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The Impact of Customer Demand Orientation on Digital Transformation of Enterprises

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Abstract

With the continuous development of science and technology, the digital transformation of enterprises has become one of the core forces to maintain competitiveness and create lasting value. However, this transformation is not only a technical change but also a strategic process that requires deep insight and flexibility. Building on theories of customer value theory and data-driven decision-making, this paper explores the impact of customer demand orientation on the level of enterprise digital transformation based on the data collected from manufacturing enterprises in China's A-share and Shanghai stock markets from 2010 to 2021. We find that the degree of customer demand orientation has a positive impact on the level of digital transformation; further, this main effect is moderated by industry concentration externally and investor interaction response internally. More specifically, the more intense the competition in the industry and the shorter the response time of enterprises to investors' questions on the interactive e-platform, the stronger the impact of customer demand orientation on the level of digital transformation. These insights introduce novel effects from several perspectives on enterprise digital transformation, offering significant theoretical and practical implications for policy-makers and enterprise decision-makers regarding business digital transformation.

Keywords: Customer demand orientation, Industry concentration, Investor interaction response, Level of digital transformation.

1. Introduction

With the rapid development of the economy and the universal popularization of the Internet, the speed of the development of the digital economy, the breadth of its radiation scope, and the extent of its far-reaching influence have reached an unprecedented point. Due to economic growth and social progress, consumer demand is constantly upgraded, and customer demand has become an important issue that enterprises must address. Customer demand orientation requires enterprises not only to meet the diversified needs of customers but also to reflect the personalized elements in products and services to enhance the sense of customer participation and experience. This requires enterprises to conduct in-depth market research and analysis to master and understand customer needs and consumption trends in order to implement precision marketing and customized services.

Digital transformation is an important means for enterprises to adapt to the development of the times and can help them improve production efficiency, reduce costs, optimize resource allocation, and enhance market competitiveness (Schweidel et al., 2022). Under the influence of customer demand orientation, enterprises need to increase investment in R&D and innovation so as to obtain technology and production capacity that can meet customer demand, and realize the common development of enterprises and customers in the process of focusing on customer demand and digital transformation.

Building on theories of customer value theory and data-driven decision-making, this paper explores the impact of customer demand orientation on the level of enterprise digital transformation based on the data collected from manufacturing enterprises in China's A-share and Shanghai stock markets from 2010 to 2021. Through text analysis to explore the key information in enterprise annual reports, we count the word frequency of keywords such as personalized, customized, and customer-oriented in these reports and take the logarithmic processing as the enterprise's score of customer demand orientation. At the same time, we define the level of digital transformation of enterprises by digital and intelligent readiness and contribution to digital intelligence. Digital and intelligent readiness is measured by CIO (Chief Information Officer), innovation-oriented foresight, innovation-oriented continuity, and innovation-oriented intensity. Contribution to digital intelligence is measured by normalizing the number of Numerical Intelligence-related patents obtained by a company each year.

Our research provides several interesting results that can inform business strategy regarding enterprise's digital transformation. Firstly, the degree of customer demand orientation positively affects digital transformation. In order to meet customers' personalized needs, enterprises need to continuously upgrade technology and digital transformation, optimize business processes and production processes, and improve their digital transformation level. Secondly, industry concentration negatively moderates the relationship between customer demand orientation and the level of digital transformation. In industries with lower industry concentration, enterprises face more intense competition, and in order to excel in the competition, they need to respond to customers' personalized needs faster and more efficiently. Finally, investor interaction response negatively moderates the relationship between customer demand orientation and the level of digital transformation. By responding quickly to investor needs and feedback, listed companies can better understand market dynamics and customer needs, and then adjust their own strategies and business models to improve their level of digital transformation.

Our research also makes the following theoretical contributions: firstly, it provides theoretical support and guidance for enterprise to facilitate digital transformation. Studying the influencing factors and evaluation methods of their digital transformation level can help enterprises clarify their advantages and disadvantages in the process of digital transformation, so as to formulate a more scientific and reasonable transformation strategy. Secondly, we bridge the gap between the research on enterprise digital transformation and customer demand which is under explored in literature. This study combines these two fields, and provides novel insights through using updated text analysis methods. Thirdly, our research provides practical guidance for policymakers and enterprise decision makers regarding digital transformation strategy. For example, policymakers can use this study to understand the difficulties and challenges faced by enterprises in the process of digital transformation, so as to formulate more targeted policy measures. With regard to enterprise decision makers, this study can help them understand the impact of customers' personalized needs on the digital transformation of enterprises, so that they can formulate more accurate marketing strategies.

2. Theoretical Background and Hypothesis Development

2.1. Customer Demand Orientation

Customer orientation refers to the degree to which an organization and its employees are committed to meeting customer needs and improving the customer experience (Kiffin-Petersen & Soutar, 2020). It guides companies to continually improve their offerings to customers (Ghouri et al., 2021), facilitate the development of new products and/or services, ensure that customer value management is more customer driven than IT driven, develop customer service quality to improve customer satisfaction, loyalty, retention.

Since the 1990s, with rapid advancements in productivity, more firms have acknowledged the impact of customer orientation on product development and performance. The higher the degree of customer orientation, the more emphasis firms place on understanding and satisfying customer needs. Correspondingly a good understanding of customer orientation is a key requirement for companies to be competitive in the marketplace (Alt et al., 2019), which in turn promotes the level of digital transformation. As a catalyst, digital marketing promotes consumer interaction, recognition of the brand, and broadening company growth (Zannat et al., 2024).

Personalization refers to tailoring products, services, or interactions based on customer data and preferences inferred from their behavior, aiming to meet their unique needs and expectations. There are three types of personalization: user-, transaction- and context-driven personalization. User-driven personalization refers to users specifying in advance the desired web layout and content that matches the tools and options provided (Tam & Ho, 2006). This kind of personalization enhances customer satisfaction and leads to a better overall experience (Sun & Zhang, 2021). Research also indicates that personalized demand significantly boosts customer retention and loyalty, as consumers feel more understood and valued.

Customization is the process of meeting the different preferences and personalized needs of different individual consumers; therefore, customization can also be interpreted as a set of solutions tailored to customers' specific needs and interests, and providing products or services for the personalized preferences of different customers (Shao, 2020). Due to technological advances, customizing one's own preferences has become more autonomous with the help from information technology and other means; therefore, customization can also be defined as a system that uses information technology to provide customers with a wide range of products and services for specific needs by constructing flexible design processes and organizational structures (Da Silveira et al., 2001). In addition to this, although the preferences of different consumers for customized products and services are highly heterogeneous and stylistically diverse, they have also been shown to be very attractive to consumers who could pay a significant premium and tolerate longer waiting times, which are the main reasons why companies are striving to upgrade their technological innovations to achieve mass customization (Jost & Süsser, 2020).

In the past, customization of products was oriented to individual consumers or groups with small-volume demand, and the production cost was high and difficult to be popularized. While in the digital age, production capacity and people's living standards have made rapid progress, and traditional mass production has been unable to meet the growing demand for personalization; in order to keep abreast of the times, the concept of mass customization came into being. Many scholars believe that mass customization is a mode by which manufacturing firms must accept and embrace globally in order to survive in a continuously dynamic and unstable environment (Ullah & Narain, 2018). Mass customization to some extent satisfies consumers' personalized needs, increases consumer loyalty to the brand, and enables firms to earn more profits and enhance their competitiveness.

2.2. Customer Demand Orientation and the Level of Digital Transformation

From the data-driven decision-making viewpoint, data is the basis for enterprise decision-making. Through digital intelligence technology, enterprises can better grasp the needs and expectations of customers as the basis for digital transformation and improve their level of digital intelligence. The digitalization of processes is beneficial since it transmits information in real time, allowing managers to correct problems more effectively and with less waste (Broday, 2022). In the era of digitalization, customer demand orientation has become an important factor affecting enterprises' level of digital intelligence. A certain level of process maturity can be put in relation to a certain innovation level and a certain level of digital change and an adaptable process could respond to changes in customer demands better (Sehlin et al., 2019). In the process of the market constantly calling on enterprises to improve their production quality and pay attention to consumer demand, enterprises have become more innovative in the process of being pushed forward (Fichman et al., 2014). Strengthening digital infrastructure can scale up the energy transition (Olugbenga, 2025). The challenge for a manufacturing company is not only how customer- or innovation-oriented it is, but also whether it is able to respond positively to market demands (Berthon et al., 2004) and adapt to changes in the market, which at this stage is becoming more and more personalized as people's standard of living improves and technological advances are made (Davenport et al., 2020). With regard to enterprises, once the target strategy oriented to customers' personalized needs is determined, they will attach great importance to finding ways that can provide customers with quality products and services, and in this process will also continuously promote technological innovation, which is key to the success of digital transformation (Dung & Duc, 2025).

The main mission of the enterprise is to make profits, and the main strategy to make profits is to be able to occupy enough market share. Most of the products produced by manufacturing enterprises have strong substitutability, forcing marginal returns lower and lower. As a result, how to stand out in the market has become the most important task of all enterprises. But large-scale customized production still has a large room to grow in the manufacturing industry; along with the improvement in the standard of living and consumption ability, consumers are increasingly focusing on their own personalized customization needs, and the ability of enterprises to achieve early mass customization of production will enable them in future to better capture the market. The higher the enterprise's degree of customer demand orientation, the more it will invest in upgrading its technology to better meet the personalised and customised needs of its customers, as digital transformation can improve the accuracy of demand forecasting (TRAN, 2025), correspondingly, the higher the level of its digital transformation will also be. Based on this, we formulate the following hypothesis:

Hypothesis 1: The degree of customer demand orientation will have a positive impact on the level of digital transformation of enterprises.

2.3. Industry Concentration

Industry concentration measures the degree of competition in an industry, which directly affects the enterprises' formulation of strategies and the implementation of plans. Environment significantly influences firms' investment decisions (Lueg & Borisov, 2014). Firms with market concentration and monopoly power have the financial support and risk prevention needed for R&D activities, and effective technological innovation activities will further enhance the monopoly power of the firms and secure monopoly rents. By analyzing data on firms from several countries, Cette et al. (2017) found that restricted competition significantly stimulates technological innovation and increases firms' productivity.

However, many scholars have questioned whether competition between firms has a positive effect on innovation, compared to the relatively inefficient management and low incentive to innovate of firms without competition. For example, Jiang et al. (2024) found that industry concentration enhances the positive impact of customer concentration on firm innovation performance.

Many studies on market competition and firm innovation provide an interesting insight that market competition has an inverted U-shaped effect on firm innovation (Aghion et al., 2005). In highly competitive industries, firms invest more in innovation in order to gain a relative competitive advantage. On the other hand, when firms are in a weak position to catch up with strong firms, too large a technology gap may cause them to engage in pendulum behavior.

A growing body of research suggests that a firm's strategic choices depend heavily on the nature of its external environment, the most important of which is the degree of competition among its industry peers (Rahmayati, 2021). When the market environment is very competitive, the variety of products available is more diversified, alternative products and services continue to emerge, the fierce competitive environment brings fewer market opportunities, and for firms, the profitability of homogeneous products is continually suppressed due to competition from peers (Dou et al., 2021). In order to maintain their competitive advantage, meeting customers' individual needs can help enterprises stand out better, and in this process, enterprises will continuously increase R&D investment in technological innovation, thus improving their degree of digital transformation.

Different industries have different degrees of competition, which also affects the willingness of enterprises to carry out digital transformation. For industries where enterprises are evenly matched, the more intense the competition is, the more attention these enterprises will pay to the customization and personalization needs of consumers, which can stimulate enterprises to carry out digital transformation. The higher the industry concentration, the less intense the competition within the industry. Therefore, we make the following hypothesis:

Hypothesis 2: Industry concentration negatively moderates the relationship between customer demand orientation and the level of digital transformation.

2.4. Investor Interaction Response

Based on H1, we tentatively believe that enterprises that pay attention to the personalized needs of customers have a higher degree of digital transformation, and rapid identification of external information can enable them to respond to changes in the market in a timelier manner; also, more efficient identification of the needs of customers and the ability of enterprises to acquire external knowledge can effectively promote corporate innovation. The interaction between investors and listed firms can effectively encourage managers to increase R&D investment and promote technological progress. Since technological change is a long-term uncertain and risky process, and has the characteristics of information asymmetry, it easily causes resistance from managers (Abdoh & Liu, 2021); and the openness of interactive e-platforms enables investors and corporate managers to better interact and communicate, and in the process of interaction, managers are able to better understand investor needs. If investors cannot provide timely solutions to issues related to production processes, technological innovation, etc. raised by investors, investors on the interactive platform may follow up with more questions; thereby generating the "spotlight effect". The "spotlight effect" will attract management's attention, both to stabilize investor confidence and to satisfy customer demand for products among investors, which will encourage managers to increase investment in innovation and R&D, and thus promote the level of digital transformation of the enterprise. If the firm does nothing, it may cause a large number of investors to pressure management by divesting their shares, thus strengthening their supervision (Reiter, 2021). We can therefore make the following hypothesis:

Hypothesis 3: Investor interaction response negatively moderates the relationship between customer demand orientation and the level of digital transformation.

3. Data and Methodology

3.1. Data

In this paper, we take the data of A-share listed manufacturing enterprises from 2010-2021 as a sample, and refer to the practice of existing studies, excluding the samples with missing main variables, with 16,783 effective observations to study the impact of enterprise customer demand orientation on the level of digital transformation. Financial data and corporate governance data are obtained from the CSMAR database, enterprise customer demand orientation is obtained from enterprise annual reports, and digital transformation data are obtained by crawling through enterprise annual reports and the patent network. Due to the high number of 0 values in CDO and LDT, and also to avoid the influence of outliers, we shrank the variables by 5% and 95%.

3.2. Measures

Porter et al. (2002) suggests enhancing traditional literature reviews by utilizing text mining's extensive research analysis methodology because "this extensive scanning of the contextual literature can extend the span of science by better connecting work in the research field".

Research overviews are made possible through sophisticated text-mining tools combined with modern search engines and scientific databases (Porter et al., 2002). Text mining allows for automated or partially automated processing of text; technically, it is the process of digitizing text documents and extracting patterns from them using common data mining techniques (Delen & Crossland, 2008).

3.2.1. Independent Variable

The independent variable of our research is CDO (customer demand orientation): CDO = num_CDO, where num_CDO is the frequency of keywords related to personalization, customization, and customer orientation. Through text analysis exploring key information in annual reports, we count the word frequency of keywords such as personalized, customized, and customer-oriented and take the logarithmic processing as the enterprise's score of customer demand orientation. (Data source: Annual reports of listed companies obtained after text analysis and processing).
Keyword phrases are shown in Table 1 below.

Table 1. Customer Demand Orientation Keywords.

Customer Demand Orientation
Personalization, User Needs, Customer Needs, Customer Demand, User Preferences, Customer Preferences, User Satisfaction, Customer Satisfaction, High-end Demand, Customization, DIY, Diy, Intelligent Services, Recommender Systems, User Models, E-commerce, Collaborative Filtering, Data Mining, Web Usage Mining, User Profiles, Ontology, Adapted, Information Retrieval, Privacy, Clustering, Situational Awareness, Internet, Machine Learning, Mass Customization, Product Families, Supply Chain Management, Platform Products, Genetic Algorithms, Modularity, Product Configurator, Product Development, Flexibility, Extension, Services, User Profiles, Case Studies, Design, Context-awareness

3.2.2. Dependent Variable

The dependent variable of this research is LDT (Level of digital transformation of Enterprises). The core of digital transformation is to solve the uncertainty of complex systems in an environment defined by data and algorithms by means of intelligent data services and other related technologies, so as to improve the efficiency of resource allocation and build the relative competitive advantage of enterprises. digital transformation is customer-centric, through the deep integration of digital technology with business, operations, management, and other aspects, to achieve the rapid delivery of data flow, the depth of value mining and creation, the cycle of iteration, and to re-construct a new value chain and digital ecology. For enterprises to carry out digital transformation is inevitable if they are to comply with the trend of the times; most enterprises are making an effort, to various degrees, to carry out digital transformation. How to measure the level of digital transformation of enterprises is a highlight of this paper.

Table 2. Digital Intelligence Readiness Metrics.

Variable	**Measurement**
CIO	Whether or not there is a Chief Information/Technology/Digital Officer, 0-1 dummy variable, standardized treatment
Forward_looking (Innovation-Oriented Forward-Looking)	2022 - year_first_report_digital Year of first occurrence of digital keywords in the MD&A section of the annual report, normalized
Sustainable (Innovation-Oriented Sustainability)	num_report_digital Total number of years with numerical keywords in the MD&A section of the annual report, normalized
Intensity (Intensity of Innovation Orientation)	digital_word/report_word Ratio of digitized keywords to the total number of words in the MD&A section of the annual report for each year, normalized to the total number of words in the section.

In this paper we measure the level of digital transformation from the following two perspectives: digital and intelligent readiness (DIR: Digital_intelligence_readiness) and contribution to digital intelligence (CDI: Contribution_to_digital_intelligence). Whether an enterprise has set up positions related to digital intelligence and whether it has taken digital transformation as a strategic goal are the most important reflections of an enterprise's digital transformation level. We calculate metrics to determine an enterprise's digital intelligence readiness, as seen in Table 2.

DIR = (CIO+Forward_looking+Sustainable+Intensity)/4 CDI = NUM_digital_patent, NUM_digital_patent is the normalized data of the number of digital intelligence-related patents obtained by enterprises every year.

We downloaded the patent data in the Guotai Junan csmar database and then searched for patents according to their patent codes on the PatentGuru (www.patentguru.com) website to obtain the abstract content of the patent introduction, analyze the text of the abstract to determine whether it is a patent related to digital and intelligence, and then sum up the number of digital and intelligence patents of the enterprise in the current year. The keywords of the digital and intelligence patents are shown in Table 3.

Table 3.
Digital and Intelligence Patent Keywords.

Digital and Intelligence Patents
Artificial Intelligence, AI, Business Intelligence, Image Understanding, Robotics, Machine Learning, Deep Learning, Semantic Search, Biometrics, Face Recognition, Speech Recognition, Identity Verification, Autonomous Driving, Natural Language Processing, NLP, Supervised Learning, machine translation, OCR, computer vision, machine vision, intelligent Q&A, expert systems, neural networks, automated reasoning, unmanned vehicles, drones, automated reasoning, driverless, unmanned vehicles, brain-computer interfaces, knowledge graphs, neuroscience, federated learning, automation, Gesture Recognition, Voice Interaction, Drones, Smart Driving, Digital Identity, RPA, Vehicle-Road Collaboration, Blockchain, Digital Currency, Smart Contracts, Distributed Digital Currency, Smart Contracts, Distributed Computing, Decentralization, Bitcoin, Coalition Chain, Differential Privacy, Consensus Mechanisms, Distributed Ledger, Public Chain, Cross-Chain, DLT, Cloud Computing, In-Memory Computing, Streaming Computing, Graph Computing, Multi-Party Secure Computing, Brain-Like Computing, Green Computing, Brain-like Computing, Cognitive Computing, Converged Architecture, Cloud Native, Privacy Computing, Edge Computing, BaaS, SaaS, IaaS, PaaS, Fog Computing, Cloud Services, Cloud-Network Convergence, Hybrid Cloud, Public Cloud, Cloud Technology, Cloud Storage, Cloud-Edge Collaboration, Distributed Architecture, Big Data, Data Mining, Text Mining, Data Visualization, Heterogeneous Data, Augmented Reality, Mixed Reality, Virtual Reality, Text Capture, AR, VR, MR, Data Analytics, Data Management, Cloud Platform, Anonymization, Internet of Things, Internet of Vehicles, IoT, Industrial Internet, Mobile Internet, Wireless Medical Networking, Wireless Access, Inter-vehicle Network, Smart Terminals, Smart Homes, Remote Monitoring, Mobile Terminals, Intelligent Control, Smart Factories, Digital Twins, Live Twins, Intelligent Transportation, BIM, CIM, 3D, 2D, 5G, 6G, LTE, Internet+, Quantum Secure Communication, Mobile Communication, Smart Grid, E-commerce, AGV, CNC Machine Tools, Digitization, Smart Hardware, Core Shield, Smart Wearable, Smart Manufacturing, Digital Model, Smart Construction, Smart Public Transportation, Intelligent, Digital Intelligence, Smart Ports, Smart Factories, Quantum Computing, FinTech, Supply Chain Finance, Smart Customer Service, Internet Finance, Digital Finance, Fintech, Cross-border Payment, Mobile Payment, NFC Payment, CAD, CAM, Investment Decision Aid System, Intelligent Data Analysis, Intelligent Robot, Biometrics, OCR Technology, CPO, Expert System, Learning Algorithms, Differential Privacy Technology, Billion Level Concurrency, EB Level Storage, Information Physical System, Artificial Intelligence Laboratory, Artificial Intelligence Platform, Artificial Intelligence Facility, Artificial Intelligence Equipment, Artificial Intelligence System, Intelligent Information System, Cloud Laboratory, Cloud System, Cloud Equipment, Cloud Facilities, Cloud Terminal, Cloud Community, Cloud Technology System, Big Data Lab, Big Data Platform, Big Data Facilities, Big Data Equipment, Big Data Information System, Big Data Technology System, Digital Patent, Digital Network, Digital Terminal, Digital Technology System, 3D Printing Equipment, Meta-Universe, Virtual Human, 3D Printing, 5G Technology, Mobile Internet, Digital Technology, Nano-computing, Intelligent Planning, Intelligent Optimization, Intelligent Marketing, Digital Marketing, Unmanned Retail, Unmanned Factory, Third Party Payment, NFC Payment, Human-Computer Interaction, Social Networking, Intelligent Agriculture, Intelligent Transportation, Intelligent Healthcare, Intelligent Investment, Intelligent Culture and Tourism, Intelligent Environmental Protection, Intelligent Energy, Internet Healthcare, Quantitative Finance, Open Banking, Netflix

Level of Digital Transformation (LDT): We sum the above readiness and contribution to the level of digital transformation (LDT). LDT = DIR+CDI

3.2.3. Moderating Variables

The moderating variables of our research are Reply_interval (Investor Interaction Response) and Industry Concentration (LernerIndex). The first moderating variable in this study is Reply_interval. Investor interaction response: ln(mean(answer_time - question_time)+1), answer_time for the enterprise to answer investor questions for the time, unit for the day, question_time for the investor question time, unit for the day.

The best data to measure the responsiveness of a company to its customers is based on the interaction between the company and its downstream customers, but the difficulty of obtaining this type of data, as well as the personalized differences between different companies can also make a big difference in the results (some companies have more mature system platforms, but some do not; however, there may be offline or even other ways to pay close attention to the personalized needs of customers); therefore, we decided to use the interaction time to measure the responsiveness of the company to its customers.), we therefore decided to approximate the response rate of firms to consumer comments through the interactions of investors and listed firms captured by the Interactive e platform, thus approximating the level of importance that firms attach to customer needs. We take the logarithm of the difference between investor comments and listed firms' response time by counting the difference between investor comments and listed firms' response time in each year, and then take the logarithm of the mean value as the response to investor interactions (Source: Guotai Junan csmar database).

The second moderating variable in this study is Industry Concentration. Measures of the degree of competition in a market are mainly divided into two types: objective measures and subjective evaluations. Objective measurement usually uses indicators such as industry concentration and Lerner index to quantify the actual level of market competition. On the other hand, subjective evaluation uses market questionnaires and other methods to obtain the subjective feelings of market players about the degree of market competition. These two methods have their own advantages and disadvantages. Subjective evaluation can reflect the intuitive views of market participants, while objective measurement focuses more on objective analysis through data and indicators. The combined use of these two methods can help us understand and assess the state of competition in a more comprehensive manner. Objective measures often use industry concentration, Lerner index and other related indicators to measure the intensity of competition in the market. Meanwhile, some scholars also use instrumental variables such as trade policy changes and tariff changes to replace the level of market competition. However, all these indicators are somewhat one-sided in measuring the level of market competition.

In this paper, we adopt the industry Lerner index. The industry Lerner index (also known as the industry concentration index) is a measure of the degree of monopoly of manufacturers in an industry, which assesses the market dominance of different manufacturers in an industry by comparing their output or sales. The advantage of the Industry Lerner Index is that it provides a visual measure of the degree of market monopoly and can be used to compare the market structure between different industries. In addition, the industry Lerner index can also reflect the potential monopoly power of manufacturers in the industry.

LernerIndex [Industry Lerner Index]: $si/\sum_0^n si$*Lerner_stock, obtained by weighting the Lerner Index of individual stocks using the ratio of operating income of individual companies to the operating income of individual industries.

si: Operating income of individual company

$\sum_0^n si$: Total operating income in the industry

Lerner_stock: Individual stock Lerner index cumulative

3.2.4. Control Variables

Some company-level factors that may affect the dependent variable are included. The definition of control variables (Shou et al., 2021) is shown in Table 4.

Table 4. Summary of Variable Measures.

Variable Name	Variable Symbol	Variable-Specific Measures
Customer Demand Orientation	CDO	LN(1+num_CDO), where num_CDO is the number of personalization-related word frequencies in the annual report.
Investor Interactive Response	Reply_interval	LN (1+qa_time), where qa_time is the mean value of the annual investor Q&A intervals.
Industry Concentration	LernerIndex	Individual Company Operating Income / Total Industry Operating Income * Individual Lerner Index Cumulative, obtained by weighting the Individual Lerner Index using the ratio of Individual Company Operating Income to Individual Industry Operating Income.
Level of digital transformation of Enterprises	LDT	Digital Intelligence Patents and Digital Intelligence Readiness Weighting
Firm Size	Size	LN (firm's total assets at year-end)
Firm Age	Age	LN (the number of years since the firm's incorporation)
Revenue Growth Rate	Growth	(current period amount of operating income for the current year - amount of operating income for the same period of the previous year) / (amount of operating income for the same period of the previous year)
State Ownership of Enterprise	SOE	1: state-owned; 0: non-state-owned
Leverage	Leverage	total liabilities at year-end/total assets at year-end
Return on Assets	ROA	net profit at the end of the year/total assets at the end of the year
Total Asset Turn Over	TATO	year-end sales revenue/year-end total assets
Book-To-Market Ratio	MTB	shareholders' equity/market capitalization
Tobin's Q	Tobin's Q	market capitalization A/ total assets
Share of Tangible Assets	Tangibility	(total assets - net intangible assets - net goodwill) / total assets

3.3. Regression Specification

We used spspro statistical analysis software to analyze the model selection for the hypotheses we wanted to test, and the Table 5 are illustrated as follows: based on the results of the model selection in the table above, the three tests were combined to select the most appropriate model.

Table 5. Measurement model selection.

Type of Test	Statistic	P	Conclusion
F-test	23.825	0.000***	FE model
Breusch-Pagan test	173453.271	0.000***	RE model
Hausman test	957.336	0.000***	FE model

Note: ***、**、*represent 1%, 5%, and 10% significance levels respectively.

The sample of this paper is selected as the data of manufacturing industry of A-share listed companies from 2010 to 2021, which is a panel data type. Therefore, for the empirical model of this paper, we choose the time individual fixed effect model, which can effectively remove the influence of year and enterprise. Meanwhile, because the research contains two moderating variables, in order to prevent the existence of multicollinearity between the independent variables and the moderating variables as well as the interaction terms, the independent variables and the two moderating variables are centered, and the interaction terms are constructed afterwards.

Firstly, in order to test the relationship between the core explanatory variables of this paper, customer demand orientation and the level of digital transformation, the following econometric regression model 1 is constructed.

$$\begin{aligned} LDT_{i,t} = {} & \alpha_0 + \beta_1 CDO_{i,t} + \beta_2 Age_{i,t} + \beta_3 Size_{i,t} + \beta_4 SOE_{i,t} + \beta_5 Growth_{i,t} + \beta_6 Leverage_{i,t} + \beta_7 ROE_{i,t} + \beta_8 TATO_{i,t} \\ & + \beta_9 MTB_{i,t} + \beta_{10} Tobin's\ Q_{i,t} + \beta_{11} Tangibility_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \end{aligned}$$

(Model 1)

where α_0 denotes the constant term; β_i denotes the coefficients to be estimated for the explanatory variables; i and t denote enterprise i and year t, respectively; $\varepsilon_{i,t}$ denotes the residual term; τ_t denotes the time fixed effect, and μ_i is the individual fixed effect.

In order to verify the possible moderating effect of industry concentration and response speed, we introduce the two variables of industry concentration (industry Lerner index) and investor interaction response speed as the moderating variables to construct Model 2 and Model 3 on the basis of the existing Model 1, and conduct a regression test by adding the moderating variables and interaction terms between the moderating variables and the customer demand orientation on the basis of Model 1. The regression test is conducted by adding the moderating variable and the interaction term between the moderating variable and customer demand orientation to Model 1, respectively, and the significance of the correlation coefficients is used to verify the moderating role of the moderating variable in the relationship between the customer demand orientation and the level of digital transformation. Model 2 and Model 3 are shown below:

$$LDT_{i,t} = \alpha_0 + \gamma_1 CDO_{i,t} + \gamma_2 Lernerindex_{i,t} + \gamma_3 CDO_{i,t} \times Lernerindex_{i,t} + \gamma_4 Age_{i,t} + \gamma_5 Size_{i,t} + \gamma_6 SOE_{i,t} + \gamma_7 Growth_{i,t} + \gamma_8 Leverage_{i,t} + \gamma_9 ROE_{i,t} + \gamma_{10} TATO_{i,t} + \gamma_{11} MTB_{i,t} + \gamma_{12} Tobin's\ Q_{i,t} + \gamma_{13} Tangibility_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \quad \text{(Model 2)}$$

$$LDT_{i,t} = \alpha_0 + \eta_1 CDO_{i,t} + \eta_2 Reply\_speed_{i,t} + \eta_3 CDO_{i,t} \times Reply\_speed_{i,t} + \eta_4 Age_{i,t} + \eta_5 Size_{i,t} + \eta_6 SOE_{i,t} + \eta_7 Growth_{i,t} + \eta_8 Leverage_{i,t} + \eta_9 ROE_{i,t} + \eta_{10} TATO_{i,t} + \eta_{11} MTB_{i,t} + \eta_{12} Tobin's\ Q_{i,t} + \eta_{13} Tangibility_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \quad \text{(Model 3)}$$

4. Results

4.1. Main Effect Regression Results

Summary statistics (means, standard deviations, and pairwise correlations) for all variables are provided in Table 6. The variance inflation factor (VIF) values of the regression models are all less than 10 and the correlation coefficients between the variables are all well below 0.7, suggesting that multicollinearity is not a concern.

Table 6. Descriptive Statistics and Correlations.

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1. CDO	0	0.67													
2. LernerIndex	0	0.06	.06												
3. Reply_interval	0	1.23	.04	.08											
4. Age	2.87	0.34	.05	.20	.14										
5. Size	21.98	1.17	.11	.01	.24	.23									
6. SOE	0.24	0.42	-.05	-.07	.13	.21	.34								
7. Growth	0.12	0.21	.06	.05	-.02	-.06	.02	-.09							
8. Leverage	1.34	1.02	-.07	-.10	.04	.05	.18	.16	-.11						
9. ROA	0.09	0.08	.00	.15	.04	.03	.10	-.05	.18	-.24					
10. TATO	0.63	0.38	-.04	-.16	.03	.08	.15	.11	.06	.01	.19				
11. MTB	0.36	0.16	-.08	.01	-.08	-.11	-.07	-.11	-.11	-.17	-.19	-.08			
12. Tobin's Q	2.11	1.26	.03	.09	.01	.02	-.24	-.07	.06	-.14	.22	-.06	-.63		
13. Tangibility	0.93	0.08	-.09	-.04	.04	.00	-.03	.09	-.11	.00	.08	.13	.01	-.01	
14. LDT	-0.08	1.40	.64	.03	.08	.13	.21	-.16	.03	-.05	-.01	-.05	-.13	.05	-.08

Through the above analysis, we took the time individual fixed effect model and used the OLS regression model for regression analysis so as to verify our hypothesis. In the study of customer demand orientation on the level of digital transformation, we used three models: Model 1, Model 2, and Model 3. Model 1 verifies the effect of customer demand orientation on the level of digital transformation of enterprises. In Model 2, the interaction of industry concentration with customer demand orientation is added to verify the moderating effect of industry concentration on the relationship between customer demand orientation and the level of digital transformation. In Model 3, the interaction of investor interaction response speed with customer demand orientation is added to verify the moderating effect of investor interaction response speed on the level of digital transformation. The specific regression model is shown in Table 7.

Table 7. Main Effect Regression Results.

Variable	Model 1		Model 2		Model 3	
Age	-0.041	(0.038)	-0.036	(0.038)	-0.041	(0.038)
Size	0.032***	(0.006)	0.033***	(0.006)	0.032***	(0.006)
SOE	0.007	(0.012)	0.009	(0.012)	0.007	(0.012)
Growth	-0.012	(0.009)	-0.013	(0.009)	-0.012	(0.009)
Leverage	-0.004*	(0.002)	-0.004**	(0.002)	-0.004*	(0.002)
ROA	0.003	(0.026)	0.007	(0.026)	0.003	(0.026)
TATO	0.017*	(0.01)	0.019*	(0.01)	0.017	(0.01)
MTB	-0.018	(0.022)	-0.019	(0.022)	-0.017	(0.022)
Tobin's Q	0	(0.002)	0	(0.002)	0	(0.002)
Tangibility	0.091***	(0.033)	0.093***	(0.033)	0.093***	(0.033)
CDO	0.201***	(0.004)	0.202***	(0.004)	0.201***	(0.004)
LernerIndex			-0.321***	(0.093)		
CDO*LernerIndex			-0.248***	(0.067)		
Reply_interval					0	(0.002)
CDO*Reply_interval					-0.004*	(0.003)
const	-0.752***	(0.174)	-0.78***	(0.174)	-0.749***	(0.174)
F	358.813***		309.987***		304.397***	

We use two-tailed tests for all of our regressions, among which * represents p <0.10, ** represents p <0.05, and *** represents p < 0.01 for Table 7 through to Table 10.

Model 1 is mainly to verify the influence of customer demand orientation on the level of digital transformation of enterprises. The regression analysis results in the above figure show that the coefficient of customer demand orientation (CDO; 0.201) is significantly positive at the 1% level, which indicates that the more attention is paid to customer demand, the higher the level of digital transformation of the enterprise, and hypothesis 1 is supported. Enterprises with strong customer demand orientation tend to introduce innovative digital technologies to meet the personalized needs of different customers more flexibly. With the introduction of AI technologies, companies are able to intelligently design and customize products according to customers' individual needs, improving the level of product personalization.

Model 2 mainly verifies the moderating effect of industry concentration on the relationship between customer demand orientation and the level of digital transformation of enterprises. We can find that the coefficient of the LernerIndex is -0.321 and the corresponding P-value is 0.001***, which indicates that when the competition in the industry is more intense, enterprises will try to improve their production technology in order to obtain competitive advantages, and thus improve their level of digital transformation. In order to further verify the moderating effect of industry concentration, we introduce the variable CDO *LernerIndex, and we find that its coefficient is -0.248 and the corresponding P-value is 0.000***, so we can draw the following conclusions that H2 is supported, and industry concentration can negatively modulate the effect of the orientation of customer demand orientation on the level of digital transformation.

When the competitive ability between enterprises in the industry is similar, in the face of customer demand, only the enterprises that take the lead in meeting customer demand more efficiently through technological transformation can achieve competitive advantage; therefore, in a fiercely competitive environment, customer demand orientation stimulates enterprises more to carry out digital transformation. Intense competition under low industry concentration forces enterprises to seek differentiation and innovation to stand out in the market. This competitive pressure prompts enterprises to pay more attention to the personalized needs of customers, thus promoting digital transformation. In a competitive market, customers have more choices, so enterprises are more willing to listen to and satisfy customer demand, and provide customized services through digital technology to gain market share.

Model 3 verifies the moderating role of investor interactive response in the relationship between customer demand orientation and the level of digital transformation of enterprises. Through the above analysis results, we can find that the coefficient corresponding to CDO * Reply_interval is -0.004 and the corresponding P-value is 0.000*, which suggests that the shorter the response time of the enterprise to investor questions, the more effective the promotion of customer demand orientation on the level of digital transformation. We can conclude that H3 holds that the faster the response time to investor interactions of listed companies, the more effective they can be in promoting the impact of customer demand orientation on the level of digital transformation.

A faster response rate of investor interaction helps to reduce the information asymmetry between enterprises and investors, which makes enterprises more aware of market demand and investor concerns. Reducing information asymmetry helps enterprises more accurately grasp market dynamics, better meet customer demand, and promote the in-depth implementation of digital transformation. Rapidly responding to investor opinions and issues enables companies to adjust their strategies more quickly and better adapt to market demand. Faster strategic adjustments enable companies to meet customer demand more flexibly, thus promoting the smooth implementation of digital transformation.

4.2. Causality Test

In order to conduct a reverse causality test for the effect of CDO on LDT, we select the last three years of data in 2020 to conduct a Granger causality test with a lag order of 2. The results of the ADF test can be seen in Table 8.

Table 8. ADF Test Results.

Variable	t	p	Threshold Value		
			1%	5%	10%
CDO	-5.083	0.000***	-3.435	-2.864	-2.568
LDT	-20.15	0.000***	-3.435	-2.864	-2.568

Based on the variable CDO shrinkage treatment, the significance P-value is 0.000***, presenting significance and rejecting the original hypothesis that the series is a smooth time series. Based on the variable LDT, the significance p-value is 0.000***, presenting significance and rejecting the original hypothesis that the series is a smooth time series. Granger causality tests were conducted on CDO and LDT and the results of the tests are shown in Table 9.

Table 9. Granger Causality Test Results.

Matched Sample		F	p
CDO	LDT	6.774	0.001***
LDT	CDO	0.203	0.816

Based on the variable CDO with LDT, the significance p-value is 0.001***, presenting significance and rejecting the original hypothesis, that CDO can cause changes in LDT. Based on the variable LDT with CDO, the significance p-value is 0.816, which does not present significance, and the original hypothesis cannot be rejected, i.e., LDT cannot cause changes in CDO. Therefore, there is no reverse causality between CDO and LDT.

4.3. Robustness Checks

In order to avoid the problem of endogeneity to affect the results, we changed the measure of the outcome variables to avoid the problem of endogeneity.

Considering that there are various ways to measure the level of digital transformation, different measures may affect this paper's results. In order to further calibrate the robustness of the model, we chose the digital transformation index in the CSMAR database to replace our outcome variables. The regression results are shown in Table 10.

Table 10. Robustness Check Results.

Variable	Model 4		Model 5		Model 6	
Age	-0.011	(0.019)	-0.008	(0.019)	-0.011	(0.019)
Size	0.032***	(0.003)	0.033***	(0.003)	0.032***	(0.003)
SOE	-0.004	(0.006)	-0.003	(0.006)	-0.004	(0.006)
Growth	-0.012***	(0.004)	-0.013***	(0.004)	-0.012***	(0.004)
Leverage	-0.003***	(0.001)	-0.003***	(0.001)	-0.003***	(0.001)
ROA	-0.014	(0.012)	-0.009	(0.012)	-0.014	(0.012)
TATO	0.011**	(0.005)	0.012**	(0.005)	0.011**	(0.005)
MTB	-0.028***	(0.011)	-0.03***	(0.011)	-0.028**	(0.011)
Tobin's Q	0	(0.001)	0	(0.001)	0	(0.001)
Tangibility	-0.02	(0.016)	-0.019	(0.016)	-0.018	(0.016)
CDO	0.101***	(0.002)	0.102***	(0.002)	0.101***	(0.002)
LernerIndex			-0.308***	(0.046)		
CDO*LernerIndex			-0.108***	(0.034)		
Reply_interval					0.001	(0.001)
CDO*Reply_interval					-0.003**	(0.001)
const	2.934***	(0.086)	2.912***	(0.086)	2.94***	(0.086)
F	358.813***		309.987***		304.397***	

Model 4. The coefficient (0.101) of customer demand orientation (CDO) is significantly positive at the 1% level, further verifying that H1 holds;

Model 5. The coefficient of CDO*LernerIndex (-0.108) is significantly negative at the 1% level, further verifying that H2 holds;

Model 6. The coefficient of CDO*Reply_interval (-0.003) is significantly negative at the 5% level, further verifying that H3 holds.

5. Discussion and Limitations

In today's market environment, customer demand orientation has become an important driving force for the digital transformation of enterprises. This paper focuses on the impact of firms' customer demand orientation on the level of digital transformation with two moderating variables incorporated: industry concentration and investor interaction response respectively. We summarized our findings as follows:

Firstly, the degree of customer demand orientation positively affects the level of digital transformation. The higher the degree of customer demand orientation, the higher the level of digital transformation of enterprises. Against the backdrop of the increasing speed of product renewal and iteration, enterprises pay more and more attention to customers' personalized needs. To meet these needs, enterprises need to continuously upgrade technology, optimize business and production processes, and improve their digital transformation level.

Secondly, industry concentration negatively moderates the relationship between customer demand orientation and the level of digital transformation. The lower the industry concentration, the more intense the competition within the industry, and the more it can strengthen the impact of customer demand orientation on the level of enterprises' digital transformation. In industries with lower industry concentration, enterprises face more intense competition, and in order to stand out from the competition, they need to respond to customers' personalized needs faster and more efficiently, so as to win market share.

Finally, investor interactive response negatively moderates the relationship between customer demand orientation and the level of digital transformation. Shorter and faster response time of investor interaction of listed firms can effectively promote the impact of customer demand orientation on their digital transformation level. Investor interaction is one of the important ways for enterprises to obtain market feedback, and the interval time of investor interaction Q&A is an important indicator of enterprises' market feedback, reflecting the timeliness of their access to external information.

While summarizing the above research results, we also need to acknowledge the limitations of this research. First of all, the influence mechanism of factors such as customer demand orientation, industry concentration, and the response speed of listed companies' investor interaction on the level of digital transformation needs to be further explored; our measurement of the market response speed of enterprises is relatively rough; and the use of investor Q&A response time to measure the speed of enterprises' acquisition of external information is not precise enough. Secondly, the focus of this study is mainly on the analysis of the current situation, and future development trends and possible solutions have not been explored in depth. In addition, the generalizability to different industries, different types of enterprises, and different regions needs to be further explored.

References

Abdoh, H., & Liu, Y. (2021). Does R&D intensity matter in the executive risk incentives and firm risk relationship? *Economic Modelling, 96*, 13–24. https://doi.org/10.1016/j.econmod.2020.12.007

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics, 120*(2), 701–728. https://doi.org/10.1093/qje/120.2.701

Alt, R., Ehmke, J. F., Haux, R., Henke, T., Mattfeld, D. C., Oberweis, A., … Winter, A. (2019). Towards customer-induced service orchestration: Requirements for the next step of customer orientation. *Electronic Markets, 29*(1), 79–91. https://doi.org/10.1007/s12525-018-0305-y

Berthon, P., Hulbert, J. M., & Pitt, L. (2004). Innovation or customer orientation? An empirical investigation. *European Journal of Marketing, 38*(9/10), 1065–1090. https://doi.org/10.1108/03090560410548948

Broday, E. E. (2022). The evolution of quality: From inspection to quality 4.0. *International Journal of Quality and Service Sciences, 14*(3), 368–382. https://doi.org/10.1108/IJQSS-03-2021-0045

Cette, G., Lopez, J., & Mairesse, J. (2017). Upstream product market regulations, ICT, R&D and productivity. *Review of Income and Wealth, 63*(S1), S68–S89. https://doi.org/10.1111/roiw.12269

Da Silveira, G., Borenstein, D., & Fogliatto, F. S. (2001). Mass customization: Literature review and research directions. *International Journal of Production Economics, 72*(1), 1–13. https://doi.org/10.1016/S0925-5273(00)00079-7

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48*, 24–42. https://doi.org/10.1007/s11747-019-00696-0

Delen, D., & Crossland, M. D. (2008). Seeding the survey and analysis of research literature with text mining. *Expert Systems with Applications, 34*(3), 1707–1720. https://doi.org/10.1016/j.eswa.2007.01.029

Dou, W. W., Ji, Y., & Wu, W. (2021). Competition, profitability, and discount rates. *Journal of Financial Economics, 140*(2), 582–620. https://doi.org/10.1016/j.jfineco.2020.11.010

Dung, N. N., & Duc, P. M. (2025). Digital transformation strategy in the logistics sector of emerging markets: A case study of Indotrans, Vietnam. *Asian Business Research Journal, 10*(7), 60–66.

Fichman, R. G., Dos Santos, B. L., & Zheng, Z. (2014). Digital innovation as a fundamental and powerful concept in the information systems curriculum. *MIS Quarterly, 38*(2), 329–353. https://doi.org/10.25300/MISQ/2014/38.2.01

Ghouri, A. M., Akhtar, P., Haq, M. A., Mani, V., Arsenyan, G., & Meyer, M. (2021). Real-time information sharing, customer orientation, and the exploration of intra-service industry differences: Malaysia as an emerging market. *Technological Forecasting and Social Change, 167*, 120684. https://doi.org/10.1016/j.techfore.2021.120684

Ho, S. Y. (2006). The attraction of internet personalization to web users. *Electronic Markets, 16*(1), 41–50. https://doi.org/10.1080/10196780500491350

Jiang, M., Fang, J., Yang, Y., Yu, C., & Li, J. (2024). Supply chain concentration, industry concentration and enterprise innovation performance. *Finance Research Letters, 63*, 105394. https://doi.org/10.1016/j.frl.2024.105394

Jost, P. J., & Süsser, T. (2020). Company–customer interaction in mass customization. *International Journal of Production Economics, 220*, 107454. https://doi.org/10.1016/j.ijpe.2019.07.034

Kiffin-Petersen, S. A., & Soutar, G. N. (2020). Service employees' personality, customer orientation and customer incivility. *International Journal of Quality and Service Sciences, 12*(3), 281–296. https://doi.org/10.1108/IJQSS-09-2019-0119

Lueg, R., & Borisov, B. G. (2014). Archival or perceived measures of environmental uncertainty? Conceptualization and new empirical evidence. *European Management Journal, 32*(4), 658–671. https://doi.org/10.1016/j.emj.2013.12.004

Olugbenga, A. F. (2025). Harnessing fintech innovations for renewable energy: Revolutionizing investment models to achieve Sustainable Development Goal 7. *Asian Business Research Journal, 10*(7), 92–104.

Porter, A. L., Kongthon, A., & Lu, J. C. (2002). Research profiling: Improving the literature review. *Scientometrics, 53*(3), 351–370. https://doi.org/10.1023/A:1014873029258

Rahmayati, R. (2021). Competition strategy in the Islamic banking industry: An empirical review. *International Journal of Business, Economics, and Social Development, 2*(2), 65–71. https://doi.org/10.46336/ijbesd.v2i2.164

Reiter, N. (2021). Investor communication and the benefits of cross-listing. *Journal of Accounting and Economics, 71*(1), 101356. https://doi.org/10.1016/j.jacceco.2021.101356

Schweidel, D. A., Bart, Y., Inman, J. J., Stephen, A. T., Libai, B., Andrews, M., … Thomaz, F. (2022). How consumer digital signals are reshaping the customer journey. *Journal of the Academy of Marketing Science, 50*(6), 1257–1276. https://doi.org/10.1007/s11747-022-00865-1

Sehlin, D., Truedsson, M., & Cronemyr, P. (2019). A conceptual cooperative model designed for processes, digitalisation and innovation. *International Journal of Quality and Service Sciences, 11*(4), 504–522. https://doi.org/10.1108/IJQSS-05-2018-0043

Shao, X.-F. (2020). What is the right production strategy for horizontally differentiated product: Standardization or mass customization? *International Journal of Production Economics, 223*, 107527. https://doi.org/10.1016/j.ijpe.2019.107527

Shou, Y., Shao, J., & Wang, W. (2021). How does reverse factoring affect operating performance? An event study of Chinese manufacturing firms. *International Journal of Operations & Production Management, 41*(4), 289–312. https://doi.org/10.1108/IJOPM-12-2019-0833

Sun, X., & Zhang, Q. (2021). Building digital incentives for digital customer orientation in platform ecosystems. *Journal of Business Research, 137*, 555–566. https://doi.org/10.1016/j.jbusres.2021.08.038

Tam, K. Y., & Ho, S. Y. (2006). Understanding the impact of web personalization on user information processing and decision outcomes. *MIS Quarterly, 30*(4), 865–890. https://doi.org/10.2307/25148757

Tran, N. T. M. (2025). Navigating digital disruption in emerging markets: The mediating role of demand forecasting accuracy in big data analytics capabilities–supply chain performance relationships within Vietnam's fashion e-commerce ecosystem. *Asian Business Research Journal, 10*(7), 10–22.

Ullah, I., & Narain, R. (2018). Analysis of interactions among the enablers of mass customization: An interpretive structural modelling approach. *Journal of Modelling in Management, 13*(3), 626–645. https://doi.org/10.1108/JM2-02-2017-0018

Zannat, M., Iqbal, T., & Tasnim, T. (2024). The perception and approach of Bangladeshi ready-made garment factory in the current context of digital marketing. *Asian Business Research Journal, 9*, 72–82.