second order confirmatory factor analysis. The findings are shown in Figure 2.

Variables	EXT1	EXT2	EXT3	EXT4	ODS1	ODS2	ODS3	ODS4	ODS5	ODS6	OMF1	OMF2	OMF3	OMF4	OMF5	OMF6	OMF7	OMF8	DTO1	DTO2	DTO3
EXT1	1.000																				
EXT2	.448**	1.000																			
EXT3	.418**	.373**	1.000																		
EXT4	.286**	.405**	.551**	1.000																	
ODS1	.183**	.301**	.390**	.448**	1.000																
ODS2	.341**	.297**	.308**	.315**	.496**	1.000															
ODS3	.166**	.214**	.309**	.324**	.490**	.376**	1.000														
ODS4	.325**	.153**	.284**	.323**	.360**	.439**	.424**	1.000													
ODS5	.641**	.270**	.273**	.195**	.107**	.208**	.107**	.196**	1.000												
ODS6	.277**	.687**	.310**	.313**	.234**	.197**	.192**	.119**	.361**	1.000											
OMF1	.264**	.260**	.705**	.394**	.305**	.220**	.233**	.223**	.454**	.443**	1.000										
OMF2	.173**	.268**	.398**	.761**	.339**	.244**	.277**	.227**	.264**	.507**	.534**	1.000									
OMF3	.120**	.200**	.281**	.308**	.739**	.398**	.413**	.319**	.216**	.362**	.442**	.458**	1.000								
OMF4	.210**	.200**	.232**	.266**	.393**	.724**	.316**	.355**	.274**	.315**	.280**	.347**	.473**	1.000							
OMF5	.084*	.147**	.195**	.234**	.383**	.276**	.708**	.377**	.260**	.237**	.400**	.281**	.443**	.354**	1.000						
OMF6	.166**	.084**	.214**	.232**	.320**	.351**	.366**	.727**	.194**	.176**	.237**	.303**	.344**	.412**	.386**	1.000					
OMF7	.624**	.231**	.245**	.149**	.076*	.160**	.073*	.155**	.839**	.344**	.405**	.225**	.120**	.230**	.211**	.254**	1.000				
OMF8	.279**	.728**	.304**	.301**	.199**	.189**	.159**	.105**	.334**	.891**	.364**	.387**	.277**	.264**	.224**	.219**	.390**	1.000			
DTO1	.253**	.245**	.713**	.367**	.233**	.179**	.177**	.186**	.394**	.354**	.857**	.432**	.283**	.245**	.314**	.273**	.516**	.408**	1.000		
DTO2	.170**	.284**	.400**	.774**	.292**	.235**	.234**	.219**	.204**	.394**	.444**	.897**	.361**	.283**	.274**	.370**	.261**	.449**	.492**	1.000	
DTO3	.111**	.201**	.284**	.297**	.743**	.383**	.383**	.300**	.101*	.289**	.295**	.373**	.856**	.449**	.406**	.435**	.149**	.362**	.335**	.451**	1.000
Mean	3.33	3.36	3.34	3.24	3.38	3.27	3.35	3.24	3.39	3.41	3.32	3.28	3.38	3.39	3.36	3.25	3.36	3.39	3.29	3.23	3.37
S.D.	0.80	0.79	0.83	0.84	0.76	0.83	0.81	0.82	0.77	0.76	0.82	0.80	0.74	0.78	0.79	0.74	0.74	0.72	0.77	0.75	0.70
Bartlett's Test of Sphericity = 10867.112, df = 210, p = .00, KMO = 0.697																					

**p<0.01, *p<0.05

Figure 2 Correlation matrix of latent variables in the overall measurement model

After the overall measurement model was found acceptable, the structural model was tested with the collective data (n=500). A set of statistics indicated that the proposed model showed a good fit of empirical date when chi-square = 421.676, degree of freedom = 174, □^{2} / df = 2.42, GFI = 0.90, AGFI = 0.86, NFI = 0.92, CFI = 0.97, RMR = 0.46, RMSEA = 0.068. Therefore, the proposed model is fitted to empirical data according to aforementioned goodness of fit indices. The findings are shown in Table 5 and Figure 3.

Table 5 The Validity Analysis of the Conceptual Elements of Digital Transformation Model

Variables	b	SE	t	R^2
External factors (EXT)	0.710	0.043	8.290	0.504
Customer behaviors and expectations: EXT1 (y1)	0.407	0.047	4.338	0.165
Digital shifts in the industry: EXT2 (y2)	0.509	0.046	5.507	0.259
Changing competitive landscape: EXT3 (y3)	0.586	0.039	7.537	0.343
Regulative changes: EXT4 (y4)	0.715	0.037	9.583	0.511
Operation with digital system (ODS)	0.931	0.027	17.506	0.867
Ensuring digital readiness: ODS1 (y5)	0.558	0.044	6.373	0.311
Digitally enhancing products and services: ODS2 (y6)	0.512	0.051	5.000	0.262
Embracing product innovation: ODS3 (y7)	0.553	0.049	5.681	0.306
Developing new business models: ODS4 (y8)	0.561	0.048	5.905	0.315
Improving digital channels: ODS5 (y9)	0.477	0.045	5.330	0.227
Increasing customer satisfaction: ODS6 (y10)	0.515	0.043	5.971	0.265
Organizational and management factors (OMF)	1.002	0.020	17.403	0.735
A supportive organizational culture: OMF1 (y11)	0.574	0.038	7.494	0.330
Well-managed transformation activities: OMF2 (y12)	0.634	0.038	8.398	0.402
Leveraging external and internal knowledge: OMF3 (y13)	0.631	0.038	8.362	0.398
Engaging managers and employees: OMF4 (y14)	0.587	0.047	6.244	0.344
Growing information system capabilities: OMF5 (y15)	0.601	0.045	6.661	0.362
Developing dynamic capabilities: OMF6 (y16)	0.595	0.045	6.600	0.354
Developing a digital business strategy: OMF7 (y17)	0.434	0.045	4.859	0.189

Variables	b	SE	t	R^2
Aligning business and information systems: OMF8 (y18)	0.496	0.044	5.660	0.246
Digital transformation of organization (DTO)	0.877	0.026	17.109	0.769
Reforming an organization's information system: DTO1 (y19)	0.553	0.037	7.390	0.306
New business models: DTO2 (y20)	0.717	0.035	10.335	0.514
Affecting outcomes and performance: DTO3 (y21)	0.652	0.035	9.297	0.425
Relative Chi-square (c^2 / df) = 2.42, GFI = 0.90, AGFI = 0.86**, NFI = 0.92, CFI = 0.97, RMR = 0.46, RMSEA = 0.068				

The following figure depicts a second order confirmatory factor analysis of digital transformation model.

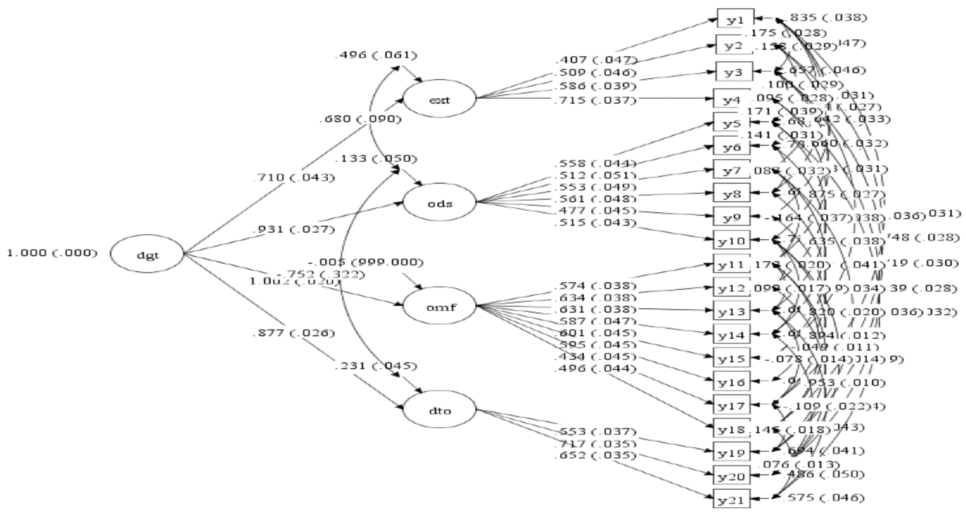

Figure 3 A second order confirmatory factor analysis of digital transformation model

Discussion

According to the finding, external factors' constraints significantly affected digital transformation of Chinese manufacturing industry because the external factors of digital transformation were instrumental in shaping the future of the Chinese manufacturing industry. Embracing these external factors enabled manufacturers to stay competitive, meet consumer expectations, and contribute to economic growth, positioning China as a leader in the global digital manufacturing landscape. The findings were compiled to the study of Mizark (2023) who sated that the external factors of digital transformation play a critical role in propelling the Chinese manufacturing industry toward a future characterized by innovation, efficiency, and competitiveness. It also was in line with Belhadi et al. (2022) who said that evolving consumer preferences and demands for personalized, high-quality products drive manufacturers to embrace digital technologies. Meeting these expectations often requires advanced technologies for customization, quick response to market trends, and efficient supply chain management. Moreover, Digital transformation serves as a catalyst for innovation in manufacturing processes, product design, and R&D. Companies investing in digital technologies can accelerate the pace of innovation, introducing new products and services to the market more rapidly than their competitors (Santarsiero et al., 2022).

The research findings also found that operation with digital system significantly affected the digital transformation of the Chinese garment manufacturing industry. The operation with digital system set by businesses in the Chinese garment manufacturing industry were instrumental in driving and shaping the course of digital transformation. The operation with digital system set by Chinese garment manufacturers played a pivotal role in guiding the digital transformation journey. Whether focused on efficiency, innovation, customer satisfaction, or global competitiveness, these operations with digital systems shaped the strategic direction and priorities of the industry, making digital transformation a key enabler for achieving success in a rapidly evolving market. The findings were consistent with Yu et al. (2022) who stated that the operation with digital system of digital transformation is closely aligned with the broader business goals of Chinese garment manufacturers. Whether the focus is on expanding market share, enhancing operational efficiency, or entering new markets, digital transformation is a strategic enabler that helps achieve these objectives. The findings were in line with Zhu et al. (2023) who said that operation with digital system often includes fostering innovation in product design and development. By incorporating technologies such as computer-aided design (CAD) and advanced prototyping tools, Chinese garment manufacturers can bring new and innovative products to market faster.

Furthermore, organizational and management factors significantly affected the digital transformation of the Chinese garment manufacturing industry. The organizational and management factors in the digital transformation of the Chinese garment manufacturing industry were crucial as they directly influence the effectiveness and sustainability of the transformation journey. These factors served as the guiding principles and determinants that contribute to achieving positive outcomes, ensuring that digital initiatives align with business objectives, enhance operational capabilities, and position the industry competitively in the global market. In essence, success factors provide the essential framework for navigating the complexities of digital transformation, fostering innovation, and adapting to the evolving landscape of the garment manufacturing sector in China. These findings were consistent with Mohammadi et al. (2023) who sated that organizational and management factors ensure that digital transformation initiatives are closely aligned with the overarching business objectives of Chinese garment manufacturers. When strategies and technologies are designed to meet specific business goals, the likelihood of success increases, fostering a more purposeful and results-driven transformation. The study of Kunduru (2023) also reported that organizational and management factors emphasize the importance of enhancing operational efficiency and adaptability. By identifying and prioritizing factors that contribute to streamlined processes and agile operations, the industry can respond swiftly to market changes, customer demands, and other dynamic factors.

In addition, digital transformation of organization significantly affected the digital transformation of the Chinese garment manufacturing industry. Digital transformation of organization significantly affected the digital transformation of the Chinese garment manufacturing industry as they encompassed the far-reaching consequences, both positive and negative, that arise from the adoption and integration of digital technologies. This digital transformation of organization guided decision-making, strategy development, and resource allocation, shaping the industry's trajectory in the digital era. Understanding the digital transformation of organization ensured that Chinese garment manufacturers can proactively address challenges, capitalize on opportunities, and navigate the complexities inherent in the transformative process, ultimately influencing the overall success and sustainability of digital initiatives in the sector. The findings were in line with Scott and Orlikowski (2022) who suggested that digital transformation of organization encompass the economic and environmental impact of digital transformation. Manufacturers need to consider how their initiatives contribute to economic growth, job creation, and sustainability goals. Understanding this digital transformation of organization ensures a holistic approach to digital transformation that aligns with broader societal objectives. The study of Holmstrom (2022) found that digital transformation of organization dictates the operational changes that come with digital transformation. Manufacturers need to understand how adopting digital technologies will reshape their internal processes, supply chain dynamics, and overall workflow. This knowledge enables them to proactively manage and optimize these changes for improved efficiency.

Recommendations

This research building upon previous theories extends the knowledge on digital transformation of Chinese garment manufacturing industry. The benefit of this study can be integrated to various sectors such as nation / government sector, business and organization and academic area. Future study should evaluate the patterns and trends in the adoption of digital technologies within the Chinese garment manufacturing sector. It also examines the prevalence of specific technologies, the rate of adoption, and factors influencing companies' decisions to embrace or resist digital transformation. Moreover, the study should analyze how digital transformation impacts operational processes within garment manufacturing. It should explore changes in design, production, quality control, and supply chain management. It also can be able to consider the implications for efficiency, productivity, and overall business performance. In addition, future studies should investigate the transformation of supply chain dynamics driven by digital technologies. Additionally, it should be considered to examine the role of blockchain, real-time tracking systems, and data analytics in enhancing transparency, traceability, and collaboration within the supply chain.

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